28

November

Luleå, Sweden

MPMM 2016

MAINTENANCE PERFORMANCE MEASUREMENT & MANAGEMENT

Editors

Galar D.

Seneviratne D.

CONFERENCE PROCEEDINGS

Proceedings of MPMM 2016

6th International Conference on
Maintenance Performance Measurement and Management,
28 November 2016, Luleå, Sweden

Editors:

Diego Galar, Dammika Seneviratne

Organized by:

Division of Operation and Maintenance Engineering, Luleå University of Technology

Published by:

Luleå University of Technology www.ltu.se
ISBN 978-91-7583-841-0

Introduction

The maintenance function is inherent to production, but its activities are not always understood or quantified. A characteristic of maintenance is that its activity involves more than a group of people or a workshop and goes beyond the limits of a traditional department.

The scope of maintenance in a manufacturing environment is illustrated by its various definitions. British Standards Institute defines maintenance as a combination of all technical and associated administrative activities required to keep equipment, installations and other physical assets in the desired operating condition or restore them to this condition, some authors indicate that maintenance is about achieving the required asset capabilities within an economic or business context, or consists of the engineering decisions and associated actions necessary and sufficient for the optimization of specified equipment 'capability' where capability is the ability to perform a specified function within a range of performance levels that may relate to capacity, rate, quality, safety and responsiveness. However, they all agree that the objective of maintenance is to achieve the agreed-upon output level and operating pattern at minimum resource cost within the constraints of system condition and safety.

We can summarize the maintenance objectives under the following categories: ensuring asset functions (availability, reliability, product quality etc.); ensuring design life; ensuring asset and environmental safety; ensuring cost effectiveness in maintenance; ensuring efficient use of resources (energy and raw materials). For production equipment, ensuring the system functions as it should is the prime maintenance objective. Maintenance must provide the required reliability, availability, efficiency and capability of production systems. Ensuring system life refers to keeping the equipment in good condition to achieve or prolong its designed life. In this case, cost has to be optimized to achieve the desired plant condition. Asset safety is very important, as failures can have catastrophic consequences. The cost of maintenance has to be minimized while keeping the risks within strict limits and meeting the statutory requirements.

For a long time, maintenance was carried out by the workers themselves, in a more loosely organized style of maintenance with no haste for the machinery or tools to be operational again. However, things have changed.

- First, there is a need for higher asset availability. With scale economies dominating the global map, the demand for products is increasing. However, companies suffer financially from the costs of expansion, purchase of industrial buildings, production equipment, acquisitions of companies in the same sector, and so on. Productive capacities must be kept at a maximum, and organizations are beginning to worry about keeping track of the parameters that may affect the availability of their plants and machinery.
- The second concern follows from the first. When organizations begin to optimize their production costs and create cost models attributable to the finished product, they start to question maintenance cost. This function has grown to include assets, personnel etc., consuming a significant percentage of the overall organization budget. Therefore, when companies are establishing policies to streamline costs, the question of the maintenance budget arises, followed by questions about the success of this budget. They start to consider availability and quality parameters.

A question that has haunted maintenance throughout history now appears: how do we maximize availability at the lowest cost? To answer this question, various methodologies, technologies and batteries of indicators are being developed to observe the impacts of improvements.

The need to measure maintenance performance

Organizations are under pressure to continually enhance their ability to create value for their customers and improve the cost effectiveness of their operations. In this regard, the maintenance of large-investment assets, once thought to be a necessary evil, is now considered a key function for improving the cost effectiveness of operations and creating additional value by delivering better and more innovative services to customers.

With the change in strategic thinking of organizations, the increasing amount of outsourcing and the separation of OEMs and asset owners, it is crucial to measure, control and improve the asset maintenance performance. Today, with the advances in technology, various maintenance strategies have evolved, including condition based maintenance, predictive maintenance, remote-maintenance, preventive maintenance, e-maintenance etc. A main challenge faced by most organizations is choosing the most efficient and effective strategies to enhance and continually improve operational capabilities, reduce maintenance costs and achieve competitiveness in the industry. Therefore, in addition to formulating maintenance policies and strategies for asset maintenance, it is equally important to evaluate the efficiency and effectiveness of these maintenance strategies by measuring their performance.

Maintenance Performance Measurement (MPM) is defined as 'the multidisciplinary process of measuring and justifying the value created by maintenance investment, and taking care of the organization's stockholder's requirements viewed strategically from the overall business perspective. It is considered an important element in understanding the value created by maintenance, re-evaluating and revising the maintenance policies and techniques, justifying investments in the adaption of new trends and techniques in providing maintenance services, revising resource allocations, understanding the effect of maintenance on other functions and stakeholders as well as on health and safety etc.

Unfortunately, these maintenance metrics have been often misinterpreted and are incorrectly used in many companies. The metrics should not be used to show the workers they are not doing their jobs. They should not be used to satisfy anyone's ego; i.e. to show that the company is working well. Performance measurements, when used properly, should highlight opportunities for improvement while also detecting problems and, ultimately, helping to find a solution.

The most relevant issue is that maintenance is seen in industry as a necessary evil, an expense or loss the organization must incur to keep its production process operative. Because of this, the priorities of many companies do not typically focus on maintaining their assets, but on production. The use of objective indicators which allow these processes to be evaluated can help to correct deficiencies and increase the production of an industrial plant. Many of these indicators may relate the costs of maintaining equipment to production or sales; others make it possible to determine whether the availability is adequate and/or what factors should be modified to achieve its increase.

This historical maintenance view mixed with traditional issues of performance measurement creates problems in developing and implementing a comprehensive package of maintenance performance management. These problems include the human factor in selecting a measurement metric, the application of the metric and the later use of the produced measurement, not to mention the need for a delineation of responsibilities in the process.

Preface

Today, it is a challenge to develop suitable maintenance strategies with the development of new technologies. Initiating strategies and legislation, based on a holistic view of the maintenance process, combined with emerging technologies and Information & Communication Technologies (ICT), gives corporate management a decision making tools to maximize the result of investments made to anticipate and mitigate the need for maintenance.

This proceedings for the "6th International Conference on Maintenance Performance Measurement and Management -2016 (MPMM)", includes pares under six themes, which are closely related to the subject area of MPMM. The themes are Asset Management, Big Data in Maintenance, Condition Monitoring, Performance Measurement, Fleet Management and New Technology and Solutions. The breadth of the thematic coverage of the MPMM 2016 contributions constitutes further evidence that maintenance is a wide and interdisciplinary area that leverages on a blend of technology, engineering and management methodologies in order to provide decisive contribution to enterprise business goals. As blending technology, engineering and management is a relevant means "to go beyond", we believe that this conference and collection of papers provide an important contribution to the maintenance discipline.

The organizing committee of the MPMM 2016 awarded the first MPMM lifetime achievement award to Jan Frånlund, the honorary Chairman of the Swedish National Maintenance Society for his contribution to the field of maintenance.

The editors would like to thank all participants, authors and reviewers for their active involvement and support, ScAIEM 2016 for sponsoring MPMM2016 and making the conference a successful event.

Diego Galar, Dammika Seneviratne
Editors

MPMM lifetime achievement award presented to Jan Frånlund by Prof. Uday Kumar, Chaired Professor, operation and maintenance division, Luleå University of Technology, Luleå.

Organization

Conference Organizers:

The conference is organised by Division of Operation and Maintenance Engineering of Luleå University of Technology

Chairpersons

- Diego Galar, General Chairman
- Uday Kumar, Co-Chairman
- Timo Kärrir, Co-Chairman
- Jose Manuel Torrs Farinha, Co-Chairman
- David Baglee, Co-Chairman
- Esko Juuso, Co-Chairman

Local Organizing Committee

- Dammika Seneviratne, Luleå University of Technology

Table of Contents

Index of Authors

Chapter 1: Keynote Presentations

ISBN 978-91-7583-841-0

Intelligent performance analysis with a natural language interface

Esko K. Juuso
esko.juuso@oulu.fi;
Control Engineering, Faculty of Technology
University of Oulu, Finland

***Abstract*— Performance improvement is taken as the primary goal in the asset management. Advanced data analysis is needed to efficiently integrate condition monitoring data into the operation and maintenance. Intelligent stress and condition indices have been developed for control and condition monitoring by combining generalized norms with efficient nonlinear scaling. These nonlinear scaling methodologies can also be used to handle performance measures used for management since management oriented indicators can be presented in the same scale as intelligent condition and stress indices. Performance indicators are responses of the process, machine or system to the stress contributions analyzed from process and condition monitoring data. Scaled values are directly used in intelligent temporal analysis to calculate fluctuations and trends. All these methodologies can be used in prognostics and fatigue prediction. The meanings of the variables are beneficial in extracting expert knowledge and representing information in natural language. The idea of dividing the problems into the variable specific meanings and the directions of interactions provides various improvements for performance monitoring and decision making. The integrated temporal analysis and uncertainty processing facilitates the efficient use of domain expertise. Measurements can be monitored with generalized statistical process control (GSPC) based on the same scaling functions.**

Keywords—Data analysis, nonlinear scaling, trend analysis, fuzzy systems, natural language.

I. INTRODUCTION

Advanced data analysis is used to integrate process and condition monitoring measurements. Dimensionless indices, which are obtained by comparing each feature value with the corresponding value in normal operation, provide useful information on different faults, and even more sensitive solutions can be obtained by selecting suitable features [1]. Generalized moments and norms include many well-known statistical features as special cases and provide compact new features capable of detecting faulty situations. A combination of real order derivatives and generalized norms [2] can be used in various applications [3]. Intelligent indices are developed from these features by the data-based nonlinear scaling introduced in [4].

There are many ways to measure, monitor and analyse maintenance and operation performance [5], e.g. harmonized indicators [6, 7], key performance indicators (KPI) [8, 9] and overall equipment effectiveness (OEE) [10, 11] provide useful numeric values. Willmott presents several examples of OEE improvements with examples of financial benefits [12].

Trend analysis systems have three components: a language to represent the trends, a technique to identify the trends, and mapping from trends to operational conditions [13]. The fundamental elements are modelled as triangles to describe local temporal patterns. The elements are defined by the signs of the first and second derivative, respectively. They are also known as triangular episodic representations [14].

Changing operating conditions need to be taken into account in prognostics since new phenomena activate gradually with time. In the condition-based maintenance (CBM), the most obvious and widely used form of prognostics is to predict how much time is left before a failure occurs. The time left before a failure is usually called remaining useful life (RUL) [15]. The wear conditions collected up to the current inspection are used in [16] to define the time for the next inspection. Wang compared Weibull and Gamma distributions in parameter estimation [17]: the distribution of residual time starts from the normal distribution and moves through skew distributions to a very narrow distribution when an actual failure progresses.

Fatigue is progressive, localised structural damage caused by repeated loading and unloading. The history of the analysis already began in 1837, when Wilhelm Albert published the first fatigue test results [18]. Wöhler concluded that cyclic stress range is more important than peak stress and introduced the concept of the endurance limit. The effects of each stress level are taken into account in the calculations of cumulative damage from individual contributions [19, 20].

Fuzzy set theory first presented by Zadeh form a conceptual framework for linguistically represented knowledge [21]. The extension principle is the basic generalisation of the arithmetic operations if the inductive mapping is a monotonously increasing function. Several fuzzy modelling approaches can be combined: fuzzy arithmetics is suitable both for processing the fuzzy inputs and outputs of the rule-based fuzzy set system; fuzzy inequalities produce new facts; fuzzy relations can be represented as the sets of alternative rules, where each rule has a degree of membership [22].

This paper focuses on the methodologies of developing intelligent performance measures based on the nonlinear scaling of measurements and domain expertise. The solutions aimed for performance monitoring and decision making is enhanced with temporal analysis, uncertainty processing and natural language interface.

II. DATA ANALYSIS

Detecting operating conditions and faults can be based on data analysis of various types of measurements (Fig. 1). The feedback information comes from performance indices. Nonlinear scaling brings all these to the same scale as numeric values and linguistic meanings.

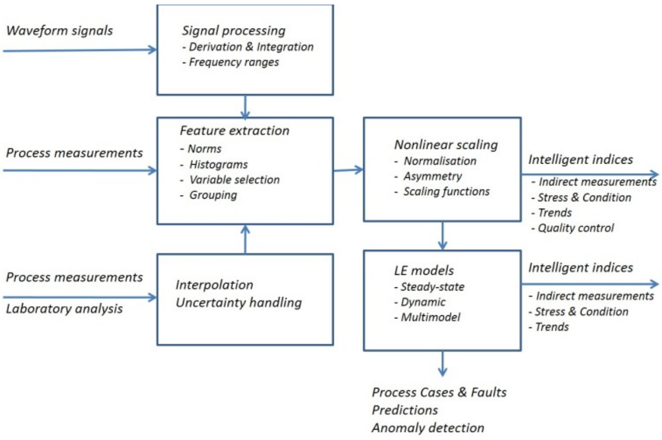


Fig.1. Detecting operating conditions and faults [23].

A. Features

Normalisation or scaling of the data is needed since measurements with considerably different magnitudes cause problems in modelling. The nonlinear scaling extends modelling to various statistical distributions and allows recursive tuning.

Arithmetic mean and standards deviation, which are the key statistical features in industrial practice, are special cases of generalized norms

$$\left\| {}^{\tau} M_j^p \right\|_p = ({}^{\tau} M_j^p)^{1/p} = \Big[\big(\frac{1}{N}\sum_{i=1}^{N} (x_j)_i^p\big)\Big]^{1/p}, \tag{1}$$

where the order of the norm $p \in \Re$ is non-zero. The analysis is based on consecutive equally sized samples. Duration of each sample is called sample time, denoted τ, and N is the number values in the sample. For waveform signals, the number of signal values $N = \tau N_s$, where N_s is the number of signal values which are taken in a second. The norm (1) has the same dimensions as the signals $x_j^{(\alpha)}$, where α is the order of derivation, e.g. α =2 for widely used acceleration signals. The analysis can also use derivated signals. The generalized norms were introduced for condition monitoring [2, 3]. The norm values increase monotonously with increasing order if all the signals are not equal.

The computation of the norms can be divided into the computation of equal sized sub-blocks, i.e. the norm for several samples can be obtained as the norm for the norms of individual samples. The same result is obtained using the norms of the sub-blocks:

$$\left\| {}^{K_S\tau} M_\alpha^p \right\|_p = \left\{ \frac{1}{K_S}\sum_{i=1}^{K_S} \left[({}^{\tau} M_\alpha^p)_i^{1/p} \right]^p \right\}^{1/p} = \left[\frac{1}{K_S}\sum_{i=1}^{K_S} ({}^{\tau} M_\alpha^p)_i \right]^{1/p}, \tag{2}$$

where K_s is the number of samples. Each sample has N variable values. As the aggregation can be continued to longer and longer time periods, this generalizes the practice used automation systems for the arithmetic means.

High order derivatives of the acceleration signal improve fault detection [2, 3]. Stress analysis can be done without derivation, but the sensitivity is improved when higher orders α are used. Spectral norms also answer the question of which frequency range the changes are in since they combine the time domain analysis with the frequency domain analysis [24].

B. Performance indicators

Harmonized indicators are used for monitoring maintenance actions on a management level, where the indicators are based on cost, time, man-hours, inventory value, work orders and cover of the criticality analysis [6, 7].

Key performance indicators (KPIs) are quantifiable measures which reflect the critical success factors and the goals of the organization. KPIs differ depending on the organization and can focus on different parts and levels of the process. Accurately defined and measured KPIs provide feedback information for decision making. The maintenance function covers various aspects, including quality assurance, financial, reliability, planning, execution, strategic, data completeness, logistics and competency [9]. The performance metrics can be assessed with the SMART criteria: specific, measurable, attainable, realistic and timely [8].

Overall equipment effectiveness (OEE) is a set of broadly accepted non-financial metrics which reflects the manufacturing success by availability (uptime), performance rate and quality rate [10, 11].

C. Nonlinear scaling

The z-score based linear scaling solutions are extended to asymmetric nonlinear scaling functions f defined by two second order polynomials (Fig. 2). The parameters of the polynomials are defined with five parameters corresponding the operating point c_j and four corner points of the feasible range [25]. The feasible range is defined as a trapezoidal membership function defined by support and core areas, see [26]. The scaling functions are monotonously increasing throughout the feasible range, see [22, 27]. This is satisfied if the coefficients,

$$\begin{aligned} \alpha_j^- &= \frac{(c_l)_j - \min(x_j)}{c_j - (c_l)_j} = \frac{(c_l)_j - \min(x_j)}{\Delta c_j^-} \\ \alpha_j^+ &= \frac{\max(x_j) - (c_h)_j}{(c_h)_j - c_j} = \frac{\max(x_j) - (c_h)_j}{\Delta c_j^+}, \end{aligned} \tag{3}$$

are restricted to the range $\left[\frac{1}{3}, 3\right]$.

The scaled values are obtained by means of the inverse function f^{-1}:

$$X_j = \begin{cases} 2 & with \quad x_j \geq \max(x_j) \\ \dfrac{-b_j^+ + \sqrt{{b_j^+}^2 - 4a_j^+(c_j - x_j)}}{2a_j^+} - 2 & with \quad c_j \leq x_j \leq \max(x_j) \\ \dfrac{-b_j^- + \sqrt{{b_j^-}^2 - 4a_j^-(c_j - x_j)}}{2a_j} - 2 & with \quad \min(x_j) \leq x_j \leq c_j \\ -2 & with \quad x_j \leq \min(x_j) \end{cases} \tag{4}$$

where a_j^-, b_j^-, a_j^+ and b_j^+ are coefficients of the corresponding polynomials represented by

$$\begin{aligned} a_j^- &= \frac{1}{2}(1-\alpha_j^-)\,\Delta c_j^-, \\ b_j^- &= \frac{1}{2}(3-\alpha_j^-)\,\Delta c_j^-, \\ a_j^+ &= \frac{1}{2}(\alpha_j^+ - 1)\,\Delta c_j^+, \\ b_j^+ &= \frac{1}{2}(3-\alpha_j^+)\,\Delta c_j^+. \end{aligned} \tag{5}$$

Data-based tuning by using generalized norms and skewness was introduced in [4]. The constraints are taken into account by moving the corner points or the upper and lower limits if needed. The systems can be tuned with genetic algorithms [27].

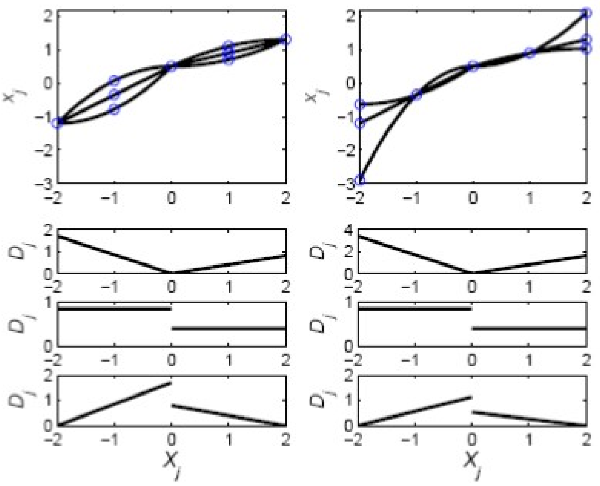


Fig.2. Feasible shapes of membership definitions f_j and corresponding derivatives D_j: coefficients adjusted with the core (left) and support (right). Derivatives are presented in three groups: (1) decreasing and increasing, (2) asymmetric linear, and (3) increasing and decreasing [27].

D. Intelligent indices

Intelligent indices are obtained from measurements and features by the nonlinear scaling approach. The indices obtained from short samples are aimed for use in the same way as indirect measurements, e.g. to indicate stress or condition (Fig. 1). Several indices can be combined in linguistic equation (LE) modelling since the indices are dimensionless. Grouping is important for large scale systems [28].

The cavitation index is an example of a stress index [4]: the approach provides four levels whose values ranges shown in TABLE I are consistent with the limits of the vibration severity ranges defined in [29, 30]. Strong cavitation can be avoided with better allocation of the energy production [31].

In a hot rolling mill, the stress indices were developed by using torque measurements: the feature is difference between the effective and average values, i.e.

$$x_T = [(\frac{1}{N}\sum_{i=1}^{N}(x_j)_i^2)]^{1/2} - \frac{1}{N}\sum_{i=1}^{N}(x_j)_i, \tag{6}$$

where x_j is the fillet split. The time interval can be different for the passes. Since the orders of the norm are here 1 and 2, also negative values of x_j can be used [32].

Stress indices for the front axle of a load haul dumper (LHD) have been developed from acceleration signals by using feature $\max(\|^5 M_2^4\|)$. The analysis provides good indications of different stress contributions in these machines, which operate in harsh conditions where failures may be difficult to repair [33]. The cumulative stress method has recently been used in the monitoring of a rod mill [34], [35].

TABLE I. SEVERITY OF CAVITATION [4]

Level	**Severity classification**		
	Cavitation index	***Cavitation level***	***Severity***
1	$I_C^{(4)} < -1$	Cavitation-free	Good
2	$-1 \leq I_C^{(4)} < 0$	Short periods of weak cavitation	Usable
3	$0 \leq I_C^{(4)} < 1$	Short periods of cavitation	Still acceptable
4	$I_C^{(4)} \geq 1$	Cavitation	Not acceptable

Intelligent indices based on two generalized norms are highly sensitive to faulty situations in the supporting rolls of a lime kiln. Surface damage and misalignment are clearly detected. The data set covers surface problems, good conditions after grinding, misalignment, stronger misalignment, very good conditions after repair work, and very good conditions one year later [4]. Sensitivity is also improved for weak friction and small fluctuations. This is useful in detecting lubrication problems. All the supporting rolls can be analyzed using the same approach throughout the data set. The results are consistent with the vibration severity criteria: good, usable, still acceptable, and not acceptable.

The condition indices of the LHD machine need to be obtained repeatedly in similar steady operating conditions [33]. Extensions to real and complex order derivatives are discussed in [36].

ISBN 978-91-7583-841-0

III. Temporal analysis

Fluctuations, trends and models are used in temporal analysis for all types of measurements, features and indices. Recursive updates of the parameters are needed in prognostics.

A. Fluctuations

The fluctuations are evaluated as the difference of the high and the low values as a difference of two moving generalized norms:

$$\Delta x_j^F(k) = \left\| {}^{K_s\tau} M_j^{p_H} \right\|_{p_H} - \left\| {}^{K_s\tau} M_j^{p_L} \right\|_{p_L}, \qquad (7)$$

where the orders $p_H \in \Re$ and $p_L \in \Re$ are large positive and negative, respectively. The norms are calculated from the latest K_s +1 values, and an average of several latest values of $\Delta x_j^F(k)$ is used as the feature of fluctuation. The feature, which was originally developed for control [37], is easy to calculate and more robust than using the difference of the actual maximum and minimum.

The fluctuation indices are calculated from features (7) by the nonlinear scaling. Similar calculations can be done for intelligent indices if the variations close to the normal conditions are important.

B. Trend analysis

For any variable x_j, a trend index $I_j^T(k)$ is calculated from the scaled values X_j with

$$I_j^T(k) = w_j \left[\frac{1}{(n_S)_j + 1} \sum_{i=k-(n_S)_j}^{k} X_j(k) - \frac{1}{(n_L)_j + 1} \sum_{i=k-(n_L)_j}^{k} X_j(k) \right], \qquad (8)$$

which is based on the means obtained for a short and a long time period, defined by delays $(n_S)_j$ and $(n_L)_j$, respectively. The weight w_j is variable specific. The index value is in the linguistic range [-2, 2] representing the strength of both the decrease and increase of the variable x_j. [38]

Episode alternatives are shown in Fig. 3. An increase is detected if the trend index exceed a threshold $I_j^T(k) > \varepsilon_1^+$. Correspondingly, $I_j^T(k) < \varepsilon_1^-$ for a decrease. The derivative of the index $I_j^T(k)$, denoted as $\Delta I_j^T(k)$, extends the analysis to nonlinear episodes. Trends are linear if the derivative is close to zero: $\varepsilon_2^- < \Delta I_j^T(k) < \varepsilon_2^+$. The concave upward monotonic increase (D) and the concave downward monotonic decrease (B) are dangerous situations, which introduce warnings and alarms. The concave downward monotonic increase (A) and the concave upward monotonic decrease (C) mean that a harmful trend is stopping.

Severity of the situation can be evaluated by a deviation index

$$I_j^D(k) = \frac{1}{3}\left(X_j(k) + I_j^T(k) + \Delta I_j^T(k)\right), \qquad (9)$$

whose absolute values are highest when the difference to the set point is very large and is getting still larger with a fast increasing speed.

The trend analysis is tuned to applications by selecting variable specific the time periods $(n_L)_j$ and $(n_S)_j$. The thresholds $\varepsilon_1^- = \varepsilon_1^+ = \varepsilon_2^- = \varepsilon_2^+ = 0.5$. Further fine-tuning can be done by adjusting the weight factors w_j^{T1} and w_j^{T2} used for the indices $I_j^T(k)$ and $\Delta I_j^T(k)$. The calculations are done with numerical values and the results are represented in natural language [39].

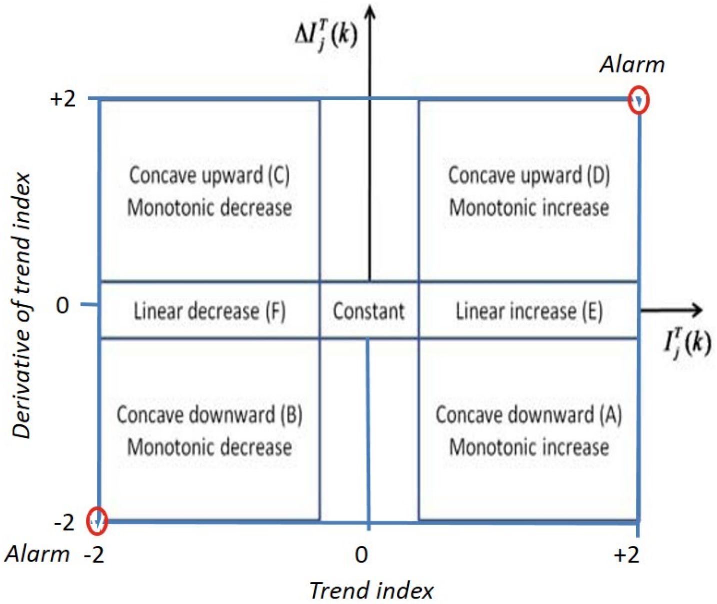


Fig.3. Intelligent trend analysis [38].

Trend indices can be calculated from the scaled values of measurements and features, intelligent indices and linguistic information. Interpretation in natural language follows the same guidelines.

C. Prognostics

In a load haul dumper (LHD), the cumulative stress increases fast during the high stress periods and increase is practically stopped when the stress is low since only stress indices are taken into account in the cumulative stress. [33] Recursive updates of the scaling functions become important in prognostics since the machine or process device is in good condition in the starting point. The rough early estimates are gradually refined if the failure predictions are not yet real. The interaction models are not changed [40].

D. Risk analysis

Varying operating conditions have been taken into account in fatigue analysis [32, 41] by representing the Wöhler curves with a linguistic equation

$$I_S = \log_{10}(N_C), \tag{10}$$

where the stress index is the scaled value of stress,

$$I_S = f^{-1}(S_i) = f^{-1}(\|{}^{\tau}M_{\alpha}^{p}\|). \tag{11}$$

The scaling of the logarithmic values of the number of cycles, $N_C(k)$, is linear. In each sample time, τ, the cycles $N_C(k)$ are obtained by (10) and added to the previous contributions by

$$C(k) = C(k-1) + \frac{\tau}{N_C(k)}, \tag{12}$$

where the value range of the sum C is scaled to provide the fatigue risk in percents (%).

The high stress contributions dominate in the summation. Correspondingly, the very low stress periods have a negligible effect, which is consistent with the idea of infinite lifetime. The summation of the contributions also reveals repeated loading and unloading, and the individual contributions provide indications for the severity of the effect. The stress levels can be followed by a generalized statistical process control approach [42]. At the risk level higher than 60%, a single high torque level can have a strong effect on the activation of a failure.

IV. Uncertainty processing

Scaling functions developed in data analysis are the basis of the uncertainty processing. All scaled values and fuzzy terms can be interpreted in natural language. The fuzzy interface is also used to introduce additional expert knowledge in the calculations.

A. Varying operating conditions

The features and indices are calculated with problem-specific sample times and the variation with time is handled as uncertainty by presenting the indices as time-varying fuzzy numbers. The classification limits can also be considered fuzzy.

The parameters of the scaling functions are specific to operating conditions, some changes can be taken into account switching the parameter sets. The parameters become fuzzy numbers if the time period includes different operating conditions. The results of the fuzzy scaling are fuzzy numbers for crisp values as well. All intelligent indices, including fluctuation, trend and deviation indices, can be presented as fuzzy numbers.

B. Knowledge-based information

Domain expertise can include information about levels which can be translated into fuzzy numbers. The labels {very low, low, normal, high, very high} or {fast decrease, decrease, constant, increase, fast increase} can be represented by number {-2, -1, 0, 1, 2}. Different shapes of membership definitions result different sets of default membership functions: the locations depend on the core, the support and the centre point. However, the linguistic data can be understood as scaled values, whose membership functions are equally spaced, i.e. {-2, -1, 0, 1, 2}. The overlap between adjacent linguistic terms expresses a smooth transition from one term to the other. [43]

The fuzzy sets can be modified by fuzzy modifiers, which are used as intensifying adverbs (very, extremely) or weakening adverbs (more or less, roughly). The resulting terms, e.g.

$$\textit{extremely } A \subseteq \textit{very } A \subseteq A \subseteq \textit{more or less } A \subseteq \textit{roughly } A, \tag{1}$$

correspond to the powers {4, 2, 1, ½, ¼} of the membership in the powering modifiers. The vocabulary can also be chosen in a different way, e.g. highly, fairly, quite [43]. Only the sequence of the labels is important. Linguistic variables can be processed with the conjunction (*AND*), disjunction (*OR*) and negation (*NOT*). More examples can be found in [44].

C. Fuzzy calculus

Fuzzy calculus is suitable for processing fuzzy inputs and outputs in the rule-based fuzzy set systems, but the rule-based system is not necessarily needed (Fig. 4). The extension principle is the basic generalisation of the arithmetic operations if the inductive mapping is a monotonously increasing function of the input. The interval arithmetic presented by Moore [45] is used together with the extension principle on several membership α-cuts of the fuzzy number x_j for evaluating fuzzy expressions [46-48]. Fuzzy inequalities produce new facts like $A \le B$ and $A = B$ for fuzzy inputs A and B.

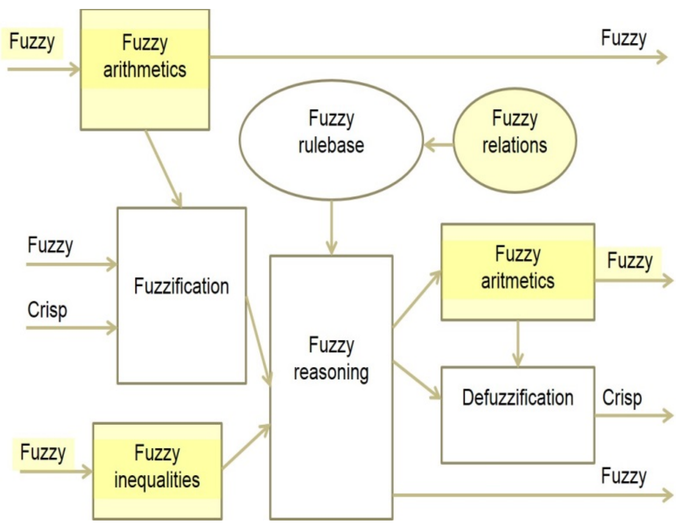


Fig. 4. Combined fuzzy set system [22].

D. Fuzzy rule-based solutions

In the combined systems, the fuzzy inputs can be fuzzy numbers or crisp inputs processed by fuzzy scaling functions (Fig. 4). The results can be defuzzified to crisp values, processed with fuzzy arithmetics or passed to other fuzzy set systems.

Type-2 fuzzy models introduced by Zadeh in 1975 take into account uncertainty about the membership function [49]. Most systems based on interval type-2 fuzzy sets are reduced to an interval-valued type-1 fuzzy set. Special cases of fuzzy linguistic equation models, which can be understood as linguistic Takagi-Sugeno (LTS) type fuzzy models, are robust solutions for applications where the same variables can be used for defining operating areas and in the submodels. No special smoothing algorithms are needed [50].

V. OPERATION AND MAINTENANCE MANAGEMENT

The nonlinear scaling approach is the basis of the consistent natural language interface.

A. Monitoring and control

The keys of the natural language interface are the monotonously increasing, nonlinear scaling functions, which are obtained by generalized norms and moments or defined manually based on domain expertise. The variable specific parameters can be recursively updated by using the corresponding norms and new data samples. Also the orders of the norms can be updated after drastic changes. Since the parameters specific to operating conditions, some changes can be taken into account switching the parameter sets. Uncertainty, fluctuations and confidence in results are estimated by a difference of norms of high positive and negative order, respectively. [39]

Feature levels, uncertainty, trends, trend episodes and severity can be evaluated by using scaled values, fluctuation, trend indices and derivatives of trend indices (TABLE II).

TABLE II. MONITORING INTERFACE [39]

Task	**Features / indices**			
	Scaled value	***Variation / Fluctuation***	***Trend index***	***Derivative of trend index***
Level	x			
Uncertainty		x		
Trend			x	
Trend episodes			x	x
Trend severity	x		x	x

All indices are in the range [-2, 2] and interpreted in natural language labels, e.g. {very low, low, normal, high, very high}. The trend index $I_j^T(k)$) represents levels {fast decrease, decrease, constant, increase, fast increase}, the derivative $\Delta I_j^T(k)$ levels {fast accelerating decrease, accelerating decrease, constant change, accelerating increase, fast accelerating increase} and the deviation index $I_j^D(k)$ {serious decrease, decrease, normal, increase, serious increase}, respectively. The fuzzy partition of all these can be refined by using more levels.

Advanced signal processing and feature extraction is combined with nonlinear scaling to obtain condition and stress indices in [33]. More information can be collected with reliability-centered maintenance (RCM) [5], and finally, all this can be monitored with statistical process control (SPC) [40].

Increased computational power in small programmable controllers and sensors open new possibilities for the efficient on-site calculations. Programmable automation controllers (PACs) make the algorithm testing efficient since the software can be updated easily and measurement setup can be customized. Several aspects connected to on-site calculations present a method for extracting meaningful numbers from high frequency vibration data [51, 52].

The monitoring interface is aimed to utilize on-line measurements in stabilizing, optimizing and coordinating control.

B. Control strategies and Maintenance

Process control systems in industry include centralized or decentralized process controllers coupled with hosts, workstations and several process control and instrumentation devices, such as field devices. Applications are related to business functions in Enterprise resource planning (ERP) or maintenance functions in computerized maintenance management systems (CMMS). Smart field devices can include equipment monitoring applications which are used to help monitor and maintain the devices. [23]

Maintenance information is collected from various sources: condition monitoring measurements, performance indicators, including harmonized indicators, key performance indicators and overall equipment effectiveness (OEE). The systems include a huge amount of event information, which is not necessarily in a numeric form. The natural language information can be understood in the range [-2, 2] through linguistic levels and modifiers related [42].

At this level, the temporal analysis and uncertainty processing become important in detecting operating conditions. Model-based predictions and recursive updates of the parameters are needed in decision making, where the adaption of the control strategies is used in scheduling the condition-based maintenance actions.

C. Management

Performance indicators are specific for different industrial areas [8], [12]. The nonlinear scaling brings the performance levels to a consistent range, which can be understood in linguistic terms. The levels and their improvements are represented in natural language, e.g. ’excellent improvement from poor performance to good performance’ [5]. Aggregation is needed for the information obtained from other levels. Uncertainty processing is increasingly important in this level.

ISBN 978-91-7583-841-0

VI. CONCLUSIONS

The nonlinear scaling approach is the main part of the data processing chain which is the integrating part of the natural language interface. The calculations are done in numeric forms, but the levels and all the indices based on them can be represented in natural language. The system includes integrated temporal analysis and uncertainty processing which facilitates the efficient use of domain expertise.

ACKNOWLEDGMENT

The author would like to thank the research program "Measurement, Monitoring and Environmental Efficiency Assesment (MMEA)" funded by the TEKES (the Finnish Funding Agency for Technology and Innovation) and the Artemis Innovation Pilot project "Production and energy system automation and Intelligent-Built (Arrowhead)".

REFERENCES

[1] S. Lahdelma, and E. Juuso, "Advanced signal processing and fault diagnosis in condition monitoring," Insight, vol. 49, no. 12, pp. 719-725, 2007, doi: 10.1784/insi.2007.49.12.719.

[2] S. Lahdelma, and E. Juuso, "Signal processing and feature extraction by using real order derivatives and generalised norms. Part 1: Methodology," The International Journal of Condition Monitoring, vol. 1, no. 2, pp. 46-53, 2011, doi: 10.1784/204764211798303805.

[3] S. Lahdelma, and E. Juuso, "Signal processing and feature extraction by using real order derivatives and generalised norms. Part 2: Applications," The International Journal of Condition Monitoring, vol. 1, no. 2, pp. 54-66, 2011, doi: 10.1784/204764211798303814.

[4] E Juuso and S Lahdelma, "Intelligent scaling of features in fault diagnosis," 7th International Conference on Condition Monitoring and Machinery Failure Prevention Technologies, CM 2010 – MFPT 2010, 7th International Conference on Condition Monitoring and Machinery Failure Prevention Technologies, Stratford-upon-Avon, UK. BINDT, vol. 2, pp. 1358-1372, June 2010.

[5] E. K. Juuso, and S. Lahdelma, "Intelligent performance measures for condition-based maintenance," Journal of Quality in Maintenance Engineering, vol. 19, no.3, pp. 278-294, 2013, doi: 10.1108/JQME-05-2013-0026.

[6] C. Olsson, and T. Svantesson, "Harmonised maintenance and reliability indicators – compare apples to apples," Maintworld, vol. 1, no. 1, 2009, pp. 9-11.

[7] C. Idhammar, "The first world class maintenance organization," Maintworld, vol. 2, no. 2, pp. 52-53, 2010.

[8] A. Parida, and U. Kumar, "Maintenance performance measurement – methods, tools and applications," Maintworld, vol. 1, no. 1, pp. 30-33, 2009.

[9] N. A. Al-Shammasi, and S. S. Al-Shakhoyry, "Improving maintenance performance in Saudi Aramco," Maintworld, vol. 2, no. 2, pp. 6-9, 2010.

[10] SCEMM Keep It Running – Industrial Asset Management, Painoyhtymä, Loviisa, 1998.

[11] B. Hägg, "Maintenance – an investment in higher profitability," Maintenance, Condition Monitoring and Diagnostics 2010, Proceedings of the International Conference in Oulu, POHTO Publications, Oulu, 29-30 September, pp. 7-14, 2010.

[12] P. Willmott, "Post the streamlining – 'where's your maintenance strategy now?" Maintworld, vol. 2, no. 1, pp. 16-22, 2010.

[13] S. Dash, R, Rengaswamy, and V. Venkatasubramanian, "Fuzzy-logic based trend classification for fault diagnosis of chemical processes," Computers and Chemical Engineering, vol. 27, pp. 347–362, 2003.

[14] J. T.-Y. Cheung, and G. Stephanopoulos, "Representation of process trends - part I. A formal representation framework," Computers & Chemical Engineering, vol. 14, no. 4/5, pp. 495–510, 1990.

[15] A. K. S. Jardine, D. Lin, and D. Banjevic, "A review on machinery diagnostics and prognostics implementing condition-based maintenance," Mechanical Systems and Signal Processing, vol. 20, no, 7, pp. 1483–1510, 2006, doi: 10.1016/j.ymssp.2005.09.012.

[16] A. H. Christer, and W. Wang, "A model of condition monitoring inspection of production plant," International Journal of Production Research, vol. 30, no. 9, pp. 2199-2211, 1992.

[17] W. Wang, "A two-stage prognosis model in condition based maintenance," European Journal of Operational Research, vol. 182, no. 3, pp. 1177-1187, 2007.

[18] W. Schütz, W. "A history of fatigue, Engineering Fracture Mechanics," vol. 54, no. 2, pp. 263-300, 1996.

[19] A. Palmgren, "Die Lebensdauer von Kugellagern," Verfahrenstechnik, vol. 68, pp. 339-341, 1924.

[20] M. A. Miner, "Cumulative damage in fatigue," ASME Journal of Applied Mechanics, vol. 67, pp. 159-164, 1945.

[21] L. A. Zadeh, "Fuzzy sets," Information and Control, vol. 8, pp. 338–353, 1965.

[22] E. K. Juuso, "Intelligent Methods in Modelling and Simulation of Complex Systems," Simulation Notes Europe SNE, vol. 24, no. 1, pp. 1-10. Selected SIMS 2013, 2014, doi: 10.11128/sne.24.on.102221.

[23] E. K. Juuso and D. Galar, "Intelligent real-time risk analysis for machines and process devices," Current Trends in Reliability, Availability, Maintainability and Safety: An Industry Perspective, Lecture Notes in Mechanical Engineering, Springer, pp. 229-240, 2016, doi: 10.1007/978-3-319-23597-4_17.

[24] K. Karioja, and E. Juuso, "Generalised spectral norms – a new method for condition monitoring," International Journal of Condition Monitoring, vol. 6, no. 1, pp. 13-16, 2016 March, doi: 10.1784/204764216819257150.

[25] E. K. Juuso, "Integration of intelligent systems in development of smart adaptive systems," International Journal of Approximate Reasoning, Vol. 35, no. 3, pp. 307–337, 2004, doi: 10.1016/j.ijar.2003.08.008.

[26] H. J. Zimmermann, Fuzzy set theory and its applications, Kluwer Academic Publishers, 1992.

[27] E. K. Juuso, "Tuning of large-scale linguistic equation (LE) models with genetic algorithms," Adaptive and Natural Computing Algorithms, Revised selected papers - ICANNGA 2009, Kuopio, Finland ICANNGA 2009, Lecture Notes in Computer Science (LNCS) 5495, pp 161-170, Springer, Heidelberg, 2009, doi: 10.1007/978-3-642-04921-7_17.

[28] T. Ahola, E. Juuso, and K. Leiviskä, "Variable Selection and Grouping in a Paper Machine Application," International Journal of Computers, Communications & Control, vol. II, no. 2, pp. 111-120, 2007.

[29] VDI 2056 Beurteilungsmaβstäbe für mechanische Schwingungen von Maschinen, VDI-Richtlinien, Oktober 1964.

[30] R. A. Collacott, Mechanical Fault Diagnosis and condition monitoring, Chapman and Hall, London, 1977.

[31] E. Juuso and S. Lahdelma, "Cavitation Indices in Power Control of Kaplan Water Turbines," 6th International Conference on Condition Monitoring and Machinery Failure Prevention Technologies, CM 2009 – MFPT 2009, Dublin, Ireland. BINDT, vol. 2, pp. 830-841, June 2009.

[32] E. Juuso, and M. Ruusunen, "Fatigue prediction with intelligent stress indices based on torque measurements in a rolling mill," 10th International Conference on Condition Monitoring and Machinery Failure Prevention Technologies, CM 2013 - MFPT 2013, 18-20 June 2013, Krakow, Poland, vol. 1, pp. 460-471.

[33] E. K. Juuso, "Intelligent indices for online monitoring of stress and condition," 11th International Conference on Condition Monitoring and Machinery Failure Prevention Technologies, CM 2014/MFPT 2014, Manchester, UK, 10-12 June, vol. 1, 2014, pp. 637-648.

[34] J. Laurila, A. Koistinen, E. Juuso, and T. Liedes, "Monitoring of a rod mill using advanced feature extraction methods," 12th International Conference on Condition Monitoring and Machinery Failure Prevention Technologies, CM2015/MFPT2015, Oxford, United Kingdom 9-11 June 2015, pp. 580-590.

[35] A. Koistinen, J. Laurila, and E. Juuso, "Rod mill liner monitoring using cumulative stress," 13th International Conference on Condition

Monitoring and Machinery Failure Prevention Technologies, CM2016/MFPT2016, Paris, France 10-12 October 2016, pp. 131-142.

[36] J. Nissilä, S. Lahdelma, and J. Laurila, "Condition monitoring of the front axle of a load haul dumper with real order derivatives and generalised norms," 11th International Conference on Condition Monitoring and Machinery Failure Prevention Technologies, CM 2014/MFPT 2014, Manchester, UK, 10-12 June, Vol. 1, 2014, pp. 407-426.

[37] E. K. Juuso, "Model-based adaptation of intelligent controllers of solar collector fields," 7th Vienna Symposium on Mathematical Modelling, February 14-17, 2012, Vienna, Austria, Part 1, IFAC, 2012, vol. 7, pp. 979–984, doi: 10.3182/20120215-3-AT-3016.00173.

[38] E. K. Juuso, "Intelligent Trend Indices in Detecting Changes of Operating Conditions," 2011 UKSim 13th International Conference on Computer Modelling and Simulation (UKSim), IEEE Computer Society, 2011, pp. 162-167, doi: 10.1109/UKSIM.2011.39.

[39] E. K. Juuso, "Informative process monitoring with a natural language interface," 2016 UKSim-AMSS 18th International Conference on Modelling and Simulation, IEEE Computer Society, 2016, pp. 105-110, doi: 10.1109/UKSim.2016.37.

[40] E. K. Juuso, "Recursive Data Analysis and Modelling in Prognostics," 12th International Conference on Condition Monitoring and Machinery Failure Prevention Technologies, 9-12 June 2015, Oxford, UK. NY, USA: Curran Associates, 2015, pp. 560-567.

[41] E. K. Juuso and M. Ruusunen, "Stress Indices in Fatigue Prediction," Maintenance, Condition Monitoring and Diagnostics & Maintenance Performance Measurement and Management - MCMD 2015 and MPMM 2015, 30th September - 1st October, 2015, Oulu, Finland. Oulu: Pohto.

[42] E. K. Juuso, "Generalised statistical process control (GSPC) in stress monitoring," IFAC-Papers OnLine, vol. 28, no. 17, pp. 207-212, 2015, doi: 10.1016/j.ifacol.2015.10.104.

[43] E. K. Juuso, "Integration of knowledge-based information in intelligent condition monitoring," 9th International Conference on Condition Monitoring and Machinery Failure Prevention Technologies, 12-14 June 2012, London, UK. NY, USA: Curran Associates, 2012, vol. 1, pp. 217–228.

[44] M. De Cock and E. E. Kerre, "Fuzzy modifiers based on fuzzy relations," Information Sciences, vol. 160, no. 1-4, pp. 173–199, 2004.

[45] R. E. Moore, Interval Analysis. Englewood Cliffs, NJ:Prentice Hall. 1966.

[46] J. J. Buckley, and T. Feuring, "Universal approximators for fuzzy functions," Fuzzy Sets and Systems, vol. 113, pp. 411–415, 2000.

[47] J. J. Buckley, and Y. Hayashi, "Can neural nets be universal approximators for fuzzy functions?" Fuzzy Sets and Systems, vol. 101: 323–330, 1999.

[48] J. J. Buckley, and Y. Qu, "On using α-cuts to evaluate fuzzy equations," Fuzzy Sets and System, vol. 38, no. 3, pp. 309–312, 1990, doi: 10.1016/0165-0114(90)90204-J

[49] J. M. Mendel, "Advances in type-2 fuzzy sets and systems," Information Sciences, vol. 177, no. 1, pp. 84–110, 2007.

[50] E. K. Juuso, "Development of Multiple Linguistic Equation Models with Takagi-Sugeno Type Fuzzy Models," 2009 International Fuzzy Systems Association WORLD CONGRESS & 2009 European Society for Fuzzy Logic and Technology CONFERENCE, IFSA-EUSFLAT 2009, 20-24 July 2009, Lisbon, Portugal, pp. 1779-1784.

[51] A. Koistinen, and E. K. Juuso, "On-site calculations of generalised norms for maintenance and operational monitoring," Maintenance, Condition Monitoring and Diagnostics & Maintenance Performance Measurement and Management - MCMD 2015 and MPMM 2015, 30th September - 1st October, 2015, Oulu, Finland. Oulu: Pohto.

[52] A. Koistinen, and E. K. Juuso, "Information from Centralized Database to Support Local Calculations in Condition Monitoring," 9th EUROSIM Congress on Modelling and Simulation, 12-16 September 2016 in Oulu, Finland. IEEE Computer Society, pp. 1049-1054. doi: 10.1109/EUROSIM.2016.86

.

Intelligent performance analysis with a natural language interface

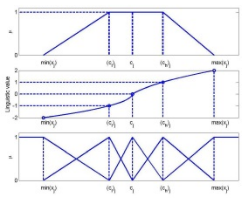
Esko K. Juuso
Control Engineering
Faculty of Technology
University of Oulu

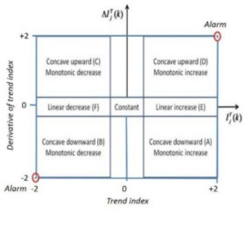
OULU
CAPITAL OF NORTHERN SCANDINAVIA

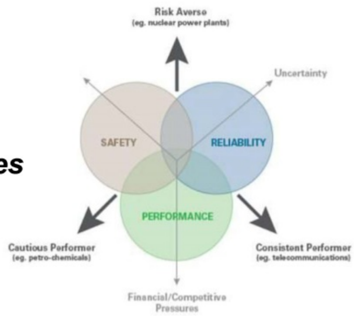
MPMM 2016
Luleå, Sweden, 28 November 2016

UNIVERSITY OF OULU

Outline







- ***Performance measures***
- ***Data analysis***
  - Generalised norms
  - Nonlinear scaling
  - Fluctuations
  - Temporal analysis
- ***Uncertainty processing***
  - Expertise & Fuzzy set systems
- ***Operation and maintenance management***
  - Monitoring & SPC
  - Maintenance
  - Management
- ***Conclusions***

MPMM 2016
Luleå, Sweden, 28 November 2016

UNIVERSITY OF OULU

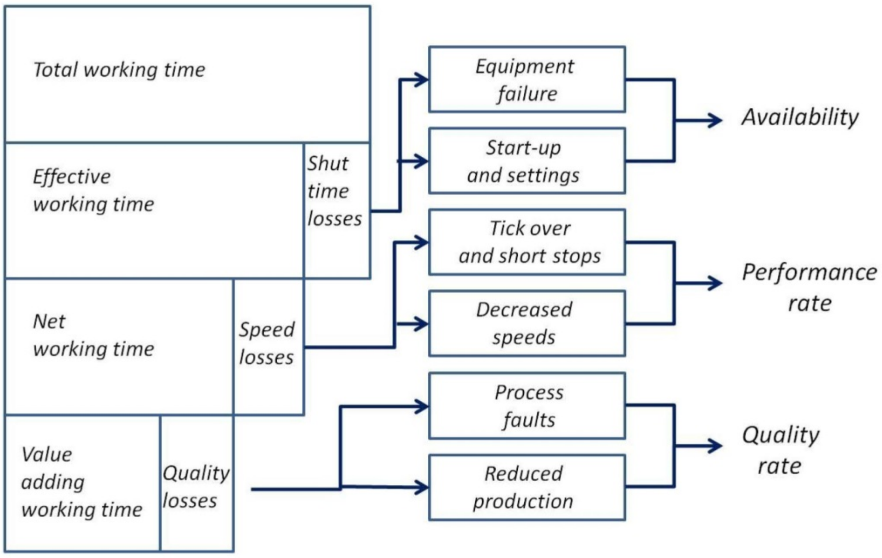
ISBN 978-91-7583-841-0

Performance measures

- Harmonised indicators
- Key performance indicators (KPIs)
- Reliability-centered maintenance (RCM)
- Overall equipment effectiveness (OEE)
- Statistical process control (SPC)
- Management
- Process units
- Statistical analysis & simulation
- Quality, speed & shut time
- Six Sigma

Harmonised indicators		
Indicator	**Nominator**	**Denominator**
Cost	Maintenance cost Internal personnel Contractor cost Corrective maintenance Condition-based maintenance	Asset replacement value Quantity of output Total maintenance cost
Inventory value	Maintenance materials	Asset replacement value
Time	Operating time Time to restore	Number of failures
Systems	Covered by criticality analysis	Total number
Work orders	As scheduled	Total number
Man-hours	Training	Total internal man-hours
Spare parts	Supplied as requested	Total number

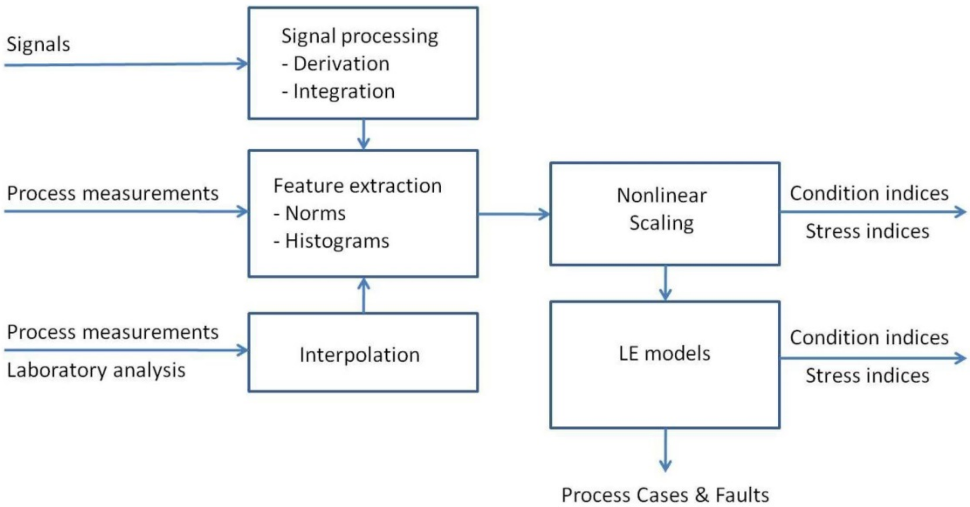
ISBN 978-91-7583-841-0



MPMM 2016
Luleå, Sweden, 28 November 2016

UNIVERSITY OF OULU

Measurements → Indices



MPMM 2016
Luleå, Sweden, 28 November 2016

UNIVERSITY OF OULU

Data analytics

- Statistical distributions
  - asymmetrical
- Generalised norms
- Scaling
  - Normalisation
  - z-score

$$p_j = \frac{x_j - c_j}{\Delta c_j} = \frac{x_j - \| {}^{\tau}M_j^1 \|_1}{\| {}^{\tau}M_j^2 \|_2}$$

- Nonlinear scaling
- Recursive analysis
- Uncertainty

MPMM 2016
Luleå, Sweden, 28 November 2016

UNIVERSITY OF OULU

Data analytics: generalised norms

- A generalised norm

$$||{}^{\tau}M_j^p||_p = ({}^{\tau}M_j^p)^{1/p} = [\frac{1}{N}\sum_{i=1}^{N}(x_j)_i^p]^{1/p}$$

Separately for each variable x_j

p is a real number

- Special cases. min ... max
  - Arithmetic mean ... Standard deviation, rms val

$$\left\|x^{(\alpha)}\right\|_{-1} = \frac{N}{\sum_{i=1}^{N}\frac{1}{\left|x_i^{(\alpha)}\right|}}, \;\ldots\; \left\|x^{(\alpha)}\right\|_1 = \frac{1}{N}\sum_{i=1}^{N}\left|x_i^{(\alpha)}\right|, \;\ldots\; \left\|x^{(\alpha)}\right\|_2 = (\frac{1}{N}\sum_{i=1}^{N}\left|x_i^{(\alpha)}\right|^2)^{1/2}$$

- A maximum from several samples

$$\max(\left\|{}^{\tau}M_{\alpha}^{p}\right\|) \equiv \max_{i=1,\ldots,K_S}\left\{({}^{\tau}M_{\alpha}^{p})_i^{1/p}\right\}$$

- Increasing

$$({}^{\tau}M_{\alpha}^{p})^{1/p} \leq ({}^{\tau}M_{\alpha}^{q})^{1/q} \qquad p < q$$

MPMM 2016
Luleå, Sweden, 28 November 2016

UNIVERSITY OF OULU

ISBN 978-91-7583-841-0

Generalised moments

- Normalised moments

$$\gamma_k = \frac{E\left[\left(X - E(X)\right)^k\right]}{\sigma_X{}^k}$$

$k = 3$ Skewness
$k = 4$ Kurtosis

Central value

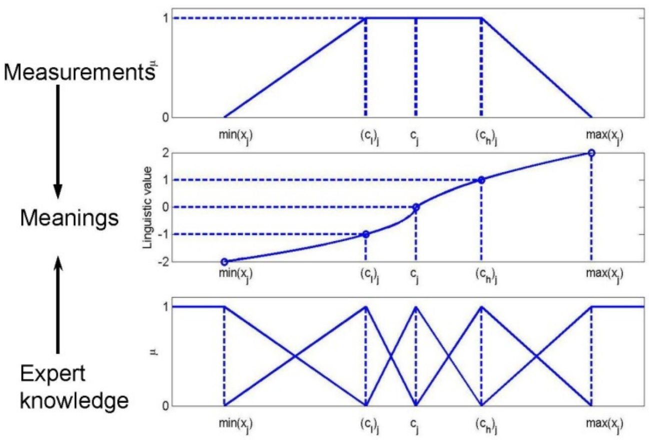
- Skewness
  - Positive $\gamma_3 > 0$
  - Symmetric $\gamma_3 = 0$
  - Negative $\gamma_3 < 0$
- Generalised moment

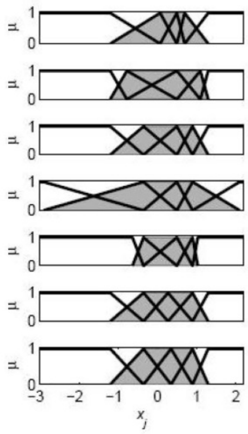
$$\gamma_k = \frac{E\left[\left(X^{(\alpha)} - \left\| {}^{\tau}M_{\alpha}^{p} \right\|_p\right)^k\right]}{\sigma_X{}^k}$$

MPMM 2016
Luleå, Sweden, 28 November 2016

UNIVERSITY OF OULU

Nonlinear scaling





- Linguistic levels can translated into numbers
- Natural language

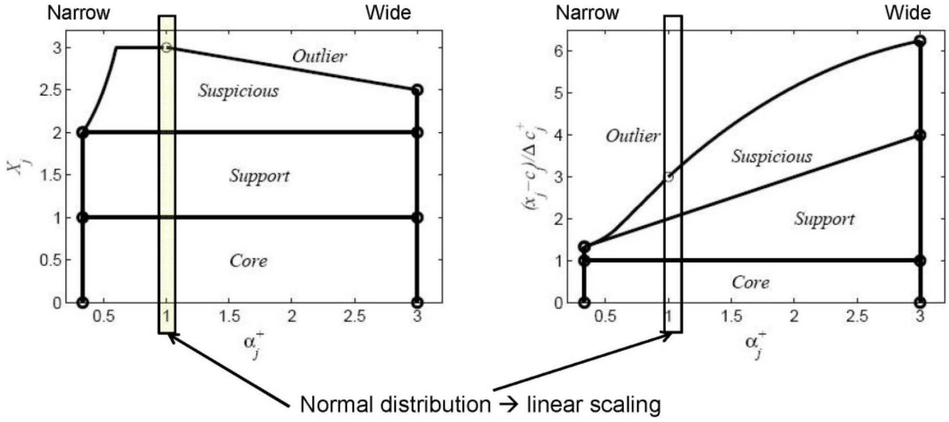
MPMM 2016
Luleå, Sweden, 28 November 2016

UNIVERSITY OF OULU

ISBN 978-91-7583-841-0

Data analysis

- Generalised norms and moments → Limits



MPMM 2016
Luleå, Sweden, 28 November 2016

UNIVERSITY OF OULU

Nonlinear scaling

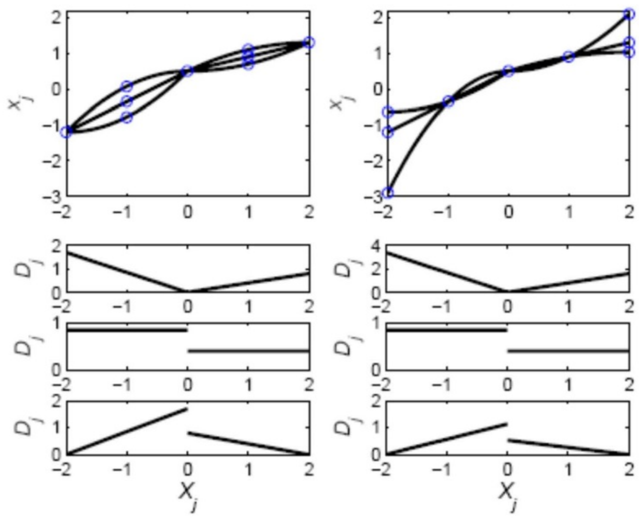
Linear

c_j and $b_j = b_j^+ = b_j^-$

or $\Delta c_j = \Delta c_j^+ = \Delta c_j^-$

Asymmetrical linear

$\Delta c_j^+ \neq \Delta c_j^-$ and $b_j^+ \neq b_j^-$



MPMM 2016
Luleå, Sweden, 28 November 2016

UNIVERSITY OF OULU

ISBN 978-91-7583-841-0

Recursive updates

- Corner points defined generalised norms

$$\left\{ (\min(x_j), -2), ((c_l)_j, -1), (c_j, 0), ((c_h)_j, 1), (\max(x_j), 2) \right\}$$

- Updates from equal sized sub-blocks →

$$\left\| {}^{K_S \tau} M_\alpha^p \right\|_p = \left\{ \frac{1}{K_S} \sum_{i=1}^{K_S} \left[({}^\tau M_\alpha^p)_i^{1/p} \right]^p \right\}^{1/p} = \left[\frac{1}{K_S} \sum_{i=1}^{K_S} ({}^\tau M_\alpha^p)_i \right]^{1/p},$$

- New operating conditions
  - Define corner points
  - New scaling functions

MPMM 2016
Luleå, Sweden, 28 November 2016

UNIVERSITY OF OULU

Uncertainties → Fluctuation indicators

- Minimum … Maximum
- Moving range for p_H = 30, p_L= -30, K_s=4

$$\Delta x_j^F(k) = ||^{K_s \tau} M_j^{p_H}||_{p_H} - ||^{K_s \tau} M_j^{p_L}||_{p_L} \qquad \begin{matrix} p_H \in R \\ p_L \in R \end{matrix}$$

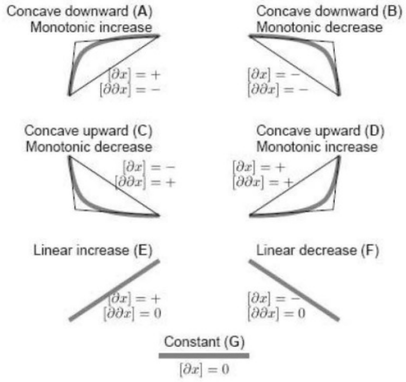
- Average of 25 moving range values

MPMM 2016
Luleå, Sweden, 28 November 2016

UNIVERSITY OF OULU

Temporal analysis

- Several sources
- Episodes
- Deviations



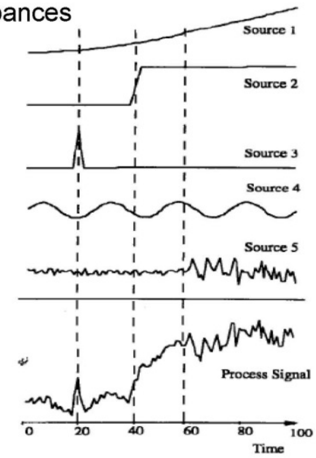
MPMM 2016
Luleå, Sweden, 28 November 2016

UNIVERSITY OF OULU

What are the components?

Components

- Slow trends
- Equipment faults
- Periodic disturbances
- Noise
- …



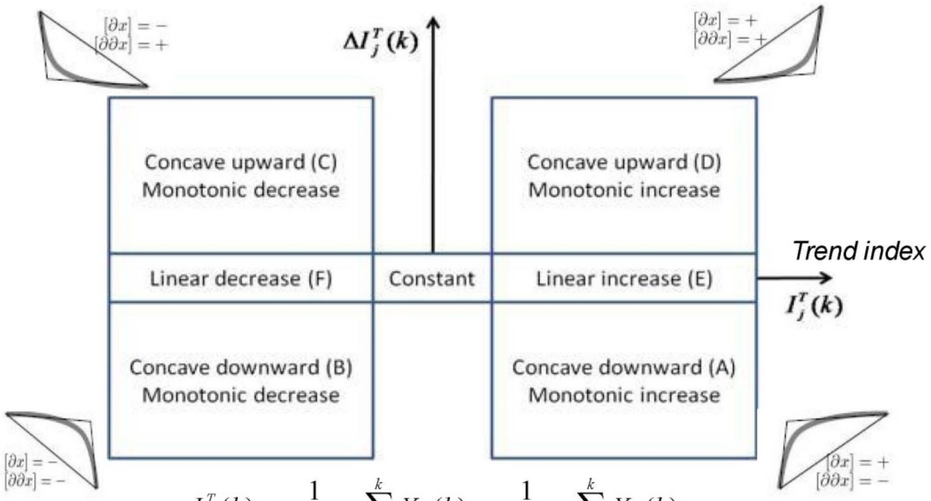
How to find them?

- Preprocessing
  - Meanings
- Trend analysis
  - (Intelligent) trend indices
  - Trend episodes
- Smoothing
  - Kalman
  - Intelligent (fuzzy, neural, LE)
- Modelling
  - Identification, parametric models
  - Intelligent (fuzzy, neural, LE)
- Residual computation
  - Model-based trend removal
  - Generalised norms

MPMM 2016
Luleå, Sweden, 28 November 2016

UNIVERSITY OF OULU

Trend analysis

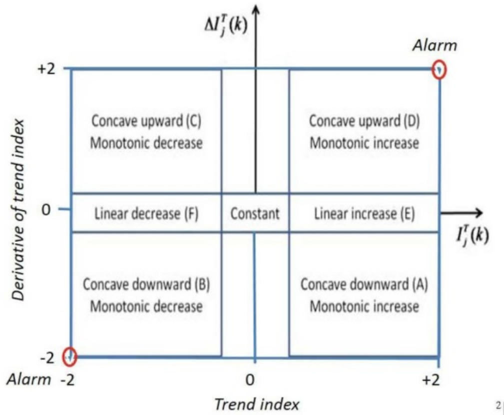


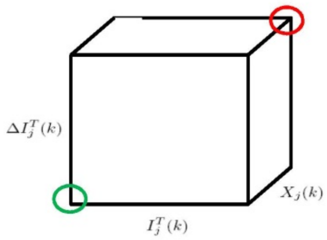
$$I_j^T(k) = \frac{1}{n_S + 1}\sum_{i=k-n_S}^{k} X_j(k) - \frac{1}{n_L + 1}\sum_{i=k-n_L}^{k} X_j(k)$$

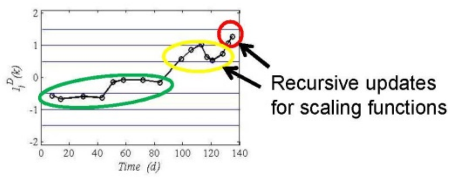
MPMM 2016
Luleå, Sweden, 28 November 2016

UNIVERSITY OF OULU

Triangular episodes & Deviation







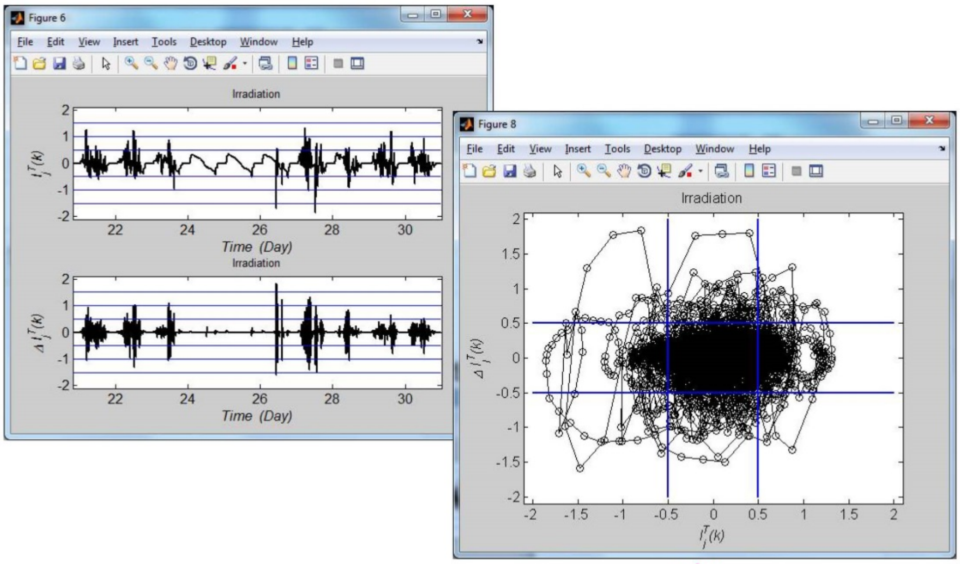
$$I_j^D(k) = \frac{1}{3}\left(X_j(k) + I_j^T(k) + \Delta I_j^T(k)\right).$$

MPMM 2016
Luleå, Sweden, 28 November 2016

UNIVERSITY OF OULU

ISBN 978-91-7583-841-0

Trend analysis



MPMM 2016
Luleå, Sweden, 28 November 2016

UNIVERSITY OF OULU

Uncertainty processing

- Scaling functions
  - Parameters represented by fuzzy numbers
- Fuzzy rule-based systems
- Fuzzy arithmetics
- Extension principle
- Fuzzy inequalities

→ ***Natural language***

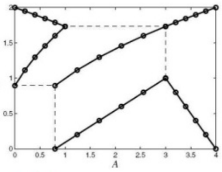
MPMM 2016
Luleå, Sweden, 28 November 2016

UNIVERSITY OF OULU

ISBN 978-91-7583-841-0

Knowledge-based information

- Labels to numbers
  - {very low, low, normal, high, very high}
  - {fast decrease, decrease, constant, increase, fast increase}
  - ...
  - → {-2, -1, 0, 1, 2}
- A gradually refining set in the range [-2, 2]
- Modifiers
  - 'extremely', 'very', 'more or less' and 'roughly'
- Combined
  - 'and', 'or' and 'not'
- Fuzzy calculus + extension principle



MPMM 2016
Luleå, Sweden, 28 November 2016

UNIVERSITY OF OULU

Modifiers and combined terms

- Terms
  extremely $A \subseteq$ *very* $A \subseteq A \subseteq$ *more or less* $A \subseteq$ *roughly* A
- Corresponding powers of the membership functions

Fuzzy number	*Fuzzy label*	*Degree of membership*
A_1	*extremely A*	μ^4
A_2	*very A*	μ^2
A_3	*A*	μ
A_4	*more or less A*	$\mu^{\frac{1}{2}}$
A_5	*roughly A*	$\mu^{\frac{1}{4}}$

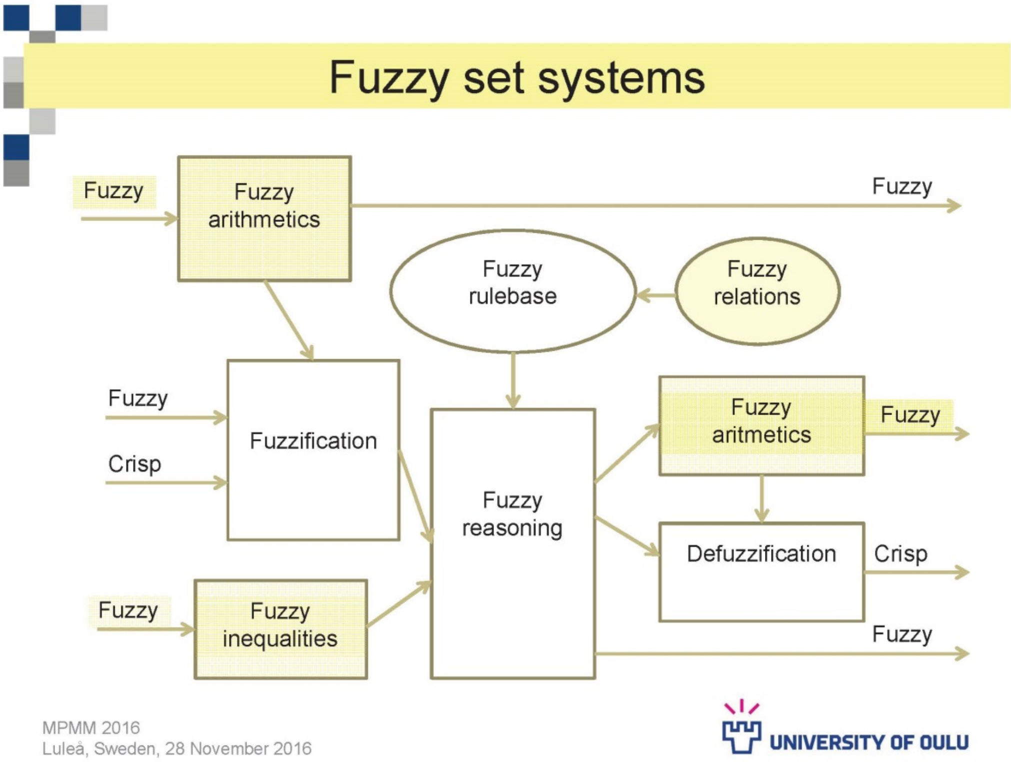
- Intersection, Conjuction, 'AND'
  - Minimum, Algebraic product, Bounded product, Drastic product, … $c_{A\cap B}(x)$
- Union, Disjunction, 'OR'
  - Maximum, Algebraic sum, Bounded sum, Drastic sum $c_{A\cup B}(x)$
- Complement, Negation, 'NOT'
- Truth values

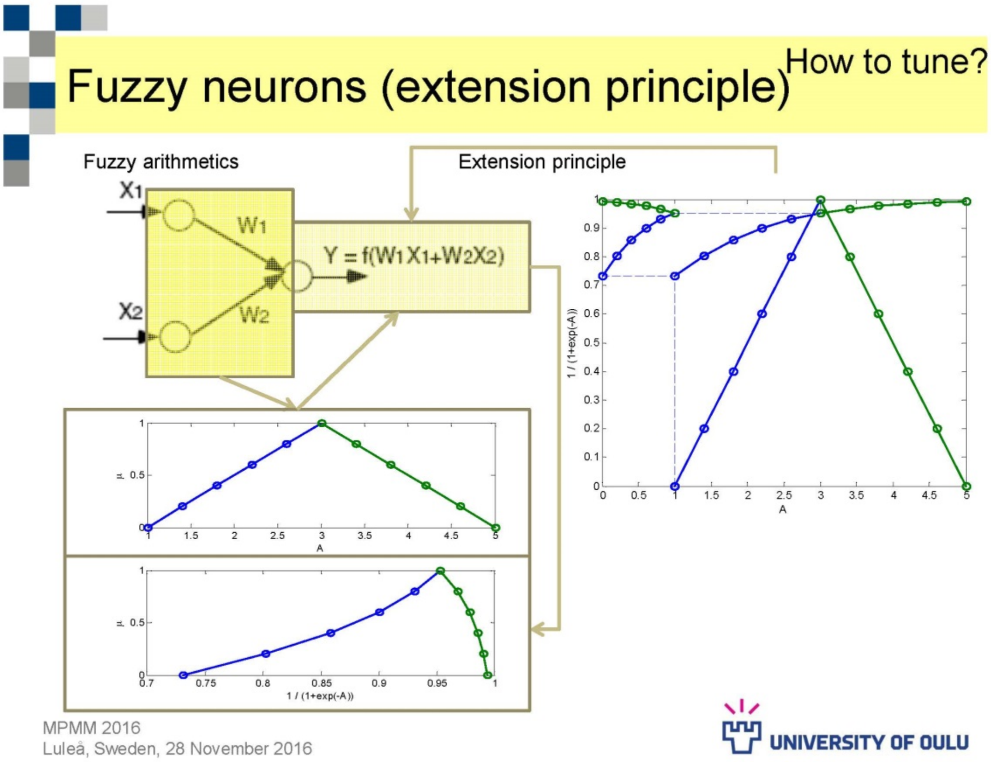
$$v(p \to q) = v(\neg p \vee q),$$
$$v(p \to q) = v((p \wedge q) \vee \neg p)$$

MPMM 2016
Luleå, Sweden, 28 November 2016

UNIVERSITY OF OULU

ISBN 978-91-7583-841-0


Fuzzy set systems
Fuzzy
Fuzzy arithmetics
Fuzzy
Fuzzy rulebase
Fuzzy relations
Fuzzy
Crisp
Fuzzification
Fuzzy reasoning
Fuzzy aritmetics
Fuzzy
Defuzzification
Crisp
Fuzzy
Fuzzy inequalities
Fuzzy
MPMM 2016
Luleå, Sweden, 28 November 2016
UNIVERSITY OF OULU


Fuzzy neurons (extension principle)
How to tune?
Fuzzy arithmetics
Extension principle
X1
W1
X2
W2
Y = f(W1X1+W2X2)
A
1 / (1+exp(-A))
MPMM 2016
Luleå, Sweden, 28 November 2016
UNIVERSITY OF OULU

Monitoring interface

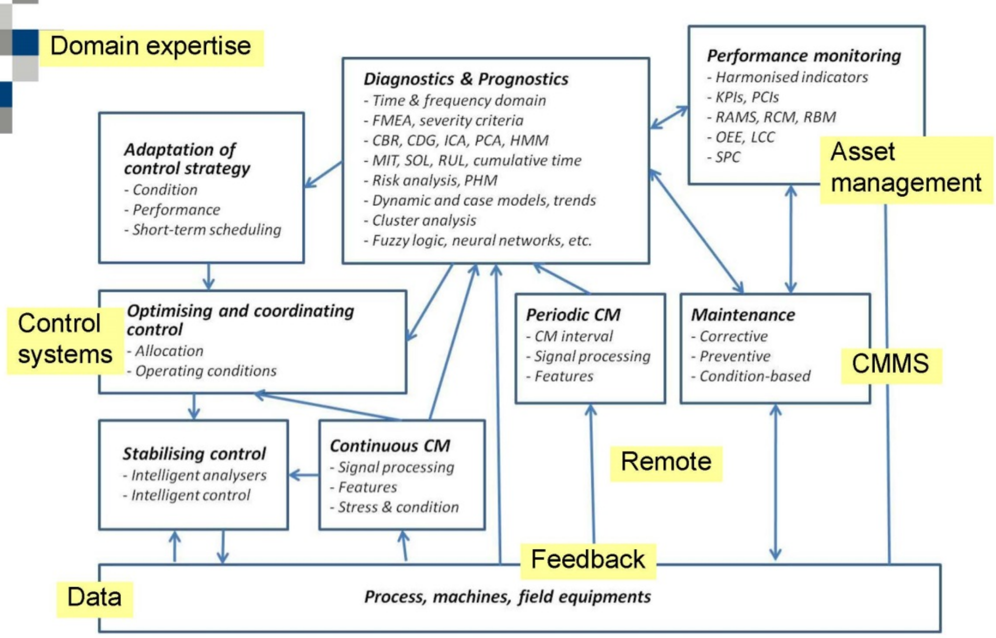
- Data analysis
- Functionalities

	Scaled value	Variation/ Fluctuation	Trend index	Derivative of trend index
Level	x			
Uncertainty		x		
Trend			x	
Trend episodes			x	x
Trend severity	x		x	x

- All in [-2, 2] → Natural language

MPMM 2016
Luleå, Sweden, 28 November 2016

UNIVERSITY OF OULU



MPMM 2016
Luleå, Sweden, 28 November 2016

UNIVERSITY OF OULU

ISBN 978-91-7583-841-0

	OEE	Scaled OEE	Limits
Excellent	95.0%	2	≥ 1.5
Very good	86.6%	1	[0.5, 1.5)
Good	76.4%	0	[-0.5, 0.5)
Acceptable	62.6%	-1	[-1.5, -0.5)
Poor	48.0%	-2	< -1.5

	From	To	From	To
Steel Plant	74 %	90 %	-0.18	1.38
White Goods	79 %	88 %	0.24	1.15
Automotive	48 %	75 %	-2.00	-0.11
Flour Mill	86 %	93 %	0.93	1.74
Chemical Plant	82 %	95 %	0.52	2.00
Filling Line 1	55 %	85 %	-1.53	0.83
Filling Line 2)	68 %	80 %	-0.62	0.33
Packing Line 1	66 %	87 %	-0.76	1.04
Packing Line 2	50 %	75 %	-1.87	-0.11

From	To	Improvement		From	To
-0.18	1.38	1.56	Very good	Good	Very good
0.24	1.15	0.91	Good	Good	Very good
-2.00	-0.11	1.89	Excellent	Poor	Good
0.93	1.74	0.81	Good	Very good	Excellent
0.52	2.00	1.48	Very good	Very good	Excellent
-1.53	0.83	2.36	Excellent	Poor	Very good
-0.62	0.33	0.95	Good	Acceptable	Good
-0.76	1.04	1.80	Excellent	Acceptable	Very good
-1.87	-0.11	1.76	Excellent	Poor	Good

MPMM 2016
Luleå, Sweden, 28 November 2016

UNIVERSITY OF OULU

ISBN 978-91-7583-841-0

Conclusions

Methodology

- Norms: a good order α, and proper p and τ
- Nonlinear scaling → Performance indices
  - Trend analysis
  - Performance measures
  - Fuzzy logic

Applications

- Monitoring
- Control and scheduling
- Maintenance
- Management
- Product and process design
- Big Data

Automatic analysis Domain expertise	Huge number of equipment and processes to monitor Extensive linguistic information

MPMM 2016
Luleå, Sweden, 28 November 2016

UNIVERSITY OF OULU

ISBN 978-91-7583-841-0

Bayesian Networks in Fault Diagnosis: Some research issues and challenges

Baoping Cai[1*], Lei Huang[2], Jing Lin[3], Min Xie[4]
[1]caibaoping@upc.edu.cn; [2]huanglei1@s.upc.edu.cn; [3]janet.lin@ltu.se; [4]minxie@cityu.edu.hk
[1, 2]College of Mechanical and Electronic Engineering, China University of Petroleum, Qingdao, Shandong 266580, China
[3]Department of Civil, Environmental and Natural Resources Engineering, Operation, Maintenance and Acoustics, Luleå University of Technology, Luleå, Sweden
[1, 4]Department of Systems Engineering and Engineering Management, City University of Hong Kong, Kowloon, Hong Kong

***Abstract*—Fault diagnosis is useful in helping technicians detect, isolate, and identify faults, and troubleshoot. Bayesian network (BN) is probabilistic graphical model that effectively deals with various uncertainty problems. This model is increasingly utilized in fault diagnosis. This paper presents bibliographical review on use of BNs in fault diagnosis in the last decades with focus on engineering systems. This work also presents general procedure of fault diagnosis modeling with BNs; processes include BN structure modeling, BN parameter modeling, BN inference, fault identification, validation, and verification. The paper provides series of classification schemes for BNs for fault diagnosis, BNs combined with other techniques, and domain of fault diagnosis with BN. This study finally explores current gaps and challenges and several directions for future research.**

Index Terms—Bayesian networks, fault diagnosis.

I. INTRODUCTION

WITH rapid development of modern industrial systems, systematic complexity increases constantly. Therefore, fault diagnosis must be utilized to obtain high reliability and availability. Fault diagnosis quickly detects process abnormality and component fault and identifies root causes of these failures by using appropriate models, algorithms, and system observations. Therefore, fault diagnosis system is useful in assisting operations staff to detect, isolate, and identify faults and to aid in troubleshooting.

In general, fault diagnosis approaches can be classified into three categories: model-based [1], signal-based [2], and data-driven approaches [3]. In model-based approach, focus is on establishing mathematical models of complex industrial systems. These models can be constructed by various identification methods, physical principles, etc. Signal-based approach uses detected signals to diagnose possible abnormalities and faults by comparing detected signals with prior information of normal industrial systems [4]. Usually, difficulty occurs in building accurate mathematical models and obtaining accurate signal patterns for complex industrial and process systems. Data-driven fault diagnosis approach requires large amount of historical data, rather than models or signal patterns [5]. Therefore, data-driven methods are suitable for complex industrial systems.

Data-driven fault diagnosis approach is also called knowledge-based fault diagnosis approach. Knowledge information can be obtained based on either statistical or non-statistical approach. Data-driven approach can be categorized into statistics-based and non-statistics-based fault diagnosis approaches [5]. The former includes principal component analysis [6], independent component analysis [7], and support vector machine [8], whereas the latter includes neural network [9], fuzzy logic [10], etc.

BN is an important probabilistic graphical model, which can deal effectively with various uncertainty problems based on probabilistic information representation and inference. As representational tool, BN is quite attractive for three reasons. First, BN is consistent and complete represents and defines unique probability distribution over network variables. Second, the network is modular; its consistency and completeness are ensured using localized tests, which are only applicable to variables and their direct causes. Third, BN is compact representation, as it allows specification of exponentially sized probability distribution using polynomial of probabilities [11]. Hence, this tool is deeply researched and widely used in many domains ranging from reliability engineering [12–14], risk analysis [15], and safety engineering [16] to resilience engineering [17].

During the last decades, BNs are studied and utilized in domain of fault diagnosis, which is typically data-driven approach. BN-based fault diagnosis models are established using huge amount of historical data. Diagnosis is conducted by backward analysis with various algorithms [18]. That is, we input observed information into evidence nodes, update posterior probabilities of fault nodes based on BN inference, and identify root causes of failure using identification rules. Research attracted considerable attention, solved some important problems of BN-based fault diagnosis, and focused on challenging problems. A large number of literatures, including theory research and project application, were about conference proceedings and technical reports. To our knowledge, literature never reviewed use of BNs in fault diagnosis.

This paper aims to review latest research results of BN-based fault diagnosis approaches to provide reference and to identify future research directions for fault diagnosis researchers and engineers. The remainder of the paper is organized as follows. Section II presents general procedures of fault diagnosis with BNs. Section III introduces types of BNs for fault diagnosis; these types include BNs, dynamic Bayesian networks (DBNs) and object-oriented Bayesian networks (OOBNs). Section IV identifies few on-going and upcoming research directions. Section V summarizes this paper.

ISBN 978-91-7583-841-0

II. PROCEDURES OF FAULT DIAGNOSIS WITH BNS

Fault diagnosis procedures with BNs consist of BN structure modeling, BNs parameter modeling, BN inference, fault identification, and validation and verification. Figure 1 provides detailed flowchart of the process.

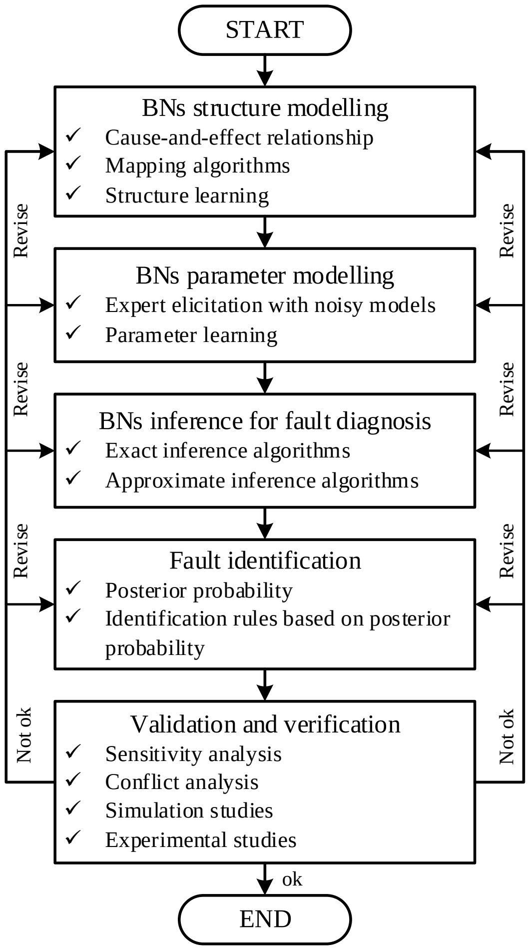


Fig 1. Flowchart of BN-based fault diagnosis

A. BN structure modelling

Several methods were reported in constructing BN structure models for fault diagnosis. Three main methods include cause-and-effect relationship, mapping algorithms, or structuring learning. Per cause-and-effect relationship method, one reflects on their knowledge and experience about faults and fault symptoms and then captures them into a BN. That is, network structure is established based on causal relationship between faults and fault symptoms.

BN structure is usually composed of two layers of events: fault layer and fault symptom layer. For example, Dey and Stori [19] presented BN-based process monitor and fault diagnosis method for combining multi-sensor data during machining operation to diagnose root causes of process variations. Root layer and evidence layer consist of structure of proposed BNs for root cause diagnosis.

Aside from two basic layers, other layers representing various information are added and established in BN structure to improve fault diagnostic performances. Cai et al. [20] developed BN-based ground-source heat pump fault diagnosis system by fusing multi-sensor data. A new layer, which is observed information layer, is established to connect to the fault layer directly for improving performance and increasing fault diagnosis accuracy.

Per mapping algorithms, one automatically synthesizes BN from other type of formal knowledge or models, such as fault tree and bow tie models. Lampis and Andrews [21] proposed a system fault diagnosis method by converting fault trees into BNs. These people built non-coherent fault tree model for fault diagnosis of systems and mapped it to BNs following a two-step rule.

According to structure learning, BN structure can be constructed based on learning from data related to faults and fault symptoms when sufficient data are available. Given that learning is inductive process, principle of induction guides construction processes, such as maximum likelihood approach and Bayesian approach. Jin et al. [22] presented BN-based fault detection and diagnosis method of assembly fixture. These scientists proposed structure learning method by using mutual information test to obtain causal relationships among fixture and sensor nodes.

Former two methods are sometimes known as knowledge representation methods, whereas the third one is known as machine learning method. Networks constructed by knowledge representation methods have different nature from those constructed by machine learning method. For example, former networks had larger sizes and placed harsher computational demands on reasoning algorithms. Moreover, these networks had significant amount of determinism (i.e., probabilities equal to 0 or 1), allowing them to benefit from computational techniques, which may be irrelevant to networks constructed by machine learning method [11]. However, the former two methods, especially cause-and-effect relationship method, may produce inaccurate models. Although structure learning method is more accurate, difficulty or impossibility sometimes arise from obtaining available and sufficient data for learning. Of course, simulation methods can be used to generate required data to fill this gap.

B. BN parameter modeling

BNs parameter model consists of prior probability of root nodes and conditional probability of leaf nodes. Prior probabilities of events are calculated before acquisition of new evidence, observation or information. These data can be achieved from expert knowledge and experience and statistical results of historical, simulated, and experimental data. With increasing prior probability, events have higher probability of happening. In general, in fault diagnosis, we assume that prior probabilities of all fault nodes are identical to emphasize posterior probabilities with new observations [20].

Conditional probabilities expectedly take place when other events are known to occur. These probabilities are usually contained in conditional probability table (CPT). Various ways exist for obtaining CPTs generally fall into two main approaches: knowledge elicitation from experts and data-driven parameterization through machine learning methods. Knowledge elicitation from experts has disadvantages, including specificity of exponential growth of parameters. To specify complete CPT for child node m with s_m states and n parent nodes, $(s_m-1)\prod_{i=1}^{n} s_i$ probabilities should be evaluated; s_i is number of states of parent node i [23]. Suppose that we have variables with n parents, and that each variable has only two values. We then need 2^n independent parameters to completely specify CPT for the variable. Modeling arises as number of parents, n,

ISBN 978-91-7583-841-0

becomes larger. Noisy-OR and noisy-MAX models were reported to simplify knowledge elicitation from experts of CPTs.

When a node is Boolean type and has normal and abnormal states, which can be detected by sensors, node CPT can be simplified with noisy-OR model. Supposing that all nodes are Boolean, several causes X_1, X_2, …, X_n lead to an effect Y, and CPT can be generated with only n parameters, and q_1, q_2, …, q_n are obtained using the following:

$$P(Y=1 \mid X_1, X_2, ..., X_n) = 1 - \prod_{i=1}^{n} q_i \qquad (1)$$

where q_i is probability for each parent with false Y when X_i is true, and all other parents are false [24].

Recently, Cai et al. utilized noisy-OR and noisy-MAX models to determine complete CPTs of BNs for fault diagnosis of complex industrial systems, such as ground-source heat pump [20] and subsea production systems [24]. Kraaijeveld and Druzdzel [25] proposed method to simplify and speed up design in constructing diagnostic BNs, and interaction among variables was modeled by noisy-MAX gates. Notably, knowledge elicitation from experts using noisy models may cause errors even in diagnostic results because of independent assumptions of these models.

Noisy models are for local structures only. Each noisy model is based on assumptions about interactions of parents with their common child. When assumption corresponds to reality, then noisy models are used for local structure. Otherwise, resulting Bayesian network will be inaccurate model (but it could be a good approximation).

CPTs are also generated through BN parameter learning from historical data. This method is similar to structure learning; its advantage includes more accurate BN parameter model, whereas its disadvantage is difficult and sometimes impossible acquisition of available and sufficient historical data. For instance, SIAM database was used for learning of CPTs of BN models for railway diagnosis [26].

C. BN inference

Based on conditional independence assumptions and chain rules, joint probability of variables $U = \{A_1, A_2, …, A_n\}$ can be calculated as follows:

$$P(U) = \prod_{i=1}^{n} P(A_i \mid Pa(A_i)) \qquad (2)$$

where $Pa(A_i)$ is parent node of A_i in BNs.

BNs can perform backward or diagnostic analyses with various kind of inference algorithms based on *Bayes' theorem*, which is as follows: [27]

$$P(U \mid E) = \frac{P(E \mid U)P(U)}{P(E)} = \frac{P(E,U)}{\sum_U P(E,U)} \qquad (3)$$

In general, inference algorithms are divided into exact inference and inferences. Exact inference algorithms can compute exact probabilities of variables and include message-passing, conditioning, junction tree, symbolic probabilistic inference, arc reversal/node reduction, and differential algorithms. Approximate inference computes approximate probabilities of variables with statistical approach. This inference includes algorithms for stochastic sampling, search-based algorithm, and loopy belief propagation algorithm. For complex BNs, inference is NP hard problem.

Exact inference algorithms, for example, junction tree, were used in fault diagnosis of single-tank systems [28] and end-to-end service quality of qualitative diagnosis [29]. Complexity in exact inference algorithms leads to surge of interest in approximate inference algorithms, which are generally independent of *treewidth*. Today, approximate inference algorithms are the only choice for networks having large *treewidth.* Yet, such algorithms lack sufficient local structure. For example, Wiegerinck, et al. [30] adapted variational methods with tractable structures to develop approximate inference algorithm of BNs for medical diagnosis.

D. Fault identification

Fault identification is conducted based on posterior probabilities of fault nodes based on provided evidence. Only probabilities of faults can be given, but definite diagnostic results cannot be drawn per posterior probabilities. Overall, corresponding fault has higher probability of occurrence with increasing posterior probability.

For some fault diagnoses, diagnostic result is directly determined by posterior probability. For instance, in BN-based fault diagnosis systems for manufacturing tests of mobile telephone infrastructure, nodes with highest posterior probability of failure state were considered as either tokens to second BN or advice nodes. When nodes were the former, existing BN was saved as case, and other BNs defined in the token were loaded. In case of the latter, nodes were considered to be advice nodes [31]. In BN-based control loop diagnosis, according to maximum a posteriori principle, the mode with biggest posterior probability is potential fault mode, and abnormalities related to this fault mode were root causes of failure [32]. Notably, used algorithm may cause some errors when posterior probability is used directly for fault identification, because some faults have inherently high prior probability (before BN inference), or simultaneous faults may exist. Therefore, to increase accuracy and robustness of fault diagnosis, a series of fault identification rules were reported for determination of diagnostic results.

In BN-based inverter fault diagnosis, the following identification methods are defined: (a) system reports a single open-circuit of switch with highest posterior probability when it is higher than 70%, or 50% higher than the second highest one; (b) system reports double open-circuit failure of switch with highest and second highest posterior probabilities when both are higher than 70% or 50 higher than the third highest one [33]. Remarkably, for different fault diagnosis systems, one should develop corresponding different fault identification rules. This goal requires complex work, because rules must be defined, tested, and revised repeatedly until achievement of satisfactory diagnostic performance.

E. Verification and Validation

Model verification and validation are significant aspects of fault diagnosis because they provide reasonable confidence to diagnostic results. Many methods, such as sensitivity analysis, conflict analysis, simulation and experimental research, are used for BN-based fault diagnosis verification and validation. Specifically, sensitivity analysis can be used for model verification, and the four methods can all be used for model validation.

Sensitivity analysis can be conducted by using mutual information of fault nodes and fault symptom nodes. Let us use an entropy function provided as Eq. (6) to represent uncertainty of a system; mutual information is defined as uncertainty reducing potential of *X* given the original uncertainty in *T* prior to consulting *X* [34]. Mutual information of *T* and *X* can be expressed as Eq. (7), as follows.

$$H(T) = -\sum_{t} P(t) \log P(t)$$

(4)

where $P(t)$ is probability distribution of random variable *T*. The next equation is then used:

$$I(T,X) = -\sum_{x}\sum_{t} P(t,x) \log \frac{P(t,x)}{P(t)P(x)} \qquad (5)$$

where $P(t)$ is marginal probability distribution of *T*, $P(x)$ is marginal probability distributions of *X*, and $P(t, x)$ is joint probability distribution of *T* and *X*.

When observations are input to BN-based fault diagnosis model as evidence, conflict may occur, indicating the weak relation of model to evidence. This evidence-driven conflict analysis can be used for detecting possible conflicts in evidence or between evidence and BN-based fault diagnosis model. This way, we can use conflict analysis approach to validate and verify BN-based fault diagnosis model.

A conflict measure is designed to indicate possible conflicts when joint probability of evidence is less than the product of probabilities of individual pieces of evidence in models. The main assumption is that pieces of evidence are positively correlated such that $P(x) > \prod_{i=1}^{n} P(x_i)$. With this assumption, general conflict measure is defined as follows [35]:

$$\mathrm{conflict}(x) = \mathrm{conflict}(\{x_1, \ldots, x_n\}) = \log \frac{\prod_{i=1}^{n} P(x_i)}{p(x)}$$

(6)

This measure implies that positive values of conflict measure (*x*) indicate possible conflict and therefore an incorrect model. Cai et al. [23] utilized this evidence-driven conflict analysis approach to validate an OOBN model for fault detection and diagnosis of complex industrial systems.

In general, sensitivity and conflict analyses are used for partial verification and validation. Simulation and experimental methods can be used for full verification and validation per various simulated and experimental faults. One good and accurate method employs verification and validation of proposed fault diagnosis approach, which is performed by comparing practical and diagnostic faults after development of fault diagnosis approach and corresponding fault diagnosis system; however, this way is not always practical or possible. Many faults cannot be injected and tested. Still, simulation methods can imitate all kinds of faults, which are good supplement of experimental methods. For instance, Ling and Mahadevan [36] utilized Bayesian hypothesis testing proposed in [37] to evaluate performance of BN-based structural damage prognosis approach by comparing predicted and observed data.

III. TYPES OF BNS FOR FAULT DIAGNOSIS

A. *BN for fault diagnosis*

BN, also known as static BN, is most widely used in fault diagnosis. As reviewed in Section III, most fault diagnosis applications correspond to BNs. This subsection emphasizes classification but does not repeat literature. When fault diagnosis is involved in temporal, system, or complex systems, inevitable difficulties with static BNs are observed. Therefore, some other types of BNs, such as DBNs and OOBNs, are used to solve these problems, which are described in detail in the next three subsections.

B. *DBNs for fault diagnosis*

Static BNs are mainly used in modeling and inference for fault detection and diagnosis. Modeling of fault diagnosis does not involve temporal features of faults, fault symptoms, and even the systems themselves. That is, static-BN-based fault diagnosis is performed at certain time point without considering temporal relations. However, given the same fault symptoms, diagnostic results may be totally different at different time periods because of performance degradation of components [38]. In other words, a new system is more likely to work well than an aged system at succeeding time point when it works well at present time. New systems can also increase accuracy and reliability of fault diagnosis by involving dynamic and temporal features in fault diagnosis models [39]. DBNs are extensional BNs with time-dependent variables and can be used to model temporal evolution of dynamic systems. DBNs include multiple copies of identical nodes, where different copies represent different states of nodes over time. Nodes in same copies are connected using intra-slice arcs, and nodes in different copies are connected by inter-slice arcs, integrating an entire DBN. DBNs have strong power in modeling, representing, and reasoning of dynamic systems and are therefore increasingly used in dynamic system diagnosis.

Arroyo-Figueroa et al. [40] introduced new formalism of BNs, i.e., temporal BN of events, to deal with uncertainty and time for fault detection and diagnosis in dynamic domains. Proposed temporal BN is actually a DBN. Lerner et al. [41] proposed a new approach based on framework of hybrid DBNs for fault diagnosis of complex systems with both discrete and continuous nodes. Kao et al. [42] utilized DBN as knowledge base of reasoning system to model causal relationships in supply chain, where diagnostic tasks are conducted. Wu et al. [43] proposed DBN-based decision support method was used in the study for safety analysis. Posterior probability distributions were used to aid technicians perform online fault diagnosis. Given that DBN model contains many time slices over a long period, BN inference and fault diagnosis are much slower than BN-based methods.

C. *OOBNs for fault diagnosis*

Object-oriented approach possesses characteristics, including encapsulation, inheritance, polymorphism, and modularity. This approach is introduced into BNs, forming OOBNs. OOBNs also utilize terminology class and objects from object-oriented approach. Class is generic network fragment, that is, a BN; object is fragment generated by instantiating the class [44]. Nodes in class or object can be classified into three categories: input node, output node, and encapsulated node. Input and output nodes are regarded as object interfaces. When object is encapsulated in other

ISBN 978-91-7583-841-0

objects, OOBNs provide an approach to achieve hierarchical representation of the model, and each level corresponds to particular level of abstraction, revealing encapsulated nodes for current layer of object.

With comparison of general BNs and DBNs, OOBNs have the following advantages: first, the model supports top-down model construction process. Second, OOBNs are constructed by integrating small and understandable network fragments, benefiting knowledge acquisition and communication between modelers and domain experts. Third, this approach reduces complexity of building BNs and improves reusability of models. Finally, OOBNs have high average rate of convergence and time efficiency because of encapsulation and hierarchy. OOBNs are therefore a powerful and suitable tool for constructing complex models [45].

According to our review, OOBN application is limited when used on fault diagnosis of complex systems. For instance, Cai et al. [23] presented novel OOBN-based real-time fault diagnosis approach. In their study, OOBNs were used to model repetitive structures and components within complex industrial systems. Huang et al. [46] used OOBNs to establish probability-based vehicle fault diagnosis model with four sub-models and three common root causes.

IV. Discussions and Research Directions

Based on BN-based fault diagnosis presented in this paper, we identify few ongoing and upcoming research directions that are of interest to fault diagnosis researchers.

A. Integrated big data and BN fault diagnosis methodology

Big data are recent data paradigm that describes not only much more voluminous data but also coupling of such data with sophisticated data analytics to acquire new knowledge or insight [47]. A large number of normal and abnormal data are created and collected in operation of complex industrial systems during long periods. These data can be used for data-driven fault diagnosis. BN-based fault diagnosis approach is typically data-driven. Integrated big data and BN fault diagnosis methodology provide definite orientation for interdisciplinary research, which could be divided into two important parts: The first will study fault feature extraction method from big data, and the second will focus on BN-based fault diagnosis method using these fault features.

B. BN-based non-permanent fault diagnosis

As reviewed in previous sections, BN-based fault diagnosis methodologies are mainly used to identify various permanent faults. Permanent fault, which is also called hard failure, causes deterioration of system performance and cannot disappear before maintenance or repair. Two types of non-permanent faults, that is, transient faults and intermittent faults, also exist in various engineering systems. Transient fault occurs with random frequency, is not easily repeatable, and usually cannot destroy systems permanently. Intermittent fault may occur repeatedly in a component and has characteristics of randomness, intermittency, and repeatability. Permanent fault may result from increasing intermittent faults and cause system failure. Transient and intermittent faults are also called soft faults. These faults are very difficult to identify and diagnose, because faults may not occur during system repair. Studies reported about BN/DBN-based fault detection and diagnosis method for transient or intermittent fault of electronic products [38] and electrical power system [48]. However, significant problems arise regarding analysis of nature and causes of these permanent, transient, or intermittent faults and identification of failed components and fault type using BN-based fault diagnosis.

C. Fast inference algorithms of BNs for on-line fault diagnosis

Real-time on-line fault diagnosis system is much more useful than off-line one in assisting operations staff to detect, isolate, and identify faults when they occur and to aid troubleshooting. For on-line fault diagnosis of complex industrial system with huge BNs, especially DBNs, exact and approximate inference algorithms may be both slow. When OOBNs are used, fault diagnosis model, including thousands of nodes, may be extremely complex. As more evidence are observed, desired hidden variables are estimated to become highly correlated. Traditional inference becomes increasingly expensive, costs lots of time, and hardly performs real-time fault diagnosis. Fast approximate inference algorithms of BNs should be developed for on-line fault diagnosis. In particular, in OOBN-based fault diagnosis model, structural information encoded in OOBNS, especially encapsulated variables in objects, can improve efficiency and speed of inference, both of which are used to study fast inference algorithms and perform real-time fault diagnosis.

D. BNs for closed-loop control system fault diagnosis

A complex industrial system usually includes numerous closed-loop feedback control subsystems. Previous BN-based methods adopted corresponding relationship of faults and symptoms to build fault diagnosis models, that is, they treated closed-loop feedback control systems as general systems. Studies did not consider effects of closed-loop feedback control algorithms on performance of fault diagnosis. BN is directed acyclic graph, indicating that networks cannot contain cycles. Challenging problems accompany establishment of fault diagnosis models of closed-loop feedback control systems with directed acyclic BNs and investigation of effects of control on diagnosis.

E. Fault identification rules

Although excellent diagnostic performance of BN-based method in fault diagnosis was demonstrated with various fault identification rules as reviewed above, industrial systems still demonstrate false alarm in fault diagnosis. False alarm rate is significant assessment indicator for fault diagnosis, and high false alarm rate cannot be accepted by users of industrial systems. Although some researchers used additionally observed information [20] and probabilistic boundary limit [49] to reduce false alarm rate, false alarm is still a challenging problem. This type of problem can be solved by development of suitable fault identification rules using posterior probability integrated with prior probability.

V. Conclusions

Over the past decades, application of BNs on fault diagnosis was well studied by researchers and practitioners. Effort was devoted to formulating BN-based fault diagnosis methodology and developing corresponding fault diagnosis systems. However, related challenges still exist. This paper

ISBN 978-91-7583-841-0

provided literature review of application of BNs to fault detection and diagnosis.

The paper presented general procedure of fault diagnosis modeling with BNs; considered processes included BN structure modeling, BN parameter modeling, BN inference, fault identification, and validation and verification. For each procedure, various methods were reviewed. This work also provided series of classification schemes of BNs in fault diagnosis. BN types, including static BNs, DBNs, and OOBNs, were reviewed in application of fault diagnosis. We pointed out potential problems of applying BNs to fault diagnosis, and upcoming research directions are addressed.

Although we reviewed as many literatures as possible, we realized impossibility of including all publications related to BNs in fault diagnosis; such publications involved non-English literature. The major contribution of this paper was presenting general BN-based fault diagnosis methodology and a series of classification schemes of BNs in fault diagnosis. We hope that this literature review can serve as useful guide in fault diagnosis with BNs and provide comprehensive reference for researchers and practitioners.

ACKNOWLEDGMENT

The authors wish to acknowledge the financial support of, National Natural Science Foundation of China (No. 51309240), Program for Changjiang Scholars and Innovative Research Team in University (No. IRT_14R58), Specialized Research Fund for the Doctoral Program of Higher Education (No. 20130133120007), and Fundamental Research Funds for the Central Universities (No.14CX02197A).

REFERENCES

[1] V. Venkatasubramanian, R. Rengaswamy, K. Yin, S. N. Kavuri, "A review of process fault detection and diagnosis: Part I: Quantitative model-based methods," *Computers & Chemical Engineering*, vol. 27, no. 9, pp. 293-311, Mar 2003.

[2] Y. Lei, J. Lin, Z. He, M. J. Zuo, "A review on empirical mode decomposition in fault diagnosis of rotating machinery," Mechanical Systems and Signal Processing, vol. 35, no. 1, pp. 108-126, Feb 2013.

[3] V. Venkatasubramanian, R. Rengaswamy, S. N. Kavuri, K. Yin, "A review of process fault detection and diagnosis: Part III: Process history based methods," Computers & chemical engineering, vol. 27, no. 3, pp. 327-346, Mar 2003.

[4] Z. Gao, C. Cecati, S. X. Ding, "A survey of fault diagnosis and fault-tolerant techniques—Part I: Fault diagnosis with model-based and signal-based approaches," IEEE Transactions on Industrial Electronics, vol. 62, no. 6, pp. 3757-3767, Jun 2015.

[5] Z. Gao, C. Cecati, S. X. Ding, "A Survey of fault diagnosis and fault-tolerant techniques—Part II: Fault diagnosis with knowledge-based and hybrid/active approaches," IEEE Transactions on Industrial Electronics, vol. 62, no. 6, pp. 3768-3774, Jun 2015.

[6] B. Mnassri, M. Ouladsine, "Reconstruction-based contribution approaches for improved fault diagnosis using principal component analysis," Journal of Process Control, vol. 33, pp. 60-76, Sep 2015.

[7] Z. Wang, J. Chen, G. Dong, Y. Zhou, "Constrained independent component analysis and its application to machine fault diagnosis," Mechanical Systems and Signal Processing, vol. 25, no. 7, pp. 2501-2512, Oct 2011.

[8] S. Bansal, S. Sahoo, R. Tiwari, D. J. Bordoloi, "Multiclass fault diagnosis in gears using support vector machine algorithms based on frequency domain data," Measurement, vol. 46, no. 9, pp. 3469-3481, Nov 2013.

[9] B. Liang, S. D. Iwnicki, Y. Zhao, "Application of power spectrum, cepstrum, higher order spectrum and neural network analyses for induction motor fault diagnosis," Mechanical Systems and Signal Processing, vol. 39, no. 1, pp. 342-360, Sep 2013.

[10] J. D. Wu, Y. H. Wang, M. R. Bai, "Development of an expert system for fault diagnosis in scooter engine platform using fuzzy-logic inference," Expert Systems with Applications, vol. 33, no. 4, pp. 1063-1075, Nov 2007.

[11] A. Darwiche. "Modeling and reasoning with Bayesian networks," Cambridge University Press, 2009.

[12] B. Cai, Y. Liu, Z. Liu, X. Tian, X. Dong, S. Yu, "Using Bayesian networks in reliability evaluation for subsea blowout preventer control system," Reliability Engineering & System Safety, vol. 108, pp. 32-41, Dec 2012.

[13] B. Cai, Y. Liu, Y. Ma, L. Huang, Z. Liu, "A framework for the reliability evaluation of grid-connected photovoltaic systems in the presence of intermittent faults," Energy, vol. 93, pp. 1308-1320, Dec 2015.

[14] B. Cai, Y. Liu, Y. Ma, Z. Liu, Y. Zhou, J. Sun, "Real-time reliability evaluation methodology based on dynamic Bayesian networks: A case study of a subsea pipe ram BOP system," ISA transactions, vol. 58, pp. 595-604, Sep 2015.

[15] B. Cai, Y. Liu, Z. Liu, X. Tian, Y. Zhang, R. Ji, "Application of Bayesian networks in quantitative risk assessment of subsea blowout preventer operations," Risk Analysis, vol. 33, no. 7, pp. 1293-1311, Jul 2013.

[16] M. Hänninen, O. A. Banda, P. Kujala, "Bayesian network model of maritime safety management," Expert Systems with Applications, vol. 41, no. 17, pp. 7837-7846, Dec 2014.

[17] N. Yodo, P. Wang, "Resilience modeling and quantification for engineered systems using Bayesian networks," Journal of Mechanical Design, vol. 138, no. 3, 031404, Mar 2016.

[18] A. Bobbio, L. Portinale, M. Minichino, E. Ciancamerla, "Improving the analysis of dependable systems by mapping fault trees into Bayesian networks," Reliability Engineering & System Safety, vol. 71, no. 3, pp. 249-260, Mar 2001.

[19] S. Dey, J. A. Stori, "A Bayesian network approach to root cause diagnosis of process variations," International Journal of Machine Tools and Manufacture, vol. 45, no. 1, pp. 75-91, Jan 2005.

[20] B. Cai, Y. Liu, Q. Fan, Y. Zhang, Z. Liu, S. Yu, R. Ji, "Multi-source information fusion based fault diagnosis of ground-source heat pump using Bayesian network," Applied Energy, vol. 114, pp. 1-9, Feb 2014.

[21] M. Lampis, J. D. Andrews, "Bayesian belief networks for system fault diagnostics," Quality and Reliability Engineering International, vol. 25, no. 4, pp. 409-426, Jun 2009.

[22] S. Jin, Y. Liu, Z. Lin, "A Bayesian network approach for fixture fault diagnosis in launch of the assembly process," International Journal of Production Research, vol. 50, no. 23, pp. 6655-6666, Dec 2012.

[23] B. Cai, H. Liu, M. Xie, "A real-time fault diagnosis methodology of complex systems using object-oriented Bayesian networks," Mechanical Systems and Signal Processing, May 2016.

[24] W. Li, P. Poupart, P. van Beek, "Exploiting structure in weighted model counting approaches to probabilistic inference," Journal of Artificial Intelligence Research, vol. 40, pp.729-765, 2011.

[25] P. Kraaijeveld, M. Druzdzel, A. Onisko, H. Wasyluk, "Genierate: An interactive generator of diagnostic bayesian network models," InProc. 16th Int. Workshop Principles Diagnosis, pp. 175-180, Jun 2005.

[26] L. Oukhellou, E. Come, L. Bouillaut, P. Aknin, "Combined use of sensor data and structural knowledge processed by Bayesian network: Application to a railway diagnosis aid scheme," Transportation Research Part C: Emerging Technologies, vol. 16, no. 6, pp. 755-767, Dec 2008.

[27] A. Darwiche, "Modeling and reasoning with Bayesian networks," Cambridge University Press, Apr 2009.

[28] C. H. Lo, Y. K. Wong, A. B. Rad, "Bond graph based Bayesian network for fault diagnosis," Applied soft computing, vol. 11, no. 1, pp. 1208-1212, Jan 2011.

[29] X. Lin, B. Cheng, J. Chen, "Context-aware end-to-end QoS qualitative diagnosis and quantitative guarantee based on Bayesian network," Computer Communications, vol. 33, no. 17, pp. 2132-2144, Nov 2010.

[30] W. A. Wiegerinck, H. J. Kappen, E. W. ter Braak, W. J. ter Burg, M. J. Nijman, J. P. Neijt, "Approximate inference for medical diagnosis," Pattern Recognition Letters, vol. 20, no. 11, pp. 1231-1239, Nov 1999.

[31] A. Chan, K. R. McNaught, "Using Bayesian networks to improve fault diagnosis during manufacturing tests of mobile telephone infrastructure," Journal of the Operational Research Society, vol. 59, no. 4, pp. 423-430, Apr 2008.

[32] F. Qi, B. Huang, "Bayesian methods for control loop diagnosis in the presence of temporal dependent evidences," Automatica, vol. 47, no. 7, pp. 1349-1356, Jul 2011.

[33] B. Cai, Y. Zhao, H. Liu, M. Xie. "A data-driven fault diagnosis methodology in three-phase inverters for PMSM drive systems," IEEE Transactions on Power Electronics, DOI 10.1109/TPEL.2016.2608842. 2016

[34] J. Pearl, "Probabilistic reasoning in intelligent systems: networks of plausible inference," Morgan Kaufmann, Jun 2014.

[35] U. B. Kjaerulff, A. L. Madsen, “Bayesian networks and influence diagrams,” Springer Science+ Business Media, vol. 200, pp. 114, 2008.
[36] Y. Ling, S. Mahadevan, “Integration of structural health monitoring and fatigue damage prognosis,” Mechanical Systems and Signal Processing, vol. 28, pp. 89-104, Apr 2012.
[37] R. Rebba, S. Mahadevan, S. Huang, “Validation and error estimation of computational models,” Reliability Engineering & System Safety, vol. 91, no. 10, pp. 1390-1397, Oct-Nov. 2006.
[38] B. Cai, Y. Liu, M. Xie, “A Dynamic-Bayesian-Network-Based Fault Diagnosis Methodology Considering Transient and Intermittent Faults,” DOI: 10.1109/TASE.2016.2574875
[39] B. Huang, “Bayesian methods for control loop monitoring and diagnosis,” Journal of process control, vol. 18, no. 9, pp. 829-838, Oct 2008.
[40] G. Arroyo-Figueroa, L. E. Sucar, A. Villavicencio, “Probabilistic temporal reasoning and its application to fossil power plant operation,” Expert Systems with Applications, vol. 15, no. 3, pp. 317-324, Nov 1998.
[41] U. Lerner, R. Parr, D. Koller, G. Biswas, “Bayesian fault detection and diagnosis in dynamic systems,” InAAAI/IAAI , pp. 531-537, Jul 2000.
[42] H. Y. Kao, C. H. Huang, H. L. Li, “Supply chain diagnostics with dynamic Bayesian networks,” Computers & Industrial Engineering, vol. 49, no. 2, pp. 339-347, Sep 2005.
[43] X. Wu, H. Liu, L. Zhang, M. J. Skibniewski, Q. Deng, J. Teng, “A dynamic Bayesian network based approach to safety decision support in tunnel construction,” Reliability Engineering & System Safety, vol. 134, pp. 157-168, Feb 2015.
[44] T. D. Nielsen, F. V. Jensen, “Bayesian networks and decision graphs,” Springer Science & Business Media, Mar 2009.
[45] D. Koller, A. Pfeffer, “Object-oriented Bayesian networks,” In Proceedings of the Thirteenth conference on Uncertainty in artificial intelligence, pp. 302-313, Aug 1997 Morgan Kaufmann Publishers Inc..
[46] Y. Huang, R. McMurran, G. Dhadyalla, R. P. Jones, “Probability based vehicle fault diagnosis: Bayesian network method,” Journal of Intelligent Manufacturing, vol. 19, no. 3, pp. 301-311, Jun 2008.
[47] A. McAfee, E. Brynjolfsson, “Big data: the management revolution,” Harvard Business Review, pp. 60-68, Oct 2012.
[48] B. Ricks, O. J. Mengshoel, “Diagnosis for uncertain, dynamic and hybrid domains using Bayesian networks and arithmetic circuits,” International Journal of Approximate Reasoning, vol. 55, no. 5, pp. 1207-1234, Jul 2014.
[49] S. He, Z. Wang, Z. Wang, X. Gu, Z. Yan, “Fault detection and diagnosis of chiller using Bayesian network classifier with probabilistic boundary,” Applied Thermal Engineering, vol. 107, pp. 37-47, Aug 2016.

Appendix: Bayesian Networks in Fault Diagnosis: Some research issues and challenges

MPMM2016

Bayesian networks (BNs) in fault diagnosis (FD): Some research issues and challenges

Dr. Baoping CAI

28 November 2016, Lulea, Sweden

Personal profile

Dr. Baoping CAI

- **Associate professor in China University of Petroleum**
- **"Hong Kong Scholar" researcher in City University of Hong Kong**
- **Visiting researcher in Norwegian University of Science and Technology**

Research interests:

- **Reliability engineering**
- **Fault diagnosis**
- **Risk analysis**
- **Bayesian networks methodology**
- **Bayesian networks application**

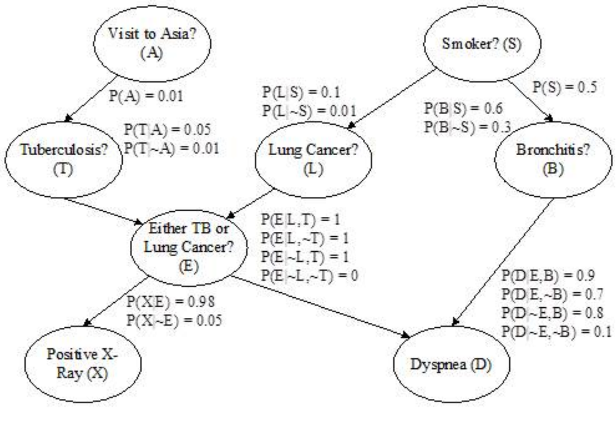
Contents

- ➢1. Overview of BNs
- ➢2. Procedures of FD with BNs
- ➢3. Types of BNs for FD
- ➢4. BNs with other techniques in FD
- ➢5. Domains of FD with BNs
- ➢6. Future research directions

1. Overview of BNs

1.1. What is Bayesian networks (BNs)?

A BN is a directed acyclic graph (DAG) in which the nodes represent the system variables and the arcs symbolize the dependencies or the cause-effect relationships among the variables.



A typical example of Bayesian Networks

1. Overview of BNs

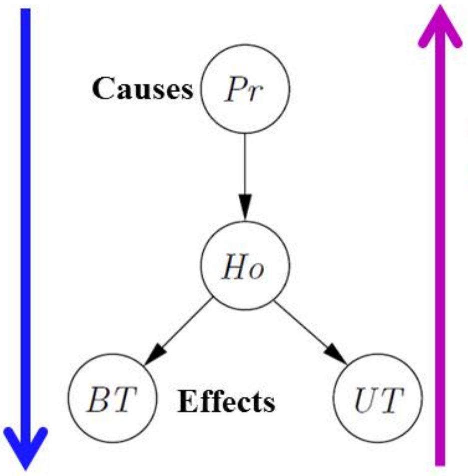
1.2. What can BNs do?

BN can perform forward or predictive analysis as well as backward or diagnostic analysis.

Forward: Predictive

Such as:

- **Reliability**
- **Risk**
- **Safety**



Backward: Diagnostic

Such as:

- **Fault diagnosis**
- **Disease diagnosis**

Contents

ISBN 978-91-7583-841-0

2. Procedures of FD with BNs

START

BNs structure modelling
- ✓Cause-and-effect relationship
- ✓Mapping algorithms
- ✓Structure learning

BNs parameter modelling
- ✓Expert elicitation with noisy models
- ✓Parameter learning

BNs inference for FD
- ✓Exact inference algorithms
- ✓Approximate inference algorithms

Fault identification
- ✓Posterior probability
- ✓Identification rules

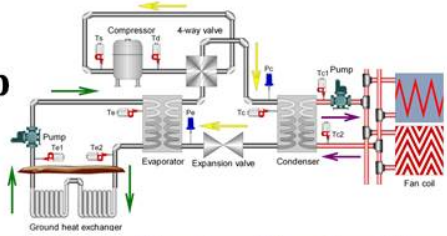
Validation and verification
- ✓Sensitivity analysis
- ✓Conflict analysis
- ✓Simulation studies
- ✓Experimental studies

END

2. Procedures of FD with BNs

2.1. BNs structure modelling

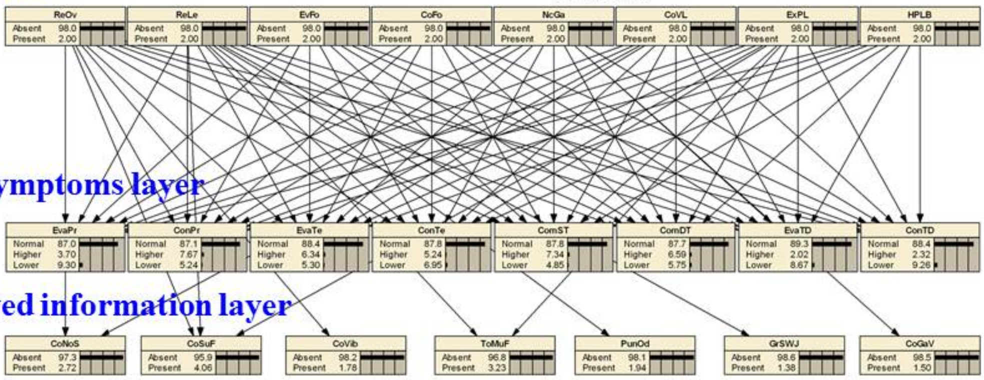
A. Cause-and-effect relationship



Fault layer

Fault symptoms layer

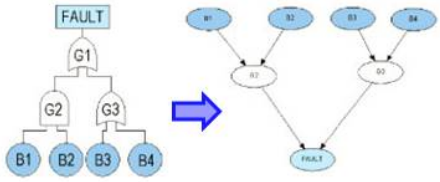
Observed information layer



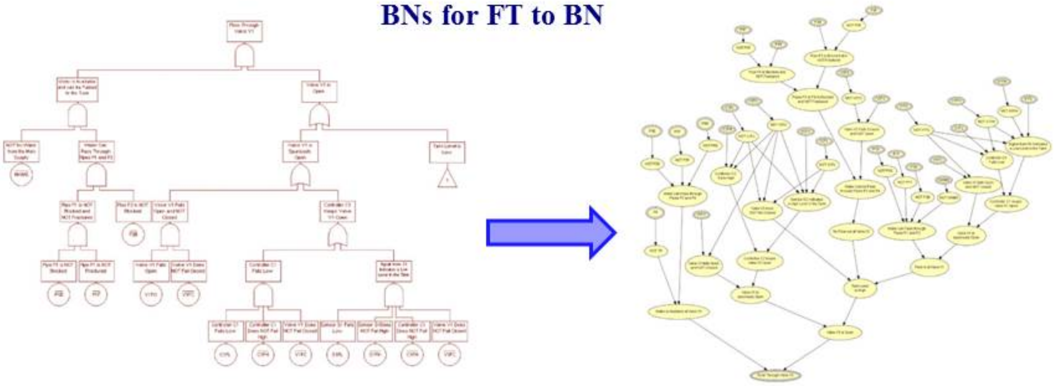
Structure of BNs for FD of ground-source heat pump (Cai, APEN, 2014)

2. Procedures of FD with BNs

B. Mapping algorithms



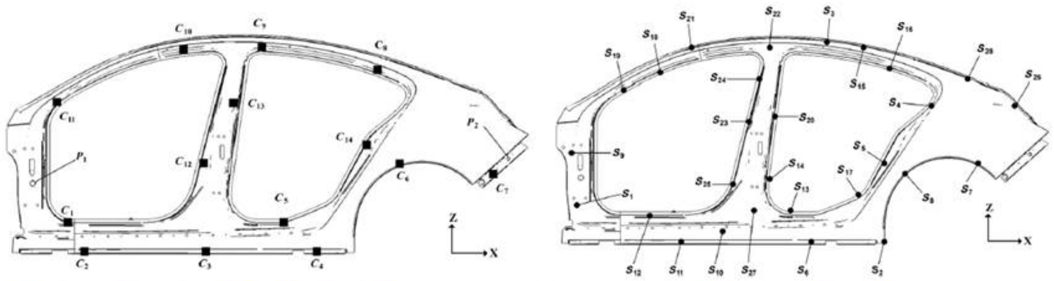
BNs for FT to BN



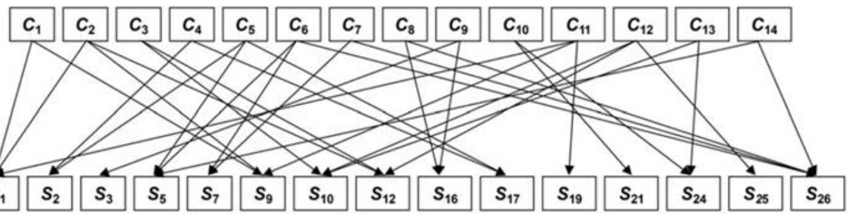
Mapping fault tree to BNs for FD of water level control system (Lampis, 2009)

2. Procedures of FD with BNs

C. Structure learning



Fixture layout of the body side component **28 sensor locations**



Learned structure of BNs for diagnosis of out-of-plane fixture failure (Jin, 2012)

ISBN 978-91-7583-841-0

2. Procedures of FD with BNs

2.2. BNs parameter modelling

A. Expert elicitation with noisy models

Table 1
Relationship between parent and child nodes for TREE_AI subnetwork.

Child node	State	Parent node (High)			
		Corrosion degree	Well fluid temperature	Operating depth	Repair frequency
PMV failure	Present	0.012	0.015	0.014	0.013
	Absent	0.988	0.985	0.986	0.987
AWV failure	Present	0.012	0.015	0.014	0.013
	Absent	0.988	0.985	0.986	0.987
XOV failure	Present	0.012	0.015	0.014	0.013
	Absent	0.988	0.985	0.986	0.987
PFL leakage	Present	0.014	0.012	0.013	0.013
	Absent	0.986	0.988	0.987	0.987
CFL leakage	Present	0.014	0.012	0.013	0.013
	Absent	0.986	0.988	0.987	0.987
AFL leakage	Present	0.014	0.012	0.013	0.013
	Absent	0.986	0.988	0.987	0.987

Noisy-OR

$$P(Y=1 \mid X_1, X_2, \ldots, X_n) = 1 - \prod_{i=1}^{n} q_i$$

Relationship between parent and child nodes for subsea X tree (Cai, MSSP, 2016)

Conditional probabilities of Noisy-MAX node E2 given F4 and F5 and its LEAK probabilities.

E2 $F_{supply} - F_{set}$	F4: Flow sensor bias fault		F5: Supply air pressure fault			LEAK
	Biased	*Fault-free*	*Positive*	*Negative*	*Fault-free*	
Positive	0.01	0	0.8	0	0	0.01
Negative	0.01	0	0	0.8	0	0.01
Within the threshold	0.98	1	0.2	0.2	1	0.98

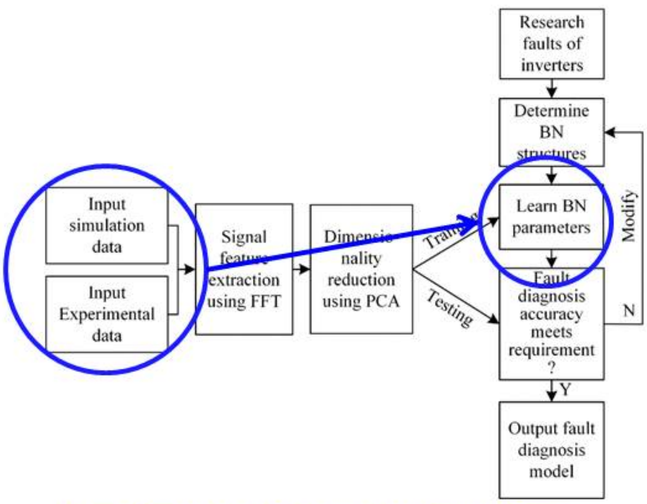
Noisy-MAX

$$P(Y \le y \mid X) = \prod_{\substack{i=1 \\ x_i \neq 0}}^{n} \sum_{y'=0}^{y} q_{i,y'}^{x_i}$$

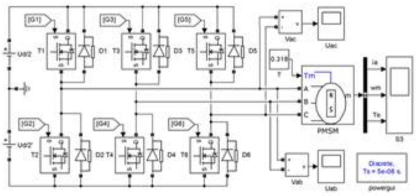
CPT of Noisy-MAX node for FD of variable air volume terminals (Xiao, 2014)

2. Procedures of FD with BNs

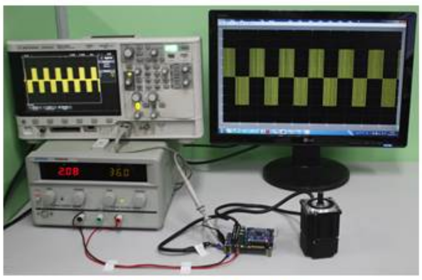
B. Parameter learning



Flow chart of the BN-based FD methodology



Simulink model



Experimental setup

A Data-Driven Fault Diagnosis Methodology in Three-Phase Inverters for PMSM Drive Systems (Cai, TPE, 2016)

ISBN 978-91-7583-841-0

2. Procedures of FD with BNs

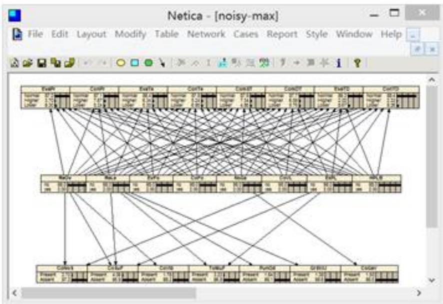
2.3. BNs inference

A. Exact inference

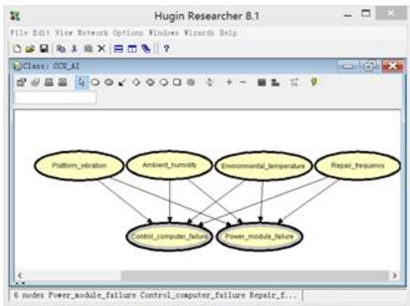
- ☐ Message-passing algorithm
- ☐ Conditioning algorithm
- ☐ Junction tree algorithm
- ☐ Differential algorithm.

B. Approximate inference

- ☐ Stochastic sampling algorithm
- ☐ Search-based algorithm
- ☐ Loopy belief propagation algorithm



Netica

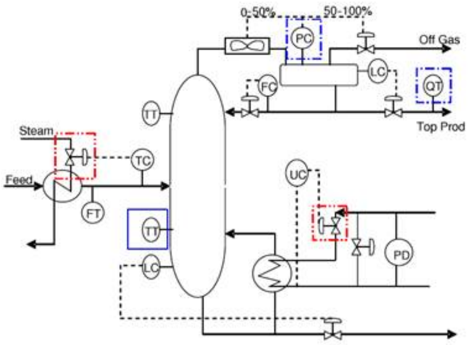


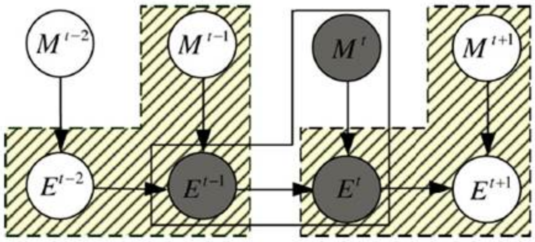
Hugin/Expert

2. Procedures of FD with BNs

2.4. Fault identification

A. Posterior probability

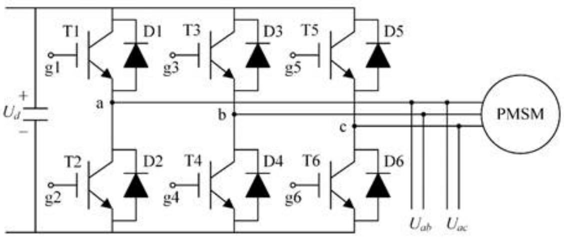


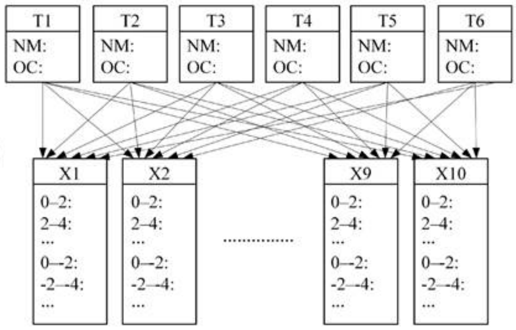


In a control loop diagnosis (Qi, 2011):
the mode with biggest posterior probability was considered to be the potential fault mode, and the abnormalities related to this fault mode were identified to be the root causes of failure.

ISBN 978-91-7583-841-0

B. Identification rules based on posterior probability





In a BN-based inverter fault diagnosis (Cai, TPE, 2016):

(a) the system reports a single open-circuit of switch with highest posterior probability, when it is higher than 70%, or 50% higher than the second highest one;

(b) the system reports a double open-circuit failure of switch with highest and second highest posterior probabilities, when they are both higher than 70% or 50% higher than the third highest one.

2. Procedures of FD with BNs

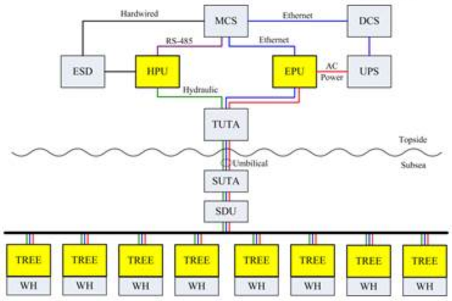
2.5. Validation and verification

A. Sensitivity analysis

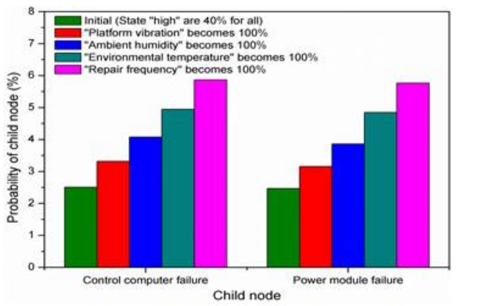
$$I(T,X) = -\sum_{x}\sum_{t} P(t,x)\log\frac{P(t,x)}{P(t)P(x)}$$

B. Conflict analysis

$$\text{conflict}(x) = \text{conflict}(\{x_1,\ldots,x_n\}) = \log\frac{\prod_{i=1}^{n} P(x_i)}{p(x)}$$



Subsea production system of Liuhua 4-1 oil field (Cai, MSSP, 2016)



Sensitivity analysis results

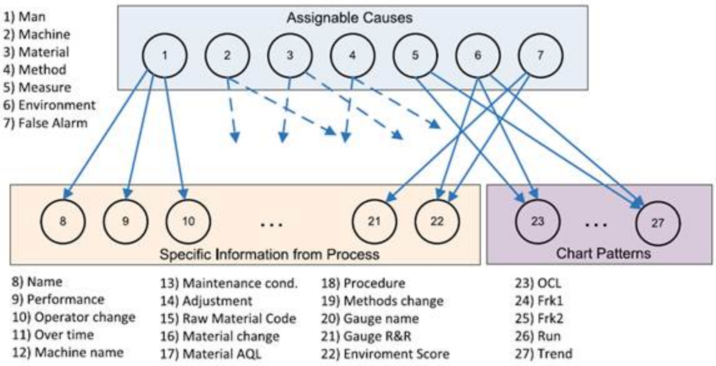
Case	Evidence	Conflict measure	Fault report	Fault warning	True fault
No. 1	TREE1-PT before PMV(Low) TREE1-PT after PMV(Low) TREE1-PT before HIV(Low) TREE4-PT before PMV(Low) TREE4-PT after PMV(High)	−8.4014	TREE1-PFL leakage (98.81%-1.2%=97.61%) TREE4-PMV failure (90.32%-1.5%=88.82%)	None	TREE1-PFL leakage TREE4-PMV failure
No. 2	HPU-PT after fill pump(Low) HPU-LM in supply tack(Low) HPU-PT after accumulator (High) HPU-PT after control valve (Low) HPU-FM after accumulator (Low)	−10.3059	HPU-Control valve failure (99.93%-1.4%=98.53%) HPU-Fill pump failure (73.47%-1.2%=72.27%)	None	HPU-Control valve failure HPU-Fill pump failure
No. 3	TREE8-PT before PMV(Low) TREE8-PT after XOV(Low) EPU-VT after line coupler(Low) EPU-CT after line coupler (Low)	−1.9307	EPU-Line coupler failure (99.62%-2.29%=97.33%)	TREE8-AFL leakage (40.23%-1.2%=39.03%) TREE8-AWV failure (33.58%-1.5%=32.08%)	TREE8-AFL leakage TREE8-AWV failure EPU-Line coupler failure
No. 4	TREE8-PT before PMV(Low) TREE8-PT after XOV(Low) EPU-VT after line coupler(Low) EPU-CT after line coupler (Normal)	3.5009	EPU-Line coupler failure (98.69%-2.29%=96.40%)	TREE8-AFL leakage (40.23%-1.2%=39.03%) TREE8-AWV failure (33.58%-1.5%=32.08%)	TREE8-AFL leakage TREE8-AWV failure EPU-Line coupler failure

Conflict analysis results

ISBN 978-91-7583-841-0

2. Procedures of FD with BNs

C. Simulation studies



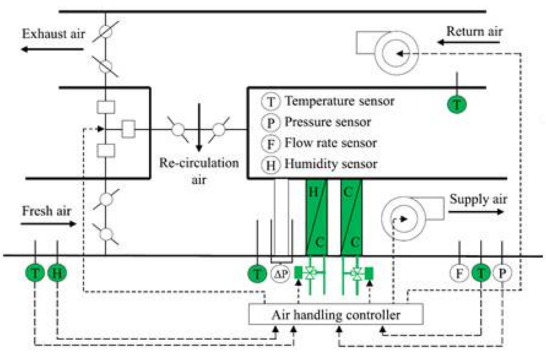
The detail structure of the BNs with the Matrix of Parent and Children relations

In a root cause analysis of statistical process control, two simulation studies have been conducted (Alaeddini, 2013):

- **the proposed method is compared with K-Nearest Neighbor (KNN) and Multi-Layer Perceptron (MLP).**
- **the proposed method is evaluated under various conditions to gain detail information about its performance.**

2. Procedures of FD with BNs

D. Experimental studies



Schematic diagram of the AHU

Diagnostic Bayesian network

In a BN-based FD system for air handling unit (Zhao, 2016):

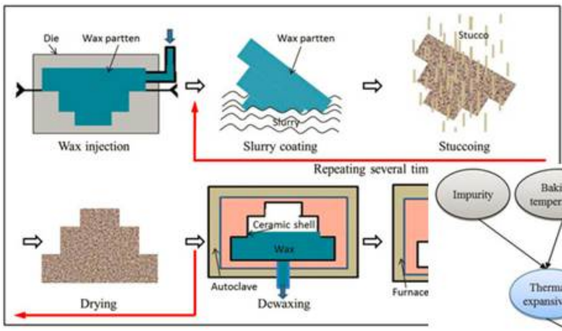
- **they used sample data in practical operating conditions to validate the fault diagnosis model of air handling unit.**

ISBN 978-91-7583-841-0

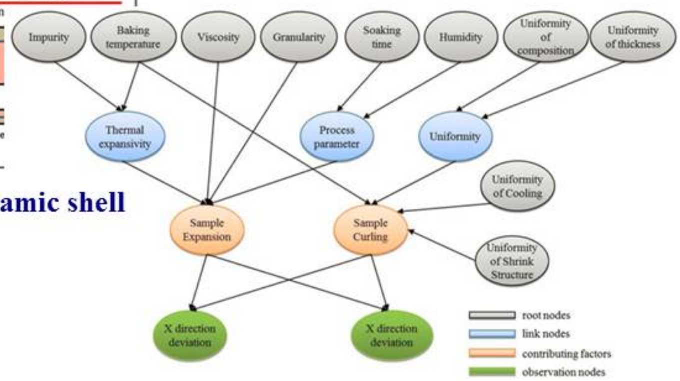
Contents

3. Types of BNs for FD

3.1. Static BNs for fault diagnosis



The process of producing ceramic shell

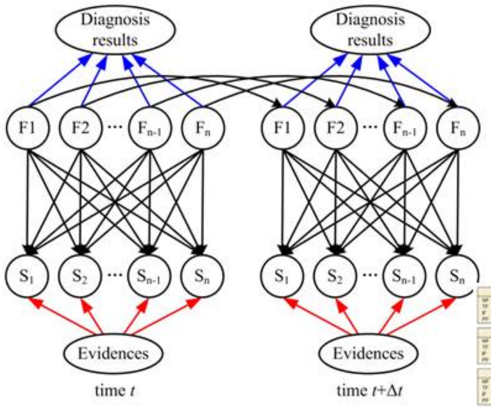


Static-BN-based FD model for the producing of ceramic shell (Jin, 2016)

ISBN 978-91-7583-841-0

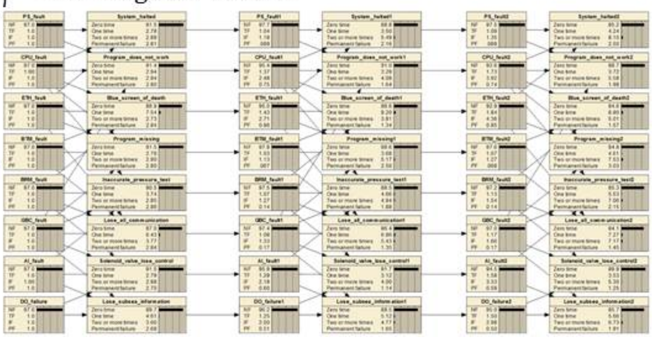
3. Types of BNs for FD

3.2. DBNs for fault diagnosis



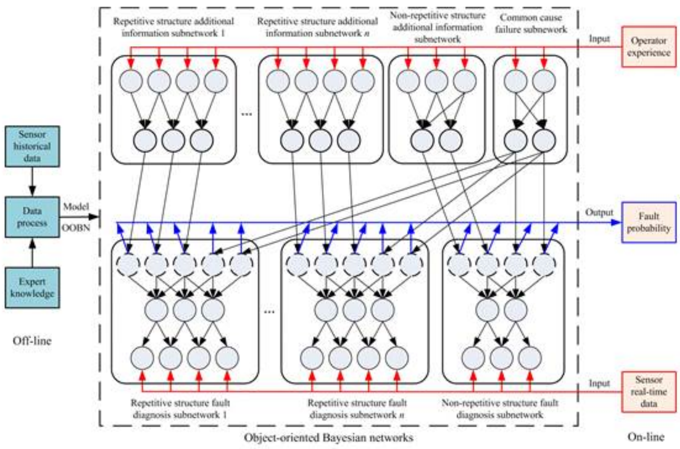
DBN-based fault diagnosis model for GMR control systems (Cai, TASE, 2016)

Given same fault symptoms, the diagnostic result may be totally different in different time periods because of the performance degradation of components.
In other words, a new system is more likely to work well than an aged system in a next time point if it works well at present time. It can increase the accuracy and reliability of fault diagnosis by involving the dynamic and temporal features in fault diagnosis models.

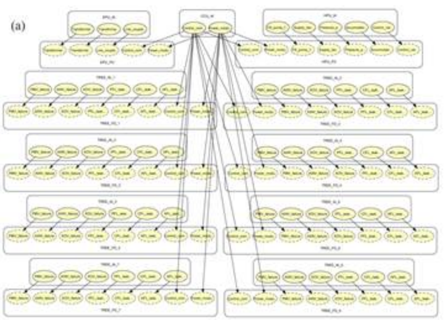


3. Types of BNs for FD

3.3. OOBNs for fault diagnosis



Object-oriented-BN-based fault diagnosis methodology (Cai, MSSP, 2016)



OOBNs have the following advantages:
(1)supports top-down model construction process;
(2)are constructed by integrating small and understandable network fragments, benefiting knowledge acquisition and communication between modelers and domain experts;
(3)reduces the complexity of building BNs, and improves the reusability of models;
(4)have high average rate of convergence and time efficiency thanks to the characteristic of encapsulation and hierarchy.

ISBN 978-91-7583-841-0

Contents

4. BNs with other techniques

Summary of BNs with other techniques in fault diagnosis

References	Types	Joint techniques	Diagnostic objects
Bennacer et al.	BNs	Case-based reasoning	Virtual private networks
Yu et al.	BNs	Independent component analysis	Process system
Hu et al.	DBNs	Functional HAZOP	Process plant
Mandal	BNs	Haar wavelets	Quality spine
Liu et al.	BNs	Ensemble empirical mode decomposition	Gear pump
Cho et al.	BNs	Recurrent neural networks	Induction motor
Sahin et al.	BNs	Distributed particle swarm optimization	Airplane engine
Li et al.	BNs	Adaptive statistic test filter	Rotating machinery
Agrawal et al.	BNs	Fuzzy logic	Coal mills
D'Angelo et al.	BNs	Fuzzy set theory	Machine stator-winding

ISBN 978-91-7583-841-0

Contents

- 1. Overview of BNs
- 2. Procedures of FD with BNs
- 3. Types of BNs for FD
- 4. BNs with other techniques in FD
- 5. Domains of FD with BNs
- 6. Future research directions

5. Domains of FD with BNs

Summary of domains of FD with BNs

Domains	References	Types	Diagnostic objects
Process systems	Verron et al.	BNs	Tennessee Eastman process
	Verron et al.	BNs	Tennessee Eastman process
	Santos et al.	BNs	Tennessee Eastman process
Energy systems	Najafi et al.	BNs	Air handling units
	Wang et al.	BNs	Wind turbine generator
	Bessa et al.	BNs	Wind turbine
Structural systems	Bartram	DBNs	Cantilever beam structure
	Oukhellou et al.	BNs	Railway
	Arangio et al.	BNs	Suspension bridge
Manufacturing systems	Chan et al.	BNs	Manufacturing test
	Sayed et al.	BNs	Assembly systems
	Li et al.	BNs	Semiconductor manufacturing
Network systems	Carrera et al.	BNs	Internet business service
	Bennacer et al.	BNs	Virtual private networks
Biomedicine domain	Arsene et al.	BNs	Heart disease
	Athanasiou et al.	BNs	Caring procedure
	Ahmed et al.	BNs	Trauma diagnosis

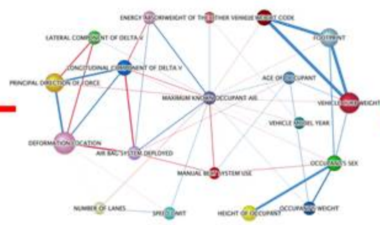
ISBN 978-91-7583-841-0

Contents

6. Future research directions

6.1. FD methodology integrated big data and BNs

+



= FD

Two important parts:

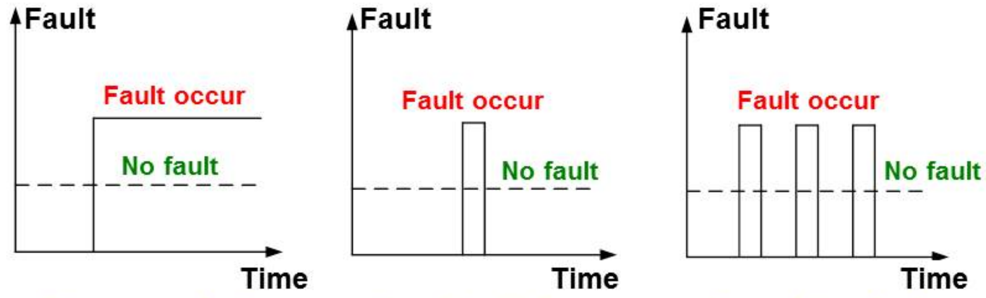
✓Fault feature extraction method from big data;

✓BN-based fault diagnosis method using theses fault features.

ISBN 978-91-7583-841-0

6. Future research directions

6.2. BN-based non-permanent FD



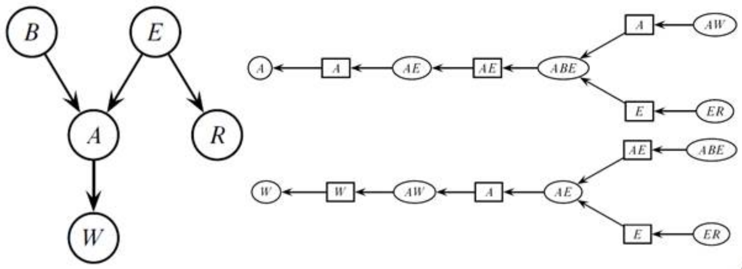
Permanent fault   Transient fault   Intermittent fault

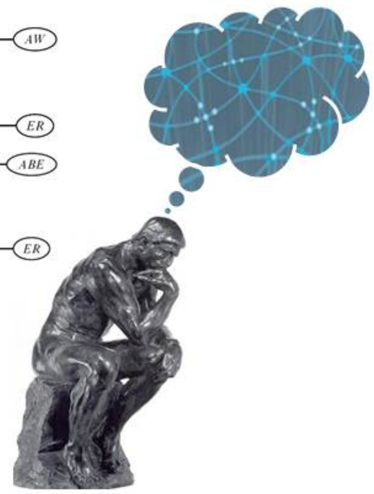
How to:

- ✓ **Analyze the nature and the root causes;**
- ✓ **Identify the failed components;**
- ✓ **Distinguish the fault type using BN-based FD.**

6. Future research directions

6.3. Fast inference algorithms of BNs for on-line FD





Traditional inference:

- **Becomes increasingly expensive;**
- **Costs lots of time;**
- **Hardly perform real-time FD.**

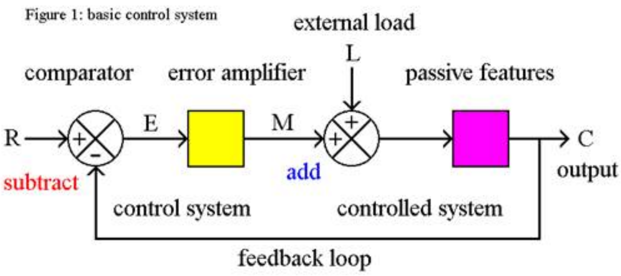
It is necessary to:

✓ **Develop fast approximate inference algorithms of BNs for on-line FD.**

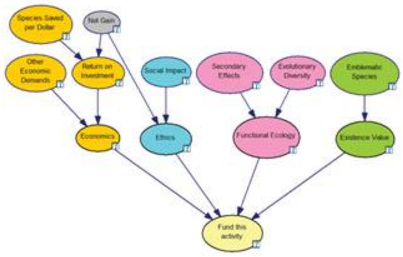
ISBN 978-91-7583-841-0

6. Future research directions

6.4. BNs for closed-loop control system FD



closed-loop control system



BN: acyclic directed graph

How to:

- ✓ Establish the FD models of closed-loop feedback control systems with acyclic directed BNs
- ✓ Investigate the effects of control algorithm on FD

6. Future research directions

6.5. Fault identification rules

False alarm rate is a significant assessment indicator for fault diagnosis, and high false alarm rate cannot be accepted by users of industrial systems.

Developing:

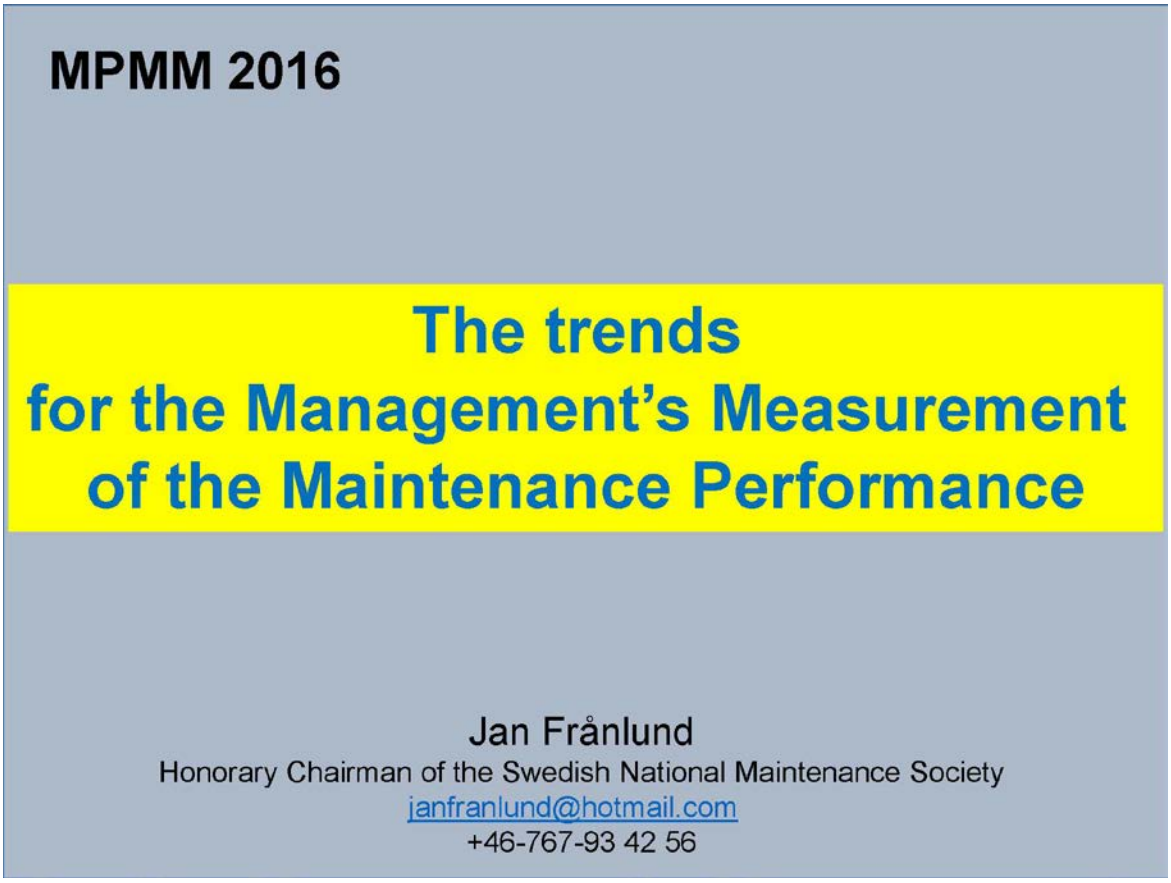
✓Suitable fault identification rules for a certain system, by

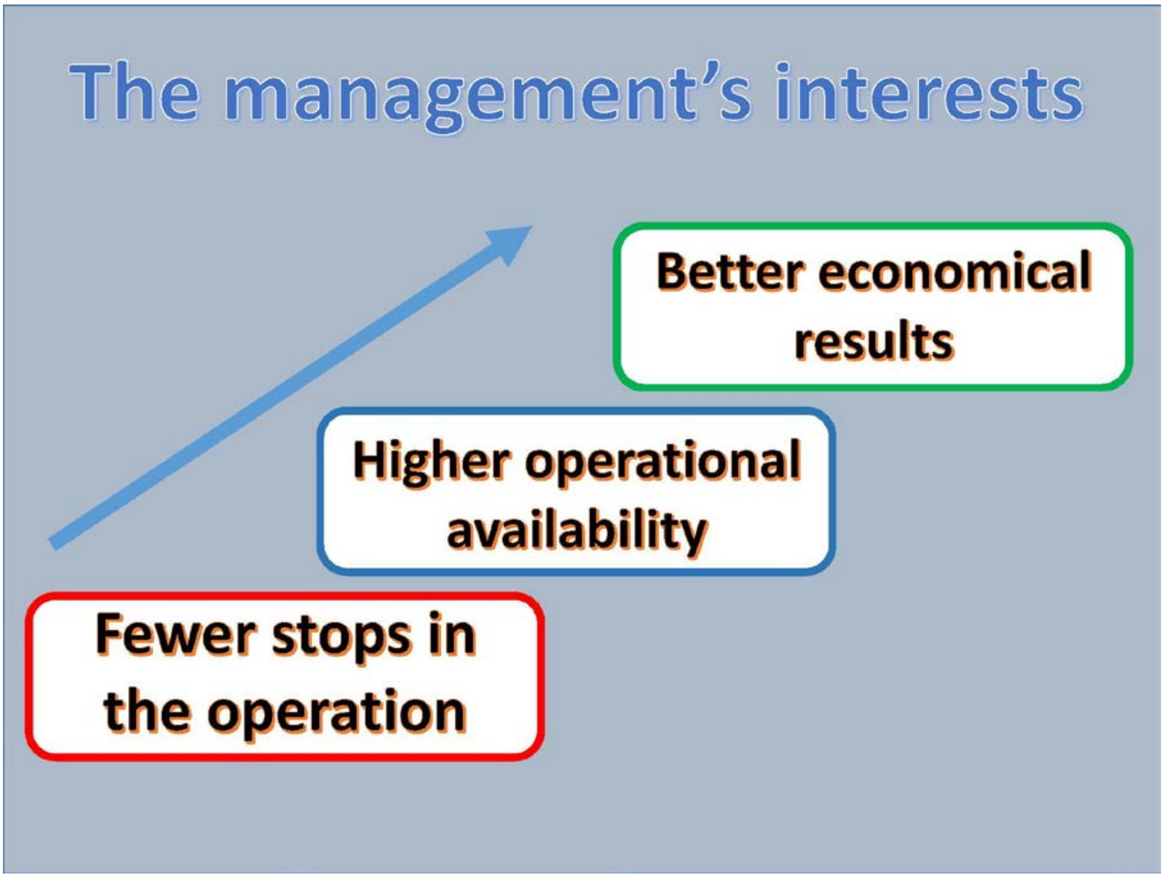
- ➢ using posterior probability directly
- ➢ integrated prior and posterior probability

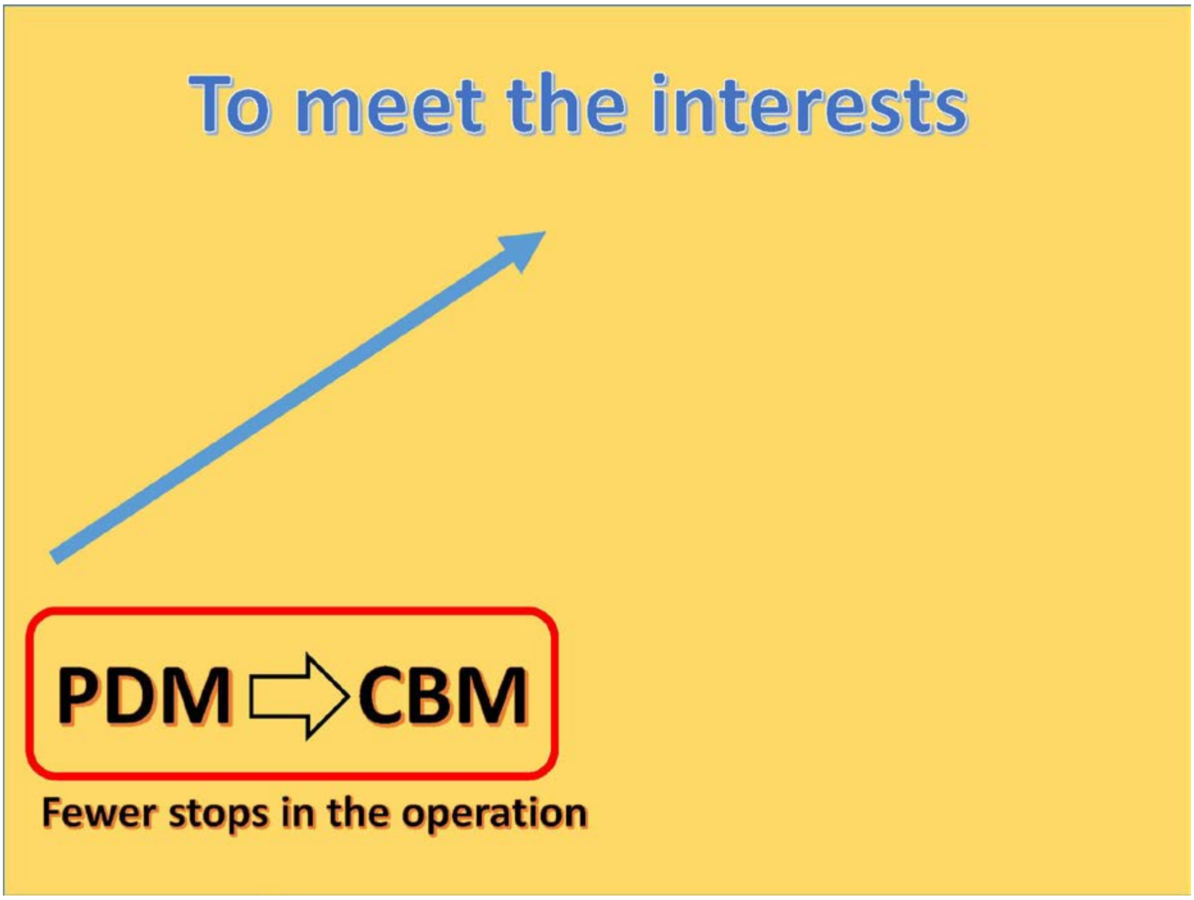
ISBN 978-91-7583-841-0

The trends for the Management's Measurement of the Management's Measurement of the Maintenance Performance

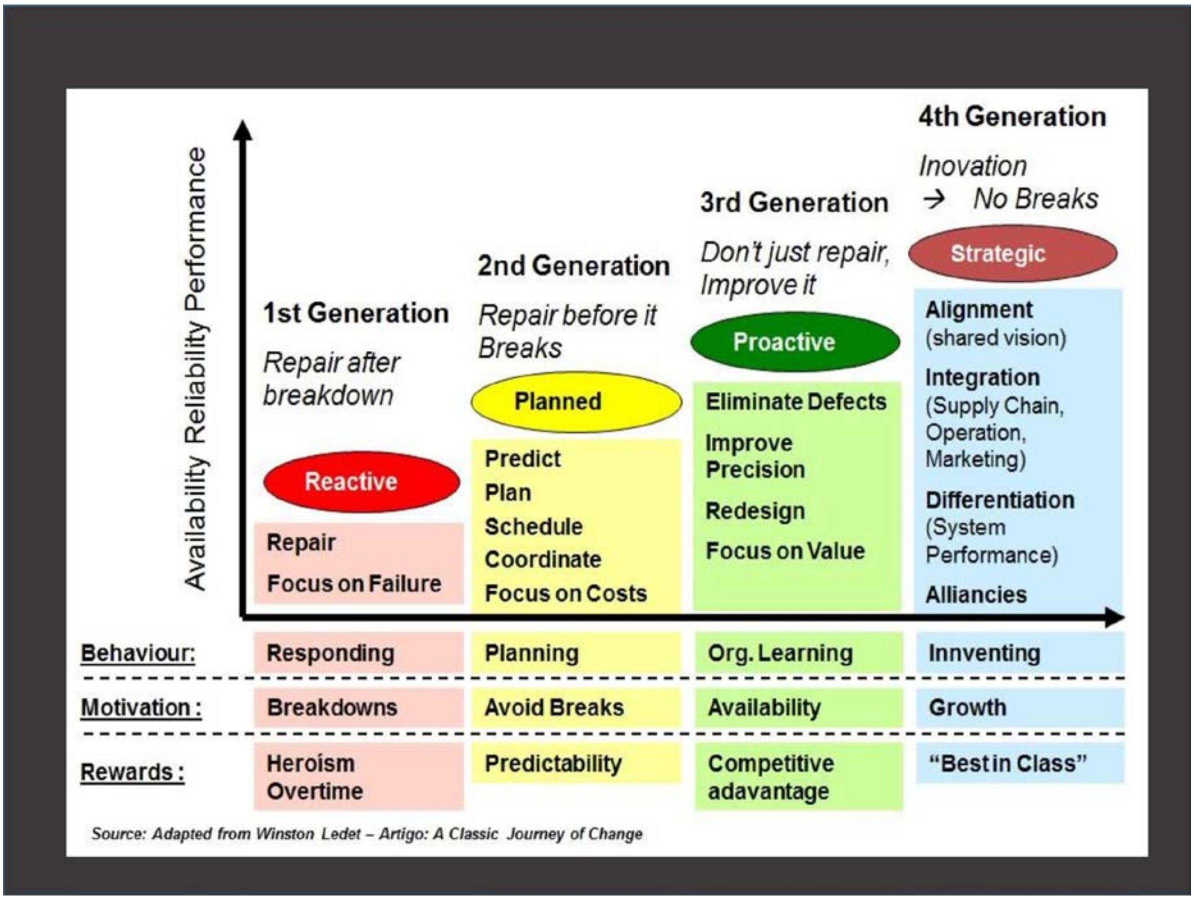
Appendix: The trends for the Management's Measurement of the Maintenance Performance



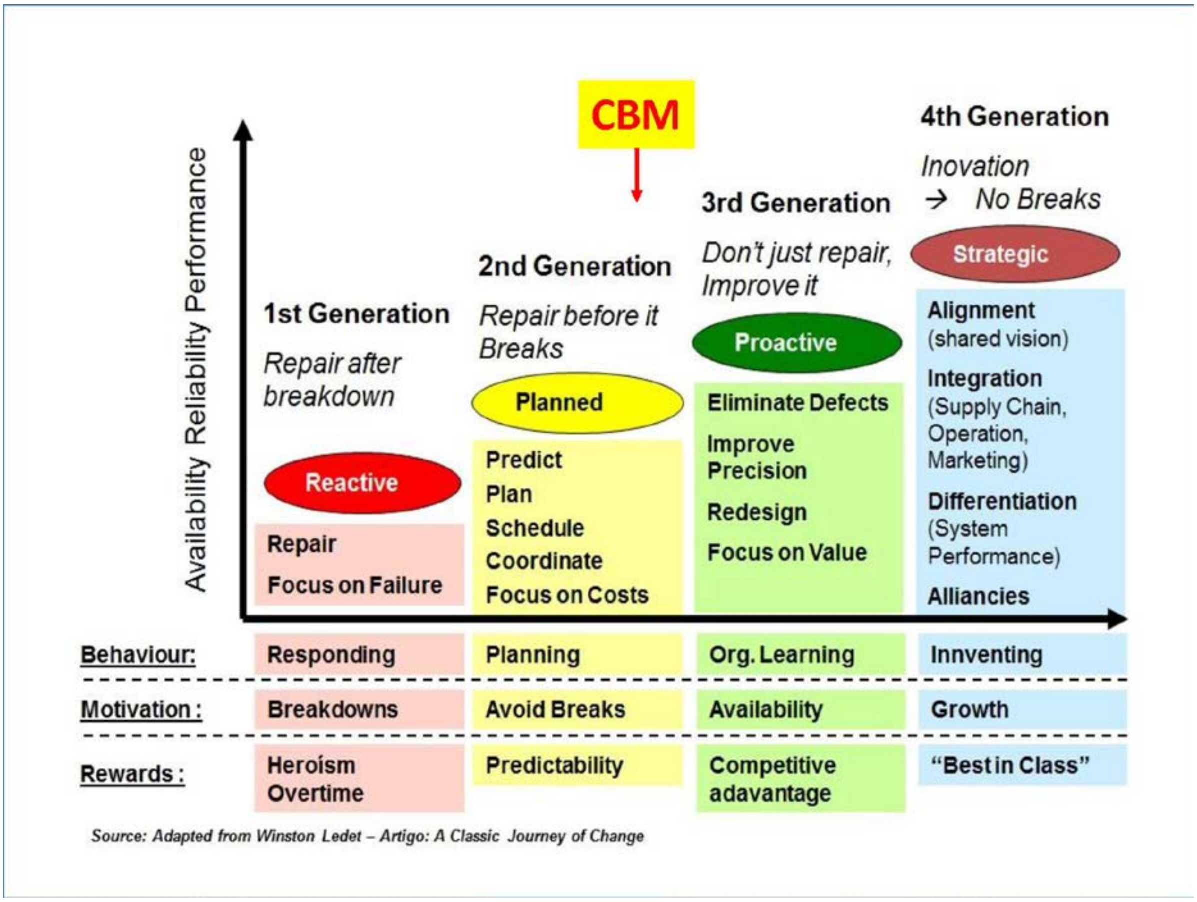




ISBN 978-91-7583-841-0



Availability Reliability Performance
1st Generation
Repair after breakdown
Reactive
Repair
Focus on Failure
2nd Generation
Repair before it Breaks
Planned
Predict
Plan
Schedule
Coordinate
Focus on Costs
3rd Generation
Don't just repair, Improve it
Proactive
Eliminate Defects
Improve Precision
Redesign
Focus on Value
4th Generation
Inovation
→ No Breaks
Strategic
Alignment
(shared vision)
Integration
(Supply Chain, Operation, Marketing)
Differentiation
(System Performance)
Alliancies
Behaviour: Responding Planning Org. Learning Innventing
Motivation: Breakdowns Avoid Breaks Availability Growth
Rewards: Heroism Overtime Predictability Competitive adavantage "Best in Class"
Source: Adapted from Winston Ledet – Artigo: A Classic Journey of Change



CBM
Availability Reliability Performance
1st Generation
Repair after breakdown
Reactive
Repair
Focus on Failure
2nd Generation
Repair before it Breaks
Planned
Predict
Plan
Schedule
Coordinate
Focus on Costs
3rd Generation
Don't just repair, Improve it
Proactive
Eliminate Defects
Improve Precision
Redesign
Focus on Value
4th Generation
Inovation
→ No Breaks
Strategic
Alignment
(shared vision)
Integration
(Supply Chain, Operation, Marketing)
Differentiation
(System Performance)
Alliancies
Behaviour: Responding Planning Org. Learning Innventing
Motivation: Breakdowns Avoid Breaks Availability Growth
Rewards: Heroism Overtime Predictability Competitive adavantage "Best in Class"
Source: Adapted from Winston Ledet – Artigo: A Classic Journey of Change

To meet the interests

MwAM

Higher operational availability

Physical Asset Management

Physical Asset Management is the optimal lifetime management of the company's physical assets, **to enable and maintain the company's ability** to achieve a necessary and sustainable condition to achieve the company's goals.

Physical Asset Management

Physical Asset Management involves a collaboration between a number of functions/processes within the company in order to achieve that one

- have the right systems and facilities for the company activities,
- ensure a desirable operation
- implement a profitable maintenance.

To meet the interests

ROMI

Better economical results

ISBN 978-91-7583-841-0

RETURN ON
MAINTENANCE INVESTMENT
(ROMI)

For each spent € in maintenance
the company will get more than one € back

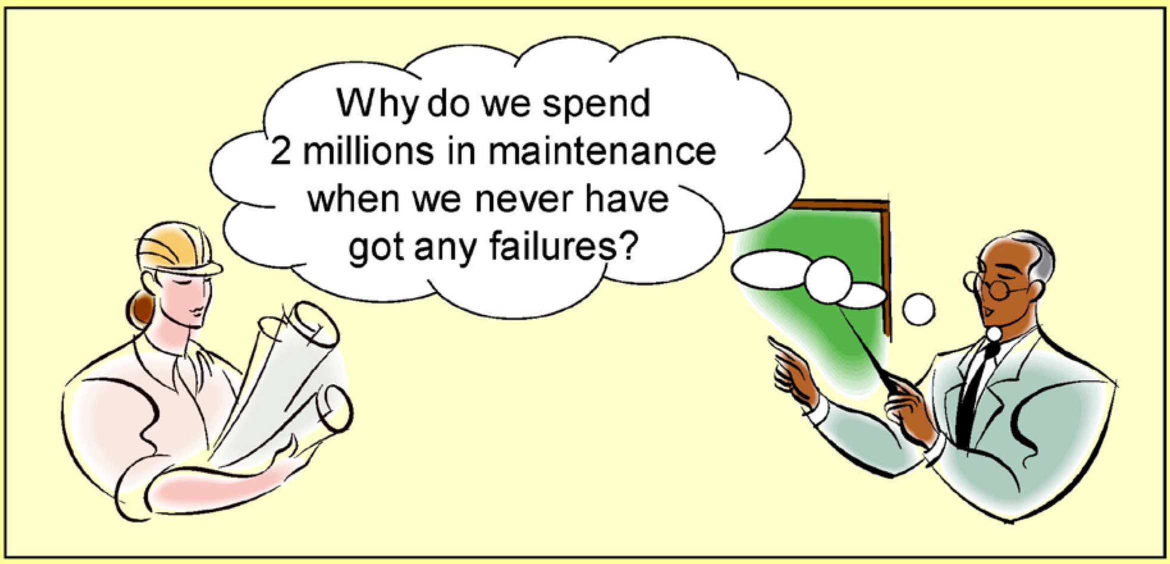
To measure
is to get facts

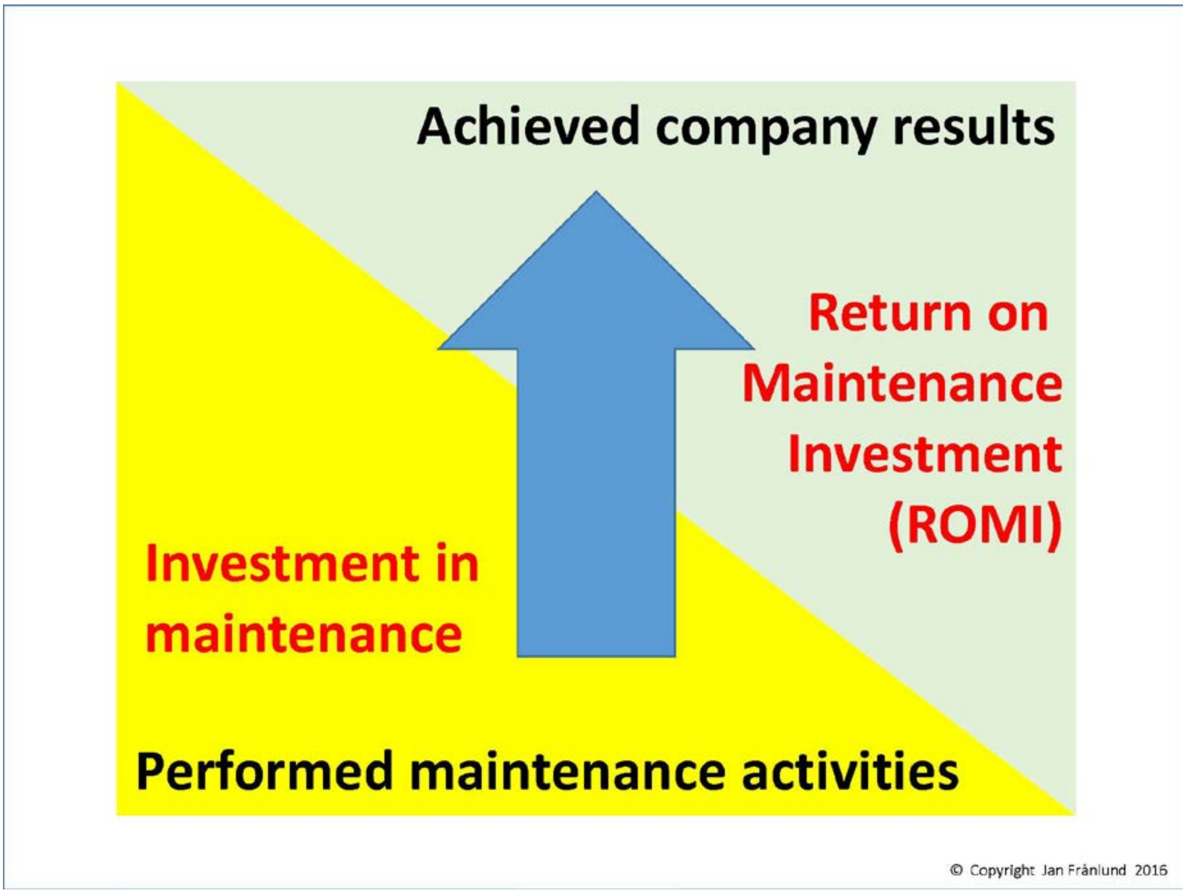
ISBN 978-91-7583-841-0

To measure
is to get facts

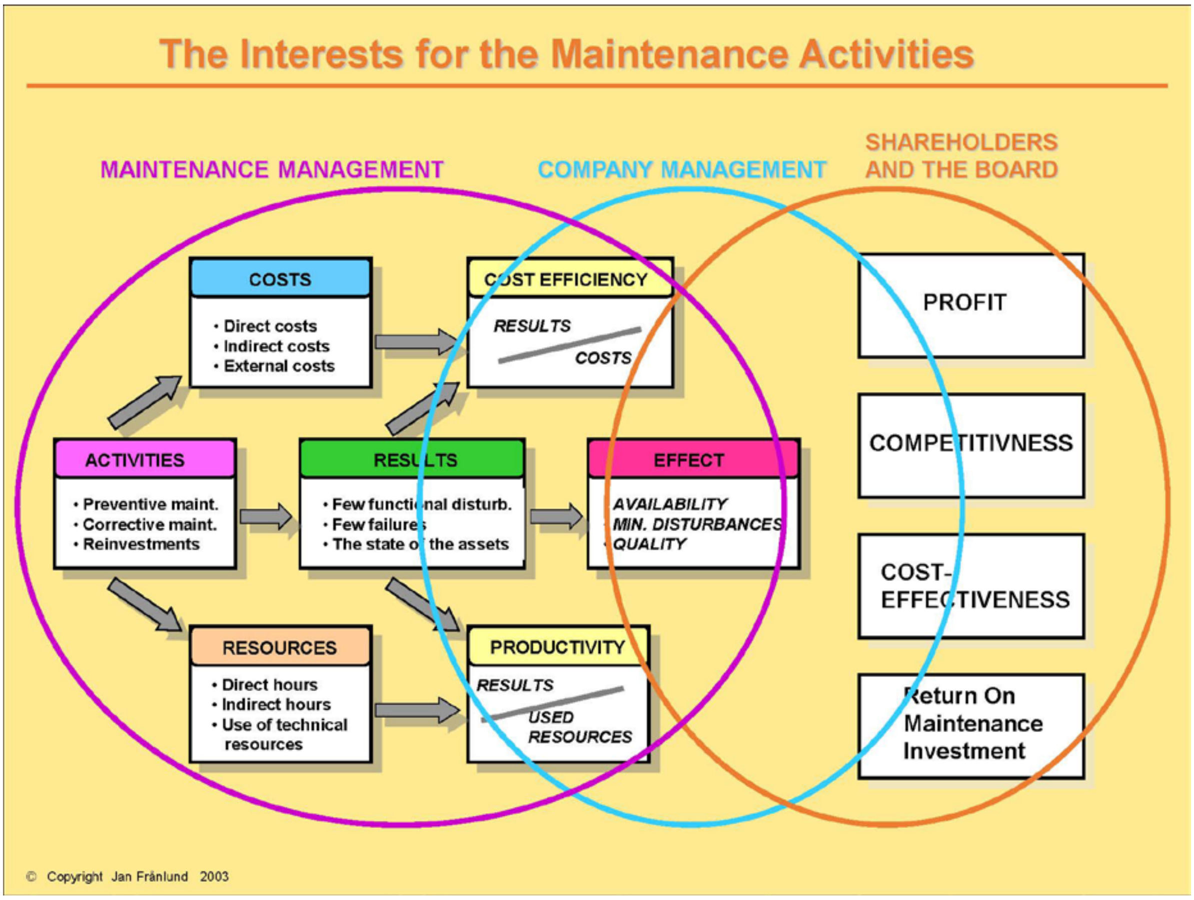
… if one can trust the measurement!

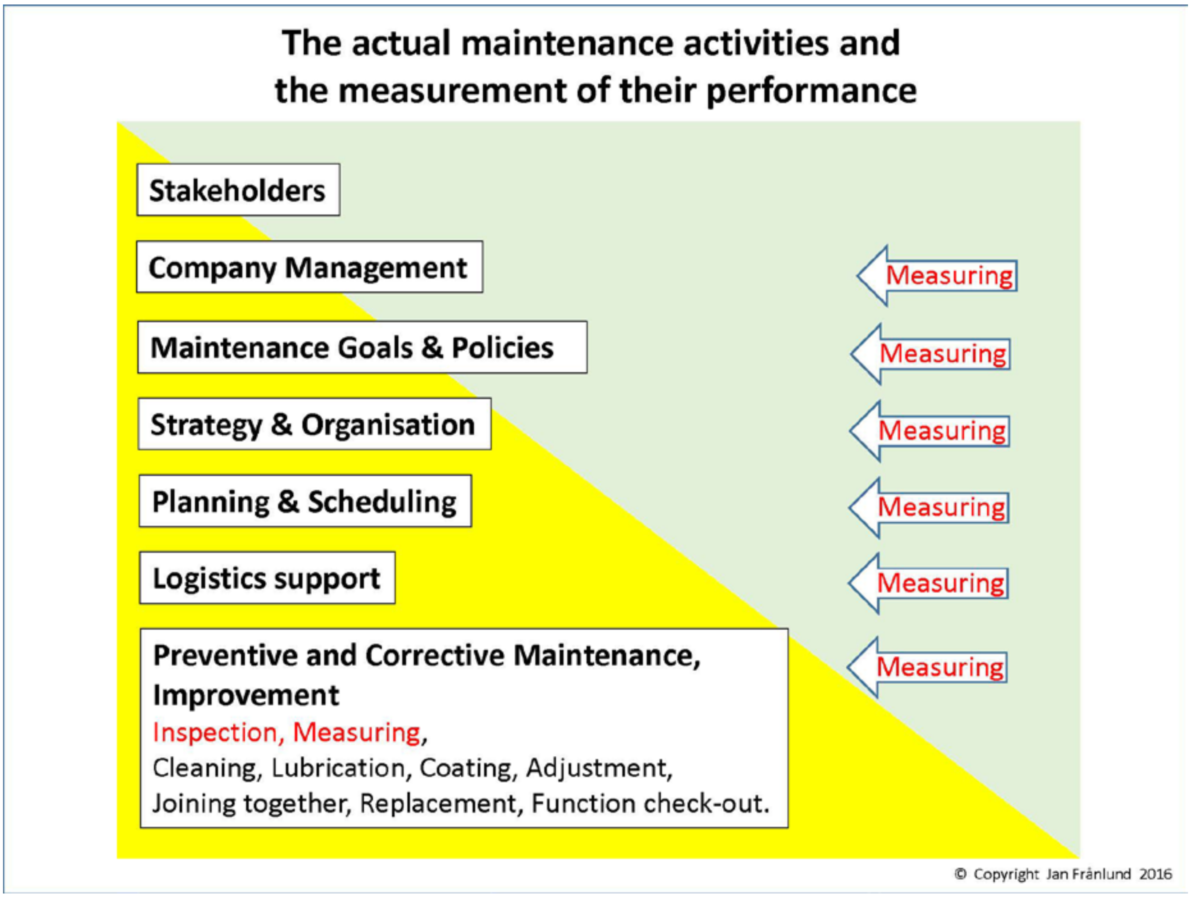
- Measure the relevant information
- Usage of the right method/technique
- Got reliable result (enough measurements)





ISBN 978-91-7583-841-0





ISBN 978-91-7583-841-0

CMMS Support for Maintenance Management

Allows for:

Control over maintenance actions (Technically and Economically)

Performance analysis of Maintenance

Enhances:

Continuous improvement

Maintenance Optimization

Requires:

<u>Good Reporting</u>

<u>Reporting done on time</u>

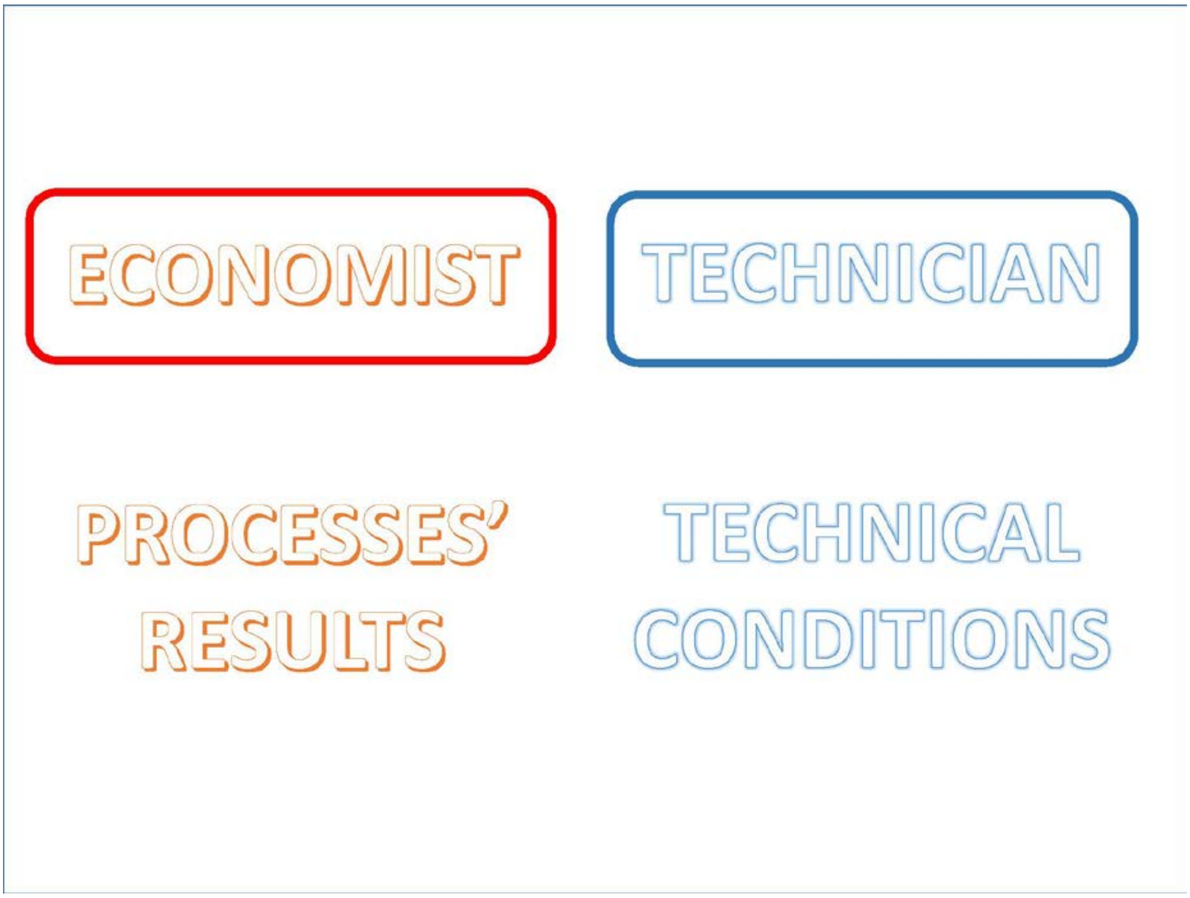
<u>Time to look at the information</u>

ECONOMIST

TECHNICIAN

COST

INVESTMENT



CEN - Comité Européen de Normalisation **CEN EN 15341**

Maintenance Influencing Factors and Maintenance Key Performance Indicators

External influencing factors

Location
Society Culture
National Labour Cost
Laws Regulations
Sector / Branches

Internal influencing factors

Market Situation
Company Culture
Process Severity
Product Mix
Plant Size
Utilization Rate
Age of Plant
Criticallity

		Levels of indicators		
		Level 1	**Level 2**	**Level 3**
Family of indicators	**Economical indicators**	E1 E2 E3 E4 E5 E6	E7 E8 E9 E10 E11 E12 E13 E14	E15 E16 E17 E18 E19 E20 E21 E23 E24
	Technical Indicators	T1 T2 T3 T4	T5 T6	T7 T8 T9 T10 T11 T12 T13 T14 T15 T16 T17 T18 T19 T20 T21
	Organizational Indicators	O1 O2 O3 O4 O5 O6 O7 O8	O9 O10	O11 O12 O13 O14 O15 O16 O17 O18 O19 O20 O21 O22 O23 O24 O25 O26

© Jan Frånlund, Sweden 2005

Which KPIs are suitable?

Based on
The CEN standard
EN 15341

	Company Manager	Maintenance Manager	Maintenance technician
Ekonomical KPIs	E1	E8	E21
Technical KPIs	T2	T6	T17
Organisational KPIs	O5	O9	O18

Which KPIs are suitable?

Based on
The CEN standard
EN 15341

	Top management	**Maintenance management**	**Maintenance technicians**
Economical indicators	Total Maintenance Cost / Asset Replacement Value	Total internal personnel cost spent in maintenance / Total maintenance cost	Cost of training for maintenance / Number of maintenance personnel
Technical indicators	Achieved up time during required time / Required time = *Op. Availability*	Total operating time / Total operating time + Downtime related to failures	Total operating time / Number of failures = *MTTF*
Organizational indicators	Planned and scheduled maintenance man-hours / Total maintenance man-hours available	Production operator maintenance man-hours / Total production operators man-hours	Preventive maintenance man-hours / Total maintenance man-hours

ISBN 978-91-7583-841-0

Gauging Work The Management Process

Proactive Work Capacity index (PWCi)

- PWCi = (Schedule Compliance) x (Resource Load) x (Wrench Time)
- World class levels would be:
  - PWCi (World Class) = (0.90) x (0.90) x (0.65) = 0.53
- This index should be calculated weekly and trended over time

SAMI Europe AB We deliver change

Seven areas of contribution

MAINTENANCE related

- Availability
- Health
- Safety
- Environment
- Asset Preservation
- Cost Efficiency
- Productivity

ISBN 978-91-7583-841-0

Availability

To make sure that the production equipment are ready to be used according to the specified function during agreed calendar time.

Health

To make sure that no failures will occur in the production equipment or failures in the safety installations that will cause any injuries of any people in the company

Safety

To make sure that no failures will occur in the production equipment that will cause damage on the company assets

Environment

To make sure that no failures will occur in the production installations that will cause any environmental damages

Asset Preservation

To make sure that the value of the production equipment - due to technical reasons - will not degrade more than what is normal for the actual type of equipment

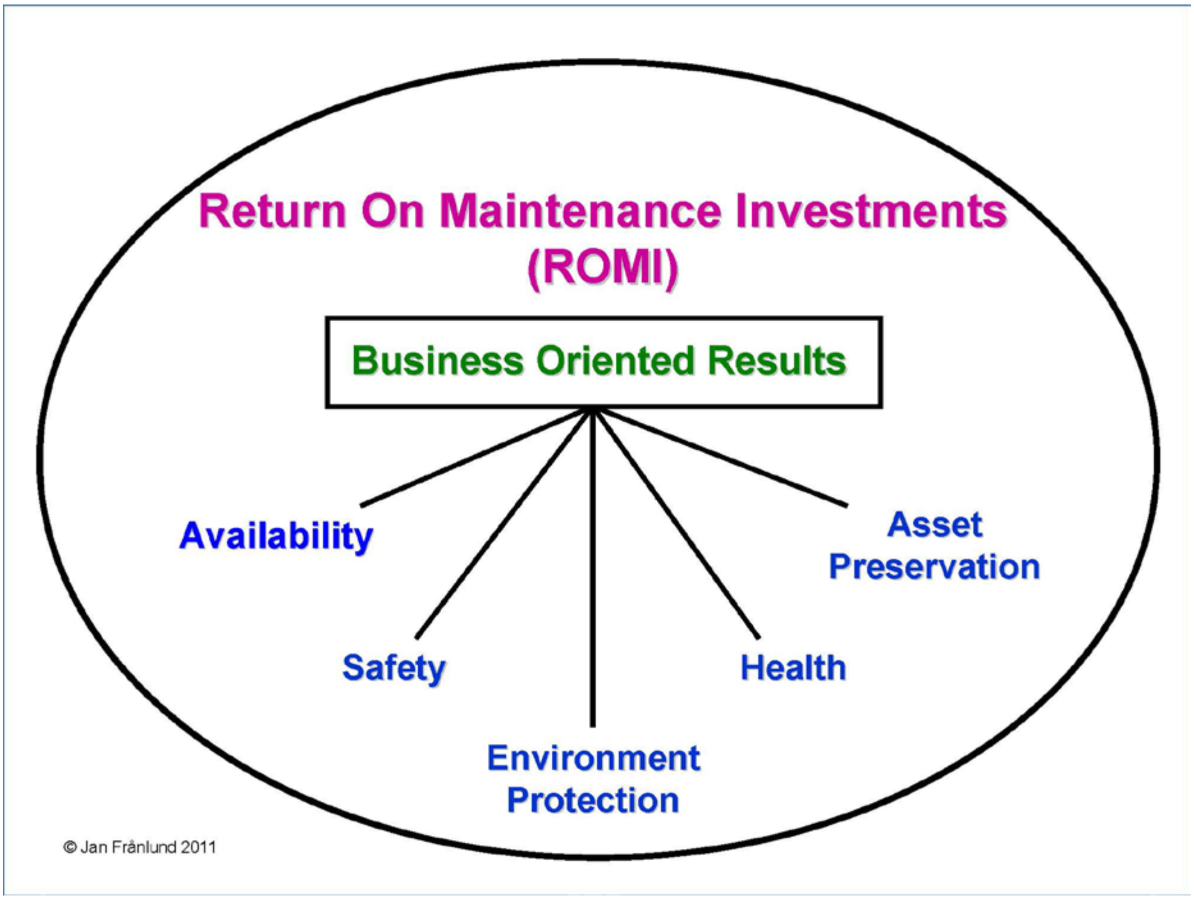
Cost Efficiency

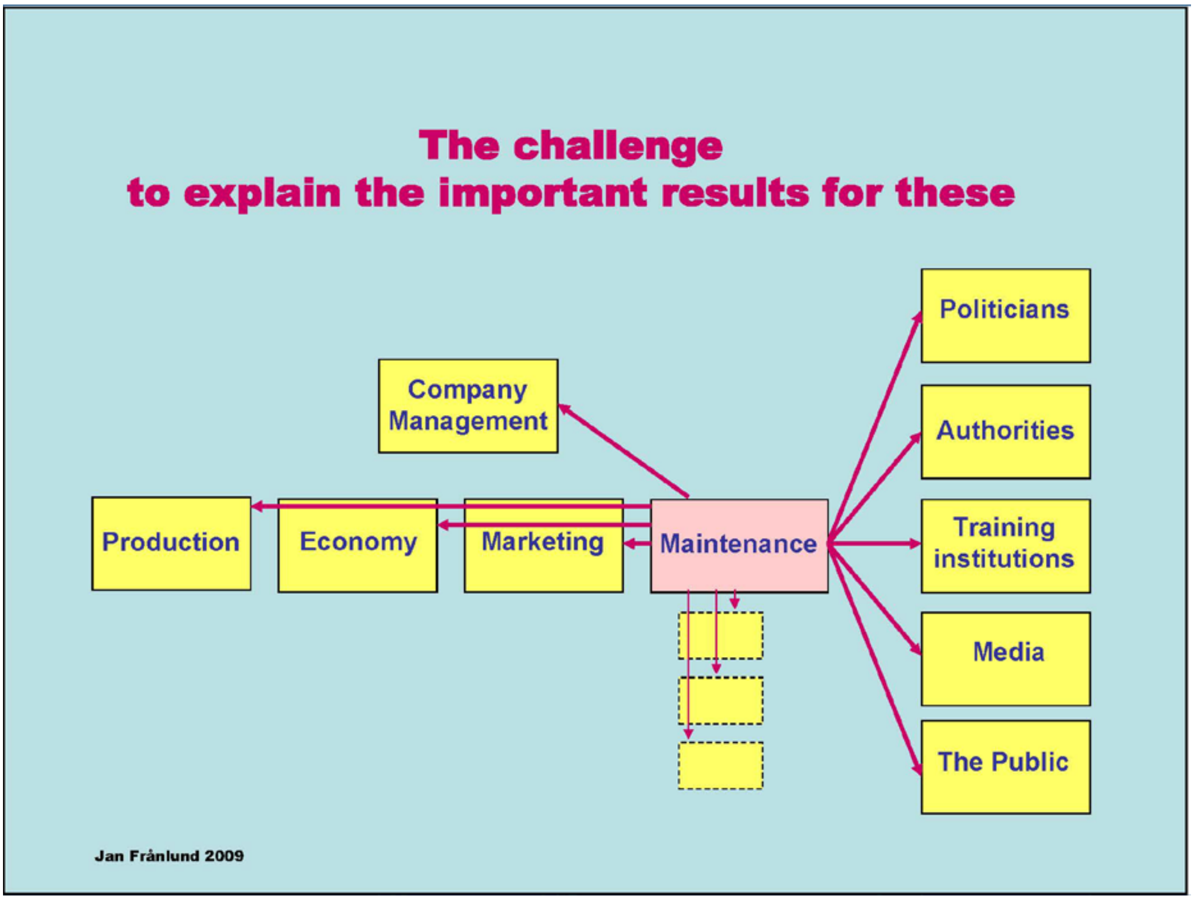
The achieved results by the maintenance function versus the costs for that achievement.

Productivity

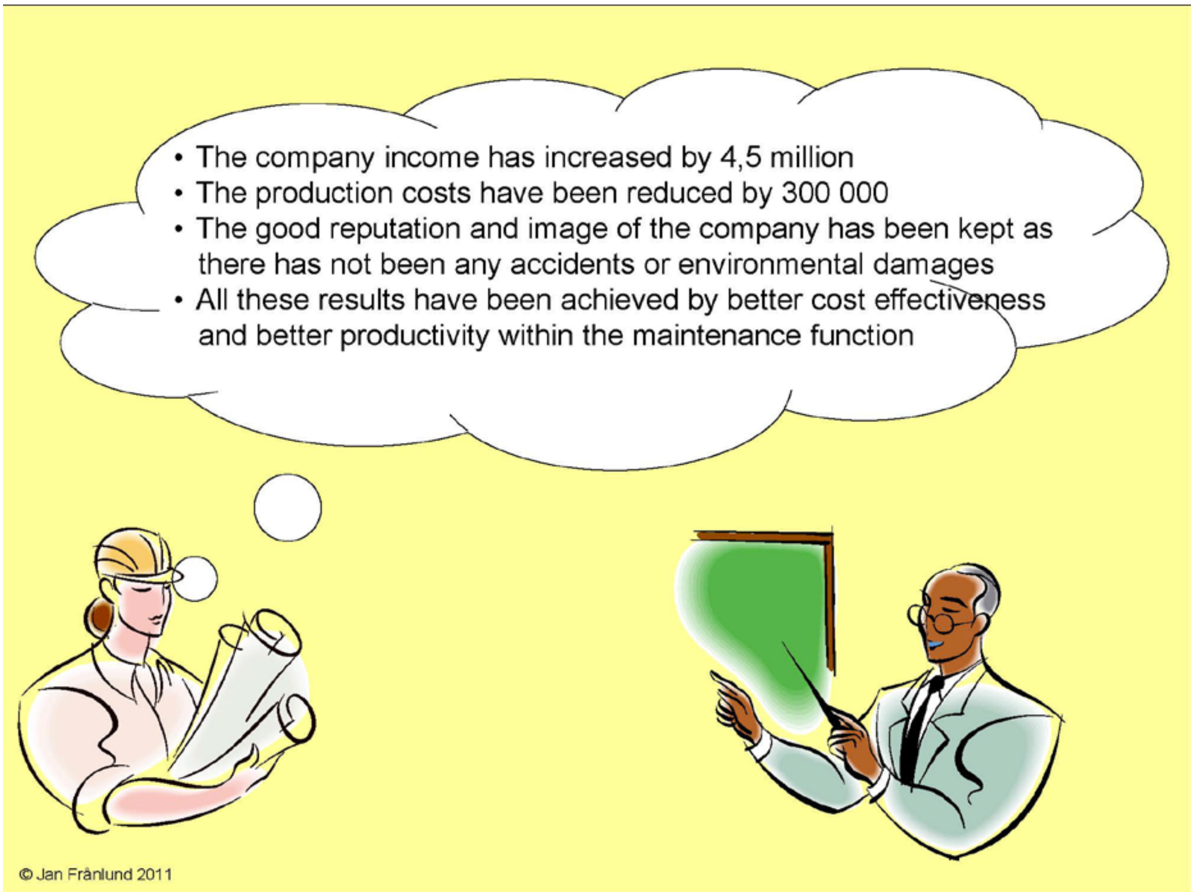
The achieved results by the maintenance function versus the used resources for that achievement.

ISBN 978-91-7583-841-0





ISBN 978-91-7583-841-0



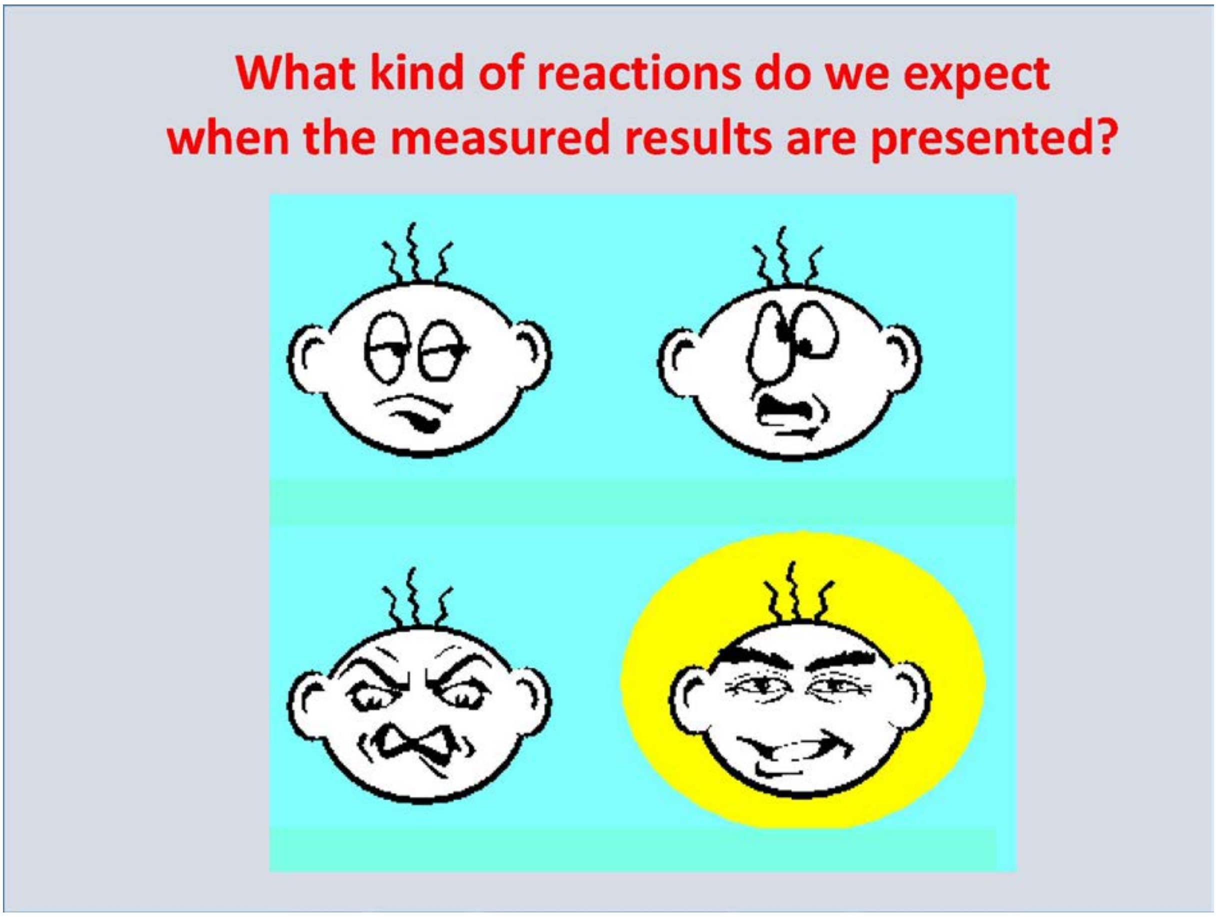
Everyone has to understand

that each Euro spent in maintenance

will give more than one Euro back

as profit for the company

ISBN 978-91-7583-841-0



ISBN 978-91-7583-841-0

Chapter 2: Asset Management

ISBN 978-91-7583-841-0

An ecosystem perspective on asset management information

Lasse Metso[1]; Mirka Kans[2]
[1] Lasse.Metso@lut.fi; [2]Mirka.Kans@lnu.se
[1]School of Business and Management, Industrial Engineering and Management, Lappeenranta University of Technology
Lappeenranta, Finland
[2]Department of Mechanical Engineering, Linnaeus University
Växjö, Sweden

***Abstract* —Big Data and Internet of Things will increase the amount of data on asset management exceedingly. Data sharing with an increased number of partners in the area of asset management is important when developing business opportunities and new ecosystems. An asset management ecosystem is a complex set of relationships between parties taking part in asset management actions. In this paper, the current barriers and benefits of data sharing are identified based on the results of an interview study. The main benefits are transparency, access to data and reuse of data. New services can be created by taking advantage of data sharing. The main barriers to sharing data are an unclear view of the data sharing process and difficulties to recognize the benefits of data sharing. For overcoming the barriers in data sharing, this paper applies the ecosystem perspective on asset management information. The approach is explained by using the Swedish railway industry as an example.**

Keywords— Open data, data sharing, information management, information model, business ecosystem, Asset as a Service.

I. INTRODUCTION

Open data sources, for instance in the form of Big Data (BD) and the Internet of Things (IoT) have changed the business models in several ways. The increased number of partners involved in value creation, and access to a large amount of data allows for more complex business models and collaboration patterns. Rong et al. [1] claim that IoT is more than a support for the supply network; IoT should be understood as a business ecosystem. They also note that there is very limited research in IoT ecosystems. Thus, there is a need to understand the new business patterns and map the information requirements within business ecosystems. One attempt to model the influences of big data on different actors in the business ecology dynamically is found in [2]. Asset Management (AM) is a domain in which BD and IoT bring great opportunities, but also great challenges, for instance as regards the sharing of data. Open data can create new value by intensive and creative use of data, for instance resulting in the optimization of maintenance and operations, and prolonged asset lifetime. The service provider can for example give support for decision making by collecting data from several plants and identifying similarities in the data, and create new and better analysis based on the combined data.

One of the challenges is that a lot of open data appears in situations and activities that are different in context and time of its definitive use. When data is taken out of context, it loses its meaning. Operational data is usually defined at the point of creation in just enough detail to support the people who operate the system or use the data directly. According to [3], data collection, management, access, and dissemination practices have a strong effect on the extent to which datasets are valid, sufficient, or appropriate for further use. Data quality is generally understood in terms of accuracy, but studies have identified multiple aspects of information; quality is more than just accuracy of the data [4]. In [5] data quality is described as data fit for use by data consumers, including dimensions of accuracy, consistency and security, as well as relevancy and understandability.

Applying the ecosystem perspective in asset management is a way to overcome some of the challenges in information sharing. The purpose of this paper is to address the barriers for data sharing within AM by suggesting an ecosystem solution. First, an understanding of the barriers and opportunities for data sharing is created by using an empirical approach. Thereafter, a conceptual solution is suggested with support from contemporary ecosystems research. The paper is organized as follows: in the next section the relevant background regarding asset management is given. Next, the concept of data and information sharing is introduced, and the results of an empirical study of opportunities and barriers for information sharing within AM are presented. Thereafter, the ecosystem approach is utilized for conceptual modeling of a solution to the barriers for information sharing in AM. Finally, concluding remarks are given.

II. ASSET MANAGEMENT AND ITS INFORMATION NEEDS

Assets are entities that bring potential or actual value to an organization [6]. The value varies with the context, organization and situation, and could be tangible or intangible, as well as financial or non-financial. Asset management can be described as a set of activities for reaching a given business or organizational objective [7], including identifying the required assets and funding, acquiring the assets, providing logistics and maintenance support, and disposing or renewing the assets.

An organization defines the internal and external communications relevant with respect to the assets, asset management and asset management system: what, when, to whom, and how to communicate [8]. An asset management information system is designed to create and maintain documentation of asset management functions [7]. Asset management information systems are used to identity equipment, locations and activities. These systems are also known as Computerized Maintenance Management Systems (CMMS). Figure 1 shows the main applications of asset management information systems, which correspond with the information requirements for an asset [9].

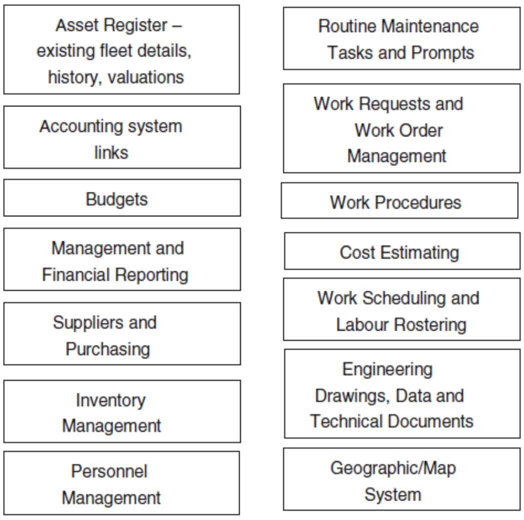


Fig.1. Asset management information system [7].

The data requirements are different between fixed and mobile equipment. The main difference is location. In mobile equipment, Global Positioning Systems (GPS) and maps are probably needed [7]. The organization has to take into consideration the risks, roles and responsibilities, as well as the processes, procedures and activities in asset management, information exchange, and the quality and availability of information in the decision making processes [8]. Information in asset management activities is listed under the relevant subject areas: data management, condition monitoring, risk management, quality management, environmental management, etc. [10]. The organization determines the attribute requirements and the quality requirements of information, and how and when the information is to be collected, analyzed and evaluated [8].

III. OPEN DATA ACCESS

Open Data was originally a concept in which governmental data were available to anyone with a possibility of redistribution in any form without any copyright restrictions [11]. Nowadays the definition of Open Data is wider: "Open data is data that can be freely used, shared and built-on by anyone, anywhere, for any purpose" [28]. A clear and consistent understanding of what Open Data means is important if the benefits of openness are to be realized, and to avoid the risks of compatibility between projects [12]. All Open Data is publicly available, but not all publicly available data is open. Open Data does not mean that an organization releases all of its data to the public. Open Data means that data is released in a specific way to allow the public to access it. The focus is on what data is available and how the data is available. If Open Data is misread as releasing all data, privacy becomes an issue [13].

Data sharing has been recognized as a good behavior in science and technology research. Data sharing enables researchers to ask new questions based on shared data, as well as advance research and innovation [14, 15]. The medical community has found the benefits of data sharing [16, 17], such as the system of open access that was released to the pharmaceutical industry by GlaxoSmithKline in May 2013. The system contains patient-level data from clinical trials of approved drugs and failed investigational compounds. An independent panel decided which data was available to responsible users. Jansen et al. [18] classify the benefits of open data into political and social, economic, and operational and technical benefits. Political and social benefits include for example transparency, more participation, creation of trust, access to data, new services, and stimulation of knowledge development. Economic benefits are economic growth, stimulation of competitiveness, new innovations, improvement of processes/products/services, new products and services, availability of information, and creation of adding value to the economy. Examples of operational and technical benefits are reuse of data, creation of new data by combining data, validation of data, sustainability of data, and access to external problem-solving capacity.

In [18] the barriers to Open Data are identified as follows:

- institutional level barriers,
- task complexity of handling the data,
- the use of open data and participation in the open data process,
- legislation,
- information quality, and
- technical level barriers.

Institutional barriers are: unclear values (transparency vs. privacy), no policy for publicizing data, no resources, and no process for dealing with user input. Task complexity includes lack of understanding the potential of data, no access to original data, no explanation of the meaning of data, information quality, duplication of data, no index on data, the data format and dataset being complex, and no tools available to support. Barriers for the use of open data and participation are: no time, fees for the data, registration to download data, unexpected costs, and lack of knowledge to handle data. Legislation barriers are: privacy, security, licenses and limitations to use data, and agreements. Information problems are: lack of information, lack of accuracy of information, incomplete information, non-valid data, unclear value, too much information, missing information, and similar data stored in different systems yields different results. Technical barriers are: the data is not in well-defined format, absence of standards, no support, poor architecture of data, no standard software, fragmentation, and no systems to publicizing data.

Other ways to group the barriers also exist. For instance Saygo and Pardo [19] define the barriers from four perspectives: 1) technological barriers, 2) social, organizational, and economical barriers, 3) legal and policy barriers, and 4) local context and specificity.

ISBN 978-91-7583-841-0

IV. Empirical study on practitioners' view

In this section, the results of an empirical study of the barriers and benefits of shared information for asset management are presented. The study included seven interviews in total. The interview data was collected from managers and directors of four different departments at a Finnish Original Equipment Manufacturer (OEM), and from managers and directors of companies who purchase those products. Theme interviews were used, and the answers were coded with NVivo. The interviews and coding took place in Finnish, and the main findings were translated into English. The findings were classified according to the barriers and benefits to open data presented in [18]. The barriers were classified to the institutional level, the task complexity of handling the data, the use of open data and participation in the open data process, legislation, information quality, and technical level barriers. The benefits were classified to political and social, economic, and operational and technical benefits.

A. Barriers for data sharing

1) The institutional level barriers

The ownership of data is important. The customer owns data and wants to own it in the future: "Our equipment, our data". For example, customers do not want to reveal the location of equipment and health data. Data containing the customer's identification are not allowed to be shared. The same goes for production quality data and product recipe data. Other data can be shared if the advantages of sharing are clear. There is a prejudice against cloud computing in companies. A lot of data is available, but companies do not want to give the role of the data manager to anyone else, even though support is needed to analyze big data. The customer does not share data because they think that the supplier wants to take the maintenance to its own business. The demand for the monopoly of data is a challenge. The maintenance playground is fragmented and it has hundreds of doers, who have their own systems which do not work together. It is impossible to define a common platform, and there is no evidence that a common platform would appear. For data-driven maintenance, predictability and pricing models are challenges. The cost should be minimized, but remote control costs a lot. It is a challenge to sell data-based service because the customers are used to getting also maintenance staff at the same time.

2) Task complexity in handling the data barriers

The complexity in data management is growing, and it is difficult to notice important data automatically in a very large amount of collected data. Different data in different databases are seen as a challenge or as a barrier. In the future, the target is to use data better than today. The amount of process data is big, and it can be used for something else than just process control. Defining the monitoring of data is difficult. Process data is not collected by equipment, but health data is collected and used. There is no link between maintenance databases and automation systems.

Putting data into a database should happen only once, and the data should also be pre-selected in order to minimize mistakes. It is a problem that there is no data available of maintenance actions made in the past and about the condition of the equipment now. It is not known what data it is possible to collect from new relays. The data when the relay needs maintenance and the fault history are needed. The customer's needs are important, but not all wishes can be fulfilled. Technical skills and own knowledge can limit the offering of new services to the customer.

3) Barriers for the use of open data and participation in open-data process

The barriers to sharing data are lack of knowledge and insufficient grounds of value added for sharing data. The win-win situation is not understood. Many doers are afraid that someone else will have better understanding, and this prevents the sharing of data. Online data is not available but it can be organized in an emergency. Online data would offer other information, but customers do not have online data systems. Big data is not shared between divisions, although the advantages of sharing data are obvious. Now data is shared and combined only case by case when needed. With strategic partners, data could be shared more to do better analysis. Data is shared with the maintenance staff but not with the customer, and also combinations of data from different data sources are not used properly.

4) Legislation barriers

There are barriers for changing the processes (e.g. in the oil industry) because regulations specify the periods between maintenance operations. That is why it is not realistic to implement health monitoring. The regulations and laws are unclear. Regulations in the marine are local. Global emission measurement are not used as widely as local e.g. in the Baltic Sea. One could therefore ask whether continuous emission measurements are needed or not in maritime industry. Regulations will be tighter and more accurate than now in the future, and that will set up new demands for data collection and the presentation of data. When a supplier has a more eco-friendly solutions than others, then from their point of view tighter regulations is not a bad thing.

5) Information quality barriers

There is enough data, but the problem is that the data from Enterprise Resource Planning (ERP) is not accurate enough. There can be errors in feeding information to the computer and exploiting of it can be difficult. The biggest problem is the quality of the data from ERP systems because people can make mistakes when inputting data. The data is formatted "badly", it is on paper, or somehow else difficult to automate. Manual data is difficult to use.

6) Technical level barriers

Technology is available to collect big data, but standards are missing. It is difficult to define which data to collect. Integrated systems record data but not enough. It is impossible to see trends from insufficient data. The amount of data can be very big. Only Key Performance Indicator (KPI) data is analyzed and the whole data is checked if needed when problems are noticed. Integration is a challenge: how can all the needed data be collected through one cable and then used?

B. Benefits of information sharing

1) Political and social benefits

In the future, open data can be described as a “sharing economy” which affects positively between companies and service networks. Transparency in data sharing enables new business models. New ecosystems are spoken of, but when creating a new ecosystem a lot of dialog with different parties is needed. More responsibility is needed from both supplier and customer when implementing new models. If “risk and revenue sharing” is the target, also the supplier needs to give more and take more risk and responsibility in order to get the client come in.

2) Economic benefits

There is need to consider the value of the service for the customer. Different data from the divisions can be combined and new services can be offered. The potential of big data is interesting, as well as knowing the risks. The service plan is based on existing technology and know-how. The business view is essential when developing new service products, and production is more important than one client's needs. Training is needed when business is transferred to data-based services.

3) Operational and technical benefits

With more automation decision support proposals can be created to maintenance staff. The equipment could create data for the maintenance staff automatically, e.g. work orders. The clients want both support for decision making and data analysis to be used in decision making. Data is collected, and support to optimize energy consumption is given. Also remote support, fault diagnosis, health monitoring are possible because the equipment is “intelligent”. The supplier cannot lock itself to the business model used. Some clients want to try new models and some want to change action only when forced. The ability to offer services for different environments is needed. Data analysis and decision support are needed, as well as traffic lights to observations of data.

4) Potentials for data sharing

The more aware the client is, the more data they will demand. Data user rights need to be defined. Online data is not yet in use, but with measurements, the data can help to recognize the need for maintenance, as well as point out the benefits of maintenance services. The amount of big data is huge, but it is used at quite a low level. The target is to prevent failure situations by managing big data. Data can be transferred from clients also with remote control to create new services for them.

The client company collects data and understands what is needed. The supplier should pay attention to data analysis and give support to the clients in their decision making. Is the data analysis done in order to develop the supplier’s own business and processes or to create added value to customers? Usually companies have strategic-level support decision tools, but they expect the service providers to offer tools for operational-level decision support. Service contracts are based on condition monitoring of equipment and in the next step on data, and then right services are available at the right time. E.g. history data is now only used in troubleshooting but there is potential for forecasting the need of maintenance and using databases better, as well as using life-cycle data. Developing processes and automation systems can be seen as a possibility to develop data management. Now data is collected time-based on-line. It is easy to share data which is collected by equipment, also analysis and reports to the customer are quite normal actions.

V. BUSINESS ECOSYSTEMS

A. Introduction to ecosystems

The traditional view of value creation is in the form of a stream, or a chain, where the actors interact by refining input e.g. in the form of raw material to output in the form of a finished product. The value chain could also describe service creation, such as the Swedish railway industry value chain depicted in Figure 2.

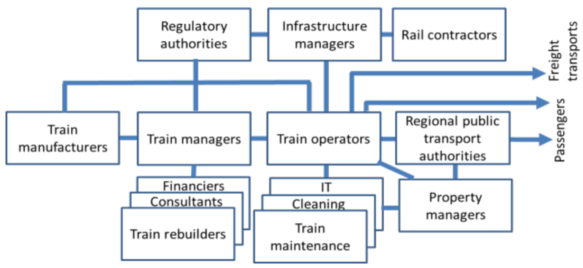


Fig.2. The value chain of the Swedish railway industry [20].

In reality, the situation is often more complex than that, as outsourcing and n-party collaborations also connect players to each other in star-like or network patterns [21]. Moore has introduced the concept of business ecosystems as a way to describe the changed business environments characterized by uncertainty and co-evolution [1, 22]. According to [22], a business ecosystem is an economic community consisting of interacting organizations and individuals, which are the organisms of the business world. The ecosystems create value for the customers in the form of goods and services. The traditional actors in a value chain (customers, producers and suppliers) are included in the ecosystem, but also other stakeholders are recognized as actors, such as competitors and public authorities [20]. Figure 3 is an example of a graphical model of an ecosystem describing the Swedish railway industry. Formal relationships between the actors are marked with full lines, while the dotted lines denote informal relationships. In this example the most influential actor, the Swedish Transport Administration, is placed in the middle of the graph.

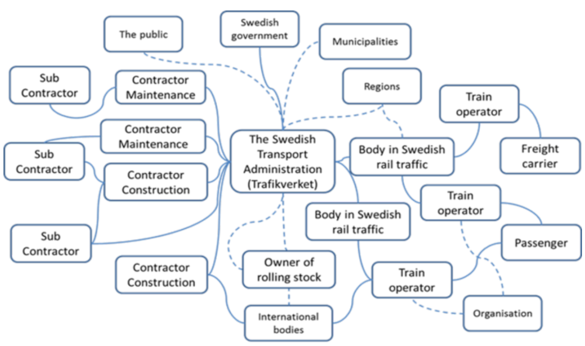


Fig.3. Business ecosystem, railway traffic in Sweden [20].

ISBN 978-91-7583-841-0

The business ecosystem is not formalized or fixed in context or time; looking at a limited incision of a business ecology at a particular point in time could reveal business structures with different actors of different power, which changes if the viewpoint or time changes. Moreover, a certain business ecology has different meanings for different actors; for some actors it may be central and to others highly peripheral [23]. New actors might enter and others leave, making the business environment of the ecosystem highly dynamic. The business ecology could be large, and thus it is important to define the limitations, identify the key stakeholders, adapt the value offerings according to the stakeholder requirements, and find out which business models and pricing models are the most viable.

B. *Addressing the barriers and reaching benefits through the ecosystem perspective*

The use of open data sources is accompanied with technical, organizational and cognitive barriers, which hinders the individual actors from reaching the potential benefits. The global and dynamic market forces different actors within asset management to join competences and collaborate in manufacturing service ecosystems [24].

A huge barrier for achieving this is the distrust between the stakeholders; customers are reluctant to share data with the supplier because they are afraid that their business will be in danger. At the same time, many actors lack knowledge of efficient data management. Extending the business environment by adding a neutral information provider and a regulator could be a way to overcome these barriers. The information provider is an actor with knowledge of data management, while the regulator provides support and control mechanisms for the different actors' behavior, including that of the information provider's [2]. The information provider should be a trusted third party with the purpose of managing the asset information for all involved stakeholders for mutual benefits, such as focusing on the core business and development of new business opportunities. A basic premise is that shared data results in data of higher relevance, accuracy and utility for all stakeholders. But it is hard to distinguish relevant data from the large data sets available. Applying the ecosystem perspective lifts the question of what data is relevant to the full value chain level and beyond [1], thus avoiding sub optimization or contradicting goals. The regulator is responsible for creating and governing the holistic view, for instance in the form of common standards, while the information provider enables this process.

Other barriers can be found in the current information systems. The systems are not designed for data sharing, leading to technical difficulties in identifying relevant data sets, fusion of different data sources and creating a coherent database. In addition, parts of the required data are not recorded in the current systems. Hirsch et al. [24] suggest a service-oriented approach to asset management data in the form of Assets as a Service (AaaS). Assets as a Service can be explained as a virtual representation of tangible and intangible assets that facilitate communication and collaboration between actors in the business ecosystem in the form of generic ontologies. AaaS could be used as the basis for creating a holistic process view, as well as for designing information systems supporting data sharing.

C. *An asset management information example: Swedish railway industry*

The Swedish railway industry is characterized by technical, organizational and operational complexity [25]. Within a period of thirty years, the number of actors in the railway transport industry has increased from less than ten to more than a thousand. Technology advancement for the rolling stock, as well as infrastructure and increased capacity utilization have added to the complexity. The complexity has affected the railway operations as well as maintenance. The root causes of maintenance-related problems have been connected to three main areas: information handling and management, regulation and control, and lack of key resources [20]. Among the causes are lack of appropriate IT systems, poor reporting structures, passive governmental management, conservative buyer's culture, poor quality charging system, lack of appropriate maintenance resources, incomplete contractor abilities and competence, and inaccurate analysis models. The tendency is that the actors sub-optimize instead of cooperating. Moreover, traditional contract forms and the conservative buyer's culture result in lack of information and knowledge sharing between the actors [26]. The existing asset information model with the major information flows is presented in Figure 4. Information is shared between the direct actors and regulated in contracts, which results in information isles and interrupted flows, for instance between the different Subcontractors. Moreover, there exist separation in working areas as well as life cycle phases, resulting in low information transfer between the actors, such as the Infrastructure maintainer and the Train maintainer. Information transfer within the value chain is also affected. The Train maintainer, for instance, has no direct access to failure reports and feedback from the Freight carriers or Passengers. The actors are reluctant to share information that could have business value, either real or perceived.

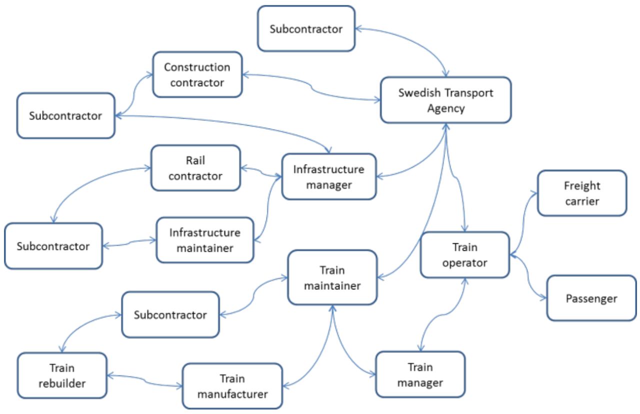


Fig.4. Existing asset management model.

In Figure 5, AaaS allows for smooth information flows to all actors, which improves information handling and management by the creation of a common asset management ontology for the specific context. The Asset Management Information Provider organizes the data/information fusion and sharing as to which data is shared and with whom it is shared.

This way, the data shared by several actors is available in the appropriate format and distribution form, while the safety and integrity of the data is secured. The Regulator assures the relevancy and accuracy of the AaaS ontology with respect to the overall ecosystem objectives, which are to ensure the traffic to move forward with the promised delivery of quality now and in the future [27]. In the case of the Swedish railway, the Regulator should be assigned by the Swedish government.

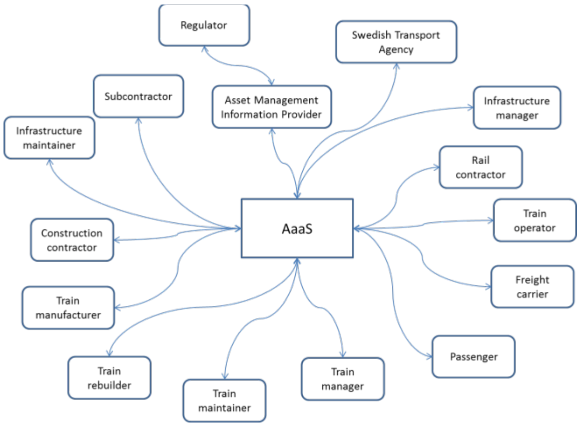


Fig.5. Alternative asset information management model.

VI. CONCLUSIONS

Data sharing has a good potential, but the ownership of data is perceived as very important to companies. They do not want to share data with others because they are afraid of harmful use of the data. Another barrier is lack of knowledge to analyze big data. Companies do not identify the advantages of data sharing because they do not understand the data well enough, or the possibilities available in combining data. The maintenance playground is complex and fragmented, and all parties have they own computerized systems, making it hard to orchestrate data flows and data sharing. The new solutions must be suitable for integrating with the manufacturers' equipment. A very large amount of data is collected but it is difficult to define what data should be shared. Many doers are afraid that someone else can have more advantages of the shared data which lead to data sharing is not done enough in companies or between companies. Win-win thinking has not become popular in data sharing, and customers do not understand the potential of new services based on data sharing.

In the future, transparency can be seen as a "sharing economy". The big question is how it can be implemented in a multi-company environment with a positive attitude. Data sharing rules must have been agreed with the partners beforehand. Finding an outside facilitator whom all trust could be challenging. The Asset Management Information Provider is an information manager offering the needed information to all actors with Asset as a Service. The problem of trust between the actors can probably be solved with the AaaS concept. Sharing data can create potential for new business, e.g. new services can be developed, such as remote support, data combination and analysis services, etc. The sharing economy adds transparency, which can work positively between companies and service networks. Better data management can help to make better decisions, and online data enables creating new business models, especially for service providers.

REFERENCES

[1] K. Rong, G. Hu, Y. Lin, Y. Shi, and L. Liang, "Understanding business ecosystem using a 6C framework in internet-of-Things-based sectors," International Journal of Production Economics, 159, pp. 41-55, 2015.

[2] I. Perko, and P. Ototsky, "Big data for Business Ecosystem Players," Our Economy, 62(2), pp. 12-24, 2016.

[3] S. Dawes, and T. Pardo, "Maximizing knowledge for program evaluation: critical issues and practical challenges of ICT strategies." Proceedings of the 5th International Conference, EGOV. Springer: Lecture Notes in Computer Science, 2006.

[4] S. Dawes, "A realistic look at open data." Center for Technology in Government, University at Albany/SUNY, 2012. Available at http://www. w3. org/2012/06/pmod/pmod2012_submission_38. Pdf.

[5] D. M. Strong, Y.W. Lee, and R. Y. Wang, "10 potholes in the road to information quality." Computer 30(8), 38-46, 1997.

[6] ISO 2014. Asset management – Overview, principles and terminology, ISO55000:2014 Corrected version 2014-03-15, IDT.

[7] N. A. Hastings, "Physical asset management" (Vol. 2). London: Springer, 2010.

[8] ISO 2014. Asset management — Management systems — Requirements, ISO 55001:2014. First edition 2014-01-15.

[9] M. Kans, and A. Ingwald, "Functionality Gaps in IT Systems for Maintenance Management," International Journal of COMADEM, 15, pp. 38-50, 2012.

[10] ISO 2014 C. Asset management — Management systems — Guidelines for the application of ISO 55001, ISO 55002:2014, Corrected version 2014-03-15.

[11] P. Murray-Rust, "Open data in science," Serials Review, 34 (1), pp. 52–64, 2008.

[12] L. James, "Defining Open Data", Open knowledge international blog, 2013. Available http://blog.okfn.org/2013/10/03/defining-open-data/#sthash.k9hxc6ER.dpuf

[13] M. Chernoff, " What "open data" means – and what it doesn't", Opensource.com, Discover an open source word, 2010. Available: https://opensource.com/government/10/12/what-%22open-data%22-means-%E2%80%93-and-what-it-doesn%E2%80%99t

[14] J. C. Wallis, E. Rolando, and C. L. Borgman, "If we share data, will anyone use them? Data sharing and reuse in the long tail of science and technology," PloS one, 8(7), p.e67332, 2013. Available: http://journals.plos.org/plosone/article?id=10.1371/journal.pone.0067332

[15] Y. Kim, and J. M. Stanton, "Institutional and individual influences on scientists' data sharing practices," Journal of Computational Science Education, 3(1), pp.47-56, 2012.

[16] B. L. Strom, M. Buyse, J. Hughes, and B. M. Knoppers, "Data sharing, year 1—access to data from industry-sponsored clinical trials, " New England Journal of Medicine, 371(22), pp.2052-2054, 2014.

[17] C. Harrison, "GlaxoSmithKline opens the door on clinical data sharing," Nature Reviews Drug Discovery, 11(12), pp.891-892, 2012.

[18] M. Janssen, Y. Charalabidis, and A. Zuiderwijk, "Benefits, adoption barriers and myths of open data and open government," Information Systems Management 29, no. 4 pp. 258-268, 2012.

[19] D. S. Sayogo, and T. A. Pardo, "Exploring the determinants of scientific data sharing: Understanding the motivation to publish research data." Government Information Quarterly, 30, pp.S19-S31, 2013.

[20] A. Ingwald, and M. Kans, "Service Management Models for Railway Infrastructure, an Ecosystem Perspective," Proceedings of the 10th World Congress on Engineering Asset Management (WCEAM 2015), pp. 289-303, 2016.

[21] P. Cousins, R. Lamming, B. Lawson, och B. Squire, "Strategic Supply Management. Principles, Theories and Practice," Pearson Education Limited: Essex, UK, 2008.

ISBN 978-91-7583-841-0

[22] J. F. Moore, "Predators and Prey," Harvard Business Review 71(3), pp. 75-86, 1993.

[23] N-G. Olve, M. Cöster, E. Iveroth, C-J. Petri, and A. Westelius, “Prissättning - Affärsekologier, affärsmodeller, prismodeller,” Lund: Studentlitteratur, 2013.

[24] M. Hirsch, D. Opresnik, C. Zanetti, and M. Taisch, “Leveraging Assets as a Service for Business Intelligence in Manufacturing Service ecosystems,” 2013 IEEE 10th International Conference on e-Business Engineering (ICEBE), Los Alamitos, CA, USA.

[25] M. Kans, D. Galar, and A. Thaduri, “Maintenance 4.0 in Railway Transportation Industry,” Proceedings of the 10th World Congress on Engineering Asset Management (WCEAM 2015), pp. 317-331, 2016.

[26] S. Lingegård, “Integrated product service offerings for rail and road infrastructure – reviewing applicability in Sweden,” Dissertation, Linköping University, Sweden, 2014.

[27] Trafikverket, “Drift- och underhållsstrategi”, TDOK 2014:0165, 2014-06-01, 2014.

[28] Open Knowledge International, “The Open Definition”, 2005. Available: https://okfn.org/projects/open-definition/.

Value of Fleet Information in Asset Management

Sini-Kaisu Kinnunen1; Salla Marttonen-Arola2; Timo Kärri3
[1]sini-kaisu.kinnunen@lut.fi; [2]salla.marttonen-arola@lut.fi; [3]timo.karri@lut.fi
[1,2,3] School of Business and Management, Industrial Engineering and Management, Lappeenranta University of Technology
Lappeenranta, Finland

Abstract*—Internet of Things (IoT) is enabling massive data gathering and data exploitation but at the moment the full potential of data utilization is not tapped. Technologies enable the collection of wide-ranging data from assets which then can be used as a support of asset management, varying from operative decisions concerning one asset to the management of asset fleets. The fact that the data related to assets have not fully been made of use may partly be because the value is difficult to perceive and concrete benefits are hard to quantify. The purpose of this paper is to illustrate how the value of fleet data is shaped up and how the value could be quantified. As a result, we are presenting a conceptual framework for quantifying the value of fleet data. The value is illustrated from theoretical point of view and the value determination is based on cost-benefit approach where the costs and benefits develop along certain variables, such as the level of data refining, the size of the fleet and time. The results advance the knowledge of how the value of data could be quantified and thus create a basis for further research which will focus on modelling the value of fleet data

***Keywords*—fleet data, value of information, benefit, cost, asset management, asset fleet**

I. Introduction

The emergence of new technologies enables more effective maintenance and the achievement of various benefits including cost savings and support for asset management related decision making. Cost savings are related to e.g. improved reliability and safety, reduced maintenance work costs, reduced downtime and improved availability. Data availability and utilization provide support for e.g. investment decisions, service development and maintenance planning. Although data collection has increased due to the emergence of technologies, the benefits of data utilization are unclear. The value of information is inadequately researched and models quantifying the benefits of data utilization are limited. The issue is topical as companies are struggling with data and information overload and are considering if they should invest in data refining processes. The profitability aspects of data utilization are often neglected in literature while the research is focusing on the applications and utilization possibilities. Modelling the costs and benefits of IoT technologies are valuable knowledge for supporting decision making in maintenance.

Maintenance research has recently discussed the management of large asset groups, in other words fleets. Various models have been developed to different fleet management decision needs, such as replacement investments of fleets [1], to improve resource allocation [2], to estimate remaining useful life of fleet [3], to plan maintenance strategy for fleet [4], to plan proactive maintenance [5], and optimal spare part inventory management [6]. Technologies enable the collection of fleet wide data and enable the collection and utilization of fleet wide data in order to achieve cost savings. However, the full potential of collected data has not been captured as the value for business is difficult to define and quantify. Research is needed to clarify the impact of data utilization on the maintenance costs at fleet level.

This paper contributes to the previous discussion by exploring the costs of data refining and the benefits that can be achieved through data utilization in maintenance management at fleet level. The purpose of this paper is to find out the factors affecting the value of fleet information. The research question of this paper is the following:

What kind of factors affect the value of fleet information?

The research is conducted as a concept analysis where the framework is constructed based on existing literature. Literature and concepts related to value of information and benefits of fleet management are analyzed. As a method of valuation, the cost-benefit method is utilized. The factors affecting the value of fleet information are studied from cost-benefit perspective considering the viewpoint of managing a fleet. As a result a conceptual framework is developed and the results are discussed.

II. Value of Fleet Infromation

A. Value of Information

In order to understand how the value of information can be defined, the literature is reviewed. By reviewing the literature related to the value of information we can create understanding and the basis for the theoretical framing of fleet data valuation. Although it has been generally acknowledged that data and information have more and more significance as assets for companies [7], the actual value and benefits of data are partly unknown. Evans and Price [8] have named the lack of understanding about costs, value and benefits of data as one of the barriers to information asset management. They have also mentioned the challenge that the value of data is often contextual.

Moody and Walsh [9] have presented the issue of data valuation in detail. They regard information as assets and define the nature of information as an asset by identifying a number of general principles which they call the seven laws of information. These laws describe incisively how the value of information behaves in relation to certain variables, such as amount of usage, time, accuracy, integration, and volume. According to Moody and Walsh [9] the seven laws of information can be presented as follows:

1) Information is (infinitely) shareable and can be shared with others without a loss of value.

2) The value of information increases with use, and it does not provide any value if it is not used at all.

3) Information is perishable and it depreciates over time.

4) The value of information increases with accuracy.

5) The value of information increases when combined with other information.

6) More information is not necessarily better.

7) Information is not depletable.

Although these kind of laws can be defined the challenge is to define the economic value of information and the literature does not give any exact solution for this purpose. However, it is commonly agreed that the benefits of information can be considered as benefits from using information (value-in-use) or selling information (value-in-exchange). It can also be concluded that the value of information increases when the data is refined further. In other words, the value of data and information increase when they are analyzed further and then used in decision making. Also Moody and Walsh [9] state in the second law that value is provided only if the information is used. In addition, Moro et al. [10] have studied how the value of data increases when the data is analyzed further in data-driven models. The usage of the model and therefore the value of refined data is reflected by the improvements in performance indicators.

Data-based models in asset management are aiming to create value; for instance condition based maintenance models are pursuing costs savings in maintenance and improving the performance of assets. When data-based models are increasing due to massive data collection, this sets requirements for data quality in order that the value creation from data is possible. In asset management the increased data gathering and technologies enable to develop new kinds of models to support value creation of asset related data. Especially, the data concerning the fleets of assets should be more easily available and can be used as a support of decision making and value creation. Thus, in order to create value from fleet information they need to be utilized in decision making. Kinnunen et al. [11] have reviewed different kinds of fleet decision making situations. These are the fleet management related decision making situations where the collected fleet data can be utilized and transformed into benefits and value. Adopting the perspective of the whole fleet of assets enables benefits such as e.g. multiplying best practices, predictive maintenance concepts and optimizing spare part utilization for the whole fleet of assets [1–6].

B. Cost-Benefit Approach to the Value of Fleet Information

Cost-benefit approach is often used to estimate and quantify the benefits and costs of e.g. an investment, in order to see if the benefits outweigh the costs. Cost-benefit analysis is commonly used as it is suitable to the variety of usage purposes. In each situation the total costs and total benefits are expressed in monetary terms and the time value of money is taken into account as well.

In this paper, cost-benefit approach is utilized to evaluate the value of fleet information. In order to get to the outcome value, the benefits and costs of fleet information need to be examined separately. When considering the benefits in fleet asset management, we need to examine the benefits that can be achieved by utilizing more accurate analysis and models as a support of decision making. The benefits are the savings or increased revenues that can be achieved by making better decisions. The benefits can be e.g. savings in maintenance work, savings in spare parts, the longer life cycles of equipment, diminished production losses and better quality [1–6]. Especially when considering the benefits of fleet data utilization in maintenance management, the following benefits have been identified [12]:

a) Fault prediction,

b) Improved planning of maintenance and production,

c) Improved safety and quality

d) Diminished unscheduled maintenance, and

e) Reduced production losses.

These savings can be achieved by supporting mostly decision making at operative level. But when we are considering the whole fleet there are decision making situation also at strategic level [11]. Strategic level decision making can be related to e.g. replacement investment of whole fleet or R&D development of product and services [1, 11]. Therefore, the benefits can be realized at the different levels of decision making which makes it challenging to evaluate the total benefits of data utilization. Some benefits are generated during a shorter time while others are generated e.g. at the end of the asset's life cycle.

Evans and Price [8] have also considered the benefits that can be achieved with data utilization and they are considering the issue not only from asset management perspective but more generally. They are suggesting that there are the benefits of data utilization such as value-creation, reduced costs, mitigated risks, improved productivity, competitive advantage, and increased staff morale. It can be concluded that there are several kinds of benefits related to the benefits of data utilization and they are studied to some extent. Benefits of data utilization can be evaluated in certain cases but the big picture of all the benefits of data utilization is challenging to attain.

In addition, it is challenging to define what are the costs related to the data utilization. Moody and Walsh [9] suggest that the major costs are related to the capture, storage and maintenance of information. There are costs related to data collection such as sensor technologies or entering task information manually. As the data are increasingly produced the warehousing of the data is causing significant costs as well. Maintenance of information is consisting of e.g. data preprocessing related costs. After these phases, the data needs to be utilized in decision making in order to create value, thus the analysis and modelling work are causing significant costs as well. The costs of data utilization include investments in

ISBN 978-91-7583-841-0

connectivity and systems integrity. Some of the costs are very challenging to direct for the data utilization of certain assets. For example the costs related to systems integrity are often related to the organization level and it is challenging to define what the costs of data integrity are for a certain asset fleet.

III Analyzing the Value of Fleet Information

A. Factors Affecting to the Value of Fleet Information

When we are analyzing the value of fleet information we need to drill into the special features of fleet data utilization and their impact on the benefits and costs. We need to examine how e.g. the size of fleet, the selected time period and the level of data refining affect the benefits and costs.

First, the impact of the fleet size is considered. It can be assumed that if data is gathered of multiple similar kind of assets and the data are analyzed, the more assets we have the better and the more accurate decision can be made (Law 4 by [9]). In other words, the larger size of fleet is increasing benefits as the large-scale data can be utilized and e.g. better prediction models can be made. On the other hand, the size of fleet is increasing benefits as the better decision can be made concerning the whole fleet and thus the benefits are multiplied. It can be assumed that the benefits increase significantly to some extend while the size of fleet increases but there is a limit when larger fleet size does not increase the accuracy of analysis any more (Law 6 by [9]).

The costs can be assumed to grow along with the size of fleet. This applies when regarding costs related to data gathering, data pretreatment and warehousing as the amount of produced data increases with the size of fleet. However, the larger size of fleet can be assumed to have advantages when e.g. prediction models are developed and the development costs can be divided to all the assets in fleet. Thus, there can be economies of scale when utilizing fleet data in the development of models or services to large-sized fleets of assets.

Secondly, the selected time period has impact on the total value of fleet information. Time influences the value by several ways. Time affects the amount of interest when the forecasted future benefits and costs are discounted to the present time. In addition, some benefits are realized after longer time periods and therefore the selected time period needs to be selected according to the asset features and the purpose of the value assessment. The potential benefits of fleet data utilization in asset management are affected by the typical failure behavior of the assets in question. Generally assets follow certain failure patterns, some of which predict the failure rates to increase with the age of the assets. Thus, with better fleet analysis more benefits can be achieved depending on the age of the fleet. This way the selected time period has an impact on the total benefits of fleet data utilization. Costs related to the data gathering, data processing and analysis work can assumed to be constant over time except for the above mentioned impact on the interest.

Thirdly, the level of data refining affects the amount of benefits and costs. The level of data refining can be viewed as an input to the phases of data utilization, including data collection, preprocessing, as well as analysis and modelling work. The level of data refining represents how much resources are invested in data refining. It can be assumed that the amount of benefits increases significantly when the level of data refining increases. Better decisions can be made with more accurate analysis and decision support and thus more benefits can be achieved (Laws 2 and 4 by [9]). The level of data refining affects the costs of fleet data utilization as well. The costs increase with the higher level of data refining. However, it can be presumed that the costs of data refining are increasing significantly if the models are wanted to be extremely predictive and reliable. Thus there is a limit when it needs to be considered if it is profitable to develop models further and if the additional benefits can still outweigh the costs of data refining. Often it is enough that the models give adequately reliable information for decision makers but in some cases more accurate predictions are required.

B. Framework for the Value of Fleet Information

Different factors affecting the value of fleet data utilization have been discussed and the value of fleet information can be seen to comprise these factors. In this section, we assemble the factors affecting the value of fleet information and we present a conclusion about how the value of fleet information can be approached from a cost-benefit perspective (Figure 1).

The value of fleet information can be viewed as the difference or the ratio between the discounted total benefits and total costs. Total benefits consist of multiple benefits which can be achieved with the analysis of fleet data. The benefits were discussed in detail in section 2.2. Total costs consist of components such as investments in hardware, software and data refining work.

The amounts of costs and benefits are affected by the data refining level as was discussed in section 3.1. The level of data refining is affecting e.g. the amount of analysis costs and on the other hand the amount of benefits. Better decisions and more benefits can be achieved with advanced data analysis and models. The size of the fleet affects the costs and benefits as discussed in section 3.1. The DuPont type of chart in Figure 1 summarizes the factors affecting the value of fleet information.

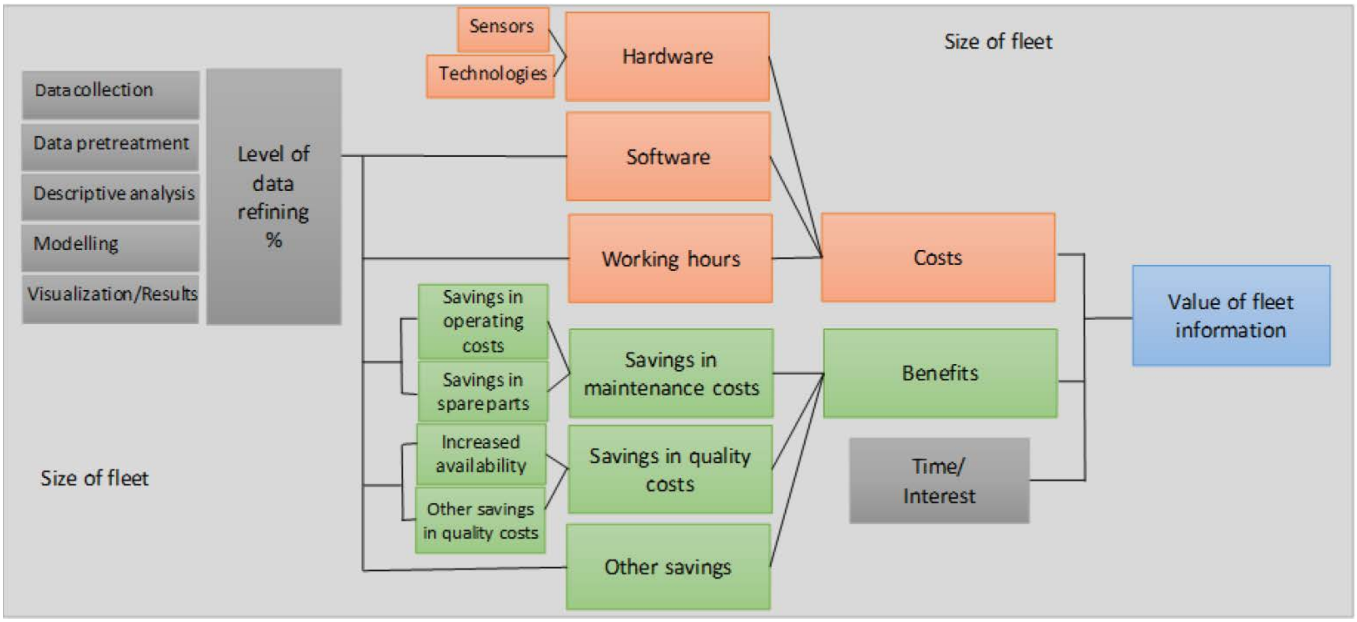


Fig. 1. The factors affecting the value of fleet information

IV. Discussion and Conclusions

This paper extends the discussion about the value of information in asset management by utilizing the cost-benefit approach. The purpose was to evaluate the factors affecting the value of fleet information. As a result, we are presenting a framework where the value consists of the costs of data refining, including hardware, software and data processing work related costs, and the benefits that can be achieved through data utilization in maintenance management at fleet level. New technologies in data collection and data utilization are topical in scientific discussion but the profitability of these investments is inadequately researched. We are contributing to the field by examining the costs and benefits of fleet data utilization and developing a framework to assess the value of fleet information. As practical implications managers get better understanding about the value of data refining. It is important to acknowledge that the benefits of investing in IoT technologies are not self-evident, and that accurate analyses and practical models are needed in order to make better decisions and achieve benefits.

The framework in Figure 1 summarizes the answer for the research question, and combines the factors affecting the value of fleet information. The framework is based on the presumption that more accurate and multifaceted fleet level data enable better decisions which are converted into cost savings and other benefits. The realization of cost savings depends on the quality of decision support analysis and models. Figure 1 is a basis for further research that will concentrate on quantitatively modelling the value of fleet information.

The value assessment in the developed framework takes only one company into consideration. However, fleet data are inter-organizational by nature and thus also other stakeholders who deal with the asset fleet and fleet data need to be taken many companies and the value of fleet information should be observed from a network or ecosystem perspective. Considering the value of fleet information from ecosystem perspective would make it possible to divide the costs of data collection and the costs of other data processing between various actors in the ecosystem, influencing the value of fleet information. The value of fleet information at ecosystem level is an important topic for further research.

Acknowledgment

The authors gratefully acknowledge DIMECC (Digital, Internet, Materials & Engineering Co-Creation) for organizing Service Solutions for Fleet Management program (S4Fleet), and the Finnish Funding Agency for Technology and Innovation for funding the program and the companies involved in the research.

References

[1] T. H. Stasko and H. Gao, “Developing green fleet management strategies: Repair/retrofit/replacement decisions under environmental regulation”, Transportation Research Part A: Policy and Practice, Vol. 46, pp. 1216-1226, 2012.

[2] S. Mishra, S. Sharma, S. Khasnabis, and T. V. Mathew, “Preserving an aging transit fleet: An optimal resource allocation perspective based on service life and constrained budget”, Transportation Research Part A: Policy and Practice, Vol. 47, pp. 111-123, 2013.

[3] S. Al-Dahidi, F. Di Maio, P. Baraldi, and E. Zio, “Remaining useful life estimation in heterogeneous fleets working under variable operating conditions”, Reliability Engineering and System Safety, Vol. 156, pp. 109-124, 2016.

[4] Q. Feng, X. Bi, X. Zhao, Y. Chen, and B. Sun, “Heuristic Hybrid Game Approach for Fleet Condition-Based Maintenance Planning”, Reliability Engineering and System Safety, accepted manuscript, 2017.

[5] S. Borguet, O. Léonard, and P. Dewallef, “Regression-based modeling of a fleet of gas turbine engines for performance trending”, Journal of Engineering for Gas Turbines and Power, Vol. 138, No. 2, pp. 1-9, 2016.

[6] S. Yongquan, C. Xi, R. He, J. Yingchao, and I. Quanwu, “Ordering decision-making methods on spare parts for a new aircraft fleet based on a two-sample prediction”, Reliability Engineering and System Safety, Vol. 156, pp. 40-50, 2016.

[7] W. Engelsman, “Information assets and their value”, In Proceedings of the 6th Twente student conference on IT. Enschede, Netherlands: University of Twente, 2007.

[8] N. Evans and J. Price, “Barriers to the Effective Deployment of Information Assets: An Executive Management Perspective”. Interdisciplinary Journal of Information, Knowledge, and Management, 7, pp. 177-199, 2012.

[9] D. Moody and P. Walsh, “Measuring the value of information: an asset valuation approach”, In Morgan, B., Nolan, C. (eds): Guidelines for Implementing Data Resource Management, 2002.

[10] S. Moro, P. Cortez, and P. Rita,). “A framework for increasing the value of predictive data-driven models by enriching problem domain characterization with novel features“. Neural Computing and Applications, 2016, to be published.

[11] S-K. Kinnunen, S. Marttonen-Arola, A. Ylä-Kujala, T. Kärri, T. Ahonen, P. Valkokari, and D. Baglee, ”Decision making situations define data requirements in fleet asset management”, In Koskinen, K. T., Kortelainen, H., Aaltonen, J., Uusitalo, T., Komonen, K., Mathew, J., and Laitinen, J. (Eds.), Proceedings of the 10th World Congress on Engineering Asset Management (WCEAM 2015), Lecture Notes in Mechanical Engineering, Springer, pp. 357-364, 2016.

[12] E. Jantunen, C. Emmanouilidis, A. Arnaiz, and E. Gilabert, ”e-Maintenance: trends, challenges and opportunities for modern industry”, In IFAC Proceedings Volumes, Vol. 44, No. 1, pp. 453–458, 2011.

Circular economy models – opportunities and threats for asset management

Jyri Hanski[1]; Pasi Valkokari[1]; Helena Kortelainen[1]; Toni Ahonen[1]
[1]jyri.hanski@vtt.fi; [1]pasi.valkokari@vtt.fi; [1] helena.kortelainen@vtt.fi; [1]toni.ahonen@vtt.fi
[1]VTT Technical Research Centre of Finland
Tampere, Finland

***Abstract*— Companies increasingly focus on their long-term sustainability and ecological footprint. Circular economy models are a step towards more sustainable business in networked companies. Majority of business and operating models contain elements of circular economy. These models have implications for the asset management strategies, processes and practices in companies. They create new kinds of opportunities and threats and enable new asset management related innovations.**

In this paper, the general archetypes of circular economy models are presented. Two assessment frameworks are utilized to identify the different types of models. The circular economy models are analyzed from the asset management perspective. Opportunities and threats produced by the circular economy models for asset management were identified.

***Keywords*— Asset management, circular economy, threats, opportunities**

I. Introduction

Often, industrial processes and supply chains are understood and operated as a linear sequence such as extraction, transport, conversion, consumption, waste and disposal, or take, make and dispose [1, 2]. Linear supply chains are designed to improve the efficiency of each life cycle phase aiming to ensure maximum output at minimal cost. In such a system, returning or repairing products for reuse creates additional costs and forms a disturbance to the optimized flow. [1.]

In comparison, according to circular economic principles a product is designed to create minimal waste by for instance, allowing it to be easily repaired, or the materials or components to be upgraded or reused [1]. Circular economy aims to be a continuous positive development cycle that preserves and enhances natural capital, optimizes resource yields, and minimizes system risks by managing finite stocks and renewable flows [2]. In circular models, value creation is built on longevity and new consumption forms [1].

The concept of circular economy is restorative and regenerative by design aiming to keep products, components, and materials at their highest utility and value at all times [2]. Adoption of circular economy business models has been low [3, 4]. Currently, companies have started to exploit untapped potential along the value chains and to promote resource and energy management concepts. Major global companies such as Google, Unilever and Renault have been recently paying attention to circular economy, however, it should concern also smaller companies that are increasingly affected by the shift to circular economy model [5]. The evolution of companies toward the circular economy implies radical changes not only in their business and operating models, but also in the ensemble of their supply chains, partnerships and value networks. The challenge is how the companies can exploit the business opportunities resulting from the transition to a more sustainable economy.

A shift to circular economy is seen beneficial from the environmental and social perspectives but also from the economic standpoint. It is estimated that a shift to a circular economy would reduce each European nation's greenhouse-gas emissions by up to 70% and grow its workforce by about 4% [6, 7]. Ellen MacArthur Foundation et al. [8] present that adopting circular economy principles would, in addition to social and environmental benefits, generate a net economic benefit of 1.8 trillion € by 2030.

Circular economy has implications for the asset management strategies, processes and practices in companies. It creates new kinds of threats and opportunities and enables new asset management related innovations. Circular economy and asset management both aim at more efficient resource usage. Physical assets contain many scarce materials and thus, asset management is a key circular economy research area [9]. All things considered, asset management has a major role in reaching the social, environmental and economic targets set to circular economy.

However, asset management literature has paid little attention to circular economy [9]. There is a lack of guidance for taking sustainability aspects into account in asset management [10]. Relation of circular economy principles and asset management is not defined clearly [9, 10]. Additionally, there is a lack of methods to support circular economy based asset management decisions [9]. Many of the circular economy models presented in the literature discuss the role of asset management, its requirements and possible enablers and barriers only at a general level if at all. The special requirements for maintenance are also not considered. Circular economy examples mostly focus on the material flows between the producers and customers, while the information flows between the key stakeholders required to deliver, maintain and dispose the product or service are usually not covered.

In this study, we identify typical circular economy models and analyze them from the asset management perspective. In addition, we discuss the threats and opportunities produced by the circular economy models for asset management.

ISBN 978-91-7583-841-0

II. CIRCULAR ECONOMY MODELS

Several authors have provided classifications for circular economy business and operating models [e.g. 11, 12, 13]. In this paper, we do not analyze the characteristics of these business or operating models. We present the classifications of Bocken et al. [11] and Lacy and Rutqvist [12] as these classifications are complementary and offer different perspectives to circular economy models i.e. sustainability and business perspectives respectively.

Bocken et al. [11] divide circular economy strategies into three categories:

1. **Slowing resource loops**
2. **Closing resource loops**
3. **Resource efficiency or narrowing resource flows**

Firstly, slowing resource loops is achieved through designing long-life goods and extending product-life. Product-life can be extended through, for instance, repair and remanufacturing. The extension or intensification of product-life increases the utilization period of products and, thus, results in a slowdown of the flow of resources. For the slowing of resource loops, four circular economy models are introduced: access and performance model, extending product value, classic long-life model and encouraging sufficiency.

Secondly, closing resource loops is reached through recycling. In this archetype, the loop between post-use and production is closed resulting in a circular flow of resources. Two models for closing loops are presented: extending resource value and industrial symbiosis. Thirdly, resource efficiency or narrowing resource flows aims at using fewer resources per product.

Lacy and Rutqvist [12] present a more business oriented view of circular economy models (A-E):

A. Circular supply-chain, where supply resources are designed for regeneration. In the circular supply chain fully renewable, recyclable or biodegradable inputs are used as substitutes for linear ones. Examples of products offered with business models belonging in this category are renewable energy, and bio-based and recyclable materials. These products can be produced for other companies or for own operations. Examples of companies using this business model type include CRAiLAR (biomass), Natureworks (biopolymers), AkzoNobel (paints and coatings) IKEA (producing and using renewable energy) and Ecovative (mushroom based plastics).

B. Recovery and recycling, where sources hiding in companies' production outputs and discarded products are protected, recaptured, and reused. The goal of this circular economy model is to find value in all material streams. Examples of companies using recovery and recycling model are General Motors (zero waste program), Interface (reuse nylon from fishnets in carpet manufacturing) and PUMA (bring me back bins).

C. Product life extension, where products that are built to last. The goal of this model is to increase the value from the invested resources and provide as long as possible useful life and maximized profitability over life cycle of products. Product life extension includes activities such as built to last, resell, repair, upgrade, refill, refurbish and remanufacture. Companies using product life extension approach include, for instance, Electrolux (modularity in products) and Caterpillar (remanufacturing).

D. Sharing platform, where the goal is to boost the productivity of assets. For instance, companies such as AirBnB, LiquidSpace and Lyft are utilizing this model. Sharing platform provides a means to connect product owners with individuals or companies that would like to use them.

E. Product as a service (PaaS), where performance is on focus over ownership. Unlike in sharing economy, companies retain ownership of a product and offer it to customers in a product-service system, PSS. Examples of companies using this circular economy model type include, for instance, Michelin [7].

Table 1 introduces the connections between the taxonomies of Bocken et al. [11] and Lacy and Rutqvist [12].

TABLE I. CIRCULAR ECONOMY MODELS ANALYSED IN THIS STUDY.

Taxonomy of Lacy and Rutqvist [12]	**Taxonomy of Bocken et al.** [11]
A. circular supply-chain	2. closing resource loops
B. recovery and recycling	2. closing resource loops 3. resource efficiency or narrowing resource flows
C. product life extension	1. slowing resource loops 3. resource efficiency or narrowing resource flows
D. sharing platform	1. slowing resource loops 3. resource efficiency or narrowing resource flows
E. product as a service	3. resource efficiency or narrowing resource flows

III. ASSET MANAGEMENT AND CIRCULAR ECONOMY

Asset management can be defined as "coordinated activity of an organization to realize value from assets". Realization of value involves balancing of costs, risks, opportunities and performance benefits. [14.] This definition takes into account the increasing complexity, uncertainty and requirements that the asset managers have to face. Current industrial networks involve a number of organizations as key stakeholders including asset operators and owners, regulatory and statutory bodies, service providers, engineering contractors, technology developers, equipment manufacturers, spare part vendors and logistic providers [15]. Brown et al. [16] list sustainability, interaction between built assets and natural environment, resilience, life cycle management, community demands, information management and new types of governance arrangements as issues that the current asset management systems need to take into account. On the whole, asset management systems contain multiple stakeholders and value elements that should be considered when making asset related decisions.

ISBN 978-91-7583-841-0

The effect of circular economy on asset management can be discussed through asset management fundamentals presented in ISO 55000 [14]:

- **Value**. The goal of asset management is to provide tangible or intangible value to the organisation. The value is determined by the organisation and its stakeholders so that it is aligned with the organisational objectives. Use of lifecycle approach is emphasised.

- **Alignment**. Organisational objectives are translated into technical and financial plans and decisions by asset management. Organisations should have risk-based and information-driven planning and decision-making processes, integration of asset and functional management processes (e.g. finance, human resources, information systems, logistics and operations) and the specification and implementation of supporting asset management system in place.

- **Leadership**. Leadership and workplace culture are elements determining the realization of value. Organisations should consider having clearly defined roles and responsibilities, ensuring that its employees are aware, competent, and empowered, and consulting with employees and stakeholders regarding asset management.

- **Assurance**. Asset management should give assurance that assets fulfil their required purpose. In order to fulfil the needs of assurance, organisations should implement processes for connecting the purposes and performance of the assets to the organizational objectives, for assurance of capability and for monitoring and continual improvement, and providing the necessary resources and competent personnel for demonstrating assurance.

IV. Methodology

Figure 1 presents the research methodology used in this study.

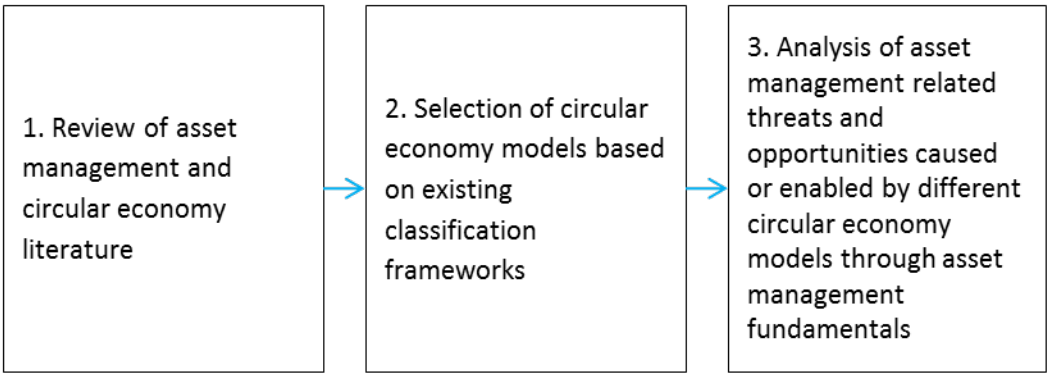


Fig.1. Research methodology.

Firstly, asset management and circular economy literature is reviewed. Secondly, two assessment frameworks, Bocken et al. [11] and Lacy and Rutqvist [12], are identified and utilized to classify the different types of circular economy models. Thirdly, the models are analyzed for the asset management related threats and opportunities. Asset management fundamentals described in ISO 55000 [14] are used as a basis for the analysis. The evaluation of the opportunities and threats is conducted in a workshop in which the authors analyze the circular economy models one by one from the perspective of the asset management fundamentals. Examples of circular economy models were used to help to focus on the specific circular economy models. The evaluation is based on the expert opinion of the authors. The authors have altogether over 50 years of experience from the asset management field.

V. Results

Circular economy models bring new business opportunities and threats for companies [e.g. 17]. In this paper, the focus is on the opportunities and threats for asset management activities and processes when changing from linear to circular economy models. In Table 2, the threats and opportunities for asset management fundamentals are presented. The fundamentals are divided into two categories; value and activities supporting value creation (alignment, leadership and assurance). The threats and opportunities are considered especially from the asset owner's perspective.

ISBN 978-91-7583-841-0

TABLE II. IMPLICATIONS OF CIRCULAR ECONOMY MODELS FOR ASSET MANAGEMENT.

Circular economy model	Threats	Opportunities
Circular supply-chain - closing resource loops **Example:** Production of biomaterials from the side streams of pulp/paper production	**Value** - Obsolescence of old assets **Alignment, leadership & assurance** - More actors and stakeholders in the value chain increase the complexity of the production system and the organisation and cause new challenges for decision-making, leadership and the assurance of performance - biological contamination →same or better quality requirements as for nonbiological products (a challenge for producers)	**Value** - New purposes for old assets **Alignment, leadership & assurance** - Demand for new asset management system is an opportunity for improved asset management system - New asset management system enables better leadership & assurance
Recovery and recycling - closing resource loops - resource efficiency or narrowing resource flows **Example:** Recycled paper production	**Value** - Recycled raw materials may cause disturbances to production machinery (e.g. contaminated materials and products) - Increased complexity of machinery fleet (new types of machinery needed) **Alignment, leadership & assurance** - Increased system complexity → limited availability of information →challenges for decision-making - More actors and stakeholders in the value chain increase the complexity of organisation and cause new challenges for leadership and the assurance of performance - Are the products produced from recycled materials as good as from virgin materials? - Unavailability of recycled raw material may lead to unplanned production stoppages→ failures may occur during ramp-up	**Value** - New purposes for old assets **Alignment, leadership & assurance** - Demand for new asset management system is an opportunity for improved asset management system - New asset management system enables better leadership & assurance
Product life extension - slowing resource loops - resource efficiency or narrowing resource flows **Example:** Caterpillar's remanufacturing concept	**Value** - Performance of assets → Remanufacturing machinery that is obsolete from the economic perspective **Alignment, leadership & assurance** - Availability of information →better information of utilization, condition and location of machinery needed - How to assure that purpose is fulfilled? →can new features be built on old chassis? →how to implement assurance processes for new kind of life cycle phases?	**Value** - cost reduction →reduction of new materials and energy consumption in production **Alignment, leadership & assurance** - Demand better monitoring of performance of the product and the supporting processes to be successful →other benefits such as decreased failures and disturbances, new service opportunities and concepts
Sharing platform - slowing resource loops - resource efficiency or narrowing resource flows **Example:** Concept for renting machinery and power tools (e.g. Cramo)	**Value** - Large amount of different users→ challenge for durability and asset management **Alignment, leadership & assurance** - Information need (location, condition, operational environment of the machine) →how to implement supporting asset management system effectively - How to assure that the asset fulfil the needs of the user/customer?	**Value** - More efficient use of resources (utilization rate) **Alignment, leadership & assurance** - Information need (location, condition, operational environment of the machine) → better availability of information - Demand better monitoring of use and performance to be successful →new service potential for increased customer value such as decreased failures and disturbances through usage optimization
Product as a service - resource efficiency or narrowing resource flows **Example:** Cost per performance concept (e.g. Rolls Royce power by the hour)	**Value** - Up-front investment - Market risk? **Alignment, leadership & assurance** - Distributed asset base→ challenges for alignment of processes and assurance of performance - Conflicting interests between customer and owner - Usage of machinery (different users and ways of use, owner cannot necessarily affect) - Information needs (location, use, condition etc.)	**Value** - Predictability and increased information about the condition, use, etc. of the machinery →opportunity for lifetime value capture **Alignment, leadership & assurance** - Closer customer relationship related to management of assets →increased capability to assure that assets fulfil their purpose - Predictability enables better personnel resource allocation

ISBN 978-91-7583-841-0

Circular supply chain model is contemplated through an example of biomaterials production from the side streams of pulp/paper production. In this model, old production assets may become obsolete if they are not suitable for producing new types of materials. Increased system complexity, increased number of actors and stakeholders in the value chain and the limited availability of information may cause challenges for decision-making and leadership. Additionally, there is a risk of biological contamination in the production process and the quality requirements for biomaterials are the same or better as for non-biological materials.

Opportunities include identifying new purposes for old assets and the potential indirect benefits from the necessary improvements to the asset management system, leadership and assurance processes.

Recovery and recycling is considered from the perspective of recycled paper production. The identified threats include disturbances to production machinery caused by recycled raw materials (e.g. contaminated materials and products), increased complexity of machinery fleet because of the need for new types of machinery, increased system complexity, increased number of actors and stakeholders in the value chain and the limited availability of information which may cause challenges for decision-making and leadership, securing the quality of products that are not produced from virgin materials, and the uncertainties related to the availability of recycled raw materials that may cause production stoppages and further on failures during ramp-up. Opportunities for recovery and recycling are similar to those in the circular supply chain model: new purposes for old assets and indirect benefits from the improved asset management system, leadership and assurance processes.

Product life extension is reflected from the perspective of Caterpillar's remanufacturing concept. From the asset management perspective, threats for this model include poor performance of assets due to remanufactured machinery that is obsolete from the economic perspective, increased need for information on utilization, condition and location of the machinery, and risks related to assurance of fulfilling the purpose of assets such as building new features on old chassis and implementing assurance processes for new kind of life cycle phases. Identified opportunities for this model include cost reduction due to reduction of new materials and energy consumption in production, and the indirect benefits caused by the need for better monitoring of performance of the product and the supporting processes to be successful such as decreased failures and disturbances, and new service opportunities and concepts.

Sharing platform is considered through a concept for renting machinery and power tools (e.g. Cramo). Threats for this concept include challenge for durability and asset management caused by a large amount of different users, increased information need such as location, condition and operational environment of the machine, and the challenge for effectively implementing the supporting asset management system, and assuring that the assets fulfill the needs of the users and customers. Opportunities for this model include increased utilization rate of the machinery, better availability of information and new service potential for increased customer value such as decreased failures and disturbances through usage optimization due to the need for monitoring of use and condition of the machinery.

Product as a service model is contemplated through an example of cost per performance concept (e.g. Rolls Royce power by the hour). From asset management perspective, threats for this model include large up-front investment need and the market risk for the investment in case of disruptive events (volcano eruptions, etc.). Market risk can be either business or asset management risk as it has both asset management (resource planning, etc.) and business (costs, etc.) implications. Additionally, distributed asset base is a challenge for process alignment and performance assurance, there may be conflicting interests between the customer and owner caused by market related reasons or other reasons, users may have different ways of using the machinery and the owners may not be able to control the way the machinery is used, and the model involves increased information needs such as location, use and condition related information.

Opportunities for this model include lifetime value capture enabled by increased predictability and information about the condition and the use of the machinery. In other words, the increased amount and quality of asset data enables new and better asset related services, maintenance operations and processes. In addition, this model enables increased capability to assure that assets fulfil their purpose caused by closer customer relationship related to management of assets. Increased predictability helps the leadership fundamental and enables better personnel resource allocation.

VI. CONCLUSIONS

Asset management objectives are derived from the strategic objectives of an organisation and aim at maintaining and improving the value of the asset base. When moving from linear operating models to circular models asset managers have to consider many new factors related to the asset management fundamentals presented in ISO 55000 [14]. However, the asset management literature has not yet paid attention to the changing requirements and needs of circular economy models. In fact, the circular economy has been paid little attention in the asset management literature [9]. The goals of asset management and circular economy are at large aligned, as both aim at increased resource efficiency and prolonging the useful life of machinery.

In this paper, we identify asset management related threats and opportunities in circular economy models from the asset owner's perspective. Based on the analysis, the opportunities and threats for asset management are different in different circular economy models. In addition, they are different from the many generic circular economy opportunities and threats identified in the literature [e.g. 17]. The circular economy models, in general, introduce asset management threats related to complexity of the supply chain and information systems, new value elements and their management and the assurance of quality in the new ecosystem. The opportunities for asset management include, for instance, potential for new purposes for the old equipment, potential for an improvement asset management system, and cost savings and quality improvements through better availability and quality of information.

This paper is our first attempt to assess the effects of asset management on the circular economy models and how the selection of a specific circular economy model affects the requirements for asset management. We argue that asset management is one of the most important factors to be considered when developing, implementing and using circular economy based business models.

Additionally, the goal of this study is to further develop the archetypes of circular economy models presented in this paper from the perspective of asset management. Depending on the examples and companies, the opportunities and threats for asset management change. In addition, some operating models that contain circular economy elements, such as virtualization and dematerialization, and producing on demand are not considered in these archetypes. Our goal is to create representative case examples that consider the information and material flows, as well as asset management perspectives. Ultimately, we aim at creating a new classification of circular economy models based on the asset management perspective. The cases and archetypes help companies and organizations to better assess and develop their processes and business models towards circular economy.

ACKNOWLEDGMENT

The research leading to these results has received funding from the Finnish Funding Agency for Innovation (Tekes). The authors gratefully acknowledge Tekes for the financial support that made this study possible through "Data to wisdom" project.

REFERENCES

[1] U. Schulte "New business models for a radical change in resource efficiency," Environmental Innovation and Societal Transitions, Volume 9, Pages 43–47, 2013.

[2] Ellen MacArthur Foundation "Circular Economy Overview," Website of Ellen MacArthur Foundation. Available at: https://www.ellenmacarthurfoundation.org/circular-economy/overview/concept, 2015.

[3] A. Sommer "Managing Green Business Model Transformations," Dissertation. Springer Verlag, 2012.

[4] M. Linder, M. Williander "Circular Business Model Innovation: Inherent Uncertainties," Business Strategy and the Environment. DOI: 10.1002/bse, 2015.

[5] M. Lewandowski "Designing the Business Models for Circular Economy – Towards the Conceptual Framework," Sustainability, 8, 43, 2016.

[6] A. Wijkman, K. Skånberg "Circular Economy and Social Benefits: Jobs and Climate Clear Winners in an Economy Based on Renewable Energy and Resource Efficiency," A study report at the request of the Club of Rome with support from the MAVA Foundation, 2015.

[7] W. Stahel "The circular economy," Nature 23 March 2016. Available at: http://www.nature.com/news/the-circular-economy-1.19594, 2016.

[8] Ellen MacArthur Foundation, SUN and McKinsey Center for Business and Environment "Europe's circular-economy opportunity," Report. Available at: http://www.mckinsey.com/business-functions/sustainability-and-resource-productivity/our-insights/europes-circular-economy-opportunity, 2015.

[9] M. Korse, R.J. Ruitenburg, M.E. Toxopeus, A.J.J. Braaksma "Embedding the circular economy in investment decision-making for capital asset – a business case framework," Procedia CIRP 48, pp. 425-430, 2016.

[10] S. Niekamp, U.R. Bharadwaj, J. Sadhukhan, M.K. Chryssanthopoulos "A multi-criteria decision support framework for sustainable asset management and challenges in its application," Journal of Industrial and Production Engineering, 32:1, 23-36, 2015.

[11] N.M.P. Bocken, I. de Pauw, C. Bakker, B. van der Grinten "Product design and business model strategies for a circular economy," Journal of Industrial and Production Engineering, 33:5, pp. 308-320, DOI: 10.1080/21681015.2016.117212, 2016.

[12] P. Lacy, J. Rutqvist "Waste to Wealth: The Circular Economy Advantage," Palgrave Macmillan, 2015.

[13] Ellen MacArthur Foundation "Towards the Circular Economy: Economic and Business Rationale for an Accelerated Transition," Report. Available at: https://www.ellenmacarthurfoundation.org/assets/downloads/publications/Ellen-MacArthur-Foundation-Towards-the-Circular-Economy-vol.1.pdf, 2013.

[14] ISO 55000 "Asset management. Overview, principles and terminology," Standard, 2014.

[15] J.P. Liyanage "Smart Engineering Assets Through Strategic Integration: Seeing Beyond the Convention," In: van der Lei T, Herder P, Wijnia Y (2012) Asset Management – The State of the Art in Europe from a Life Cycle Perspective. Springer Netherlands, 2012.

[16] K. Brown, M. Laue, J. Tafur, M.N. Mahmood, P. Scherrer, R. Keast "An Integrated Approach to Strategic Asset Management," In: Infranomics: Topics in Safety, Risk, Reliability and Quality Volume 24, 2014, pp 57-74, 2014.

[17] B. Mentink "Circular Business Model Innovation," Master's thesis, TU Delft, 2014.

Chapter 3: Big Data in Maintenance

ISBN 978-91-7583-841-0

ISBN 978-91-7583-841-0

Business performance measurements in asset management with the support of big data technologies

Jaime Campos[1]; Pankaj Sharma[2];Erkki Jantunen[3;] David Baglee[4;] Luca Fumagalli[5]
[1]Jaime.Campos@lnu.se; [2]Pankajtq@gmail.com; [3]Erkki.Jantunen@vtt.fi; [3]David.Baglee@sunderland.ac.uk; [3]luca1.fumagalli@polimi.it
[1,] Linnaeus University, Faculty of Technology, Department of Informatics, Sweden
[2]Department of Mechanical Engineering, IIT Delhi, New Delhi, India
[3]VTT Technical Research Centre of Finland, Ltd, P.O. Box 1000, FI-02044 VTT, Finland
[4]Department of Computing, Engineering and Technology, University of Sunderland, UK
[5]Department of Management, Economics and Industrial Engineering, Politecnico di Milano, Italy

***Abstract*—The paper reviews the performance measurement in the domain of interest. Important data in asset management are further, discussed. The importance and the characteristics of today's ICTs capabilities are also mentioned in the paper. The role of new concepts such as big data and data mining analytical technologies in managing the performance measurements in asset management are discussed in detail. The authors consequently suggest the use of the modified Balanced Scorecard methodology highlighting both quantitative and qualitative aspects, which is crucial for optimal use of the big data approach and technologies.**

Keywords—business performance measurements, asset management, big data technologies,

I. Introduction

In manufacturing there is a strong need to diminish and eliminate costly, unplanned downtime as well as unexpected breakdowns. Within the manufacturing environment, with growing complexity of equipment and high degree of automation, expectations from maintenance are now growing. In addition, the diversity of data to support maintenance strategy development adds more complexity for data sharing and exchanging. A system-wide communication approach is needed to efficiently process and distribute the data [1]. The emergence of Information and Communication Technologies (ICTs) and the e-maintenance approach in the industry has resulted in a promising move from the era of *fix when failed* into the era of *predict and prevent*. The move into the latest era is facilitated by the development of sophisticated sensors and Information Communication technologies (ICTs) that are adept to deliver data about the machines health condition, i.e. status and performance. However, according to Lee et al. [2], there is slightly and/or almost no practical use of the existent data that are produced by the machines or other related data that could possibly increase the efficiency of the asset management process. The data produced in a company is extremely important for improved decision making. Performance Measurement is a well-recognized and important area in the manufacturing strategy literature [3]. The maintenance performance measurement is both quantitatively and qualitatively grounded [4]. The quantitative measures are inter alia economic and technical values, statistical and partial maintenance productivity indices. The qualitative measures are mostly the human factors. In the case of asset management, customers form a major part of this qualitative measurement. The qualitative methods complement the quantitative methods in order to present a larger clearer picture of the performance. The data mining and big data technologies provide several "new" opportunities with the emergent algorithms to find hidden patterns on the data that the performance indices are based on. This becomes crucial, since companies that use the latest technologies in an optimal manner can acquire competitive advantages, which is crucial in today's aggressive markets.

Consequently, the paper suggests the use of a modified Balanced Scorecard in conjunction with the Big data and performance measurement process, since it provides a clear connection to the asset management strategy chosen and its objectives. Further, it gives an understanding of the needed Information Systems (IS) and ICTs (in this case the big data technologies) depending on the strategy, objectives and critical success factors.

The current paper is structured in the following way. Section 2 briefly reviews the area of performance measurements and highlights essential characteristics of it in the domain of interest. Next, in Section 3, big data and its relation to the performance indices are discussed. In Section 4, the use of a modified Balanced Scorecard is suggested for the strategic management of the ICTs, especially the big data technologies in connection to the domain of interest.

II. THE PERFORMANCE MEASUREMENTS

In this section, a discussion on common performance measuring methods is carried out including a brief on the development of Balanced Scorecard. Adaptation of balanced scorecard methodology to measure the performance of maintenance and assets is also discussed in the section.

The authors, Srimai et al. [5] explain the evolutionary paths of performance measurement from the 1980s to the present. Historically, performance measurement has been examined through the prism of financial measures. In the 1970s, researchers examined how organizations used management accounting systems especially budgeting as tools for performance measurement. In the 1980s, the focus was placed essentially on the budgeting process and its impact on performance [6]. Limitations of financial data as the basis for

ISBN 978-91-7583-841-0

decision making in organisations has been recognised for a long time [7]. Olve et al. [8] emphasized on the need to include non-financial measures in the performance measurement system. Recent literature in this area also suggests that organizations should place more emphasis on non-financial measures in their performance measurement systems; that organizations must use new performance measurement approaches; and that measures should be aligned with contextual factors such as strategy and organizational structure [6].

The field of performance measurement slowly evolved from considering only financial aspects to a more holistic methodology that included non-financial aspects as well, such as the Balanced Scorecard developed by Kaplan and Norton [9]. In addition, Keegan et al. [10] introduced a performance measurement matrix. It aimed at assessing the performance of the organization on financial, non-financial, internal and external aspects. Fitzgerald et al. [11] and Azzone et al. [12] also introduced different techniques of performance measurement. Cross and Lynch [13] posited the Strategic Measurement Analysis and Reporting Technique system (SMART). Some other approaches include Integrated Performance Measurement Systems [14], the Performance Prism [15], etc.

In addition, Nonaka [16] argues that performance Indices is not just the connection between performance measures and strategy in an enterprise that is important, but also the knowledge required for the organization to achieve their strategic goals.

The IS/ICTs provides companies with, and in this case maintenance, with many opportunities [17]. Use of IS/ICT's is also important for the creation, storage, and dissemination of knowledge for the employees' various work tasks. The performance indices are important for the successful accomplishment and control of the enterprises strategic goals [9; 18]. Pintelon et al. [19] mention that the performance measures are important, this to be able to react in time for threats or opportunities that the company might experience. While Dwight [20;21] mention that they are important for the measurement of the various activities that the enterprise undertakes. Neely et al. [18] says that it is a function of the effectiveness and efficiency of every action the company undertakes, therefore, it is crucial for any company.

In addition, Performance Management is a process by which a company manages its performance [14]. There is evidence to suggest that companies using an integrated balanced Performance Management System perform better than those that do not measure their performance [22; 23]. Neely [24] posited that the approach of performance measurement must be practically feasible and cost effective. It is important to know what to measure and how to measure. The performance measures are needed to be relevant, interpretable, timely, reliable and valid [25]. Bititci et al. [14] highlighted that performance management of an organization should be "in line with its corporate and functional strategies and objectives".

However, the most widely used method for measuring performance was the Balanced Scorecard. Kaplan and Norton developed Balanced Scorecard as a method to use financial as well as non-financial data for informed decision making by the managers [9]. Balanced Scorecard for performance measures provides an insight into four management perspectives, i.e. financial, internal business processes, customer perspective and innovation & learning, which separately and together show the benefits of linking long term strategic objectives with short term actions [9]. It provides support to reach a decision whether or not the activities of the organization/department are aiding in meeting the objectives in line with the company's strategy or vision. The choice of non-financial data points is made with strategic considerations in mind.

Lawrie and Cobbold [26] listed the important attributes of a scorecard which are the following, i.e. it is a mixture of financial and non-financial measures, a limited number of measures, measures are clustered into four groups called perspectives, originally called "Financial", "Customer", "Internal Process" and "Innovation and Learning". The last two were renamed "Internal Business Process" and "Learning and Growth" in Kaplan and Norton [27]. The measures are chosen to relate to specific strategic goals. The different measures should be chosen in a way that they gain the active endorsement of the senior management of the organization where some of the measures attempt to represent causality.

The 1st generation balanced scorecard struggled in application because of vague definitions. There were design challenges that limited its usage. There were problems resulting because of adverse effects of poor measure selection. The common problem being encountered was of filtering the measures and classifying them in clusters. There was no clarity on the measure selection process in the initial literature on balanced scorecards. In the 2nd generation balanced scorecards, Kaplan and Norton [28] addressed the issues of vagueness by introducing 'strategic objectives in each of the cluster/perspective. Newing [29] added the concept of causality. Further work during this period moved from defining causal relations between the clusters/perspectives, strategic objectives and performance measures. However, the problems of correctly identifying the causal relations that spanned over the clusters started emerging. There were additional problems of determining the correct composition of people who will decide the strategic objectives. The key issue remained of building confidence in the methodology to somehow indicate that the balanced scorecard reflects the strategic objectives of the organization [26]. This key issue was addressed by adding 'vision' or 'destination statements' in the 3rd generation of balanced scorecards. In the earlier literature, these destination statements were created after the design of balanced scorecard was complete. This statement was made to reflect the likely impacts of the objectives that were chosen. These statements acted as reference points while the organisations were in the process of pursuing the strategic objectives. Kotter [30] argued that it is easier to arrive at objectives and measures if a vision statement is available ab-initio. This led to a change in the balanced scorecard methodology and preparation of ‘destination statement’ became the first step in the process.

Wide applicability of balanced scorecard method has prompted researchers to use it for assessing performance of other functions. Maintenance performance measurement (MPM) is one such usage of the method. Parida and Kumar [31] have listed the factors for demand of MPM, such as measuring value created by the maintenance, justifying investment, revising resource allocations, health safety and environmental (HSE) issues, focus on knowledge management, adapting to new trends in operation and maintenance strategy, organizational structural changes, etc.

Moreover, a major part of any performance management system is the measurement of the performance of the assets. Societal responsibilities for prevention of loss of life and injuries, besides high maintenance cost are compelling the management to undertake Asset Performance Assessment (APA) as part of the business management and measurement system. Different APA frameworks need to be developed in line with the “Balanced Scorecard” (Kaplan and Norton, [27] to ensure that all operational and maintenance activities of the assets are aligned to the organization’s corporate strategies and objectives in a balanced manner [32]. A Multi-criteria hierarchical APA framework for Engineering Asset has been developed by Parida and Chattopadhyay [33]. This framework makes use of both financial and non-financial measures to assess the asset performance. It includes seemingly intangible items including customer and employee satisfaction in addition to financial factors including Return on Investment (RoI). The framework provides a measure of the asset performance of the organization.

Consequently, global organizations have realized the importance and necessity of a good performance management system. The efficacy of these management systems can be drastically improved through use of big data analytics. In the next section of the paper, big data analytics and its characteristics as applicable to performance management are discussed.

III. BIG DATA AND PERFORMANCE MEASUREMENTS IN ASSET MANAGEMENT

In this section, the Big data approach for measurement of performance indices is discussed. The shift of the performance measurement techniques from pure financial data to a mix of financial and non-financial data increased the subjectivity of the measurement system. There have been continuous improvements in the measurement system such that the subjectivity of intangible data can be reduced. The three generations of balanced scorecards have aimed at achieving more objectivity in the measures by removing vagueness through introduction of strategic objectives and destination statements [26]. Increased data inputs from customers and employees through techniques of crowd-sourcing have improved the efficiency of the measurement systems. Big data analytics has the potential to make the measurement systems even better.

Big data has two important characteristics; high dimensionality and large sample size. High dimensionality of the data helps in accurately predicting the future [34]. On the other hand, a large sample size helps the analysis in two ways; firstly, exploring the hidden structures of each sub-population of the data, which is traditionally not feasible and might even be treated as ‘outliers’ when the sample size is small; and secondly, extracting important common features across many sub-populations even when there are large individual variations [35].

Large volumes of heterogeneous data is another characteristic of big data. The same type of data can be represented in different forms, depending on the choice made by different organizations. The data is collected through autonomous data sources with distributed and decentralized controls. Being autonomous, each data source is able to generate and collect information without involving (or relying on) any centralized control. The complexity and the relationships underneath the data are also increasing as the data is becoming big. In an early stage of data centralized information systems, the focus is on finding best feature values to represent each observation [36].

The major portion of the data that constitutes big data is from the social media and the internet. The social media and Internet contain large amount of information on the consumer preferences and confidences, leading economic indicators, business cycles, etc. It is anticipated that the social network data will continue to explode and be exploited for many new applications [35]. To summarize, big data has the characteristics of heterogeneous data which has high dimensionality and large sample size, collected by autonomous and decentralized sources that is used for exploring complex and evolving relationships between variables. In the next section, the paper discusses the applicability of these features of big data to performance measurement of organizations.

Performance management systems are a holistic system of measuring the performance of an organization. They base the measurement on financial, non-financial, external and internal factors. The data is gathered from a host of different sources that vary from figures to tweets. These data sources are autonomous with no centralized control. Customers that are located on all parts of the globe key in the feedbacks through twitter, Facebook, product review sites, complaints on the internet, to name a few amongst many other methods. Most of this data is through subjective comments, though some of it may be in terms of ranking on point scale. This constitutes a large part of big data that can be analysed. In addition to the customers, employees pitch in with more data through written suggestions, complaints and feedbacks. Each member of the organization and its customers act as sensors that are sending in data into the management system. The data from maintenance department gets added to it too. There are often complex relationships that exist between the data points that get highlighted because of the large volume of data coming into the system. This is very similar to big data analytics and has similar characteristics that were discussed previously in this section 4. The data collection and analysis part in asset management scenario is depicted as framework in figure 1.

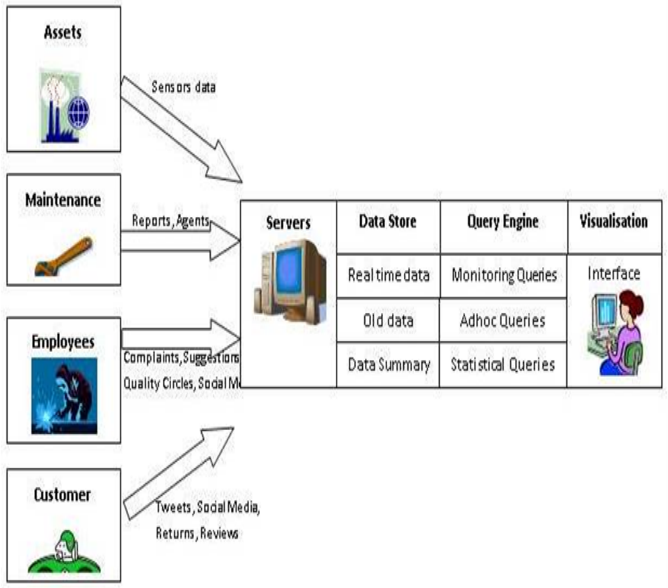


Fig.1. Performance Management through Big Data (Adapted from Jagadish et al. [36])

The data in the storage is of three different types; real time data, old data and summary of the data. Real time data is used to monitor the condition of the assets, quality of the products, reaction of the customers to new launches, morale of the employees, etc. Old data and the summary of the data are used to answer statistical queries that indicate trends which can foretell future. An important part of this performance management system is the way the final results are presented to the user. It has to be made sure the end points - humans - can properly "absorb" the results of the analysis and not get lost in a sea of data [37].

It is important when working with big data to keep in mind the quality of data and quality of models that are developed. For example, it is clear from statistics that most people die in horizontal position i.e. in bed. From this, it could be wrongly concluded that the easiest way to guarantee a long life would be avoiding horizontal position and in order to do so to buy a bed in which one can sleep in vertical position. Another example is how eating ice-cream correlates with drowning accidents. In maintenance the running hours are often collected and based on those statistical studies are carried out in order to optimize the interval for maintenance. Unfortunately, the running hour is a very poor measure of the condition of production machinery because the loading of the machinery is actually a more important factor. Consequently, it is important whenever big data is used to be able to understand the process that is monitored and to realize what should be measured and how this information can be integrated to provide meaningful results.

IV. MANAGING THE PERFORMANCE MEASUREMENTS WITH THE SUPPORT OF THE BIG DATA TECHNOLOGIES

The decision of selection of a suitable performance measurement can vary depending on the industry, organization and business unit. The implementation methodology of a performance measurement system can also vary depending upon recommendation, frameworks, systems and inter-organizational performance measurement [38]. However, selection of suitable ICTs, especially the big data technologies, that will support the decision making process for the specific performance measurement is an important activity. It is, therefore, crucial to have an understanding of the big data, machine learning and data mining technologies to be able to develop big data systems that provide the right recommendations to the person that will take the decisions. Consequently, the complex picture of all the involved factors that matter both technically as well as financially can be understood by the use of the model shown in Figure 2. Since both technological as well as business aspects of a system are considered, the model can be seen as a more accurate version. The figure highlights the importance of choosing a clear asset management strategy with well laid out mission and vision statements. The selected mission and vision are connected to certain objectives that need to be measured and/or controlled. From this flow out the actions that need to be taken in order to achieve the objectives. These actions are called as Critical Success Factors (CSF). The actions need to be continuously supported with the right and proper Information Systems (IS) and ICTs for their successful implementation.

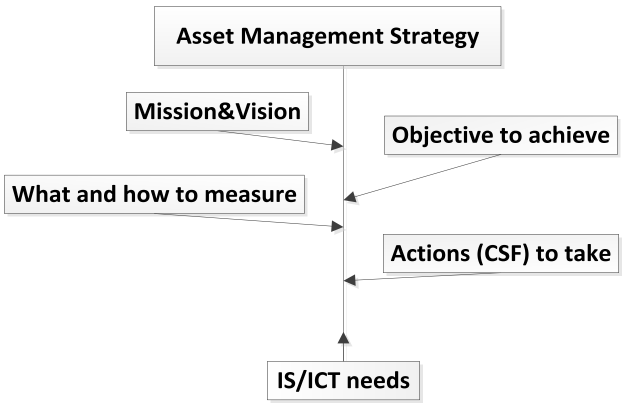


Fig.2. Strategy and IS/ICT alignment.

The model in Figure 2 is inspired by the DIKAR model [39], which highlights the Data, Information, Knowledge, Action, and Results in a system and uses the well-known Balanced Scorecard (BSC) as a part of the model such that the strategy chosen is in balance with both qualitative and quantitative aspects. The IS and ICTs that are selected must be capable of capturing the data and converting it to information and knowledge. The actions taken and the results that are achieved should ultimately support the fulfilment of business strategy. The ICT needs are the technical support of the system, i.e. the infrastructure that supports the information system in the organization, such as, databases, servers, applications servers, cloud computing, user interfaces, etc. The BSC tries to provide to executives with a framework that is able to translate a company's vision and strategy to some coherent set of performance measures.

Figure 3 is a modified version of the conventional balanced score card developed at the Harvard Business School [27, 40]. The four aspects highlighted are the internal business perspective, the financial perspective, the customer perspective and the learning and growth perspective. The aim is to achieve a balance between the different long and short term objectives, outcomes desired and the performance indicators/drivers of those outcomes and between hard objective measures; all aimed to achieve an integrated strategy. It means that the balance scorecard and its four perspectives aim to fulfil the company's strategy as best as it is possible. The balance scorecards (BSC) base the development of the key performance indicators (KPI) through the translation of the strategic vision and mission into a set of objectives, from which the business unit, i.e. in this case the asset management department, identifies its Key Success Factors (KSF) or Critical success factors, which then are translated into a series of quantitative KPIs.

Internal business/financial/customer/Innovation and learning perspective			
Objective to achieve	Measure(s)	Action (CSF)	IS/IT needs
Efficient Maintenance Process	OEE Availability Failures Planned Stoppages Quality Losses Speed Losses	RCM Improvement in Communication Improved Feedback System	Maintenance Performance Measurement Platform in a Big Data scenario with capabilities to • Distribute and store the data files over different nodes using HDFS • Manage Resources with application like Yarn • Analyse CSV data (Financial data) through applications like Hive • Analyse sensor data with applications like Sandbox, Splunk • Analyse live streaming data (tweets, complaints, reviews, feedbacks, etc.) with applications like Solr, MongoDB • Visualize analysis and results with Tableau etc.
Improved Financial Indicators	Cost of maintenance per unit Costs of failures Cost of lost production	Optimization of Maintenance Tasks	
Satisfied Customers	High Service level MTBF MTTR Quality Rate Feedback through social media	Good Quality Spare Parts Training and up-skilling of workforce Motivated workforce	
Better Innovation and Learning	Relations with OEM, Research Centres etc. Implementation of advanced maintenance methods	Investments in R&D	

Fig.3. Balance score card (modified) [40].

It is important to understand connections between these factors. For the internal business in asset management, the objective is to improve the efficiency of the maintenance process. Various measures that indicate the efficacy of the maintenance process are the Overall Equipment Effectiveness (OEE), availability of machines for production, Unplanned and planned stoppages, losses in quality and speed of production. The efforts should be focussed towards improving the efficacy by measuring the performance of the internal process. This can be achieved by implementing Reliability Centered Maintenance (RCM) and improvements in feedback and communication system can improve the maintenance process.

Financial data of the asset management company will be collected and stored in spreadsheets as Comma Separated Values (CSV). These spreadsheets will have measures like cost of maintenance per unit, cost of failures and cost of lost production. These costs can be brought down by optimizing the maintenance process.

Customer satisfaction is measured through Mean Time between Failures (MTBF), Mean Time to Repair (MTTR), the quality rate of the manufactured item and the service levels provided to the operations sub-department by the maintenance teams. The operations sub-department is the customer for the maintenance sub-department in a manufacturing company. The satisfaction level can be improved by using quality spare parts and highly trained motivated workforce. However, the social media feedbacks of the end-customers (those who finally buy the product from the company) can also act as a measurement criteria for the maintenance personnel. Most of this data is unstructured which normally can be found on customer feedback about the products. As the data is unstructured, there is a need to use big data as well as data mining technologies to be able to elicit information and knowledge and/or even hidden patterns from the data. In addition, in asset management it could be interesting to understand the customer complaints and the association with other important attributes, for instance to avoid specific complaints with the products. It is essential to use this technique for data analytics as the information contained in reviews, tweets, complaints, etc. is unstructured. Various methods of text mining such as information extraction, sentiment analysis, question answering, etc., are used to extract structured information from the unstructured data. Employee and customer complaints, customer reviews in the form of Facebook comments or tweets, etc., are some of the unstructured data that falls in this category. The data may, on analysis, reveal the problems in manufacturing process. It is anticipated that the social network data will continue to explode and be exploited for many new applications [35].

Improved Innovation and learning in the asset management department can be ensured through increased investments in R&D leading to higher collaborations between Original Equipment Manufacturers (OEM) and research centres.

The ICTs needed for this kind of analysis are the data mining and big data analytics, such as association or clustering, since they provide knowledge about hidden patterns. In these approaches there is no response variable that we are trying to find relationship with as in supervised approach, since in the unsupervised method it is like working blind, due to the fact that it is possible to understand relationship between variables and observations. Subsequently, better condition monitoring systems that inform about the health of the machine in connection to the faults are required to improve the whole maintenance process. The big data technologies that can be used in this case are the ones that provide diagnosis of the say, bearing fault. There are some researches that have performed clustering for diagnosis of rolling element bearing, which can be found on Wang et al. [41]. The clustering algorithm used was K-means clustering. Similar advanced maintenance techniques are available that deal with numerous other failure modes.

However, the major portion of the data that constitutes big data is from the social media and the internet which is connected to the customer's aspects of the Balance Scorecard perspective. Social media and Internet contain massive amounts of information on the consumer preferences and confidences, leading economic indicators, business cycles, etc. It is important to utilize these inputs in a performance measurement system in order to attain competency and efficiency in the maintenance process.

V. CONCLUSIONS

The strategic management and in this case the asset management strategies need a proper alignment with the appropriate IS/ICTs applications portfolio, which is a crucial factor for any company that wants to gain a competitive edge over its rivals. Consequently, the IS/ICTs should be a support for the chosen strategy and should provide the decision maker with the right information and knowledge to be able to take the right decisions resulting in the successful realization of the strategy. The modified BSC supports the former mentioned, since it provides a holistic view as well as a detailed picture of both technical and business needs of a company following an asset management strategy. The business performance measurements part of the modified BSC facilitates the follow up of various metrics and by doing so, strategic failures are avoided. The modified BSC provides a clear connection with the objectives, measurements, actions and the IS/ICTs required for each one of the objectives connected to the strategy. The use of the proposed model or similar approaches highlights existing flaws and increases the alignment between the business and its IS/ICTs. The work is especially helpful to the organizations that are in the process of deciding to implement a big data analytics based performance measurement system. It provides a formal stepwise methodology that eases the process of decision making. However, there is need to further research the customization issues for particular industries when this method is applied. There will be certain more modifications required for different industry sectors and organizations. Future research can address this issue.

REFERENCES

[1] Baglee,D Knowles, M Kinnunen. S "A Proposed Maintenance Strategy for a Wind Turbine Gearbox Using Condition Monitoring Techniques"Special Issue on: Maintenance-based Process Management as a Part of Business Competitiveness.International Journal of Process Management and Benchmarking. Vol. 6, No. 3, Pp. 386-403 2016

[2] Lee, J., Ni, J., Djurdjanovic, D., Qiu, H., Liao, H., 2006. Intelligent prognostics tools and e-maintenance. Computers in Industry, E-maintenance Special Issue 57, 476–489. doi:10.1016/j.compind.2006.02.014

[3] Taticchi, T., Tonelli, F. and Cagnazzo, L. 2010. "Performance Measurement and Management: A Literature Review and a Research Agenda." Measuring Business Excellence 14 (1): 4–18. doi:10.1108/13683041011027418.

[4] Kumar, U., Galar, D., Parida, A. Stenström, C., Berges, L. 2013. Maintenance performance metrics: a state-of-the-art review. J of Qual in Maintenance Eng vol. 19, Issue 3, pp. 233–277. doi:10.1108/JQME-05-2013-0029

[5] Srimai, S., Radford, J. and Wright, C., (2011), "Evolutionary paths of performance measurement", International Journal of Productivity and Performance Management, Vol. 60 Issue 7, pp. 662 – 687.

[6] Gosselin, M., (2005), "An empirical study of performance measurement in manufacturing firms", International Journal of Productivity and Performance Management, Vol. 54, Issue 5/6, pp. 419 – 437.

[7] Dearden, J., (1969), "The case against ROI control", Harvard Business Review, Vol. 47, Issue 3, pp. 124.

[8] Olve, N., Roy, J. and Wetter, M., (1999), Performance Drivers: A practical guide to using the balanced scorecard, John Wiley and Sons, Chichester.

[9] Kaplan R.S. and Norton D.P., (1992), "The Balanced Scorecard - Measures That Drive Performance", Harvard Business Review, Vol.70, Jan-Feb.

[10] Keegan, D.P., Eiler, R.G. and Jones, C.R., (1989), "Are your performance measures obsolete?", Management Accounting, pp. 45-50.

[11] Fitzgerald, L., Johnston, R., Brignall, T.J., Silvestro, R. and Voss, C., (1991), Performance Measurement in Service Businesses, CIMA, London.

[12] Azzone, G., Masella, C. and BerteleÁ, U. (1991), "Design of performance measures for time-based companies", International Journal of Operations & Production Management, Vol. 11, No. 3, pp. 77-85.

[13] Cross, K. F. and Lynch, R. L., (1988), “The SMART way to sustain and define success”, National Productivity Review, Vol. 8, No. 1, pp. 23 - 33.

[14] Bititci, U.S., Carrie, A.S. and McDevitt, L., (1997), “Integrated performance measurement systems: a development guide”, International Journal of Operation and Production Management, Vol. 17, No. 5, pp. 522-534.

[15] Neely, A., Adams, C. and Kennerley, M., (2002), The Performance Prism: The Scorecard for Measuring and Managing Business Success, Prentice Hall Financial Times, London.

[16] Nonaka, I (1991)"Harvard Business Review on Knowledge management", Harvard Business School Press.

[17] Pintelon, Liliane, Niek Du Preez, and Frank Van Puyvelde. "Information technology: opportunities for maintenance management." *Journal of Quality in Maintenance Engineering* 5.1 (1999): 9-24.

[18] Neely, A., Mills, J., Platts, K., Richards, H., Gregory, M., Bourne, M. and Kennerley, M., (2000), Performance measurement system design: developing and testing a process based approach, International Journal of Operations & Production Management, Vol. 20, No. 10, pp. 1119-1145.

[19] Pintelon, L,& Van Puyvdelde, F, (1997) " Maintenance Performance Reporting Systems: Some Experiences", Central for Industrial Management, Leuve, Belgium and Glaverbel, Mol, Belgium, Journal of Quality in Maintenance Engineering. Vol 3 No 1, 1997, pp, 4-15.

[20] Dwight, R. 1999. “Searching for Real Maintenance Performance Measures.” *Journal of Quality in Maintenance Engineering* 5 (3): 258–75. doi:10.1108/13552519910282728.

[21] Dwight, R.A. (1995), “*Concepts for measuring maintenance performance*”, in Martin, H.H. (Ed.), *New Developments in Maintenance: An International View*, Moret Ernst and Young.

[22] Kennerley, M. and Neely, A., (2003), “Measuring performance in a changing business environment”, International Journal of Operations and Production Management, Vol. 23, No. 2, pp. 213-229.

[23] Lingle, J.H. and Schiemann, W.A., (1996), “From balanced scorecard to strategy gauge: Is measurement worth it?”, Management Review, pp. 56-62.

[24] Neely, A., (1999), “The performance measurement revolution: why now and where next”, International Journal of Operation & Production Management, Vol. 19, No. 2, pp. 205-228.

[25] Al-Turki, U. and Duffuaa, S., (2003), “Performance measures for academic departments”, International Journal of Educational Management, Vol. 17, No. 7, pp. 330-338.

[26] Lawrie, G. and Cobbold, I., (2002), “Development of the 3rd Generation Balanced Scorecard”, 2GC Working Paper, pp. 1-16.

[27] Kaplan, R. and Norton, D., (1996), The Balanced Scorecard: Translating Strategy into Actions, Harvard Business School Press, Boston, MA.

[28] Kaplan R.S. and Norton D.P. (1993). “Putting the Balanced Scorecard to Work”, Harvard Business Review, Sept-Oct.

[29] Newing R., (1995), “Wake Up to the Balanced Scorecard!”, Management Accounting, Vol..73, No.3.

[30] Kotter, J.P., (1995), Leading Change: Why transformation efforts fail?, Harvard Business Review, March-April.

[31] Parida, A. and Kumar, U., (2006),"Maintenance performance measurement (MPM): issues and challenges", Journal of Quality in Maintenance Engineering, Vol. 12, Issue 3, pp. 239 – 251.

[32] Parida, A., (2013), Asset Performance Assessment, Asset Management, Springer Netherlands, pp. 101-113.

[33] Parida, A. and Chattopadhyay, G., (2007), Development of Multi-Criteria Hierarchical framework for Maintenance Performance Measurement (MPM), Journal of Quality in Maintenance Engineering, Vol. 13, No. 3, pp. 241-258.

[34] Fan, J. and Fan, Y., (2008), “High dimensional classification using features annealed independence rules”, Annals of Statistics, Vol. 36, pp. 2605– 37.

[35] Fan, J., Han, F. and Liu, H. (2014), “Challenges of Big Data analysis”, National Science Review, Vol. 1, pp. 293–314.

[36] Wu, X., Zhu, X., Wu, G-Q. and Ding, W., (2014), “Data Mining with Big Data”, IEEE transactions on knowledge and data engineering, Vol. 26, No. 1, pp. 97-107.

[37] Jagadish, H.V., Gehrke, J., Labrinidis, A., Papakonstantinou, Y., Patel, J.M., Ramakrishnan R. and Shahabi, C., (2014), “Big Data And Its Technical Challenges”, Communications Of TheACM, Vol. 57, No. 7, pp. 86-94.

[38] Folan, Paul, and Jim Browne. 2005. “A Review of Performance Measurement: Towards Performance Management.” Computers in Industry 56 (7): 663–80. doi:10.1016/j.compind.2005.03.001.

[39] Venkatraman, N. and Henderson, J.C. (2000). ”Business platforms for the 21st Century”, in D.A, Marchand, T.H. Davenport and T. Dickson (eds) Mastering Information Management, Harlow; FT/Prentince Hall.

[40] Ward, L., & Peppard, J. (2002). Strategic planning for information systems. Chichester: Wiley.

[41] Wang, G., Liu, C., Cui, Y. (2012). Clustering diagnosis of rolling element bearing fault based on integrated Autoregressive/AutoregressiveConditional Heteroscedasticity model. Journal of Sound and Vibration Vol. 331, pp. 4379–4387.doi:10.1016/j.jsv.2012.05.006

The Impact of Maintenance 4.0 and Big Data Analytics within Strategic Asset Management

Mirka Kans[1] Diego Galar[2]

[1]mirka.kans@lnu.se; [2]diego.galar@ltu.se

[1]Department of Mechanical Engineering, Linnaeus University, Växjö, Sweden

[2]Division of Operation and Maintenance Engineering, Lulea, Sweden

***Abstract*— The latest industrial revolution is manifested by smart and networking equipment. Realizing the full value of these machineries, and other business assets, has become increasingly important. Strategic asset management faces managerial, technical as well as methodological challenges, of which some could be reduced or overcome by applying technological solutions such as Internet of things, cloud computing, cyber-physical systems and big data analytics. This paper outlines the impact of the emerging technologies in the area of strategic management with special emphasis on the analytics as service provider for the maintenance functions.**

Keywords—maintenance 4.0, big data, cyber-physical systems, cloud computing, strategic asset management, challenges in asset management.

I. Introduction

Emerging information technologies have rapidly changed the business environment as the borders between the real world and the virtual world gradually disappear. This change is manifested in the knowledge intensive and service focused industry [1] as well as in the smart manufacturing equipped with cyber-physical machinery [2]. Industry 4.0 is understood as the fourth generation of industrial activity enabled by connected entities and systems and that brings new business opportunities for instance in form of increased individualization and flexibility in manufacturing [3]. This puts ever increasing demands on high performance of the manufacturing equipment and consequently, managing the equipment becomes important.

Asset management helps an organization in understanding the value of its assets and the role of assets in achieving organizational objectives [4]. Just as the emerging technologies have impacted the businesses on local and global level, the technology development also has impact on the area of asset management. Indeed, maintenance plays a key role in asset management and is also a principal actor within industry 4.0.

That is why one of the application areas of industry 4.0 is maintenance in the form of self-learning and smart system that predicts failure, makes diagnosis and triggers maintenance actions. These systems have high demands on data access and data quality and use multiple data sources to extract relevant information [5]. Maintenance 4.0 utilizes the advanced technologies for the predictive analytics and provides decisions based on feasibility. Maintenance 4.0 is mainly applicable for the industry 4.0 with emphasis on the prospects of maintenance that involves data collection, analysis, visualization and decision making for assets. Maintenance 4.0 also addresses a common Achilles heel in asset management: a better assets status forecasting, commonly called prognosis. The estimation of the remaining useful life establishes the basis for any operation or maintenance service in order to check the probability of mission accomplishment by the asset [6].

It is relevant to mention the need of 'Big data' approach to diverse sources of information and create new services based on the ontologies exploited and therefore knowledge discovery performed [7]. This adoption of Big data may pave the ground for better Operation and Maintenance policies bridging the gap between them considering that O&M have been historically optimized in independent silos manner. In this paper the applicability of Maintenance 4.0 and the positive effects on technology, organization and operations beings will be described from a systems perspective.

The purpose of this paper is to describe the impact of the latest industrial revolution within the area of strategic asset management. A number of managerial, technical and methodological challenges are identified. How these challenges could be overcome by the application of Maintenance 4.0 and big data analytics is thereafter discussed. Especially the potential within advanced maintenance analytics is discussed and illustrated. The new technological advancements bring opportunities but also new challenges, of which the most emergent are highlighted in the end of the paper.

II. Theoretical Overview

A. *Strategic asset management*

Asset management is according to ISO 55000 defined as the *coordinated activity of an organization to realize value from assets* [4]. The term asset refers to tangible as well as intangible items that have a value, either real or potential, to the organization. Activities are seen in a broad perspective, and can be the general approach, the planning as well as the implementation of the plans. [8] emphasizes the life cycle and sustainability perspectives of asset management, and proposes the following definition: *the optimization of the life cycle of an asset to meet performance standards in a safe and environmentally sound manner through smart Planning, Investment Financing, Engineering, Operations, Maintenance, Refurbishment and Replacement* (Lutchman, 2006, p. 18). [9] describe asset management for infrastructure asset management as the *rational decision-making process intended to satisfy the level of service demanded on assets //...// while simultaneously minimizing costs and maximizing effects* (Park et al., 2016, p. 711). [10] propose five key requirements of asset management: time, spatial, organizational, measurement and statistical generality. Asset management extends over time and across all types of assets, and at all levels of the organization. The performance measures covers economic, social and technical attributes of the assets, and on all performance levels.

ISBN 978-91-7583-841-0

The management of assets is documented in a strategic asset management plan [4]. This plan specifies how strategic objectives of the organization are to be converted into specific asset management objectives, i.e. the alignment of the asset management strategy with the corporate strategy. Continuingly, the plan describes the approach for developing asset management plans as well as the way the asset management system supports the achievement of set objectives. The asset management system and the relationships between key elements in the system are shown in Figure 1. The process flow is marked with thick arrows and information flows with thin arrows, while feedback is marked with dashed arrows.

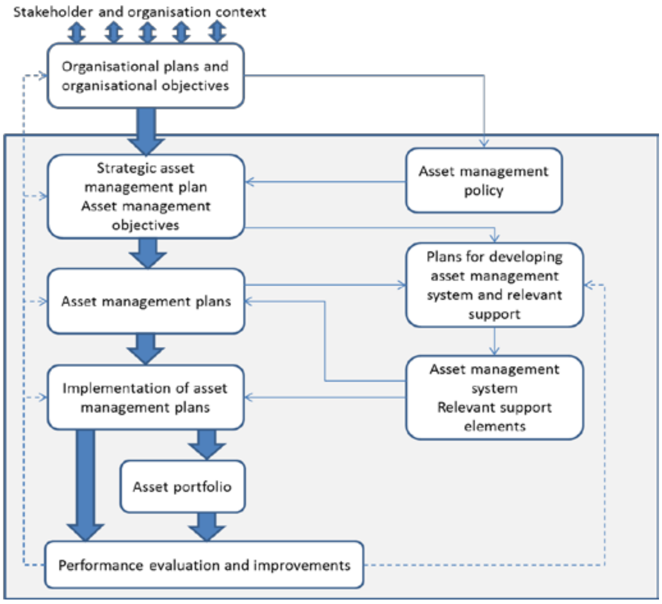


Fig.1. The asset management system, modified from ISO 55000

B. *Maintenance 4.0 and big data analytics*

The on-going industrial digitalization provides enormous capabilities for industry to collect vast amount of data and information (i.e. Industrial Big Data), from various processes and data sources such as operation, maintenance, and business processes. However, having accurate data and information available is one the prerequisites in maintenance knowledge discovery. Beside the collecting data and information, another puzzle is to understand the patterns and relationships of these data useful and relevant for maintenance decisions.

Hence, the purpose of this paper is to propose a concept for knowledge discovery in maintenance with focus on industry 4.0 which could be seen as a smart manufacturing system consisting of physical assets such as machines, components and humans that are highly connected and integrated [11]. Maintenance 4.0 is a subset of the smart manufacturing system represented by self-learning and smart machines that predicts failure, makes diagnosis and triggers maintenance actions. The smart equipment is in form of embedded or cyber-physical systems (CPS), i.e. equipment where the physical and software components are intertwined. The CPS possesses computing resources for efficient data capture, processing and communication in order to monitor and control the system [12].

The internet has undergone several development phases, from connecting different computer devices to connecting people. Today the internet could be described as a socio-technical system; a global and open information network consisting of subsystems, such as the social networks referred to as Internet of people and Internet of things that connects physical items through embedded software and sensors. Internet of things (IoT) can be understood as a global structure allowing virtual and physical assets to seamlessly be integrated into the information network, and to become an active part in socio-technical systems such as a company [13, 14]. Cloud computing covers all kinds of services offered through the internet [15, 16, 17]. Software as a Service (SaaS) refers to software available on the internet, either as freeware or for purchase. Instead of installing the software locally on a physical unit the software is available from any computer unit through the web browser. Similarly, Platform as a Service (PaaS) and Infrastructure as a Service (IaaS) utilizes the possibility to offer computer service through the internet - PaaS mainly in form of execution capabilities and IaaS for full computing capabilities in a virtual environment for the customer.

[18] propose a virtualization of tangible as well as intangible assets into an Asset as a Service (AaaS) model. The AaaS supports the gathering, monitoring and analysis of asset data by providing a common ontology for asset management. Ontologies are a means to handle big and heterogeneous data sets. The term big data describes very large data sets that cannot be handled, stored or processed using traditional database management systems [19]. Big data is characterized by 5Vs: volume, velocity, variety, veracity, and value [20, 21, 22]. The volume is large and constantly growing; especially as much of the data streams are in real-time of high velocity. The data sources and the data structures are heterogeneous which adds to the complexity; the variety of sources and structures leads to challenges regarding data quality and veracity. The vast data sets are a valuable asset to the organization if it possesses effective methods for the management and analysis. [23] explain that big data are data sets that can be aggregated and analyzed in various ways in order to visualize patterns in the data. Big data forces the organization to new ways of thinking and doing; it enables predictivity in the analyses by simulations, optimizations and statistical analysis [24]. Big data analytics utilize visualization for the interpretation of data by creating abstract or virtual representations of the information [25]. A special form of virtualization is the virtual or augmented reality, i.e. representations of the world created by mixing physical features with software features. Virtual and augmented reality could be used for simulation, training and educational purposes [17]. The main characteristics of Maintenance 4.0 are summarized in Figure 2.

ISBN 978-91-7583-841-0

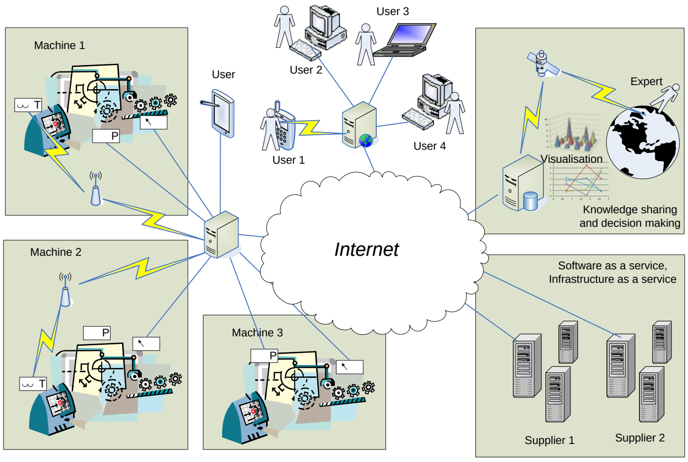


Fig.2. Maintenance 4.0

C. *Information management within asset management*

Data produced in asset management can be described in terms of the 5Vs described by [21] and [22]. Data from sensors like accelerometers or acoustic sensors can be acquired with velocity of tens of thousands of samples per second per each measuring point. Having hundreds or thousands of those points, big volume of data is being produced. Some maintenance related data are structured while some are not, such as free text comments for performed maintenance actions or failure reports. Moreover, data from different systems are in different formats. This is the source of variety of data in asset management. Those data has potential value when properly employed in asset management, but in order to achieve this, there is need to asses and man-age the veracity of the data, i.e. the data uncertainty. Finally, understanding the value of data, i.e. how data can enable efficiency and effectiveness in maintenance management, for instance for improved decision making, and to choose the most cost-effective means to process the data is important.

Data mining in big asset data can discover knowledge in terms of new patterns and relations not visible at a glance. The big data approach enables incorporation of contextual information in Maintenance Decision Support Systems (DSS) [26]. One example of useful knowledge that could be discovered is root causes of failure. This can provide an input for design improvement, as well as for more accurate maintenance planning.

To support an effective maintenance decision making process needs a trusted DSS based on knowledge discovery. The process of knowledge discovery will essentially consists of; data acquisition: to obtain relevant data and manage its content; data transition: to communicate the collected data; data fusion: to compile data and information from different sources; data mining: to analyze data to extract information and knowledge; and information extraction and visualization: to support maintenance decision; as shown in Figure 3.

The integration of data, recorded from a multiple-sensor system, together with information from other sources to achieve inferences is known as data fusion [27]. Data fusion is a prerequisite when handling data from heterogeneous sources or from multiple sensors. Knowledge discovery when applied for maintenance decision support uses eMaintenance concept for integrating the data mining and knowledge discovery. To get the right decision for the context sensing is a must. However, development of eMaintenance for industrial application faces a number of challenges which can be categorised into: 1) Organisational; 2) Architectural; 3) Infra-structural; 4) content and contextual and 5) integration [28].

Maintenance 4.0 utilizes the advanced technologies for the predictive analytics and provides decisions based on feasibility. Maintenance 4.0 is mainly applicable for the industry 4.0 with emphasis on the prospects of maintenance that involves data collection, analysis, visualization and decision making for assets.

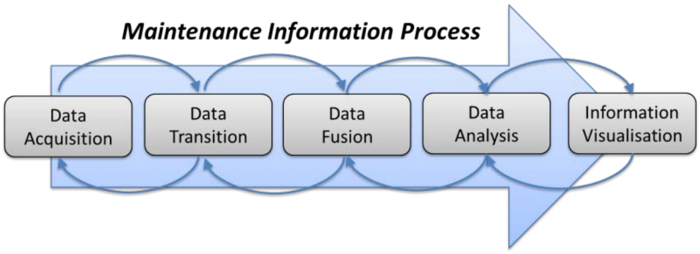


Fig.3. A generic maintenance information process

III. CHALLENGES WITHIN STRATEGIC ASSET MANAGEMENT

In this section main challenges within strategic asset management, extracted from current research in asset management and related areas, are presented. Managerial challenges cover questions related to the management of assets - how to obtain business value, the nature and purpose of the organization, and the needs and expectations of the organization and its stakeholders. Technical challenges are related to the physical assets as well as the information systems. Finally, the methodological challenges refer to the data processing and analysis methods required for reaching optimal decision making within asset management. The challenges are all aligned with the asset management system as described in Figure 3.

A. *Managerial challenges*

[29] identify several challenges within offshore asset management spanning from human resource related issues to knowledge management and economic challenges in addition to the context specific issues that lies within offshore industry. A main operational challenge is the **focus on CAPEX** (capital expenditures) **in the procurement**, often leading to higher OPEX (operational expenditures) and thus higher lifecycle costs. The **provision of skilled personnel** is another challenge. There exists a need for continuous training and personnel development as well as effective management of knowledge. The main conclusion was that these challenges interact in the socio-technological environment, and that the challenges thus should be addressed in in a holistic way rather than finding solutions for each challenge. Possessing relevant knowledge not only about the equipment, but also regarding information technology (IT), is important for successful application of IT-support. [30] for instance found that benefits of IT investments in asset management correlates with the organizational level of

knowledge; the higher the level of knowledge the higher the benefits. [31] also points out the IT maturity level as a challenge. [32] highlight the challenges that stems from **conflicting interests in the organization** and propose a holistic asset management framework connecting decision making and control on all managerial levels through the use of performance measures. Conflicting objectives is approached by [33] as well. The authors suggest a multi criteria decision making framework for finding an optimum trade-off for reaching sustainable asset management. A holistic lifecycle approach for offshore wind turbine management is also suggested by [34]. The authors point out that the **operations and maintenance aspects must be considered in the design** and that several key stakeholders are missing the design process. This impacts the cost-effectiveness of the maintenance.

B. *Technological challenges*

The **technology heterogeneity** of the physical asset management systems is a huge challenge. There are problems in integrating the **various information systems islands** for supporting the whole lifecycle management as well as handling the **diversity of physical assets**, such as in the application area of urban flood control [15], highway asset management [35] or electric power grids [36]. This induces mistakes and leads to inefficient asset management, and the sharing of assets becomes difficult resulting in increased utility rate [15]. [35] developed an ontology based solution that interconnects heterogeneous life cycle data to support decision making. The technology heterogeneity also leads to **data security and data integrity issues** [16]. [23] studied configuration management in large projects and found several challenges related to asset management. One is the long lifecycles of systems, which adds on to the data integrity problems; asset information is stored in heterogeneous IT systems, using different types of media and structures. There are also problems with handling **different versions of equipment**, and to fit in new or configured equipment into the existing systems. The **lack of real-time data** is a great challenge in many industries, for instance in logistics services, where tracing and tracking of the physical assets is important for effective planning [13]. Challenges in data management for offshore wind turbine management cover **both data retrieval and data analysis**, and the availability of real-time data [34]. The **lack of efficient IT support** affects the planning and optimization of maintenance.

C. *Methodological challenges*

The efficient asset management requires a **life cycle and systems perspective** on assets [4], which should be reflected in the methods used for data retrieval and analysis. It is well known that the adoption of condition-based maintenance and prognostic methods is a challenge for the industry. [37] found that especially the **selection of parameters and analysis methods** are not well motivated. This leads to long and costly implementation processes as the companies use a trial and error approach. In addition**, the quality level of the analyses** is not sufficient to improve the maintenance decisions. Thus, the technical features of the predictive systems are not well aligned with maintenance business impact.

IV. Impact of Maintenance 4.0 and Big data Analytics within strategic asset management

A. *Managerial impact*

The CAPEX-focused procurement strategy often applied for both simpler and more complex assets might result in ineffective investment decisions as the main part of the asset total costs is derived from the operational phase [38]. Big data creates new opportunities to combine different types of data and analyses asset performance and conditions both on aggregate and individual level [19]. This leads to better understanding of the asset operational phase and better documentation of the individual asset behavior, which is an important input for creating more accurate LCC models [38]. Moreover, operations and maintenance aspects must be considered in the design phase, which require efficient feedback mechanisms from the operational phase to the design or redesign phase. IoT and AaaS systems secure information requirements throughout the life cycle and provide feedback mechanisms from operation to design/redesign. [35] propose an ontology based exchange mechanism for this purpose, which eliminates the costly and time consuming paper based equivalent while enabling the collaboration between multiple partners involved in infrastructure projects.

Conflicting interests in the organization is not only affecting the operational efficiency, but could have impact on the strategic level in form of organizational cost ineffectiveness, or on the societal level inducing safety and environmental hazards, see for instance [32] and [39]. [39] propose applying an ecosystem for the Swedish railway industry in order to understand organizational and inter-organizational issues. According to [40], a business ecosystem could be seen as an economic community, consisting of interacting organizations and individuals that create value for the customers. The effectiveness is thus not defined at the organizational level, but at the ecosystem level, which also is reflected in the business objectives. [14] connects IoT with the business ecosystem concept, and view IoT as a means to organize the ecosystem. IoT could thus provide an ecosystem perspective where goals are connected to the value creation rather than to individual departments or individual partners.

Provision of skilled personnel is a huge challenge, especially in remote or harsh production environments. Smart equipment require less personnel for the operation and maintenance, as regular monitoring and control activities are made completely automatic, but also parts of the preventive maintenance actions such as lubrication. While the production will require less operators and technicians, the smart production will depend on workers with specialized competences such as analytical skills and management competences, and that interacts virtually with the physical assets. CPS and virtualization techniques are for instance combined in [12] for allowing the user to view and access maintenance data remotely through the internet and interact with the machine. Making the correct decision in the right time will increasingly become a key competence, not only on strategic level, but also on the operational. Consequently, the real-time and advanced analytics tools and visualization of big data will become increasingly important.

The level of information technology competence is directly correlated with the level of benefit an organization can reach with IT. Traditional IT strategies rely on in-house competence of the IT organization, often in form of centralized IT governance. [41] found the decentralized governance strategy more common in the area of maintenance management. A decentralized strategy increases the chances that the IT support is aligned with the objectives of the organization, but require IT competence within the maintenance organization, which often is lacking. Cloud computing and software as a service in general, and the concept of assets as a service in particular, reduces the need for an internal IT organization and specialized IT knowledge within the maintenance organization. Using third party agreements and cloud services could potentially lead to reduction of overall IT costs and better adaptation of IT solutions to the needs of the maintenance organization [31]. A prerequisite is that suitable SaaS solutions are available on the market.

B. Impact on technology

Cloud computing is seen as a solution to the information technology heterogeneity by several authors [15, 18, 35]. Cloud computing require less integration efforts between separate systems while enabling current systems to be connected. The variety of cloud services, from SaaS to IaaS, give opportunities to find the solution that best supports the strategic asset management objectives as well as the current technology configuration. [25] suggest a visualization approach for overcoming problems with heterogeneous and large amount of data. By visualizing how building assets degrade over time just-in-time maintenance scheduling can be achieved.

A major challenge is the lack of real-time data. Smart cloud based technologies in form of Radio-frequency identification (RFID) and Wireless Sensor Networks (WSN) is a way to overcome problems with real-time data collection of heterogeneous data [15]. [15] propose a cloud based platform for asset management, consisting of four layers. Smart assets, i.e. assets that communicate through IoT, are connected through a gateway layer while an agent wraps and represents the smart assets into a unified asset model.

Big data and cloud computing will not solve the security and integrity problems which stems from the use of network technologies, but maintenance 4.0 will at least force the stakeholders to pay attention to the issues and work towards a common solution. Applying a common ontology can assist in the integration and definition of relevant data sets from heterogeneous data sources [35]. Using a skilled third party as information provider can decrease security issues [42]. The information provider is expert in the information technology area and has appropriate resources for the secure and efficient management of information.

C. Methodological impact

Several authors propose IoT and big data solutions for ensuring life cycle approaches and systems perspectives on assets; se for instance [13, 15, 35]. The new technologies provide opportunities to create integrated and seamless data flows between physical assets as well as different stakeholders. The use of ontologies [35] and standards [16] secure a common understanding and interpretation of relevant data, making the selection of parameters easier. Moreover, the merging of asset data with other corporate data sets is supported with network architectures such as CPS and IoT [23]. Big data analytics somewhat changes the way decision making is made: instead of selecting appropriate methods for the analysis of data, BD analytics swifts through the available data and finds new patterns and correlations. This enables the decision making based not only on common understanding of the assets, but also on yet unrevealed correlations between different parameters. [37] found the selection of parameters as well as analysis methods for prognostics maintenance being poorly motivated, which in turn could affect the quality of the analyses. [43] propose an integrated approach that combines model driven and data driven diagnostics and prognostics techniques for complex CPS. CPS that automatically monitors and predicts their degradation, such as in [44], reduces the need for selecting parameters and analysis methods, as the equipment already has prognostic capabilities embedded into the physical entity.

V. MAINTENANCE ANALYTICS

The concept for Maintenance Analytics (MA) focuses in the new knowledge discovery in maintenance. MA addresses the process of discovery, understanding, and communication of maintenance data from four time-related perspectives. These time related perspective match with the determination of the past, present and future state of an asset summarised by [45] in four questions, as it can be seen in Figure 4 below. What happened, why it happened, what will happen and how can we make it happen are the issues involving the determination of the state of an asset.

A. From descriptive to prescriptive analytics

The questions are ordered by the value of the information given by each of them, in such a way that the former has the less value and the latter the higher value. Nevertheless, obtaining this valuable information requires more and more resources as the difficulty to achieve the goals proposed by the questions is higher. The last question will be in the spotlight in the coming future in order to decide how to take advantage of a future opportunity or mitigate a future risk, getting information about the implications of each decision option. The selection of the best option, based on some given parameters, will provide a meaningful tool for improving maintenance planning and production scheduling.

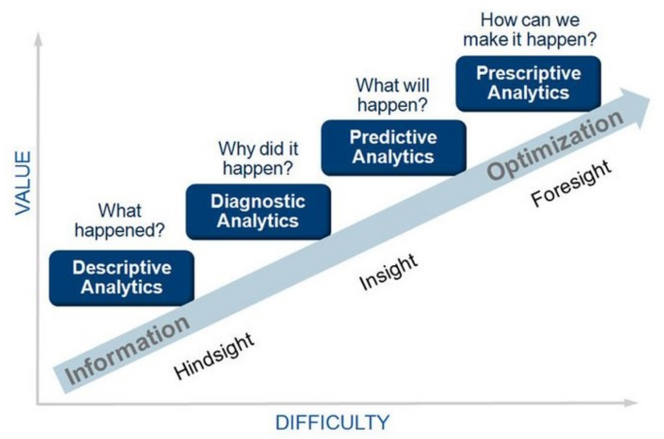


Fig.4. The way to prescriptive analysis [45]

- Maintenance Descriptive Analytics (monitoring) focuses to discover and describe what happened in the past; and why something happened; in this phase access to data related to system operation, system condition, and expected condition is highly important. Another important aspect in order to understand the relationship of events and states during the descriptive analytics is time and time frame associated with each specific log.
- Maintenance Diagnostic Analytics: It explains the possible reasons for faults or failures, i.e. why and where questions, since diagnosis is defined by EN13306 as the fault detection, identification and localization.
- Maintenance Predictive Analytics focuses to estimate what will happen in the future; The Maintenance Predictive Analytics phase of MA aims to answer "What will happen in the future?" but also why will it happen? In this phase the outcome from 'Maintenance Descriptive Analytics' is used. Additionally, in this phase, availability of reliability data and maintainability data is necessary beside the data used in descriptive phase. In addition, in order to predict upcoming failure and fault there is a need to provide business data such as planned operation and planned maintenance to this phase.
- Maintenance Prescriptive analytics which addresses what need to be done next. The Maintenance Prescriptive Analytics phase of MA aims to answer "*What needs to be done*?". When dealing with Maintenance Analytics (MA) provision of appropriate information logistics is essential. The main aim of information logistics is to provide just-in-time information to targeted users and optimization of the information supply process, i.e. making the right information available at the right time and at the right point of location [46, 47]. Solutions for in-formation logistics need to deal with: I) time management, which addresses 'when to deliver'; II) content management, which refers to 'what to deliver'; III) communication management, which refers to 'how to deliver'; IV) con-text management, which addresses 'where and why to deliver'[46, 47].

B. The need for prescriptive analytics in maintenance: a case study

There are four stages of analytics that vary depending on difficulty, value and trends of technology. The descriptive analytics (hindsight) provides what has happened based on measuring asset that was reflected after failure. Diagnostic analytics can provide the reason behind the root cause of failure. Predictive analytics (insight) in the present provides can predict the future behavior by analyzing remaining useful life. The prescriptive analytics (foresight) can assess the recommendations provided by the predictive analytics and recommend measures for corrective or preventive maintenance actions. This has the capability to design the operation and maintenance according to our requirements that adapts continually without excessive user intervention thus acts as a backend for industry 4.0 systems. Next figures show the natural deterioration and restoring process of an asset with the corresponding thresholds. Looking upon all mentioned before, the figure 5 summarizes the three potential scenarios:

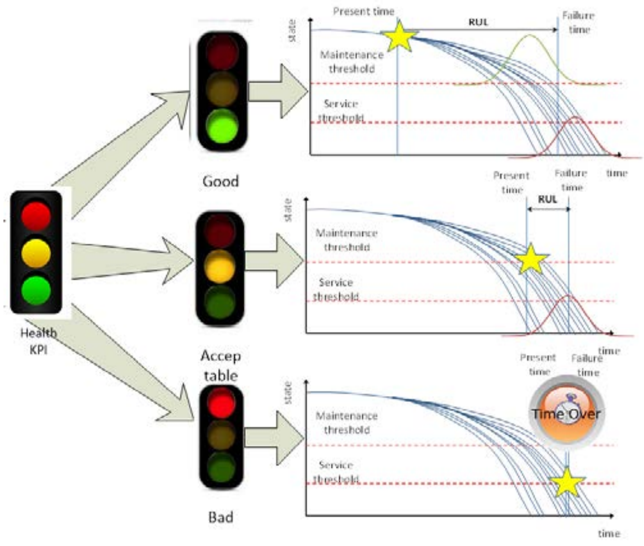


Fig.5. Maintenance scenarios

On the one hand there is the health of the component, which will be represented by a traffic light. Each of these states is related to a different scenario in terms of maintenance. It must be remarked that the diagnosis phase i.e. the answer to "what is happening" may be able to distinguish between three different states of health, limited by two thresholds: maintenance threshold and service threshold (depicted in figure 5). The first in understood as a warning limit when maintenance personnel must start considering to deploy a maintenance action. The last is formally equivalent to RUL, when the component and consequently the machine get a failure and the service is interrupted.

In the first scenario, when neither the maintenance threshold nor the service threshold has been crossed, two figures may be relevant for operators and maintainers (see figure 6):

- Remaining time to get the maintenance threshold.
- Remaining time to get the service threshold.

In this first phase of the life span, the system does not suggest to perform any maintenance action, since the component is considered in an early safety stage and the RUL estimation dictates that the risk of failure is still far.

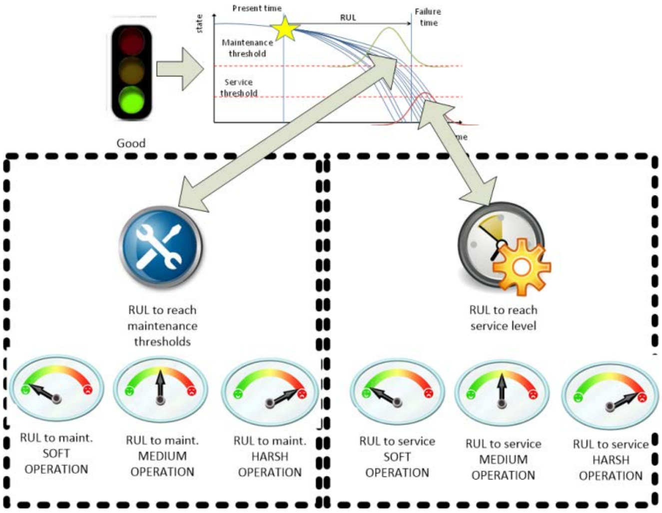


Fig.6. Good Health Scenario

Once the maintenance threshold has been crossed, the component gets into a risky stage where a maintenance action should be performed in a near future, in order to avoid a failure. In this case, the RUL estimation to get the service threshold should be presented to the end user as a result; it means that this would be the time to failure if the maintenance personnel do not perform any maintenance action ("do nothing" option) but the end user may also be interested in the consequences of taking one or another maintenance action (preventive or corrective). It is in this point where the RUL restoration parameter must be considered to decide which health state would have the component after a maintenance action.

The challenge is to know the real condition of the asset, i.e. the RUL consumed in each threshold and therefore to know if the RUL restoration of each maintenance action is a fact and the maintenance threshold has been crossed back restoring the asset to the healthy condition. If so, the component will get a good health condition; if not, it may remain in the risky situation. This mentioned situation may happen when performing a preventive maintenance action; while applying corrective maintenance in such situation it is considered that a recovery up to the good health condition is feasible. The reason is that after a corrective maintenance action the improvement is high enough to cross back the maintenance threshold but no the PM action. This is illustrated in figure 7.

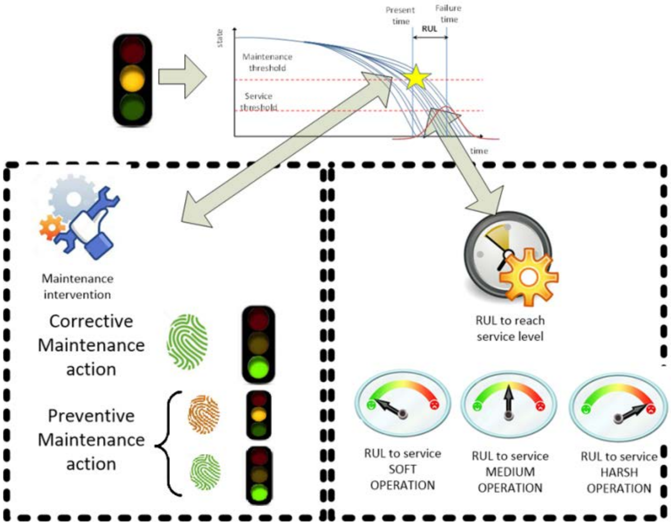


Fig.7. Risky Health Scenario

Finally, the last scenario to be covered is the one where the component reaches the service threshold. After this point, the only solution to recover the component´s health is to perform a corrective action (many times reactive). As it happened in the previous scenario, the recovery situation would get the good or risky condition depending on the threshold values (see figure 8).

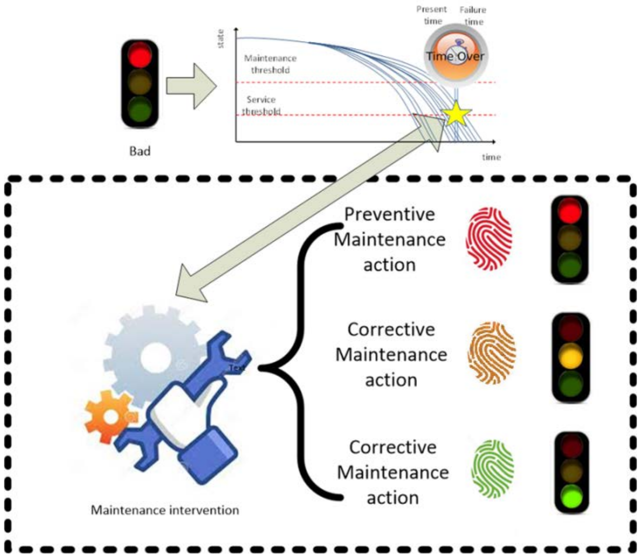


Fig.8. Faulty Health Scenario

However prediction of RUL is no longer the information requested by the user in a predictive analytics approach since this information even valuable may be considered incomplete for the decision makers. In the RUL visualization of figure below two different aspects of the prognosis techniques are shown. Since prognostics deals with predicting the future behavior of engineering systems, there are several sources of uncertainty which influence such future prediction, and

ISBN 978-91-7583-841-0

therefore, it is rarely feasible to obtain an estimate of the RUL with complete precision.

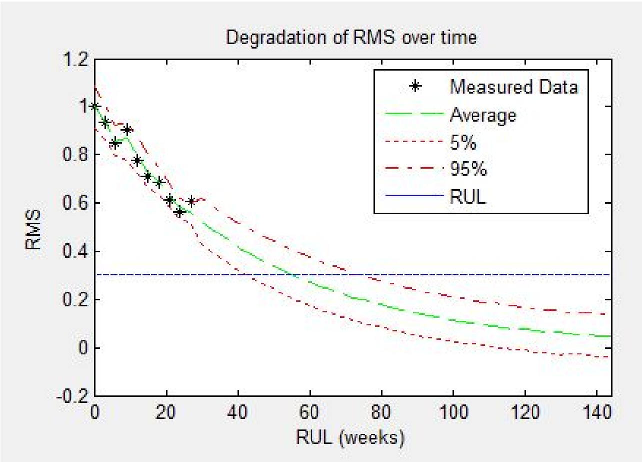


Fig.9. Degradation over time

In fact, it is not even meaningful to make such predictions without computing the uncertainty associated with RUL. In the case of prescriptive analytics the uncertainty can be meaningful for the user since one of the uncertainty sources comes from the lack of knowledge in the operation of the machine. Indeed, the most intuitive way to show a component´s degradation is drawing the evolution over time of some performance/health index. In the figure 9, the threshold that indicates the beginning of the faulty region is the blue horizontal line, and this will determine the RUL of the component. The evolution of the real data points over time is depicted with black stars. It can be observed that red lines as uncertainty measures regarding the operation of the machine provide different RUL associated with operations hard and soft against the medium or normal operation mode considered in the RUL estimation.

This estimation provides to operators and maintainers the information to schedule maintenance actions but not only that. Since, the different operational profile provide different RUL estimates then operators and maintainers have the opportunity to decide different operational sequences in order to open up maintenance windows whenever convenient for the business. These alternatives far away from static RUL predictions are the prescriptive analytics requested by O&M departments and asset managers in industry 4.0.

VI. CONCLUSIONS

This paper has described the impact of Maintenance 4.0 and big data analytics in the area of strategic asset management. It is evident that the new technologies will have a great positive impact for the effective management of assets. The gains are seen in all levels, from defining organizational objectives and connecting them to asset management objectives, to the creation of efficient plans and for performance evaluation and improvements. Thus, the whole asset management system could be supported by IoT and big data analytics. According to [23] big data challenges the existing approaches for asset integrity management and forces new ways of thinking.

The new technology paradigm brings many opportunities but also new challenges. One major challenge is providing data security and integrity in the connected and collaborating networks. Data needs to be secured throughout its life cycle, throughout the asset life cycle and throughout the full ecosystem. [16] for instance highlight that data encryption cannot be smoothly enabled in the cloud for the full exchange flow, and [13] discuss the problems related to data integrity in IoT in connection with tracking of assets using RFID tags. A problem with big data sets is the choice of appropriate analysis methods. The knowledge discovery process has to be supported by standardized methodologies, an area within big data analytics still in need of much research. Another challenge is the development of appropriate software for enabling the effective utilization of cloud computing and big data, such as commercially available AaaS. Finally, a more subtle yet highly important challenge is the change of mindset that is required with respect to strategic asset management and the new technology paradigm; companies and organizations have to understand the business impact that lies within Maintenance 4.0 both with respect to increased internal effectiveness, but also in form of new business opportunities. The latter changes focus from the traditional business models providing products to creating value for the customer in form of Service Management 4.0 [3].

In this regard, the directions identified along the paper of the further research to be performed can be summarized as follows:

- Real time KD algorithms from heterogeneous asset data sources that will cope with privacy preserved processing, feature and instance selection, discretization, data compression, ensemble classifiers and regression models, and spatial and temporal alignment of data.
- Scalable data structures based on cross-domain data sources acquisition by means of a virtualization layer between data acquisition process and data analytics. This should also include new solutions that combine new databases capabilities to integrate heterogeneous data sources on high-performance accessing systems based on Clouds.
- Enabling Big Data Communications by means of open interface gateways with monitoring systems providing timestamp and position synchronization, heterogeneous communication support, including mobility and aggregation, and priority protocols for real time transmission of information.

REFERENCES

[1] H. Meier, R. Roy and G. Seliger, "Industrial Product-Service Systems - IPS2", CIRP Annals – Man Tech, Vol. 59, pp. 607-627, 2010.

[2] B. Syed, A. Pal, K. Srinivasarengan, and P. Balamuralidhar, "A Smart Transport Application of Cyber-Physical Systems: Road Surface Monitoring with mobile devices", IEEE 6th Int Conf in Sensing Tech, pp. 8-12, 2012.

[3] M. Kans and A. Ingwald "Business Model Development towards Service Management 4.0", Procedia CIRP, Vol. 47, pp. 489-494, 2016.

[4] SIS, SS-ISO 55000:2014, Asset management – Overview, principles and terminology, 2014.

[5] J. Lee, , H.A. Kao, and S. Yang, “Service innovation and smart analytics for Industry 4.0 and big data environment”, Procedia CIRP, vol.16, pp.3–8, 2014.

[6] D.Galar, M.Palo, A.Van Horenbeek, and L.Pintelon, “Integration of disparate data sources to perform maintenance prognosis and optimal decision making”, Insight - Non-Destructive Testing and Condition Monitoring, vol.54, no.8, pp.440-445(6), 2012.

[7] D.Baglee, S.Marttonen, and D.Galar, ”The need for big data collection and analyses to support the development of an advanced maintenance strategy”, DMIN'15, The 11th International Conference on Data Mining (27–30 Jul 2015). Las Vegas, Nevada, USA, 2015.

[8] R. Lutchman, “Sustainable Asset Management. Linking Assets, People and Processes for Results, DEStech Publications, 2006.

[9] S. Park, S.I. Park and S-H. Lee, ”Strategy on sustainable infrastructure asset management: Focus on Korea’s future policy directivity”, Renewable and Sustainable Energy Reviews, Vol. 62, pp. 710-722, 2016.

[10] J. Amadi-Echendu, K. Brown, R. Willett, J. Mathew, “Definitions, Concepts and Scope of Engineering Asset Management”, Engineering Asset management Review, Vol. 1, Springer, London, 2010.

[11] G. Michalos, P. Sipsas, S. Makris and G. Chryssolouris, “Decision making logic for flexible assembly lines reconfiguration”, Robotics and Computer-Integrated Manufacturing, Vol. 37, pp. 233–250, 2016.

[12] R. Penna, M. Amaral, D. Espíndola, S. Botelho, N. Duarte, C.E. Pereira, M. Zuccolotto and E. Morosini Frazzon, “Visualization tool for cyber-physical maintenance systems” IEEE 12th Int Conf INDIN, pp. 566-571, 2014.

[13] X. Qiu, H. Luo, G. Xu, R. Zhong and G.Q. Huang, “Physical assets and service sharing for IoT-enabled Supply Hub in Industrial Park (SHIP)”, IJPE, Vol. 159, pp. 4-15, 2015.

[14] K. Rong, G. Hu, Y. Lin, Y. Shi, and L. Liang, “Understanding business ecosystem using a 6C framework in internet-of-Things-based sectors”, IJPE, Vol. 159, pp. 41-55, 2015.

[15] G. Xu, G.Q. Huang, J. Fang, X. Qiu, ”An Integrated Cloud Platform for Cooperative Smart Asset Management in Urban Flood Control”, IEEE 18th Int Conf on CSCWD, pp. 77-82, 2014.

[16] J. Campos, P. Sharma, E. Jantunen, D. Baglee and L.M. Fumagalli, “The Challenges of Cybersecurity Frameworks to Protect Data Required for the Development of Advanced Maintenance”, Procedia CIRP, Vol. 47, pp. 222-227, 2016.

[17] M. Kans, D. Galar, and A. Thaduri, “Maintenance 4.0 in Railway Transportation Industry”, Proc of the 10th WCEAM, pp. 317-331, 2016.

[18] M. Hirsch, D. Opresnik, C. Zanetti, and M. Taisch, “Leveraging Assets as a Service for Business Intelligence in Manufacturing Service ecosystems”, IEEE 10th Intl Conf on e-Business Engineering (ICEBE), Los Alamitos, CA, USA.

[19] N.O.E. Olsson and H. Bull-Berg, “Use of big data in project evaluations”, IJMPB, Vol. 8 Iss. 3, pp. 491-512, 2015.

[20] D. Galar, M. Kans and B. Schmidt, “Big data in asset management: Knowledge Discovery in asset data by the means of data mining”, Proc of the 10th WCEAM, pp. 317-331, 2016.

[21] P.Zikopoulos, and C.Eaton, “Understanding big data: Analytics for enterprise class hadoop and streaming data” New York: McGraw-Hill Osborne Media, 2011.

[22] R. K. Lomotey, and R. Deters, “Towards knowledge discovery in big data”. IEEE 8th International Symposium on Service Oriented System Engineering (SOSE), pp. 181–191, April 7–11, 2014.

[23] J. Whyte, A. Stasis and C. Lindkvist, “Managing change in the delivery of complex projects: Configuration management, asset information and ‘big data’”, IJPM, Vol. 34, pp. 339-351, 2016.

[24] G. Wang, A. Gunasekaran, E.T.W. Ngai and T. Papadopoloulos, “Big data in logistics and supply chain managemenbt: Certain investigations for research and aopplications, IJPE, Vol. 176, pp. 98-110, 2016.

[25] F. Khosrowshahi, P. Ghodous and M. Sarshar, “Visualization of the Modeled Degradation of Building Flooring Systems in Building Maintenance”, Computer-Aided Civil & Infrastructure Engineering, Vol. 29 Iss. 1, pp. 18-30, 2014.

[26] D.Galar, A.Thaduri, M.Catelani, and L.Ciani, “Context awareness for maintenance decision making: A diagnosis and prognosis approach” Measurement, vol.67, pp.137–150, 2015.

[27] D. L. Hall, and J. Llinas, Handbook of multisensor data fusion. Boca Raton, FL: CRC Press, 2001.

[28] R. Karim, J.Westerberg, U.Kumar, and D.Galar, ”Maintenance Analytics–The New Know in Maintenance”, In IFAC Workshop on Advanced Maintenance Engineering, Service and Technology: 19-21, October 2016.

[29] K. Mayang, K. Rajesh and T. Markeset, “Asset integrity management: offshore installations challenges”, JQME, Vol. 22 Iss. 3, pp. 238-251, 2016.

[30] I. Hipkin, “Knowledge and IS implementation: case studies in physical asset management”, IJOPM, Vol. 21 Iss. 9/10, pp. 1358-1381, 2001.

[31] M. Kans, “IT Practices within Maintenance from a Systems Perspective: Study of IT Utilisation within Firms in Sweden”, JMTM, Vol. 24, pp. 768-791, 2013.

[32] R.M. Ratnayake and T. Markeset, “Asset integrity management for sustainable industrial operations: measuring the performance”, Int J Sust Eng, Vol. 5 Iss. 2, pp. 145-158, 2012.

[33] S. Niekamp, U.R. Bharadwaj, J. Sadhukhan and M.K. Chryssanthopoulos, “A multi-criteria decision support framework for sustainable asset management and challenges in its application.”, JIPE, Vol. 32 Iss. 1, pp. 23-36, 2015.

[34] I. El-Thalji and J. Liyanage, “Integrated asset management practices for Offshore wind power industry: A Critical review and a Road map to the future”, Proc of The Twentieth Int OFFSHORE AND POLAR ENGINEERING CONFERENCE, pp. 934-941, 2010.

[35] T. Le and H.D. Jeong, “Interlinking life-cycle data spaces to support decision making in highway asset management”, Aut in Constr, Vol. 64, pp. 54-64, 2016.

[36] J. Taneja, R. Katz and D. Culler, ”Defining CPS Challenges in Sustainable Electricity Grid”, IEEE/ACM third Int Conf on CPS, pp. 119-128, 2012.

[37] W.W.Tiddens, A.J.J.Braaksma and T. Tinga, ” The Adoption of Prognostic Technologies in Maintenance Decision Making: A Multiple Case Study”, Procedia CIRP, Vol. 38, pp. 171-176, 2015.

[38] S. Landscheidt and M. Kans, “Method for assessing the total cost of ownership of industrial robots”, Procedia CIRP, In Press.

[39] A. Ingwald, and M. Kans, ”Service Management Models for Railway Infrastructure, an Ecosystem Perspective”, Proc of the 10th WCEAM, pp. 289-303, 2016.

[40] J. F. Moore, "Predators and Prey”, Harvard Business Review, Vol. 71 Iss. 3, pp. 75-86, 1993.

[41] M. Kans, “IT Governance from the Operational Perspective A Study of IT Governance Strategies Applied within Maintenance Management”, IJSTM, In press.

[42] I. Perko, and P. Ototsky, “Big data for Business Ecosystem Players”, Our Economy, Vol. 62 Iss. 2, pp. 12-24, 2016.

[43] C. Sankavaram, A. Kodali and K. Pattipati, ”An integrated Health Management Process for Automotive Cyber-Physical Systems”, IEEE International Conference on Computing, Networking and Communications, Workshops Cyber Physical System, 82-86, 2013.

[44] B. Kroll, D. Schaffranek, S. Schriegel and O. Niggemann, ”System modeling based on machine learning for anomaly detection and predictive maintenance in industrial plants”, IEEE Conf EFTA, 2014.

[45] Gartner IT Glossary, n.d. Gartner IT Glossary (n.d.). Retrieved from http://www.gartner.com/it-glossary/big-data/.

[46] K. Heuwinkel, W. Deiters, T. Konigsmann, and T. Loffeler, “Information logistics and wearable computing”, Proceedings of the 23rd International Conference on Distributed Computing Systems, 19-22 May 2003, pp. 283–288, 2003.

[47] Sandra Haseloff, "Context awareness in information logistics" 2005.

Data Quality of Maintenance Data: A Case Study in MAXIMO CMMS

[1]Hussan Al-Chalabi; [2]Mustafa Aljumaili
[1] hussan.hamodi@ltu.se; [2] mustafa.aljumaili@ltu.se
[1,2] Division of Operation, Maintenance and Acoustics, Luleå University of Technology
Luleå, Sweden

Abstract

Computerised maintenance management systems (CMMS) are software packages; their data include information on an organisation's maintenance, operations and costs. MAXIMO is recognised as a leading CMMS for asset management. It helps to manage maintenance data, improving data quality, making maintenance more efficient, and supporting decision making. However, MAXIMO systems have problems of data quality, with a resulting impact on efficiency and the validity of decisions based on those data. This paper investigates the quality of maintenance data in MAXIMO using the Swedish Transport Agency (Trafikverket) as a case study. It discusses the results before and after data cleaning to show the impact of data quality problems on data analysis.

***Keywords:** Asset management, CMMS, Data quality, Maintenance, Performance measurement..*

I. Introduction

Maintenance is a combination of all technical, administrative and managerial actions during the life cycle of an item intended to retain it in, or restore it to, a state in which it can perform the required function [1]. Types of maintenance include preventive maintenance, predetermined maintenance, condition based maintenance, predictive maintenance, corrective maintenance, remote maintenance, and on-line maintenance [1].

Maintenance processes are supported by heterogeneous resources, such as documentation, personnel, support equipment, materials, spare parts, facilities, information and information systems [2]. The provision of the right information to the right user with the right quality and at the right time is essential [3]. While the provision of just-in-time information to the right user is essential to maintenance, we propose adding the need for correct information, i.e. information based upon high quality data, at the correct time. A generic maintenance process consists of phases for management, support planning, preparation, execution, assessment and improvement, as shown in Figure 1 [4]. This concept is evolving, however, as emerging applications of Information and Communication Technology (ICT) allow companies to shift their manufacturing operations from a traditional factory integration philosophy to an e-factory and e-supply chain philosophy [5]. eMaintenance refers to the use of ICT solutions in the maintenance area [6].

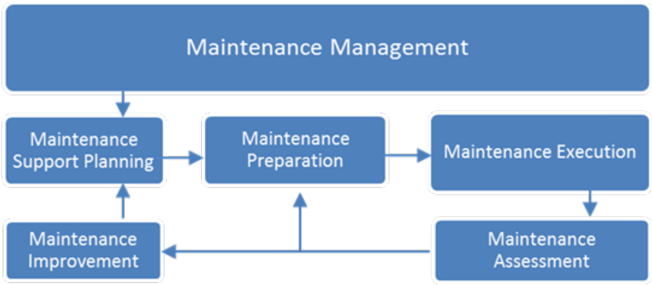


Fig.1. Phases of an overall maintenance process [4].

Performance measurement is the process of collecting, analysing and reporting information on the performance of an individual, group, organisation, system or component. It can involve studying processes within organisations or studying engineering parameters to see whether outputs are in line with what was intended or what should have been achieved. Effective performance measurement is key in ensuring that an organisation's strategy is implemented. Generally speaking, performance measurement monitors an organisation's effectiveness in fulfilling its predetermined goals or stakeholder requirements. For example, a company must perform well in terms of cost, quality, flexibility, and value. A performance measurement system that enables a company to see if it is meeting these demands is essential. It ensures better informed and more effective decision making at both strategic and operational levels [7, 8].

II. MAXIMO CMMS

The use of computers in maintenance can provide ready access to precise data and the ability to quickly search and find detailed, relevant information with ease. Such systems manage a broad range of summarised information with better quality than a manual system could ever provide. Computers have been used to assist the maintenance management process since the early 1970s; by the mid-1980s, a substantial number of maintenance organisations were using software developed for large mainframe computer systems. The software was normally designed around a central computerised database containing maintenance and repair information, and the information was manipulated to produce work schedules and job orders. In addition, work-in-progress could be monitored and statistical management information produced [9].

A CMMS is much more advanced. It is computer software that helps maintenance teams keep a record of all assets for which they are responsible, schedule and track maintenance

ISBN 978-91-7583-841-0

tasks, and retain a historical record of work performed. Therefore, it is a useful tool to help maintenance workers handle their jobs more efficiently. Other tasks can be managed by using CMMS, for example, finding where a spare part is located in the factory or calculating the cost of maintenance for a certain machine part. Users of the system can even go back and see what date a certain part was replaced or repaired and who was responsible for the job; see Figure 2. The result is better maintenance control. Today, CMMS is widely used by companies with high maintenance standards. There are various software applications on the market now, but, in general, the CMMS software can handle these different services [10].

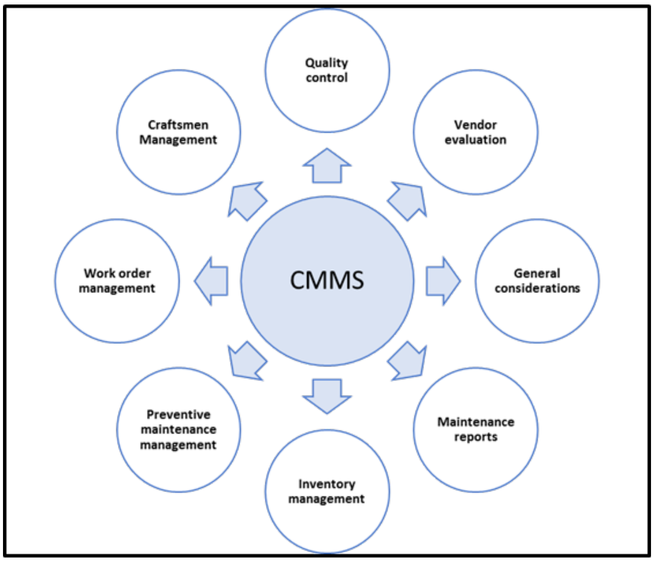


Fig. 2. Basic functions of CMMS.

The efficient use of CMMS in an organisation's maintenance activities helps ensure high quality operational and maintenance data. CMMS provides the following benefits:

- **Better system performance:** CMMS helps to schedule preventive maintenance which, in turn, helps to reduce system failures.
- **Better work management:** CMMS shows if technicians do their work on time and gives alerts when a task is complete.
- **Better work distribution:** CMMS provides better scheduling of work so maintenance teams are not idle or working overtime, and work can be distributed evenly.
- **Better data collection:** CMMS helps technicians record problems and solutions.
- **Spare parts and stock management:** CMMS's inventory planning features give users the time to shop around, instead of having to buy something in a hurry.
- **Certification and analysis:** CMMS's full record of assets and performance helps managers analyse and plan maintenance.

IBM MAXIMO asset management is an integrated productivity tool and database that can manage all asset types in a single software platform across multiple industry sectors. Built on a Service-Oriented Architecture (SOA), MAXIMO supplies a comprehensive view of all asset types, their condition, location, and the work processes required, thereby optimising an organisation's planning, control, auditing, and compliance capability.

By using the MAXIMO asset management user interface, an organisation can establish key performance indicators (KPIs) to monitor asset conditions and trigger automated actions based on changes in those conditions. The software can create, assign, monitor, notify, and report on key process components, such as work orders, service desk tickets, and purchase orders, including status, from start to finish. It short, it provides insights into an enterprise's assets, their condition, and any related work processes, thus allowing better planning and control.

MAXIMO contains six modules: Asset Management, Work Management, Service Management, Contract Management, Materials Management, and Procurement Management. The modules reflect major tasks required by companies. The program is intended for use by large companies who rely on computerised tasks; see Figure 3.

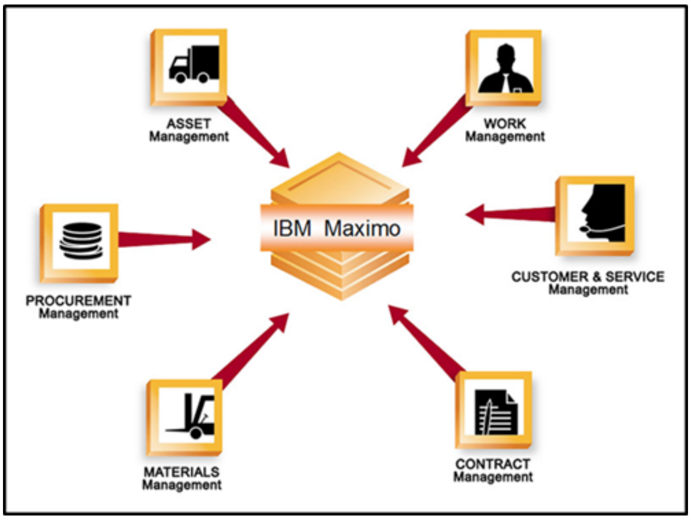


Fig. 3. Main modules of MAXIMO.

III. Data Quality

Data quality (DQ) can be defined as data fit for use by data consumers [11]. Common thinking about DQ has focused on attributes like accuracy, precision, and timeliness. Levitin (1998) [12] suggested two important ways to ensure DQ: 1) data models must be clearly defined; 2) data values must be accurate. In CMMS, three important groups may affect DQ: data producers, data custodians, and data consumers. Data producers are people or systems generating data. Data custodians provide and manage computing resources for storing and processing data. Finally, data consumers are people or systems using data. The latter are critical in defining data quality [13].

ISBN 978-91-7583-841-0

High quality information is dependent on the quality of the raw data and the way they are processed. Data processing has shifted from providing operations support to becoming a major aspect of operations, making the need for quality management of data more urgent [14].

Poor quality data results in customer dissatisfaction, lost revenue, and higher costs associated with the additional time required to reconcile data. This can lead to a decline in the system's credibility and increase the risk of noncompliance with regulations. It also increases consumer costs; increases taxes, decreases shareholder value, and can cause mission failure [15]. The following all affect data quality [16]:

1. With stand-alone IT systems, not all departments in an organisation are connected to the system.
2. Multiple sources of the same information can produce different values.
3. When information is produced using subjective judgment, this can lead to bias.
4. Systematic errors in information production lead to lost information.
5. Large volumes of stored information make it difficult to access information in a reasonable period of time.
6. Manual input and transfer of data could lead to missing or erroneous data.
7. Distributed heterogeneous systems lead to inconsistent definitions, formats and values.
8. Nonnumeric information is difficult to index.
9. System usability may cause difficulty when users are searching for relevant information.
10. Automated content analysis across information collections is not yet available.
11. Easy access to information may conflict with requirements for security, privacy and confidentiality.
12. Lack of sufficient computing resources limits access.
13. Problems with metadata may appear (the description of data, developed and added to the system database during the implementation phase of the information system).

In general, information sources can be subjective or objective. Subjective sources include human observers, experts, and decision makers. Information from such sources is normally subjective, including beliefs, hypotheses, and opinions. The quality of these data differs from one person to another.

The quality of objective information sources, such as sensors, models, and automated processes, is free of the biases inherent to human judgment but is dependent on how well the sensors are calibrated and how adequate the models are [17]. About 80% of the identified maintenance data quality problems are related to subjective sources [18].

IV. Performance Evaluation

The evaluation of performance involves, first, the development of measurable indicators that can be systematically tracked to assess progress made in achieving predetermined goals and, second, the use of these indicators to assess progress in achieving these goals.

Statistical modelling is used to determine the results of performance evaluation. The full scope of the performance of an organisation can never be obtained, however, as some parameters cannot be measured directly but must be estimated via indirect observation. In addition, a complete set of records never delivers an assessment without the compression of all figures into certain key figures [19].

In the cycle of never-ending improvement, performance measurement plays an important role in:

- Identifying and tracking progress against organisational goals,
- Identifying opportunities for improvement,
- Comparing performance against both internal and external standards.

Reviewing the performance of an organisation is an important step in formulating the direction of strategic activities as part of the Plan –Do – Check – Act cycle to ensure quality and productivity improvement. The main reasons for performance evaluation are [19]:

- To ensure customer requirements have been met,
- To be able to set sensible objectives and comply with them,
- To provide standards to establish comparisons,
- To provide visibility and a "scoreboard" for people to monitor their own performance level,
- To highlight quality problems and determine areas for priority attention,
- To provide the feedback required to drive improvement efforts.

V. Case Study

Data comprise the only resource of a CMMS, but those data are collected from different sources. If they are incorrect, incomplete, or inaccurate, the decisions based on them will be similarly incorrect. MAXIMO includes basic modules to identify and codify assets, work orders, preventive maintenance, and the activities of equipment purchasing managers and warehouse management, as well as tools for analysing information. These basic modules can provide the foundation for an effective system of maintenance management.

VI. Data Collection

The data used in this study were collected over 10 years from April 2005 to December 2015 in MAXIMO CMMS. The cost data contain corrective maintenance costs, preventive maintenance costs, and repair time. The corrective and preventive maintenance costs include spare parts and labour (repair person) costs. The data were collected from the Swedish Transport Agency (Trafikverket) and imported from MAXIMO into Excel. The data of interest in the case study describe the maintenance of road monitoring cameras used in one of Stockholm's road tunnels. They include starting and ending dates and times, maintenance and replacement costs, and other descriptive information. Data analysis revealed the problems described in the following sections.

VII. MAINTENANCE DATA QUALITY PROBLEMS

High quality information is dependent on the quality of the raw data and the way they are processed. Data processing has shifted from providing operations support to becoming a major aspect of operations, making the need for quality management of data more urgent. Poor quality data result in customer dissatisfaction, lost revenue and higher costs associated with the additional time required to reconcile data. This can lead to a decline in the system's credibility and increase the risk of noncompliance with regulations. It also increases consumer costs; increases taxes, decreases shareholder value, and can cause mission failure.

A. *Incomplete Data*

The data collected from MAXIMO have many problems, most of which are traceable to the manual input of data. The biggest issue in data quality is incomplete data. Scores of fields contain (null) values representing data neglected or forgotten by users. Table I below shows a sample of the incomplete data.

TABLE I. INCOMPLETE DATA

Work order	Work order description	Actual start	Actual finish	Problem code	Description	Cause code	Description	Action code	Description
1008456	NULL	NULL	NULL	NULL	NULL	NULL	NULL	NULL	NULL
1022565	NULL	2008-10-02	NULL	NULL	NULL	NULL	NULL	NULL	NULL
1258661	NULL	2009-01-26	NULL	NULL	NULL	NULL	NULL	NULL	NULL
1258667	NULL	2009-01-26	NULL	NULL	NULL	NULL	NULL	NULL	NULL
1315097	NULL	NULL	NULL	EFH-P04	Dålig bildkvalite	NULL	NULL	NULL	NULL
1342038	NULL	NULL	NULL	EFH-P04	Dålig bildkvalite	NULL	NULL	NULL	NULL
1342039	NULL	NULL	NULL	EFH-P04	Dålig bildkvalite	NULL	NULL	NULL	NULL
1342515	NULL	NULL	NULL	EFH-P04	Dålig bildkvalite	NULL	NULL	NULL	NULL
1359728	NULL	NULL	NULL	NULL	NULL	NULL	NULL	NULL	NULL
1359733	NULL	NULL	NULL	NULL	NULL	NULL	NULL	NULL	NULL
1359734	NULL	NULL	NULL	NULL	NULL	NULL	NULL	NULL	NULL
1368498	NULL	NULL	NULL	EFH-P04	Dålig bildkvalite	NULL	NULL	NULL	NULL
1372419	NULL	NULL	NULL	EFH-P04	Dålig bildkvalite	NULL	NULL	NULL	NULL
1372421	NULL	NULL	NULL	EFH-P04	Dålig bildkvalite	NULL	NULL	NULL	NULL
1377344	NULL	NULL	NULL	NULL	NULL	NULL	NULL	NULL	NULL
1378364	NULL	NULL	NULL	EFH-P06	Smutsigt	NULL	NULL	NULL	NULL
1381265	NULL	NULL	NULL	EFH-P04	Dålig bildkvalite	NULL	NULL	NULL	NULL
1381275	NULL	NULL	NULL	EFH-P04	Dålig bildkvalite	NULL	NULL	NULL	NULL
1388075	NULL	NULL	NULL	NULL	NULL	NULL	NULL	NULL	NULL
1389886	NULL	NULL	NULL	NULL	NULL	NULL	NULL	NULL	NULL
1389887	NULL	2009-04-27	NULL	NULL	NULL	NULL	NULL	NULL	NULL
1389889	NULL	NULL	NULL	NULL	NULL	NULL	NULL	NULL	NULL
1390227	NULL	NULL	NULL	NULL	NULL	NULL	NULL	NULL	NULL
1412876	NULL	2009-05-29	NULL	NULL	NULL	NULL	NULL	NULL	NULL
1666121	NULL	NULL	NULL	NULL	NULL	NULL	NULL	NULL	NULL
1671084	NULL	NULL	NULL	NULL	NULL	NULL	NULL	NULL	NULL

B. *Redundant Data*

Redundancy is another issue of MAXIMO data. Many columns are redundant and identified only by the work order number. This could result from bad communication or poor collaboration between users; either the same work order is entered by several different users and/or there are multiple sources of the same information. Table II shows an example of redundancy.

TABLE II. REDUNDANT DATA

Location/Componentcode	Component description	Work order	Work order description	Reported date	Actual start	Actual finish	Worktype	Problem code
AB+25131=841BV001	Tpl Åbyvägen 1R	556005	NULL	2005-06-09	2005-06-09	2005-06-09	AU	NULL
AB+25131=841BV001	Tpl Åbyvägen 1R	556006	NULL	2005-06-09	2005-06-09	2005-06-09	AU	NULL

C. *Inaccurate Data*

Accuracy is one of the most important attributes of good quality data, but MAXIMO contains a large number of inaccurate data; thousands of fields have a value of (zero) but this is clearly wrong. An example is shown in Table III.

TABLE III. INACCURATE DATA

Work order	Work order description	Actual start	Actual finish	No of Hours worked	Labor cost	Material cost	Tool cost
1008456	NULL	NULL	NULL	0	0.00	0.00	0.00
1022565	NULL	2008-10-02	NULL	0	0.00	0.00	0.00
1258661	NULL	2009-01-26	NULL	0	0.00	0.00	0.00
1258667	NULL	2009-01-26	NULL	0	0.00	0.00	0.00
1315097	NULL	NULL	NULL	0	0.00	0.00	0.00
1342038	NULL	NULL	NULL	0	0.00	0.00	0.00
1342039	NULL	NULL	NULL	0	0.00	0.00	0.00
1342515	NULL	NULL	NULL	0	0.00	0.00	0.00
1359728	NULL	NULL	NULL	0	0.00	0.00	0.00
1359733	NULL	NULL	NULL	0	0.00	0.00	0.00
1359734	NULL	NULL	NULL	0	0.00	0.00	0.00
1368498	NULL	NULL	NULL	0	0.00	0.00	0.00
1372419	NULL	NULL	NULL	0	0.00	0.00	0.00
1372421	NULL	NULL	NULL	0	0.00	0.00	0.00
1377344	NULL	NULL	NULL	0	0.00	0.00	0.00
1378364	NULL	NULL	NULL	0	0.00	0.00	0.00
1381265	NULL	NULL	NULL	0	0.00	0.00	0.00
1381275	NULL	NULL	NULL	0	0.00	0.00	0.00
1388075	NULL	NULL	NULL	0	0.00	0.00	0.00
1389886	NULL	NULL	NULL	0	0.00	0.00	0.00
1389887	NULL	2009-04-27	NULL	0	0.00	0.00	0.00
1389889	NULL	NULL	NULL	0	0.00	0.00	0.00
1390227	NULL	NULL	NULL	0	0.00	0.00	0.00
1412876	NULL	2009-05-29	NULL	0	0.00	0.00	0.00
1666121	NULL	NULL	NULL	0	0.00	0.00	0.00
1671084	NULL	NULL	NULL	0	0.00	0.00	0.00

ISBN 978-91-7583-841-0

VIII. RESULTS

The analysis of the case study data indicates DQ problems have a direct impact on the information generated from those data, for example, when using the data for life cycle cost analysis to estimate the optimal replacement time of an asset or equipment or to manage maintenance work orders. Redundant, incomplete and inaccurate data have a direct effect on maintenance decisions, often leading to wrong or delayed decisions. Ultimately, the dirty data have an adverse effect on costs – something of concern to any organisation.

IX. IMPACTS ON MAINTENANCE DECISION

The data collected from MAXIMO for the cameras used in Stockholm's road tunnels are often dirty and have numerous problems. These problems have a direct impact on the cost analyses generated from the data. Figure 4 below shows the number of cameras before and after data cleaning.

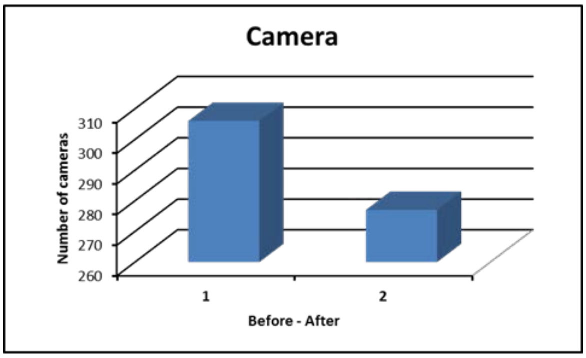


Fig. 4. Number of cameras.

The number of failures is also affected by data quality issues. Figure 5 shows the number is reduced after data are cleaned.

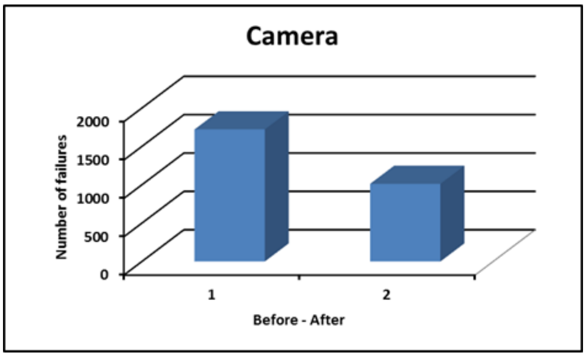


Fig. 5. Number of failures.

Figure 6-A shows the number of failures and number of cameras for each type of camera before data cleaning. Figure 6-B shows the number of failures and number of cameras for each type of camera after data cleaning. The numbers are clearly affected; this will have a negative impact on the life cycle cost estimation and the estimation of maintenance costs.

Figures 7-A shows the mean number of failures for each type of camera before data cleaning, and Figure 7-B shows the mean number of failures for each type of camera after data cleaning. Data quality problems obviously have an impact.

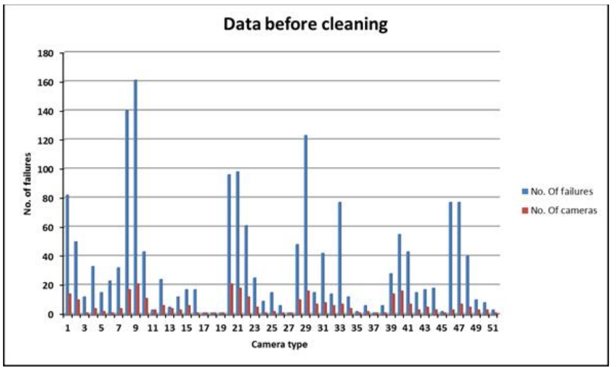


Fig. 6-A. Number of failures and number of cameras for each type of camera before data cleaning.

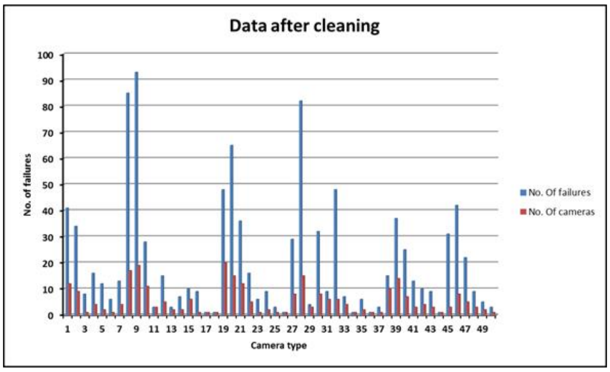


Fig. 6-B. Number of failures and number of cameras for each type of camera after data cleaning.

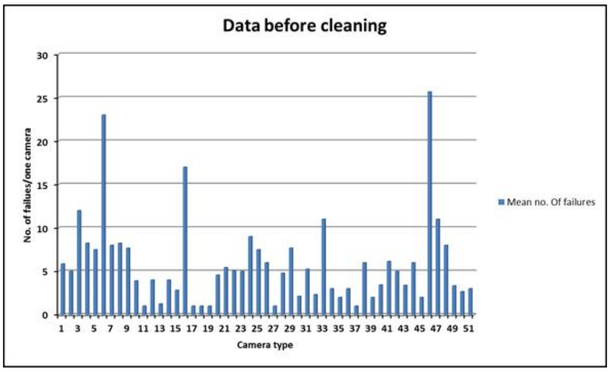


Fig. 7-A. Mean number of failures for each type of camera before data cleaning.

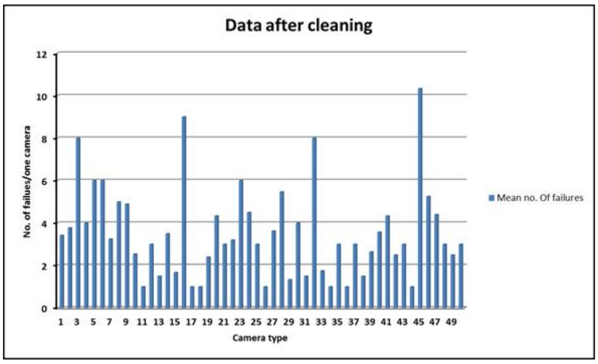


Fig. 7-B. Mean number of failures for each type of camera after data cleaning.

X. Discussion and Conclusions

As the results show, data quality problems have a direct impact on the information generated from those data, with dirty data generating faulty information. Any maintenance management activities based on MAXIMO data will be affected by their quality. This will obviously affect decision making; for example, life cycle cost analysis based on dirty data will not be accurate.

The main reason for problems is the manual input of MAXIMO data and/or multiple sources of the same information. Manual input is always subjective. Missing, redundant or inaccurate data are generated from human errors. Therefore, MAXIMO data collection needs to be automated; this is possible, given the revolution in ICT, including cloud computing and internet of things (IoT). The use of ICT tools will ensure the collection of high quality data, improve maintenance efficiency and enhance decision making.

Information is often considered an item, with data seen as its raw material. Since the nature of the item is directly related to the nature of its raw materials, organisations must put resources into improving their data if they want to improve their information. Even if they begin by constrained data profiling and information purifying exercises, they can quickly develop a powerful information quality assurance program.

Acknowledgment

The research was carried out in 2016, at the Division of Operation, Maintenance and Acoustics, Luleå University of Technology, Sweden. The research program was sponsored by the Swedish Transport Administration (Trafikverket).

The support of Trafikverke during the research is deeply appreciated, especially the help of Thomas Rolén, Manager, Planning Weighing Systems, Maintenance “Förvaltare, Planering Vägsystem, Underhåll,” and Kerstin Abrahamsson, Maximo Management “Maximo Förvaltning.”

I would like to express my sincere gratitude to Peter Söderholm for his invaluable guidance, suggestions and support. Karim, Hawzheen “organisatoriska”, Stefan Jonsson ”Projektsponsor” Lars Schillström ” Referensgrupp” are also gratefully acknowledged.

References

[1] SS-EN 13306. SS-EN 13306:2010, Maintenance – maintenance terminology, 1st ed., Brussels, Belgium: Swedish Standards Institute, Stockholm, Sweden, 2010.

[2] ISO/IEC. ISO/IEC 15288: System engineering - system life cycle processes, 2nd ed., Geneva, Switzerland: International Organization for Standardization/International Electrotechnical Commission, 2008.

[3] A. Parida, and U. Kumar, “Maintenance performance measurement (MPM): issues and challenges,” Journal of Quality in Maintenance Engineering, vol. 12, pp. 239-251, 2006.

[4] IEC. 60300 (3-14): Dependability management-part 3-14: Application guide-maintenance and maintenance support, 2004.

[5] R. Zurawski, The industrial information technology handbook. CRC Press, 2004.

[6] E. Levrat, B. Iung, and A. C. Marquez, “E-maintenance: Review and conceptual framework,” Production Planning and Control, vol. 19, pp. 408-429, 2008.

[7] M. Aljumaili, V. Rauhala, P. Tretten, and R. Karim, “Data quality in eMaintenance: a call for research,” Maintenance Performance Measurement & Management. Luleå, Sweden, pp. 69-73, 2011.

[8] H. Hamodi, J. Lundberg, and A. Jonsson, “Economic lifetime of a drilling machine a case study on mining industry,” Maintenance Performance Measurement and Management, MPMM 2013. Lappeenranta, Finland, pp. 138-147, 2013.

[9] K. Jones, and S. Collis, “Computerized maintenance management systems,” Property Management, vol. 14, pp. 33-37, 1996.

[10] N. Ruud, Computerized maintenance management system, thesis, Linköpings University, Sweden, 2009.

[11] D. M. Strong, Y. W. Lee, and R. Y. Wang, “Data quality in context,” Communications of the ACM, vol. 40, pp. 103-110, 1997.

[12] A. V. Levitin, Y. W. Lee, and R. Y. Wang, “Data as a resource: Properties, implications, and prescriptions,” MIT Sloan Management Review, vol. 40, pp. 89-101, 1998.

[13] R. L. Leitheiser, “Data quality in health care data warehouse environments,” System Sciences, Proceedings of the 34th Annual Hawaii International Conference on. IEEE, Hawaii, pp. 1-10, 2001.

[14] R. Y. Wang, and D. M. Strong, “Beyond accuracy: What data quality means to data consumers,” Journal of Management Information Systems, vol. 12, pp. 5-33, 1996.

[15] ISO/TS. ISO/TS 8000-100: data quality -- part 100: Master data: Overview 1st ed., Geneva: International Organization for Standardization, 2009.

[16] D. M. Strong, Y. W. Lee, and R. Y. Wang, “10 potholes in the road to information quality,” IEEE Computer, vol. 30, pp. 38-46, 1997.

[17] L. Rogova, and E. Bosse, “Information quality in information fusion,” Information Fusion (FUSION), 2010 13th Conference on. IEEE. pp. 1-8, 2010.

[18] M. Aljumaili, P. Tretten, R. Karim, and U. kumar, “Study of aspects of data quality in e-maintenance,” International Journal of Condition Monitoring and Diagnostic Engineering Management, vol. 15, pp. 3-14, 2012.

[19] Quality management: performance measurement factsheet, Published by the Department of Trade and Industry. www.dti.gov.uk.

ISBN 978-91-7583-841-0

Chapter 4: Condition Monitoring

ISBN 978-91-7583-841-0

Electric motors maintenance planning from its operating variables

[1]Francisco Rodrigues, [2]Inácio Fonseca, [3]José Torres Farinha, [4]Luís Ferreira, [5]Diego Galar
[1]franciscocardos0@hotmail.com, [2] inacio@isec.pt, [3] tfarinha@isec.pt, [4]lferreir@fe.up.pt, [5]diego.galar@ltu.se
[1,2,3]Instituto Superior de Engenharia de Coimbra
[3]Centre for Mechanical Engineering of the University of Coimbra
[4]Faculdade de Engenharia da Universidade do Porto
[5]Luleå University of Technology
[1,2,3,4]Portugal, [5]Sweeden

***Abstract*—The maintenance planning corresponds to an approach that seeks to maximize the availability of equipment and, consequently, increase the levels of competitiveness of companies by increasing production times.**

This paper presents a maintenance planning based on operating variables (number of hours worked, duty cycles, number of revolutions) to maximizing the availability of operation of electrical motors.

The reading of the operating variables and its sampling is done based on predetermined sampling cycles and subsequently is made the data analysis through time series algorithms aiming to launch work orders before reaching the variables limit values.

This approach is supported by tools and technologies such as logical applications that enable a graphical user interface for access to relevant information about their Physical Asset HMI (Human Machine Interface), including the control and supervision by acquisition through SCADA (Supervisory Control And data acquisition) data, also including the communication protocols among different logical applications.

Keywords: Maintenance; Planned maintenance; Electric machines; HMI / SCADA.

I. INTRODUCTION

Nowadays, maintenance is one of the key factors for business productivity.

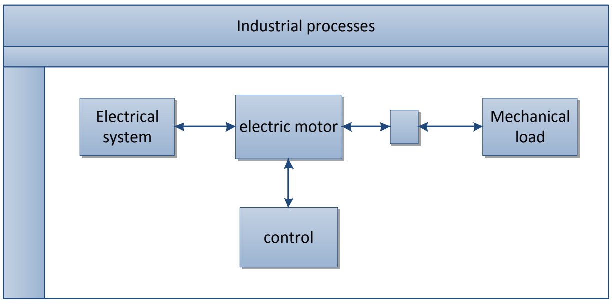


Fig. 1 - General construction of industrial processes

In most industrial processes the electric motor is an indispensable asset due to the fact that it is a core element. However, there is a permanent increase in power consumption and, at the same time the need to reduce the consumption of fossil fuels. Since the electric motors are fundamental components for industrial systems, accounting for over 60% of its total electrical energy consumption, they must be balanced between a target maximum availability and the optimization of its electrical energy consumption.

The breakdown of an electric motor is quite simple and there is a limited number of components where just few of them can be considered critical for failure. Indeed, the operational life cycle of these devices depends on almost exclusively on the winding insulation systems. However, it can be affected by many factors such as moisture, vibration, corrosive environments, and poor design.

The preventive maintenance based on the threshold value determined by a control variable, usually allows to extend the operating life of electric motors [1].

It is this subject that is discussed throughout the article, whose structure is as follows:

Chapter I - Introduction;
Chapter II - State of the art;
Chapter III - Data acquisition;
Chapter IV - Operation variables and condition;
Chapter V - Maintenance Management
Chapter VI - Used hardware and software;
Chapter VII - Monitoring and condition monitoring;
Chapter VIII - Application GESP;
Chapter IX - Conclusions;
Chapter X - Future developments.

II. STATE OF THE ART

The maintenance planning based on the control and monitoring of operating variables is not a cross-cutting approach to Computer Maintenance Management System (CMMS) on the market. Two of the most paradigmatic programs are as follows:

- Maximo [2] - is a CMMS developed by IBM [3], which allows to manage maintenance through its main aspects,

ISBN 978-91-7583-841-0

having an IBM Maximo Calibration module where is possible to monitor the equipment;

- SAP R / 3 [4] - is a CMMS developed by SAP AG, being a very horizontal system, i.e., is an integrated, modular software, but not specialized in CMMS shed. Due to SCADA Software Zenon interface with SAP R/3 it is possible to monitor the equipment and provide data to the application.

Given some limitations found therein a program it was developed an academic software tool, designated Gesp. This makes maintenance planning based on the monitoring and control of the operating condition variables and with the aid of the HMI / SCADA Zenon tool.

III. DATA AQUISITION

With the development and advent of SCADA, monitoring of physical variables can be performed by means of sensors and measurement devices using PLC [5] (Programmable Logic Control), which send the monitored data through protocols communication (ModBus [6] OMRON FINS [7], among others) which use several devices and software applications. The connections go through Fieldbus systems, and complex redundant network structures that can be compatible with all standards, such as OPC UA [8] (OLE for Process Control Unified Architecture), several IEC protocols [9] or Modbus, and with proprietary systems and several types of hardware.
Through the information provided by SCADA [10] systems, it can monitor default values and other control tasks. The SCADA system allows to perform monitoring, control, and draw up reports in real-time and historical data. Such systems correspond to HMI (Human Machine Interface) applications [11], which tend to grow due to the incessant demand, allowing secure, more flexible processes, and reducing users working time. The values of the operating variables and condition are the data provided by SCADA applications to different systems / maintenance applications [12] dealing with specific algorithms (Figure 2).

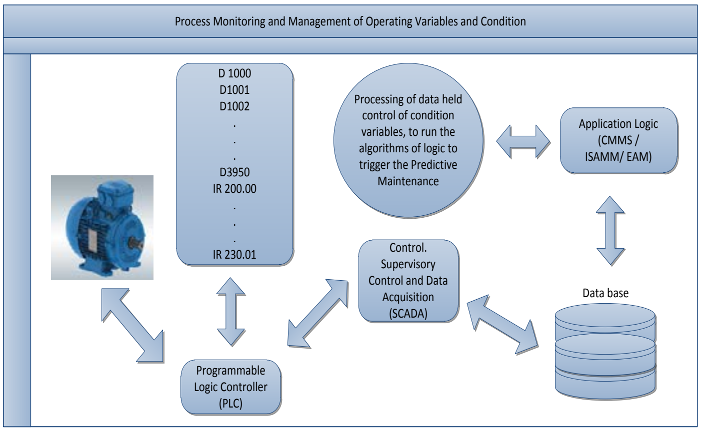


Fig. 2 - Process for monitoring the operating and condition variables.

IV. VARIABLE WORKING AND CONDITION

The main variables to consider in an electric motor are: the chain; the tension; torque; and temperature. If the measured parameter values do not fall within the ranges that have been dimensioned, then current operation may affect the life of electric motors and deterioration of the materials and components that constitute them. Through monitoring tools they are triggered the alarm conditions giving rise to interventions (Figure 3) - the sampling of the variables can be performed through either aperiodic or periodic cycles. The use of these tools allows to monitor the operation of electric motors through its most significant variables for their performance to be the most appropriate.

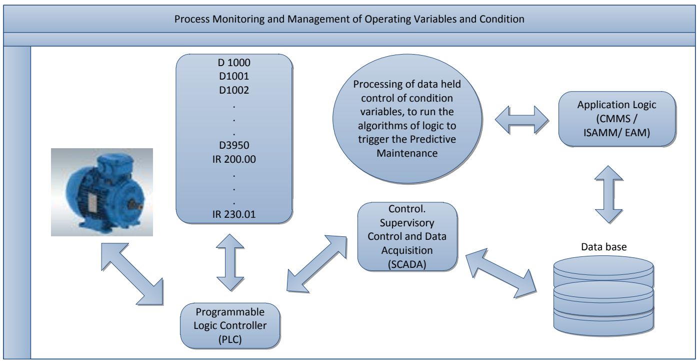


Fig. 3 – Operating variables and condition for triggering intervention

V. MAINTENANCE MANAGEMENT

The treatment of the variables mentioned in the previous chapter can be provided to a CMMS, either directly or through auxiliary modules. Thus, the maintainers can adjust not only their parameterization, but also their maintenance contracts as well as improvement actions [13] (Figure 4).

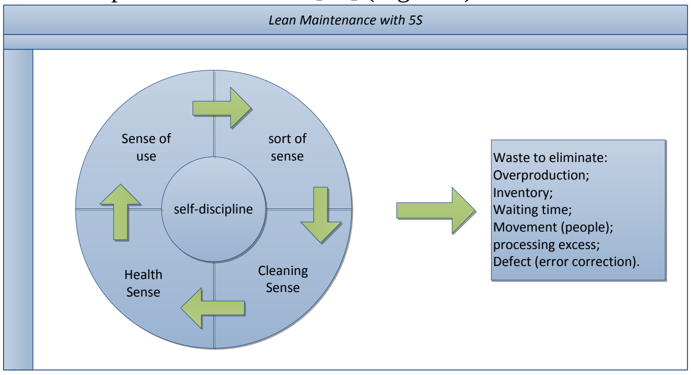


Fig. 4 - New aspects for asset management

Predictive maintenance [14] is performed according to the state of "health" of the equipment, including damage, if this is the previously planned condition. In general, associated to operating variables and condition, measures a given unit which, when they reach a certain threshold, giving rise to an intervention, as illustrated in Figure 3.

VI. HARDWARE AND SOFTWARE USED

The hardware and software used are illustrated in Figure 5. In hardware stands out a variable speed drive, a power meter, an

ISBN 978-91-7583-841-0

engine, an automaton and a module expansion analog inputs and outputs.

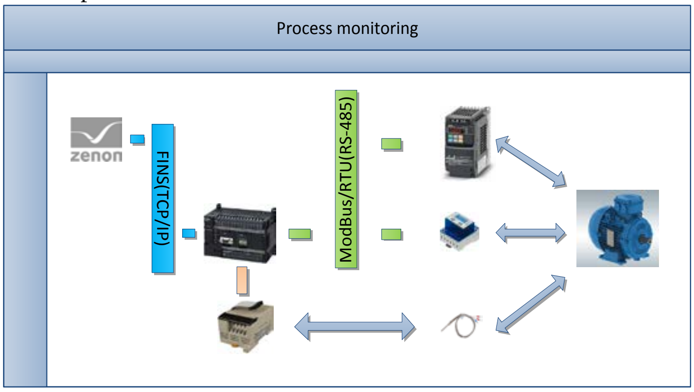


Fig. 5 - electric motor monitoring modules

The FINS Protocol (TCP/IP) was used to obtain the data monitored by the PLC (via Ethernet), which, in turn, communicates with the energy meter through ModBus / RTU (RS-485 physical environment). The ModBus protocol uses the client-server type communication model (master / slave) - the server should not initiate any communication on the media until it has been requested by the customer. To perform the communication via ModBUS protocol with the MX2 inverter, it must be set the parameters shown in Table 1.

TABLE I. MODBUS PROTOCOL PARAMETERS USED IN THE MX2 INVERTER

	Parâmetro N.º	Nome da função	Variação do monitor ou de dados	Unidade
FUNÇÃO DE COMUNICAÇÃO	C071	Seleção da Velocidade de Comunicação	03: 2.400 bps 04: 4.800 bps 05: 9.600 bps 06: 19,2 kbps 07: 38,4 kbps 08: 57,6 kbps 09: 76,8 kbps 10: 115,2 kbps	-
	C072	Seleção do Nº. da Estação de Comunicação	1, a 247,	-
	C074	Seleção da Paridade	00: Sem paridade 01: Par 02: Ímpar	-
	C075	Seleção do Bit de Parada	1: 1 bit 2: 2 bits	-
	Parâmetro N.º	**Nome da função**	**Variação do monitor ou de dados**	**Unidade**
FUNÇÃO DE COMUNICAÇÃO	C076	Seleção de Operação sob Erro de Comunicação	00: Trip (Desligamento) 01: Trip (Desligamento) após parada de desaceleração 02: Ignorado 03: Parada em inércia 04: Parada por controle em desaceleração	
	C077	Limite de Tempo de Erro de Comunicação	0,00: Limite de tempo desabilitado 0,01 a 99,99	s
	C078	Tempo de Espera de Comunicação	0, a 1000,	ms

	Parâmetro N.º	Nome da função	Variação do monitor ou de dados	Unidade
FUNÇÃO DE COMUNICAÇÃO	C096	Seleção de Comunicação	00: Comunicação Modbus (Modbus-RTU) 01: Comunicação como coinversor 02: Comunicação como co-inversor (inversor gerenciador da rede)	-
	C098	Número da Estação de Início de Comunicação como Co-Inversor	1, a 8,	-
	C099	Número da Estação de Conclusão de Comunicação com o Co-Inversor	1, a 8,	
	C100	Seleção de início de comunicação como co-inversor	00: Via 485 01: Sempre iniciado	-

For the selection of the material used for monitoring the engine parameters it is necessary to know which are the values of its operating system given by the manufacturer. This data is contained in signage plate of the electric motor, as shown in Figure 6.

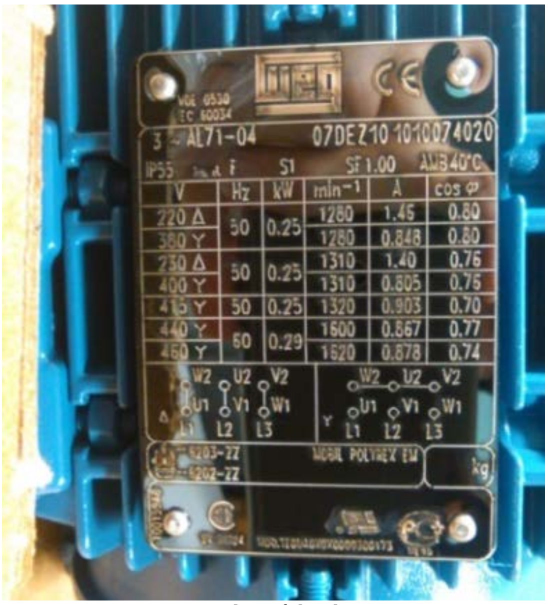


Fig. 6 - Nameplate of the electric motor

ISBN 978-91-7583-841-0

To perform the logic control and monitoring of the operating variables and conditions, it is used the PLC [15] shown in Figure 7, that performs the logic control through its bit input and output and or analog S MAD01 connecting the analog input / output of the inverter as shown in Figure 9. Another possible configuration is through an inverter control by the RS-485 network, as well as the energy meter, as illustrated in Figure 10 - running both through ModBus protocol - which provides control and data storage of operating variables and conditions in the PLC memory area.

.

1 Fig. 7 - PLC OMRON CP1L-EM30DR-D model

To perform engine control frequency for the analog inputs of the inverter and to monitor the temperature, it is necessary to use a module, illustrated in Figure 8, for converting the analog values for input / output of data to the PLC [16]. If the current is high it will be necessary to use IT (current transformers), such as illustrated in Figure 11, with characteristics adapted to the energy meter used - in this case it was used the counter illustrated in Figure 10.

Fig. 8 - OMRON Module analog inputs and outputs CPM1A-MAD01

For the control of electric induction motor it is used a static frequency converter [17] (Figure 9) that is a solution that has been adopted increasingly in industry. The drive in question allows for control and monitoring the engine parameters. The inverter can be controlled by analog inputs, by control panel, and also through the Modbus communication protocol. The modes of control are configurable either on local keyboard or by specific OMRON software. The inverter is parameterized as described in Table 2.

Fig. 9 - MX2 Inverter Omron

According to Figure 10, between the drive and the engine it is included an energy meter [18] which allows the energy monitoring that is supplied to the motor (current, voltage, active power, reactive power, and the cos factor power). The temperature measurement can also be performed through the ADC, or the energy meter, given that it has a system of inputs for the acquisition of analog signals [19].

TABLE II PARAMETERS TABLE TO MONITOR THE INVERTER MX2

Parâmetro N.°	Nome da função	Variação do monitor ou de dados	Unidade
d001	Monitor de Frequência de Saída	0,00 a 99,99 100,0 a 1.000, (Modo de alta frequência)	Hz
d002	Monitor da Corrente de Saída	0,0 a 655,3	A
d003	Monitor do Sentido de Rotação	F: Avançar o: Parar r: Recuar	-
d004	Monitor do Valor de Feedback para PID	0,00 a 99,99 100,0 a 999,9 1000, a 9999, 1000,a 9999,(10000,a 99990,) ⊠100 a ⊠999(100000,a 999000,)	-
d005	Monitor de Entrada Multifunção	ON OFF S7 S6 S5 S4 S3 S2 S1 (Exemplo) Terminal S1, S2: Terminal S3 a S7:	-
d006	Monitor de Saída Multifunção	ON OFF MA P2 P1 (Exemplo) Terminal P1, P2: Terminal AL: OFF	-
d007	Monitor da Frequência de Saída (após conversão)	0,00 a 99,99 100,0 a 999,9 1000, a 4000, (9999,) 1000, a 4000, (9999/ ⊠100)	-
d008	Monitor da Frequência Real	(–100/–999 ,) –400 , a –100, –99,9 a –10,0 –9,99 a –0,00 0,00 a 99,99 100,0 a 400,0 (400,1 a 999,9/1000,)	Hz
d009	Monitor de Referência de Torque	–200, a +200,	%
d010	Monitor de Tendência (Bias) de torque	–200, a +200,	%
d012	Monitor de Torque de Saída	–200, a +200,	%
d013	Monitor de Tensão de Saída	0,0 a 600,0	V
d014	Monitor da Potência de Entrada	0,0 a 100,0	kW

ISBN 978-91-7583-841-0

Parâmetro N.º	Nome da função	Variação do monitor ou de dados	Unidade
d015	Monitor de Consumo	0,0 a 999,9 1000, a 9999, 1000,a 9999, (10000,a 99990,) Γ100,a Γ999, (100000,a 999000,)	-
d016	Tempo de Trabalho	0,0 a 9999, 1000,a 9999, (10000,a 99990,) Γ100,a Γ999, (100000,a 999000,)	h
d017	Tempo Energizado	0,0 a 9999, 1000,a 9999, (10000, a 99990,) Γ100,a Γ999, (100000,a 999000,)	h
d018	Monitor de Temperatura do Dissipador	- 20,0 a 150,0	°C
d022	Monitor de Avaliação da Vida do Produto	1: Capacitor no quadro de circuito principal 2: Ventilador de resfriamento	-
d023 a d027	(Reservado)	-	-
d029	Monitor de Comando de Posição	-268435455 a 268435455 (Exibe 4 dígitos de MSB incluindo "-")	-
d030	Monitor de Posição Real	-268435455 a 268435455 (Exibe 4 dígitos de MSB incluindo "-")	-
d050	Monitor de Seleção de Usuário (2 tipos)	Exibe os dados do monitor selecionados por b160/b161.	-
d060	Monitor de Modo do Inversor	O modo atualmente determinado é exibido. I-C (Motor de Indução para carga pesada) I-V (Motor de Indução para carga leve) H-I (Motor de Indução para alta frequência)	-
d080	Contador de Falhas	0, a 9999, 1000,a 6553, (10000,a65530,)	Tempo
d081	Monitor de Falhas 1 (Recente)	Causa - Frequência (Hz) - Corrente (A) - Tensão entre PNs (V) - Tempo de TRABALHO (h) - Tempo ENERGIZADO (h)	-
d082	Monitor de Falhas 2		
d083	Monitor de Falhas 3		
d084	Monitor de Falhas 4		
d085	Monitor de Falhas 5		
d086	Monitor de Falhas 6		
d090	Monitor de Alerta	Código de Alerta	-
d102	Monitor de Tensão de DC	0,0 a 999,9 1000,	V
d103	Monitor de Nível de Frenagem Regenerativa (%)	0,0 a 100,0	%
d104	Monitor de Relé de Proteção Térmica - Sobrecarga (%)	0,0 a 100,0	%

Fig. 10 - Three-phase energy meter SBC SAbyIA-ALE3D5F11 Class B

A possible solution for the monitoring of motors phase currents is through the use of IT [20] if the current range is beyond the limits of the energy meter (Figure 11) or, if the model energy meter requires IT external (the ALE3 [21] does not require IT to current until 65 Ampere).

Fig. 11 - CTY intensity transformers

For the selection of IT, it is necessary to know the range of current values which the engine operates taking into account the values of the upper and lower current limits. In this case, the motor runs at a nominal current of 1.40 A. From the table of the FLEX-CORE manufacturer [22] and data of IT mentioned above, reported in Table 3 (CTY model) the selected IT for that current range is CTY-A. The IT is selected by the thicknesses of the wires through which the current, the current range in which they will work, and the necessary capacity with which the IT needs to monitor the streams.

TABLE III. INTENSITY TRANSFORMERS RANGE FROM CITY MODEL FLEX-CORE

INPUT AC AMPS	STANDARD OUTPUTS MODEL CTY-						SENSOR SIZE
	0-0.1Aac*	0-1Aac	0-5Aac	0-0.333Vac	0-1Vac	0-5Vac	
0-50	050A-.1	050A-1	NA	050A-.3V	050A-1V	050A-5V	A
0-100	100A-.1	100A-1	NA	100A-.3V	100A-1V	100A-5V	A
0-200	200A-.1	200A-1	NA	200A-.3V	200A-1V	200A-5V	A
0-100	100B-.1	100B-1	100B-5	100B-.3V	100B-1V	100B-5V	B
0-200	200B-.1	200B-1	200B-5	200B-.3V	200B-1V	200B-5V	B
0-300	300B-.1	300B-1	300B-5	300B-.3V	300B-1V	300B-5V	B
0-400	400B-.1	400B-1	400B-5	400B-.3V	400B-1V	400B-5V	B
0-500	500B-.1	500B-1	500B-5	500B-.3V	500B-1V	500B-5V	B
0-600	600B-.1	600B-1	600B-5	600B-.3V	600B-1V	600B-5V	B
0-800	800B-.1	800B-1	800B-5	800B-.3V	800B-1V	800B-5V	B
0-800	800C-.1	800C-1	800C-5	800C-.3V	800C-1V	800C-5V	C**
0-1000	1000C-.1	1000C-1	1000C-5	1000C-.3V	1000C-1V	1000C-5V	C**
0-1200	1200C-.1	1200C-1	1200C-5	1200C-.3V	1200C-1V	1200C-5V	C**

The engine manufacturer [23] used in this project has four solutions, as shown in Table 4, comprising devices that have its own thermal protection. For the triggering of maintenance through the temperature control, only the first three solutions can be used because they are the ones that allow their monitoring.

TABLE IV. THERMAL PROTECTION DEVICES PRESENTED BY WEG

	Term resistance	Thermistor (PTC e NTC)	Thermal protector bimetal	Phenolic Thermal Protector
Protection mechanism	Resistance calibrated	Avalanche resistance	Movable contacts Bimetallic	Movable contacts
Disposition	Head wound	Head wound	Inserted in the circuit Bobbin Head	Inserted in the circuit
Acting form	External operation s command in protection	External operations command in protection	Direct action External control protection to work	Atuação direta
Current limit	Chain of command	Chain of command	Motor current chain of command	Motor current
Sensitivity Type	Temperat ure	Temperatur e	Current and	Current and

			Temperature	Temperature
Number of motor units	3 or 6	3 or 6	3 or 6 1 or 3	1
Command types	Alarm and / or cut	Alarm and / or cut	Court Alarm and / or cut	Court
technological feasibility	Very good	Satisfactory	Good	Unsatisfactory
Affordability	Unsatisfactory	Very good	Satisfactory	Satisfatória
Technological and financial viability	Satisfatória	Satisfactory	Good	Unsatisfactory

Resistance Term (Pt-100) - are temperature sensors with a high degree of accuracy and sensitivity response, but correspond to a very viable solution economically due to the sensors and the electronics associated to the control is costly.
The thermistors (PTC and NTC) - temperature control in the implementation of thermistor has a low cost when compared to the Pt-100. Although it is necessary to use a relay for the control and actuation.
Thermal protectors Bimetallic / Thermostats - the use of thermostats for the maintenance trigger has to be appropriate for action by raising the expected engine temperature.
Protective Thermal Phenolic - they have the particularity of being sensitive to current and temperature, enabling automatic control. It is limited to the current in the case the protector is connected directly to the coil of the single-phase motor and can only be used in three-phase motors connected in Y.

VII. CONDITION MONITORING AND CONTROL

In most industrial processes that use electric motors, the sensors described above, not only for their protection but also for their monitoring, have been integrated. In this case, a simulation was made with the engine running without load. The main objective was to monitor and control engine operation, as illustrated in Figure 12, including the simulation of a fault.
To perform the test trigger a condition of intervention, it is necessary to monitor the feeding phases of the induction motor. Cutting the power stage (with a switch) of the engine it was carried out. In this case, the current will tend towards a minimum predetermined value in the algorithm implemented in the control system. The engine malfunction gives rise to this work with only two phases, thus unbalancing the operating system, which means that its temperature rise [24], and may exceed the upper limit of good operating system and activate other maintenance trigger. The cause of the simulated fault can damage the engine due to the material properties do not have ability to withstand such high temperatures. In the event of a threshold value which lead to the triggering of an intervention, a Work Order is issued with a set of procedures, such as checking the status of the electrical connections of the engine, among others.

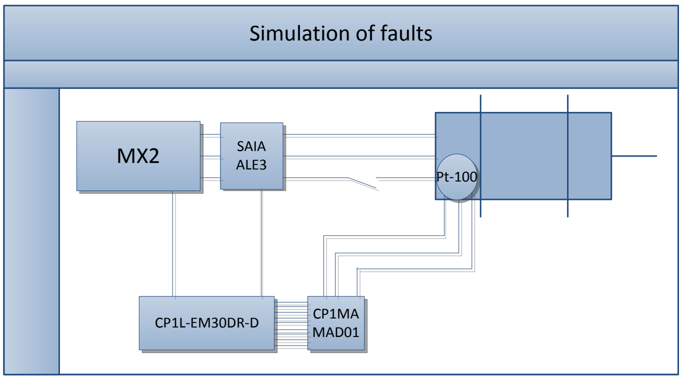


Fig. 12 - Fault simulation monitoring

VIII. GESP APPLICATION

To support the study presented in the previous chapters it has been developed an information system [25] that allows initiating the maintenance interventions according to the value of equipment monitoring data. The data communicationfrom the application is carried out through the use of SCADA Software Zenon [26], which allows data acquisition through a PLC that monitors information from an inverter through whitch engine is running. The data monitored by Zenon can be saved by communicating with the SQL Server database [27] through SQL system driver. Data acquisition by PLC is made by OMRON FINS driver (TCP / IP). Both variables, to be created, are allocated in the same function, as can be seen in Figure 13.

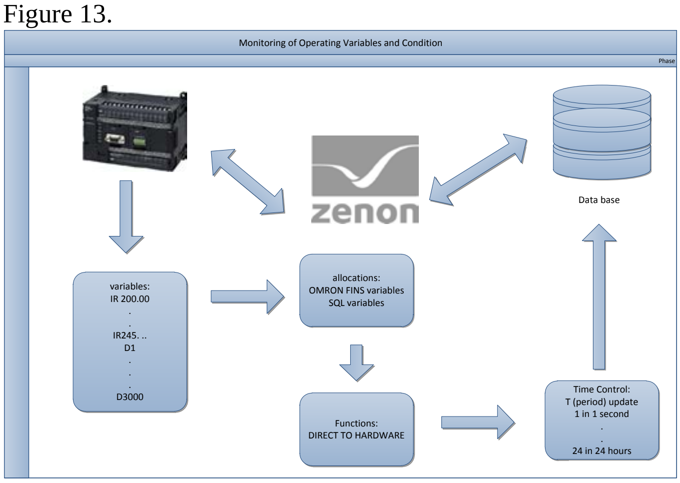


Fig. 13 – Monitoring and allocation of the operating and condition variables

System monitoring is carried out according to the scheme illustrated in Figure 14. It uses two different system technologies, both of which have to be synchronized to perform both operations.

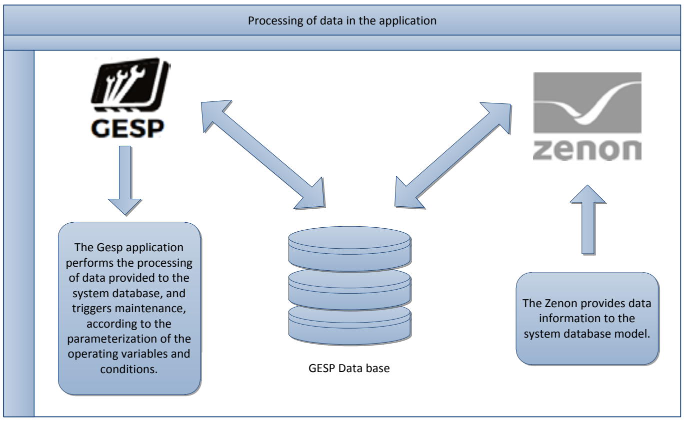


Fig. 14 - Monitoring and control of planned maintenance

Operating variables and condition are monitored by the Scheduling Meter.

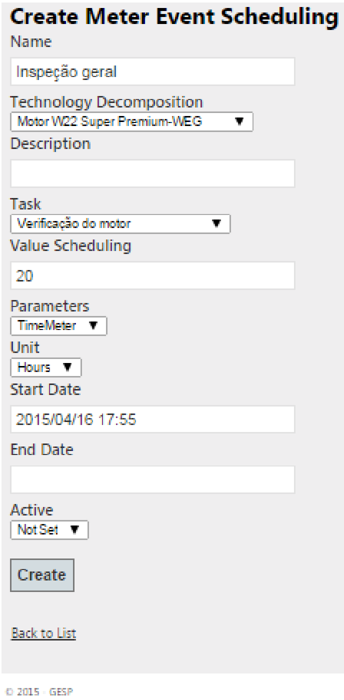


Fig. 15 - Creation of view of conditional maintenance trigger

As shown in Figure 15, triggering a maintenance intervention is made using two types of monitoring: (1) Meter Scheduling; (2) Control and Scheduling.

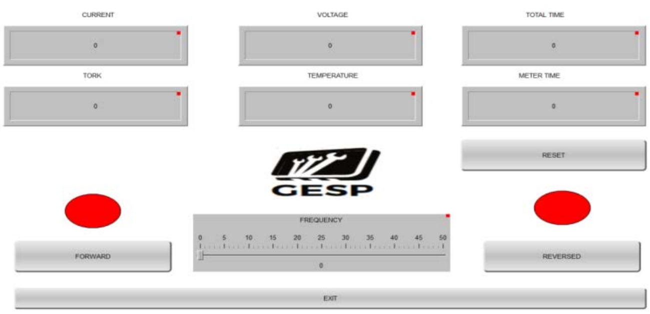


Fig. 16 - View of the monitoring of operating variables and conditions in the HMI-SCADA application (Zenon)

As shown in Figure 16 it is used the Zenon SCADA software to send the data of the variables monitored by Gesp database application to perform the interventions. This software SCADA, in addition to the monitoring variables from the electric motor interface, and its associated logic CP1L-EM30DR-D programming (programming software, Ladder) can monitor and control the electric motor.

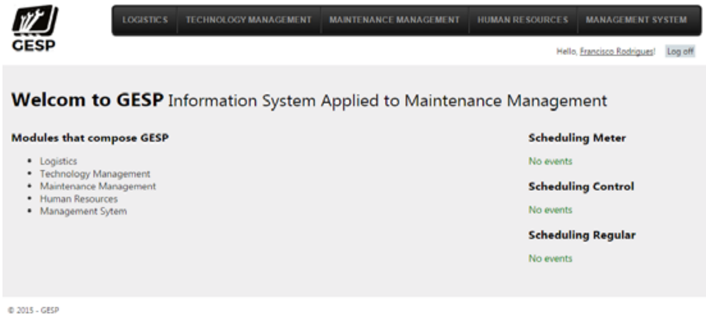


Fig. 17 - View from the main menu of the software application yasmim GESP

According to illustrated in Figure 17, the application permits users to know whether occurs or not trigger an intervention.

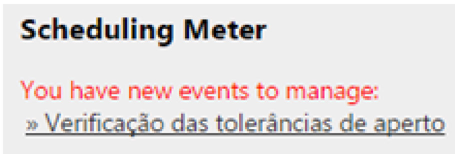


Fig. 18 - Illustration of the trigger intervention

According to illustrated in Figure 18 it is possible that the user knows if there was a request.

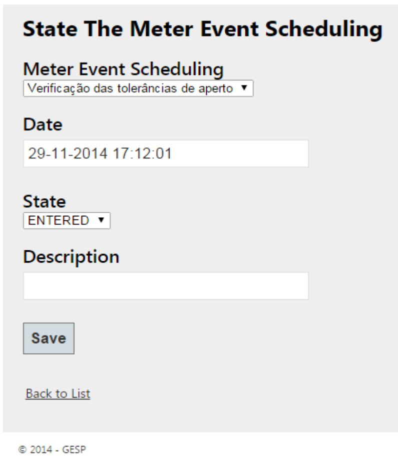


Fig. 19 - Illustration of state of an intervention trigger

Users who have permission to selecting the trigger switch also access the respective state of the same (Figure 19). Figure 20 illustrates how the trigger works, and opens directly the view state.

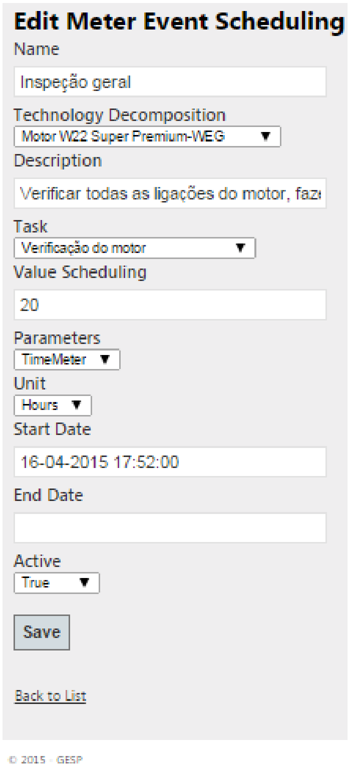


Fig. 20 - Edit view of the trigger intervention

Figure 21 shows the process of monitoring and control of operating variables and condition for triggering an intervention in GESP application.

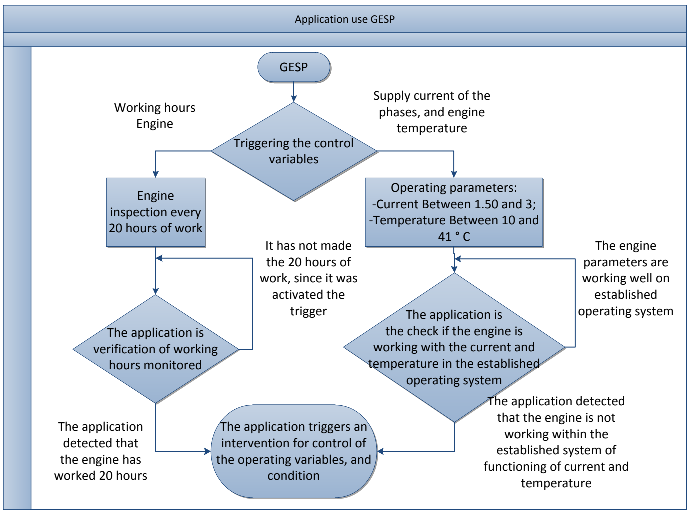


Fig. 21 – GESP Application

IX. FUTURE DEVELOPMENTS

The next challenge to be reached by the system is the development of a scheduling system in real-time, prospecting an automatic maintenance management, embedded with a failure prediction model based on dynamic modeling, where a historical analysis of the physical assets, the monitoring and the analysis of critical features will be made.

The next version of the proposed system (GESP) aims to manage maintenance operations with greater autonomy and robustness, being the tasks selected automatically by the system and evaluated the alternatives with respect to human resources.

It is estimated that the maintenance condition assumes particular relevance in the following years as well as the application of e-Maintenance concept [13]. In maintenance condition sector several studies were performed, one of them highlights a prediction model applied to wind generators based on vibration analysis [14], or a failure prediction by the analysis of other variables based on the historical of physical assets [15].

Due to the high degree of complexity of performing maintenance interventions, paper-based instructions are falling into disuse, being replaced by its equivalent in electronic version to be accessed by tablets or smartphones. The use of these devices opens doors to new horizons as the introduction of augmented reality in industrial environments [16], a technology that consists of superimposing virtual content to the real environment, which allows to display, on intuitive way, the sequence of instructions that technician must perform.

X. CONCLUSIONS

Planning maintenance from its operating variables helps to maximize the availability of equipment and therefore to increase the levels of competitiveness of companies by increasing production times. For its implementation the papers shows that through the use of adequate technology and algorithmic tools applied to operating variables and the equipment condition through periodic and aperiodic sampling cycles can be reached better planning. The monitoring and control are made by integrating SCADA (Supervisory Control and Data Acquisition) using communication protocols between the several application logics which allow reliable transmission of data. The triggering of the maintenance work is done by processing the data of the control variables using specific algorithms to monitor and launch automaticaly the Work Orders before damage can occur with reference values previously specified limit.

REFERENCES

[1] J. M. T. Farinha, “Ferramentas de Apoio à Manutenção,” em A Terologia e as Novas Ferramentas de Gestão, Lisboa, Monitor, 2011, pp. 56-58.

[2] International Business Machines Corporation (IBM), “IBM Software,” [Online]. Available: http://www-01.ibm.com/software/tivoli/. [Accessed in 2012.09.22].

[3] Internacional Business Machines Corporation (IBM), “IBM Home,” [Online]. Available: http://www.ibm.com/us/en. [Accessed in 2012.08.05].

[4] SAP AG, “SAP R/3,” [Online]. Available: http://help.sap.com/r3/. [Accessed in 2012.09.26].

[5] Wikipedia, “Programmable logic controller,” [Online]. Available: http://en.wikipedia.org/wiki/Programmable_logic_controller. [Accessed in 2014.10.05].

[6] ModBus Organization, “ModBus,” [Online]. Available: http://www.modbus.org/. [Accessed in 2014.09.05].

[7] Wikipedia , “FINS,” [Online]. Available: http://en.wikipedia.org/wiki/FINS. [Accessed in 2014.09.05].

ISBN 978-91-7583-841-0

[8] OPC Foundation, “Home,” [Online]. Available: https://opcfoundation.org/. [Accessed in 2014.09.07].

[9] International, [Online]. Available: http://www.iec.ch/. [Accessed in 2014.09.08].

[10] Wikipedia, “SCADA,” [Online]. Available: http://en.wikipedia.org/wiki/SCADA. [Accessed in 2014.09.08].

[11] wikipedia, “User interface,” [Online]. Available: http://en.wikipedia.org/wiki/User_interface. [Accessed in 2014.09.08].

[12] Wikipedia, “Computerized maintenance management system,” [Online]. Available: http://en.wikipedia.org/wiki/Computerized_maintenance_management_system. [Accessed in 2014.09.08].

[13] J. M. T. Farinha, “Novas Vertentes da Gestão,” em A Terologia e as Novas Ferramentas de Terologia, Lisboa, Monitor, 2011, pp. 79-82.

[14] J. M. T. Farinha, “O conceito de Manutenção e Sua Evolução,” em A Terologia e as Novas Ferramentas de Gestão, Lisboa, Monitor, 2011, pp. 8-10.

[15] OMORON, “Catalogue Programmable Logic Controller Compact PLC Series CP1L,” [Online]. Available: http://industrial.omron.eu/en/products/catalogue/automation_systems/programmable_logic_controllers/compact_plc_series/cp1l/default.html. [Accessed in 2014.09.04].

[16] Newark element 14, “OMRON INDUSTRIAL AUTOMATION CPM1A-MAD01 ANALOG I/O MODULES,” [Online]. Available: http://www.newark.com/omron-industrial-automation/cpm1a-mad01/analog-i-o-modules/dp/19C7862. [Accessed in 2014.09.04].

[17] OMRON, “Frequency Inverters Compact Solutions MX2,” [Online]. Available: http://industrial.omron.eu/en/products/catalogue/motion_and_drives/frequency_inverters/compact_solution/mx2/default.html. [Accessed in 2014.10.20].

[18] SBC-SAIA BURGESS CONTROLS, “Saia PCD® Energy Meters,” [Online]. Available: https://www.sbc-support.com/en/product-index/axx-energy-meters/. [Accessed in 2014.11.06].

[19] SBC-SAIA BURGESS CONTROLS, “Energy management-Capture consumption,” [Online]. Available: http://www.saia-pcd.com/en/energy-management/the-system/).. [Accessed in 2014.11.06].

[20] Flex-Core, “CURRENT TRANSFORMERS/TRANSDUCERS,” [Online]. Available: http://www.flex-core.com/current-transformers-transducers.htm. [Accessed in 2014.11.06].

[21] SBC-SAIA, “System Catalogue Pag.136,” [Online]. Available: https://www.sbc-support.com/flippingbooks/SystemCatalogue/26-215_en12/index.html#136/z. [Accessed in 2014.11.20].

[22] Flex-Core, SPLIT CORE CURRENT TRANSFORMERS MODEL CTY, McVey Blvd. Columbus, Ohio: Flex-Core.

[23] WEG, “Guia de Especificações - Motores Elétricos,” em Careterísticas em Regime, Jaraguá do Sul, Grupo WEG, 2014, pp. 37-38.

[24] Wikipedia, “Resistance thermometer,” [Online]. Available: http://en.wikipedia.org/wiki/Resistance_thermometer. [Accessed in 2014.11.05].

[25] F. Rodrigues, I. Fonseca, R. Oliveira e J. T. Farinha, “Maintenace Management in Web ASP.NET MVC Applications,” em “MPMM2014,” em Proceedings of Maintenance Performance Measurement and Management (MPMM, Vols. %1 de %2ISBN 978-972-8954, Coimbra, ISBN 978-972-8954-42-0 | http://dx.doi.org/10.14195/978-972-8954-42-0_14, Coimbra Universty Press, 2014, pp. 95-101.

[26] Copa Data, “zenon Supervisor,” [Online]. Available: http://www.copadata.com/. [Accessed in 2014.12.06].

[27] Microsoft, [Online]. Available: http://www.microsoft.com/en-us/server-cloud/products/sql-server/. [Accessed in 2012.06.05].

[28] OMRON, “CP1L CPU Unit Operacional Manual,” December, 2014.

[29] OMRON, “MX2 Manual,” November 2014.

[30] Omoron, “Using Expansion Units and Expansion I/O Units,” 2014.

[31] Omron, “Omron,” [Online]. Available: http://www.omron.com/. [Accessed in 2014.11.20].

[32] WEG, “WEG,” [Online]. Available: http://www.weg.net/. [Accessed in 2014.11.04].

[33] Flex Core, “Current Transducers,” [Online]. Available: http://www.flex-core.com/current-transducers.htm. [Accessed in 2014.11.05].

Local regularity analysis with wavelet transform in gear tooth failure detection

Juhani Nissilä
juhani.nissila@oulu.fi
Applied and computational mathematics,
Faculty of Information Technology and Electrical Engineering, University of Oulu
Oulu, Finland

***Abstract*—Diagnosing gear tooth and bearing failures in industrial power transition situations has been studied a lot but challenges still remain. This study aims to look at the problem from a more theoretical perspective. Our goal is to find out if the local regularity i.e. smoothness of the measured signal can be estimated from the vibrations of epicyclic gearboxes and if the regularity can be linked to the meshing events of the gear teeth. Previously it has been shown that the decreasing local regularity of the measured acceleration signals can reveal the inner race faults in slowly rotating bearings. The local regularity is estimated from the modulus maxima ridges of the signal's wavelet transform. In this study, the measurements come from the epicyclic gearboxes of the Kelukoski water power station (WPS). The very stable rotational speed of the WPS makes it possible to deduce that the gear mesh frequencies of the WPS and a frequency related to the rotation of the turbine blades are the most significant components in the spectra of the estimated local regularity signals.**

***Keywords*-epicyclic gearbox; spectral analysis; Hölder regularity; wavelet modulus maxima, water power station;**

I. Introduction

Gear tooth and and rolling bearing faults often cause high frequency vibration which may be more evident in the higher derivatives of acceleration. In many cases the highest relative change between a faulty state and normal condition of the machine occurs when the fractional order of derivative is a real number. In [1] Kotila, Lahdelma and Ruotsalainen suggested that this may be the result of reduced regularity of the vibration signal. They also used the signal's wavelet transform to estimate its local regularity and showed that the locations of the negative Hölder regularities corresponded to where the rolling elements hit the faults on the inner race of a bearing. Here we apply the same methods to the accelerometer data from the two-stage epicyclic gearbox of the WPS.

In Chapter II we present the signal processing methods. We will use the Discrete Fourier Transform (DFT) for spectral analysis, and the modulus maxima ridges of the continuous wavelet transform for local Hölder regularity estimation. This is possible due to Theorem 1, which was proved by Mallat and Hwang in 1992 [2].

Vibration measurements from the WPS are described in Chapter III and frequencies of the gearbox components are calculated. The Chapter continues with the numerical analysis of the vibration signals. Finally the obtained results are discussed in Chapter IV.

II. Signal processing theory

A. Fourier transforms

The vibration measurements are stored as sampled sequences $\mathbf{x} = (x_0, \ldots, x_{N-1})$ of length $T = \Delta t \cdot N$, where Δt is the sampling interval. The spectrum of this sampled signal is calculated with the *Discrete Fourier transform* (DFT)

$$\mathcal{F}\{x_n\} = X_k = \frac{1}{N} \sum_{n=0}^{N-1} x_n e^{-i2\pi kn/N}. \tag{1}$$

Its *inverse transform* (IDFT) is

$$\mathcal{F}^{-1}\{X_k\} = x_n = \sum_{k=0}^{N-1} X_k e^{i2\pi kn/N}. \tag{2}$$

Here we have equated the inverse as x_n, because it returns the original signal at the sample points [3].

The continuous analogue of the DFT is the *Fourier transform* $\hat{x}$ of x

$$\mathcal{F}\{x(t)\} = \hat{x}(\nu) = \int_{-\infty}^{\infty} x(t) e^{-i2\pi\nu t} \, \mathrm{d}t. \tag{3}$$

Its *inverse transform* is defined as

$$\mathcal{F}^{-1}\{\hat{x}(\nu)\} = \int_{-\infty}^{\infty} \hat{x}(\nu) e^{i2\pi\nu t} \, \mathrm{d}\nu. \tag{4}$$

B. Continuous wavelet transform

Wavelet is informally defined as an oscillation with compact support. Theoretically we also allow wavelets whose amplitude decays to zero at the infinities. An *admissible wavelet* ψ satisfies

$$\int_{-\infty}^{\infty} \frac{\left|\hat{\psi}(\nu)\right|^2}{|\nu|} \, \mathrm{d}t < \infty. \tag{5}$$

The *wavelet transform* of x is then the inner product

$$Wx(s,t) = \frac{1}{s} \int_{-\infty}^{\infty} x(\tau) \psi\left(\frac{\tau - t}{s}\right) \mathrm{d}\tau. \tag{6}$$

Here t is the point of interest in the signal and s is the positive *scale* at which the wavelet is dilated. The admissibility

ISBN 978-91-7583-841-0

condition enables the reconstruction of the original function from its wavelet transform in suitable function spaces, see for example [4]. To make this definition useful for the theory and also for the actual vibration signals, x must be from the class of generalised functions called tempered distributions. Interested reader may read details about distribution theory for example from [5]. We only note that (6) is well defined if x is a tempered distribution of order m and if the wavelet ψ is m times continuously differentiable. The Fourier transform of a tempered distribution is also a tempered distribution and the inverse returns the original signal.

A wavelet has *m vanishing moments* if

$$\int_{-\infty}^{\infty} t^k \psi(t)\,\mathrm{d}t = 0, \qquad \text{for all } k = 0, 1, \ldots, m-1. \tag{7}$$

It should be noted that in practise the continuous wavelet transform is computed using only a finite sequence and summations instead of integrals. The word continuous is still used to separate the definition from the actual discrete wavelet transform where the scale s is sampled at such points that the wavelets form an orthogonal set.

C. Hölder regularity and wavelet modulus maxima

A function x is *μ-Hölder* continuous for some $\mu \geq 0$ at the point t_0 if

$$|x(t_0 + h) - P_m(h)| \leq C|h|^{\mu}, \tag{8}$$

for small values of $|h|$ and P_m is a polynomial of degree $m \leq \mu$. If μ is non-integer, it turns out that P_m is actually the $m+1$ first coefficients of the Taylor polynomial of x at t_0. If for all $t_0 + h$ on an interval the condition (8) is satisfied, then we say that μ is the *uniform Hölder exponent* of x on that interval.

To extend the definition to negative Hölder exponents, we utilise again distributions. Let μ be a non-integer. We say that a tempered distribution x of finite order is uniformly μ-Hölder on the interval $]a, b[$ if its primitive is $\mu+1$-Hölder on the same interval (primitive = indefinite integral for integrable functions, see [5] for the definition for tempered distributions).

We are interested in how to detect isolated irregularities in the signal. This means that we want to locate points t_0 where f is μ-Hölder and also uniformly m-Hölder with $m > \mu$ elsewhere on the interval.

A series of local maxima or minima in the time-scale half-plane of the wavelet transform are called *modulus maxima ridges*. In [2] Mallat and Hwang proved that if no such ridges exist at the fine scales in a given interval, then f is uniformly Hölder continuous on that interval. Thus we expect that the modulus maxima ridges will reveal the isolated irregularities in the signal and this is indeed the case. Even more is true, since the Hölder exponent can be read from the decay rate of the ridges converging to t_0 at fine scales. The next theorem is also proved in [2].

Theorem 1: Suppose that the admissable wavelet ψ has compact suppport, is m times continuously differentiable and is the mth derivative of a smoothing function. Let x be a tempered distribution and its wavelet transform well defined on $]a, b[$ and let $t_0 \in]a, b[$. If there exists a constant C and a scale s_0 such that all modulus maxima of $Wx(s, t)$ belong to the cone

$$|t - t_0| < Cs, \tag{9}$$

then x is uniformly m-Hölder in a neighbourhood of all the points $t \in]a, b[, t \neq t_0$. Let $\mu < m$ be a non-integer. Then x is μ-Hölder at t_0 if and only if

$$|Wx(s, t)| \leq As^{\mu}, \tag{10}$$

at each modulus maxima inside the cone (9).

The estimation of the local regularity is thus done in the following manner (this is a modified version of the procedure presented in [1]).

1) Compute the wavelet transform with a wavelet which has the desired number of vanishing moments.
2) Find the local minima and maxima at each computed scale.
3) Follow the minima and maxima from the smallest available scale upwards to register the modulus maxima ridges. The ridges spread approximately linearly at small scales and thus the location of maxima/minima at the next scale can be guessed by linear extrapolation.
4) Estimate also the point where the ridge ends at the fine scales by linear extrapolation in the other direction.
5) If enough maxima/minima are lined up, estimate the regularity using (10) and logarithms

$$\log(|Wx(s, t)|) \leq \log(A) + \mu \log(s) \tag{11}$$

and the slope of a least squares line gives μ.
6) Of all the lines converging to the same point, choose the smallest value as μ.

III. Measurements and regularity calculations

Gear tooth numbers are almost always *relative primes*, i.e. their *greatest common divisor* is 1. Thus it takes a long time for a gearbox to mesh through all of its tooth pairs. The number of revolutions it takes for all the gears to return to their original positions can be calculated with the help of some elementary number theory and these computations were done for the gearboxes of the WPS in [6]. The solutions are typically several minutes and thus not quite practical for numerical work in most cases. It is quite adequate to use signal lengths which correspond to the revolution time of the slowest rotating component in the gearbox.

A. Water power station gearboxes

The Kelukoski water power station has a two-stage epicyclic gearbox. The first (slower) is called gearbox 1 and the second (faster) will be called gearbox 2. Both were monitored with one WBS CM301 sensor with sampling frequency 5000 Hz. Every 15 minutes an acceleration signal of length 7 s was recorded from both measurement points as WAV files. There were four continuous periods of data collection between 4.4.2013 and 22.8.2013.

ISBN 978-91-7583-841-0

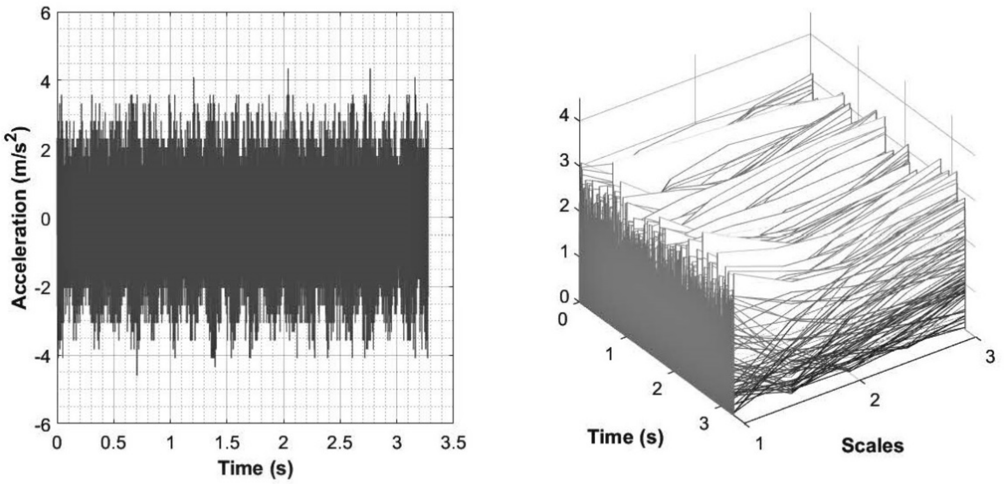


Fig. 1: Acceleration signal from the gearbox 1 recorded on 4.4.2013 and its wavelet transform modulus

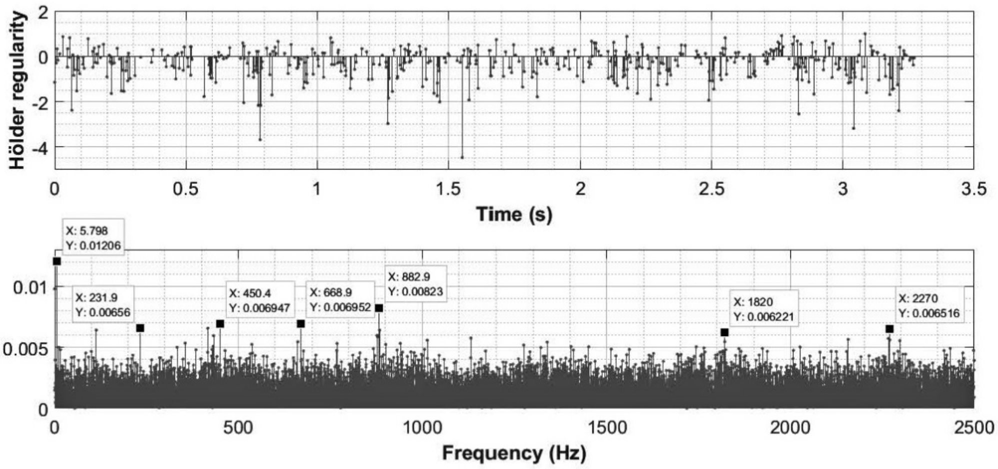


Fig. 2: Local Hölder regularity of the signal from Fig. 1 and the amplitude spectrum of the regularity signal

Since the WPS is connected to the Finnish power grid, its output frequency is to a high precision 12,5 Hz (the frequency of the power grid is four times this, i.e. 50 Hz). The characteristic frequencies of the gearboxes are now calculated backwards starting from this output. Gearbox 2 is in the star configuration, which means that it has a stationary planet carrier and six planet gears (25 teeth). Output is provided via the sun gear (36 teeth), $\nu_{sunWPS2} = 12{,}5\,\mathrm{Hz}$, and input from the gearbox 1 via the ring gear (86 teeth). The gear teeth are double helical and the gearboxes have plain bearings. The formulas for the frequencies are very simple in the star configuration [7]

$$\nu_{ringWPS2} = -\frac{36}{86}\nu_{sunWPS2} \approx -5.23\,\mathrm{Hz},$$

$$\nu_{planetsWPS2} = \frac{86}{25}\nu_{ringWPS2} = -18.00\,\mathrm{Hz},$$

and the mesh frequency $\nu_{meshWPS2} = 36 \cdot \nu_{sunWPS2} = 450.00\,\mathrm{Hz}$.

Gearbox 1 is in planetary configuration, meaning that it has a stationary ring gear. The sun gear is the output and has 31 teeth and the planetary gears have 25 teeth. The ring gear has 81 teeth. We have $\nu_{sunWPS1} = \nu_{ringWPS2}$ (this middle part of the two gearboxes is a floating installation) and the frequencies are

$$\nu_{carrierWPS1} = \frac{31}{31+81}\nu_{sunWPS1} = \frac{31}{112}\nu_{sunWPS1} \approx -1.45\,\mathrm{Hz},$$

$$\nu_{planetsWPS1} = -\frac{81-25}{25}\nu_{carrierWPS1} = -\frac{56}{25}\nu_{carrierWPS1} \approx 3.24\,\mathrm{Hz},$$

and finally the mesh frequency

$$\nu_{meshWPS1} = 81 * |\nu_{carrierWPS1}| \approx 117.31\,\mathrm{Hz}.$$

Measurements from the WPS have previously been studied in [6], [8], [9]. Unfortunately, before the previous breakdown of gearbox 1 several years ago, it had a slightly different set of gears with 35 teeth in the sun gear, 27 in the planetary gears and 91 in the ring gear. These give the same ratio for the output of the gearbox, but the frequency of the planetary gears was 3.45 Hz and most importantly the mesh frequency was 131.80 Hz. Due to some problems with communication these wrong gear numbers were used in the publications [8], [9]. Obviously the lack of frequency 131.80 Hz and the appearance of frequency 117.3 Hz in the spectra was a puzzle before this error was spotted.

B. Local regularity analysis of measurements from the WPS

One measurement from both gearboxes was analysed from the beginning and end of the measurement period. The output power of the WPS was about 7.6 MW during those measurements. The signals were shortened to $2^{14} = 16384$ samples, which gives a length of 16384 / (5000 Hz)= 3.2768 s. Next the continuous wavelet transform (6) was computed at scales $1, 1.5, 2, 2.5$ and 3 using the Mexican hat wavelet. It is the negative normalised second derivative of a Gaussian function and has two vanishing moments. Obviously it does not have exactly compact support but in practise this has little effect on the results. Computations were carried out with MATLAB. In the algorithm, a ridge was confirmed if a maxima was found from all the computed scales and they were approximately linearly spaced (a deviation of one discrete sample in both directions was allowed here in the search of a maxima from the current scale).

Fig. 1 and 3 show the measured vibration signals from gearbox 1 and the modulus of their wavelet transforms. The measurements were recorded on 4.4.2013 and 22.8.2013 respectively. The resolution of the accelerometer is clearly visible in these low vibration levels. There seem to be both ascending and descending ridges with increasing scale, which implies both positive and negative Hölder regularities in the signals. Fig. 2 and 4 show the estimated local regularities from these signals and also their amplitude spectra. We see that indeed both signals oscillate between positive and negative regularities and that the maximum regularity value we can analyse with the Mexican hat wavelet (which is 2 according to Theorem 1) is enough for these signals. For the calculation of the DFT of the regularity signal, the missing values are assumed to be zero. This is convenient, since the DFT needs an equally spaced vector. It must be mentioned though, that the signal is possibly infinitely smooth at these points and thus inserting Hölder coefficient 0 to them is a crude simplification to make the DFT easily computable.

It seems that the vibrations of gearbox 1 have not changed noticeably during this short measurement period (although in [6] a slight increase in the norms calculated from the second derivatives of these acceleration signals was observed), so we will discuss the two measurements simultaneously. It is interesting that although the spectra of both local regularity signals contains an almost uniform base across frequencies (that is the spectral content of white noise), there are also spikes at certain frequencies. Most of these are near the multiples of the mesh frequencies of the gearboxes, such as $2 * \nu_{meshWPS1} \approx 234$ Hz, $4 * \nu_{meshWPS1} \approx 469$ Hz and $2 * \nu_{meshWPS2} = 900$ Hz, $4 * \nu_{meshWPS2} = 1800$ Hz, $5 * \nu_{meshWPS2} = 2250$ Hz. The higher speed and bigger vibration levels explain why the multiples of the mesh frequency of gearbox 2 is also visible here. The sidebands which are 18 Hz apart from $\nu_{meshWPS2}$ and its multiples are sometimes even more noticeable than the center frequencies. Thus the frequency ≈ 469 Hz mentioned above may actually be such a sideband also. These are of course caused by the rotation of the planetary gears of gearbox 2.

The biggest change with time is the increase in the frequencies near 2250 Hz. Interestingly, this was also the only major change observed in the spectra which were calculated directly from the acceleration signals from the same measurement period in [6]. It should also be noted that since these frequency spikes are so discrete, this change is not so huge if one notices that the closest neighbouring frequencies of 2270 Hz in Fig. 2 are also quite noticeable.

There is also one very low frequency spike at about 5.8 Hz. This oscillation with period 1/5.8 Hz $\approx 0.17.$ s is visible in the time domain signals as well. This frequency could be $4 * \nu_{carrierWPS1}$ or even maybe $\nu_{ringWPS2}$ due to inaccuracies in the numerical work and the frequency resolution. The turbine has four blades and is connected to the carrier of the gearbox 1, which suggests that $4 * \nu_{carrierWPS1}$ is probably the correct answer. Thus we could deduce that that local irregularities in the acceleration measurements from the gearbox 1 are caused by the rotating turbine blades and the gear meshes from both gearboxes.

Fig. 5 and 7 show the measured vibration signals and their wavelet transform modulus at the beginning and at the end of the measurement period from the gearbox 2. Now almost all of the wavelet maxima modulus ridges increase towards fine scales and we thus expect a lot of negative regularities. Fig. 6 shows the estimated local Hölder regularity of the signal from the beginning of the measurement period and the amplitude spectrum of this signal. We see that the signal has mainly Hölder exponents between 0 and -3. The amplitude spectrum is dominated by $\nu_{meshWPS2} = 450$ Hz and its multiples. The higher multiples also have sidebands which are about 50 Hz above them. Fig. 8 shows similar results from the end of the measurement period, although now we also see more clearly the sidebands 18 Hz apart from $\nu_{meshWPS2}$ and its multiples.

The higher speed gearbox 2 thus shows quite clearly that the local irregularities of its measured acceleration signals are mostly caused by the meshing events of its gears. Comparing the spectra from Fig. 6 and 8 we also see that $\nu_{meshWPS2}$ and its multiples have decreased. This is also visible in the fewer amount of irregularities in the time domain signal in Fig. 8. It may just be that the algorithm failed to recognise as many ridges in the later signal or perhaps the vibration has actually become smoother with time.

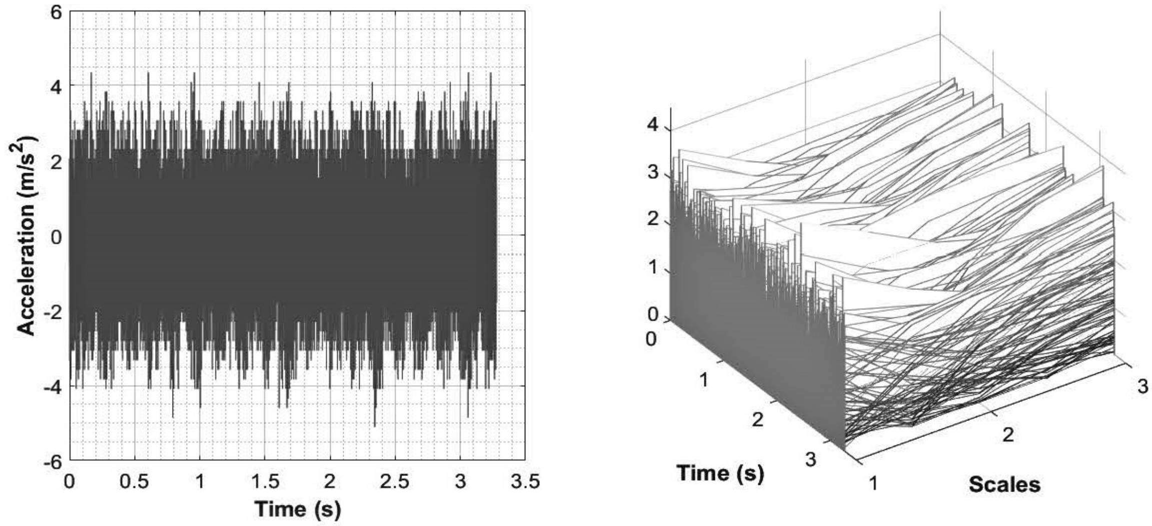


Fig. 3: Acceleration signal from the gearbox 1 recorded on 22.8.2013 and its wavelet transform modulus

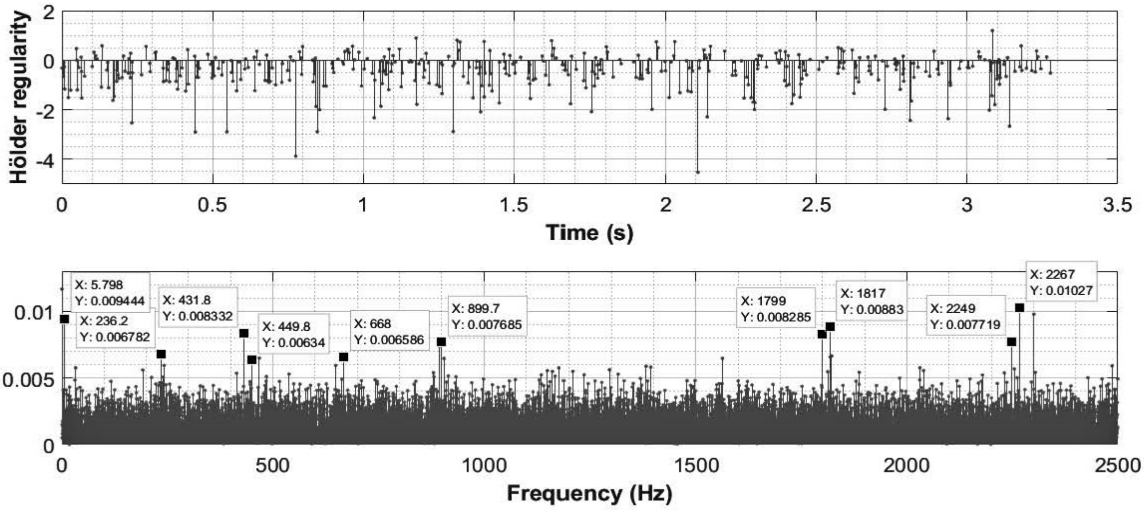


Fig. 4: Local Hölder regularity of the signal from Fig. 3 and the amplitude spectrum of the regularity signal

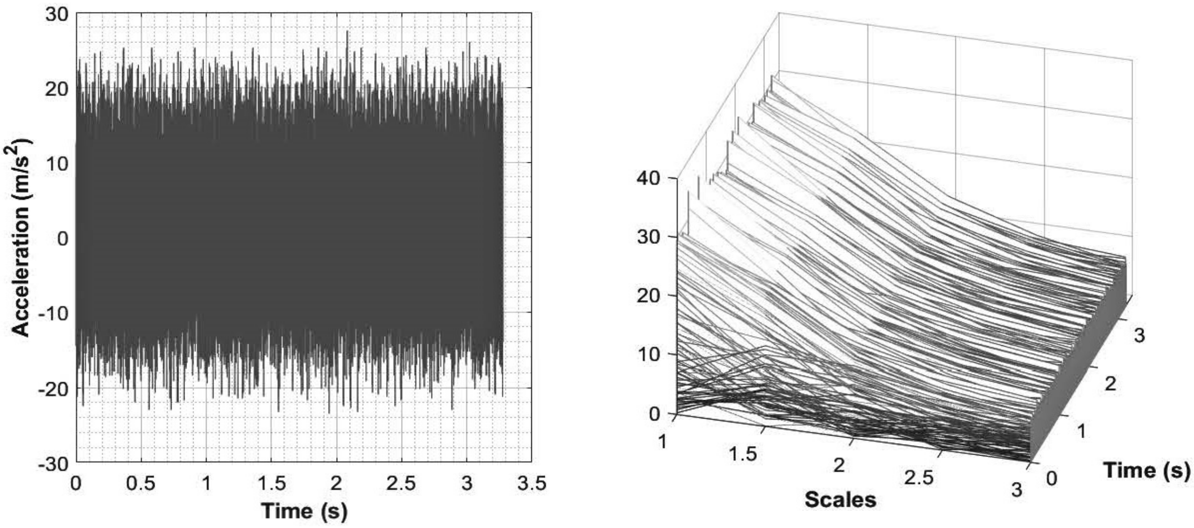


Fig. 5: Acceleration signal from the gearbox 2 recorded on 4.4.2013 and its wavelet transform modulus

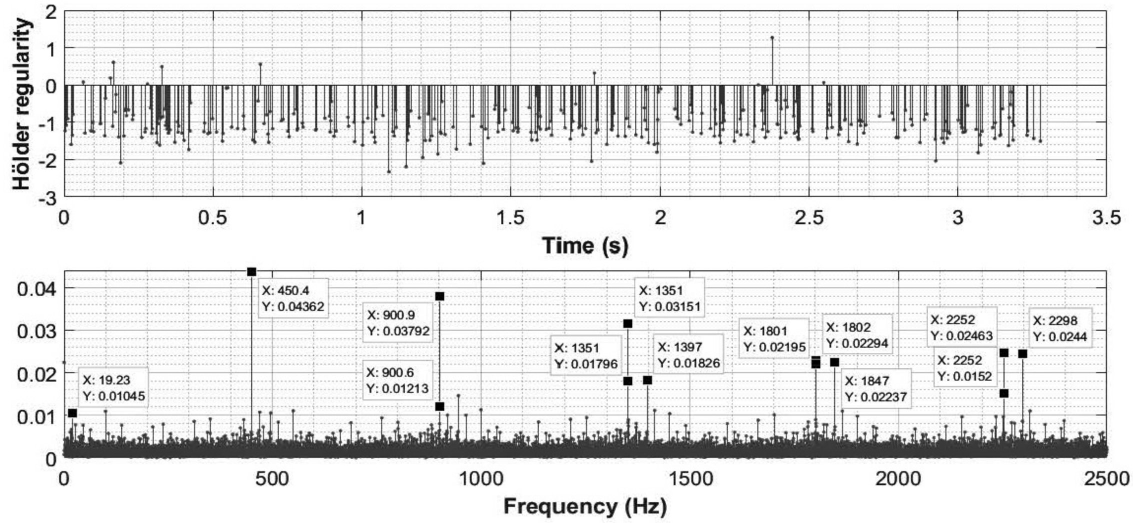


Fig. 6: Local Hölder regularity of the signal from Fig. 5 and the amplitude spectrum of the regularity signal

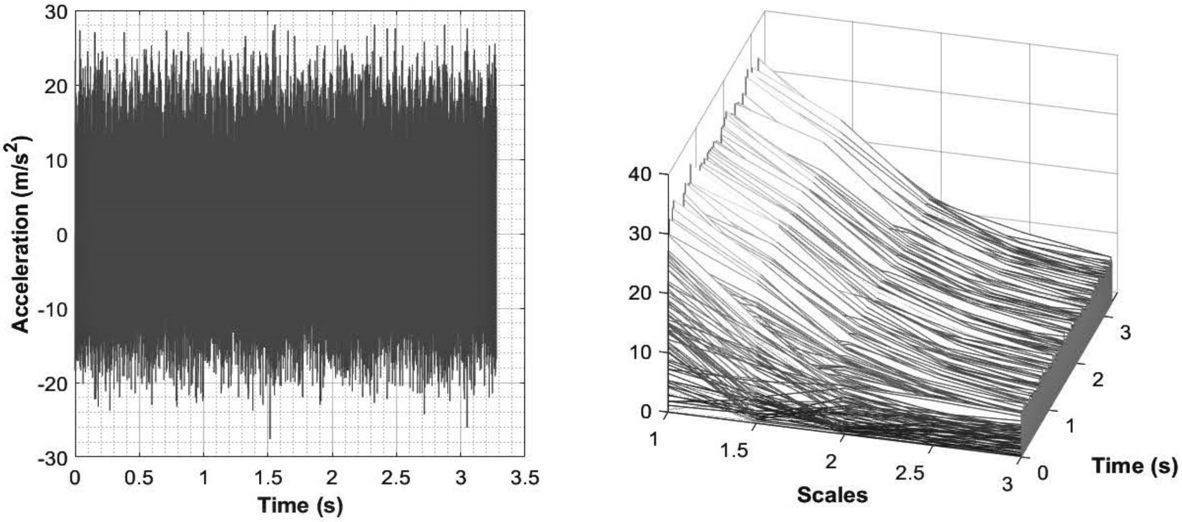


Fig. 7: Acceleration signal from the gearbox 2 recorded on 22.8.2013 and its wavelet transform modulus

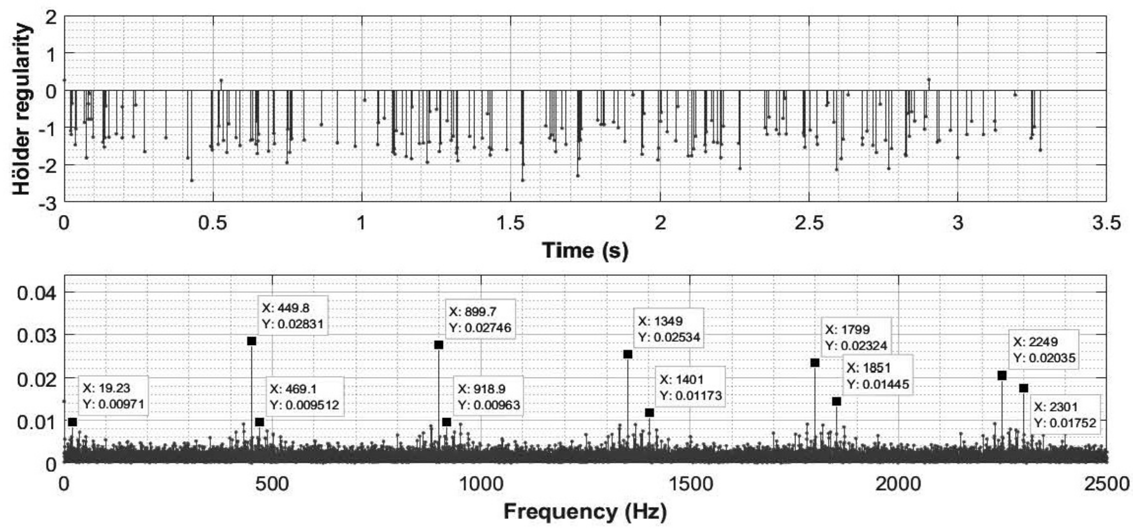


Fig. 8: Local Hölder regularity of the signal from Fig. 7 and the amplitude spectrum of the regularity signal

ISBN 978-91-7583-841-0

IV. Conclusions

For machines which rotate very precisely at a constant speed it is possible to calculate the DFT of the estimated local regularity signal and it may contain sharp spikes related to the rotating components of the machine. In this paper we have shown this using measurements from the two-stage epicyclic gearbox of a water power station.

Minor changes in these spectral components were also observed during the almost four-month long measurement period. This could be an indication of wear on the gears, but this is far from certain. The measurement period was very short considering that we cannot rule out for example seasonal effects which may cause different levels of stress on the gearbox. The true condition of the gears is also unknown. The estimation of the irregularities in the signals is also a nontrivial pattern recognition task and thus the results obviously contain errors. Averaged results from many signals could provide more reliable results. Spectral content directly from the acceleration signals from the same measurement period was analysed in [6] and very minor changes were observed in those as well.

The newest version R2016B of MATLAB introduced the built-in function wtmm for locating the wavelet modulus maxima ridges and estimating the local regularity. Unfortunately, it is not yet thoroughly documented and it seems that it searches the ridges starting from the big scales and then occasionally fails quite badly in locating the point where the ridge should converge. For this reason the author wrote his own code for the task.

Longer studies from industrial sites as well as test bench studies will be done to learn more about the connection between the regularity of vibration and the machine's health. If the machine does not rotate exactly at a constant speed, then it is unlikely that the DFT could catch any discrete spectral components from the regularity signal. In these cases the signal should at first be order-tracked. This can be done relatively easily if a tacho signal, which reveals the rotational speed of the shaft, is available. Another option could be to utilise the cyclostationarity of such a signal with the methods of cyclic spectral analysis.

Acknowledgement

The measurements at the WPS were part of the "Integrated condition-based control and maintenance (ICBCOM)" project. Author wishes to thank Otto A. Malm Foundation for their support on his doctoral studies.

OTTO A.MALM
lahjoitusrahasto

References

[1] V. Kotila, S. Lahdelma and K. Ruotsalainen, "Wavelet-based Ho¨lder regularity analysis in condition monitoring," in Inte- gral Methods in Science and Engineering vol. 2, Computa- tional methods, C. Constanda and M. E. Pe´rez, Eds, Boston: Birkha¨user, 2010, pp. 233-242.

[2] S. Mallat and W.L. Hwang, "Singularity detection and process- ing with wavelets," IEEE Transactions on Information Theory, vol. 38, no. 2, pp. 617-643, 1992.

[3] W. Briggs and V. E. Henson, The DFT An Owner's Manual for the Discrete Fourier Transform. Philadelphia, PA: Society for Industrial and Applied Mathematics, 1995.

[4] M.A. Pinsky, Introduction to Fourier analysis and Wavelets, Pacific Grove: Brooks/Cole, 2002.

[5] A.H. Zemanian, Distribution Theory and Transform Analysis, An Introduction to Generalized Functions with Applications, New York: Dover Publications, Reprint, slightly corrected, 1987.

[6] J. Nissila¨and E. Juuso, "Extracting vibration severity time histories from epicyclic gearboxes," in Proc. The 9th Eurosim Congress on Modelling and Simulation (EUROSIM 2016), Oulu, Finland, Sep. 2016, 7 pp.

[7] C. M. Vicun˜a, Contributions to the analysis of vibrations and acoustic emissions for the condition monitoring of epicyclic gearboxes. Aachen: Aachener Schriften zur Rohstoff- und Entsorgungstechnik des Instituts fr Maschinentechnik der Rohstoffindustrie, Verlag R. Zillekens, 2010.

[8] J. Immonen, S. Lahdelma and E. Juuso, "Condition monitoring of an epicyclic gearbox at a water power station," in Proc. The 53rd Scandinavian Conference on Simulation and Modelling (SIMS2012), Reykjavik, Iceland, Oct. 2012, pp. 99–105.

[9] R.-P. Nikula, K. Leiviska¨ and K. Karioja, "Epicyclic gearbox monitoring in a hydroelectric power plant with varying load," in Proc. 11th International Conference on Condition Monitoringrevention Technologies (CM 2015 and MFPT 2015), Oxford, UK, Jun. 2015, 12 pp.

Condition based maintenance using open hardware IoT

Christer Stenström
christer.stenstrom@ltu.se
Division of Operation and Maintenance Engineering, Luleå University of Technology
Luleå, Sweden

***Abstract*— Internet of Things (IoT) has grown as electronic circuits have become cheaper, more efficient, smaller in size and received benefits from open hardware and software. Efficient condition monitoring is often essential for internationally competitive and sustainable production. However, in production where thousands of sensors are required, cheap microcontroller and sensors is a prerequisite. With open hardware and software, data logging solutions can be made cheap, as organisations can procure customized products from a large number of suppliers, to a small product cost, instead of procuring proprietary products from a few suppliers. Also, open hardware and software promote open innovation.**

In this study, open hardware is presented as an enabler for IoT. It gives a brief review of open hardware, open electronics, their support community, as well as security and safety application considerations. Examples are given with microcontrollers and sensors from Arduino, Particle, Intel Edison, Sparkfun and Adafruit.

In the project to which this abstract relates to, IoT solutions are developed and field tested in rail infrastructure, which includes prototypes, energy management/harvesting, data logging, usability of data, reliability and cost/benefit.

Keywords—IoT, Condition based maintenance, open hardware, open software, 3D printing.

Chapter 5: Performance Measurement

ISBN 978-91-7583-841-0

Optmization In Performance-Based Logistics Contracts

Julio C. O. Lopes[1]; Rodrigo Scarpel[2]; Fernando T. M. Abrahão[3]; Diego Galar[4]; Alireza Ahamadi[4]
[1]juliojcl@ita.br; [2]rodrigo@ita.br; [3]abrahao@ita.br, [4]diego.galar@ltu.se;
[1,4] Division of Operation and Maintenance Engineering, Luleå University of Technology
Luleå, Sweden
[2]Division of Mechanical Engineering, Technological Institute of Aeronautics
São José dos Campos, Brazil
[3]Laboratory of Logistics Engineering, Technological Institute of Aeronautics
São José dos Campos, Brazil

***Abstract*—Performance-based Logistics (PBL) contracts require metrics and methodologies set in a systemic way to provide readiness for the warfighter at reasonable costs. There must be a clever and verifiable connection of metrics in order to access and analyze data and to deliver sound and consistent inputs for the entire support system to accomplish its goals. A system of incentives and penalties usually takes place and suggests functions to be maximized and/or minimized in a multi-criterion and highly integrated environment. This study deals with the optimization of the entire setup of Performance-Based Logistics contracts and is limited to a preliminary study in a simple scenario that has showed a promises results. A mixed method, using both the Ɛ-Constraint and Goal Programming is proposed to model the case. Results indicate that metrics used for reliability, maintainability, availability and supportability (RAMS) and costs can be optimized simultaneously for clever contracts.**

***Keywords*—optimization, contracts, PBL.**

I. Introduction

Performance-based Logistics (PBL) is a type of contract based on a strategy of integrated acquisition and sustainability for enhancing weapon system capability and readiness. PBL includes a long term relationship and incentives with service providers in order to support the end user´s objectives [1].

In programs following this type of contract, the Office of the Assistant Secretary of Defense for Logistics & Material Readiness (ASD - L&MR) has found an annual saving of 5-20 % in costs for serving. This could represent an economy of about U$ 10 millions in the logistic support contract for the 36 Gripen NG, which is estimated at a cost of U$ 78 millions[2].

The requirements in a PBL contract, frequently, include operational availability, and many authors have done a research to optimize this indicator [3,4, and 5], while Kumar [6] has developed a goal programming model to optimize some logistics functions. Other authors have focused on the implementation of the PBL contract, studying the enablers and barriers in the implementation process with the objective to guarantee the success of the PBL contract [1,7, and 8]. As the PBL contract involves many key performance indicators (KPI), and some of those indicators can be conflicting and calculated with non-linear functions, the objective of this work is to built a multi-objective model to simultaneously optimize reliability, maintainability, and supportability.

This paper briefly reviews the metrics normally involved in PBL implementation associated with reliability, maintainability, and supportability. Those metrics are expressed as mathematical functions and are dependable of some variables. This paper also reviews some mathematical functions used and cited in literature related to Reliability, Availability, Maintainability and Supportability (RAMS), what will be used as objective functions. As some of these functions are nonlinear, a heuristic method for a solution must be applied.

II. Background

A. Types of PBL contracts

The definition of metrics in a PBL contract depends on the type of contract. In the literature, it is possible to find some types of contracts used in PBL. As described by Kirk [9], a "Full Contract" is a type of contract where the contractor is responsible for the inventory control while responsible for fulfilling of specific metrics. All the Integrated Logistics Support can be covered in this type of contract.

For a PBL-Partnership, there are the same characteristics of a Full PBL contract that incorporates a partnership between a commercial entity and an organic depot, where, for example, the government entity can be sub-contracted to perform a portion of the support required by and for the contractor.

A Mini-Stock point contract, the government entity owns the inventory but the contractor receives, stores, issues, and may also repair the material.

A PBL-organic is a type of contract with an organic activity to procure, repair, store and issue material. In PBL-commercial, commercial items are supplied by the contractors. In the Contractor Logistics Support the contractor manages most of the Integrated Logistics Support Elements, and finally the Long Term Contract with an arrangement longer than usual contracts[9].

This work is addressing a Full PBL contract and, therefore, the contractor is responsible for the performance achieved. This type of contract emphasizes the necessity to consider RAMS metrics and involves a multi-criteria optimization.

B. *Reliability Metrics*

Reliability is defined as a probability that a system or a component will work for a certain period of time, without failures, operating under specific conditions [10]. Reliability management is a managerial function related to the coordination and supervision of activities such as design, manufacturing and so on, in the life cycle of the system, to achieve the established reliability goals and the most efficient life cycle costs [11].

Reliability management in the design phase of a product or service is fundamental for the whole process. Reliability management includes activities such as the development of reliability programs and other documents, the control of the production process, the built of failure reports, the analysis of the system, among others [12].

In a PBL contract, the reliability management shall be considered, and reliability goals must be defined. These goals involve some usual metrics, such as mean time to failure (MTTF) and refers to the expected time between two consecutive failures for a nonrepairable item or mean time between failures (MTBF) for a repairable system or item [13], besides the reliability itself.

The reliability can be estimated using expressions such as [13]:

where ti represents the operation time between two consecutives failures and n is the number of observations. MTBF has a mathematical relation with reliability as described bellow [13]:

$$MTBF = \frac{1}{n}\sum_{i=1}^{n} t_i \qquad (1)$$

Where R(t) is the mathematical expression for the Reliability function.

$$MTBF = \int_0^{\infty} R(t)dt \qquad (2)$$

Therefore, these expressions depend on the distribution wich has the better fitness to the available data.

A study has been done by United Airlines (UAL) as a part of the more general questioning that preceded Reliability Centered Maintenance (RCM). UAL has used this database to develop the age-reliability patterns for the nonstructural components in their fleet. The failure density distributions were developed from the component operating history files, and the hazard rate (or instantaneous failure rate) was derived as a function of time. It was found that 95 % of the nonstructural components has a long period of time with a constant hazard rate (hazard rate function) [14].

For this reason, a constant hazard rate is used in this work, and the equations for reliability can be expressed as R(t) = e-λt and the MTBF = 1/λ [13].

C. *Maintainability Metrics*

Maintainability deals with the duration of maintenance outages or how long it takes to complete the maintenance actions. Maintainability characteristics are usually determined by equipment design, which then sets maintenance procedures and determine the length of repair times [15]. In general, maintenance optimization models cover four aspects: (i) a description of a technical system including the function and importance, (ii) a modeling of the deterioration of the system in time including possible consequences for the system, (iii) a description of the available information about the system and (iv) an objective function and an optimization technique for the involved trade-off [16].

Maintenability can be estimated using the total downtime for maintenance, including all time for diagnosis, troubleshooting, tear-down, removal/replacement, active repair time, verification testing that the repair is adequate, delays for logistic movement, and administrative maintenance delays. It is often expressed as

$$M(t) = (1- \exp(-t/MTTR)) = 1- \exp(-\mu t), \qquad (3)$$

where μ is the rate of repair (number of repairs per unit of time) and MTTR is mean time to repair [15]. This equation is based on some assumptions.

i. Both failure and repair rates are considered constant over time and are statistically independent.

ii. MTBF and MTTR are exponentially distributed.

iii. Repaired units are as good as new ones.

iv. Repair or replacement is carried out in the case of failures only.

v. Separate repair facility is provided for each subsystem. All the subsystems remain in two states i.e. Operating and failed states [15].

The maintainability model used, depend on the type of maintenance policy applied. In the literature, there are some types of police such as Age-dependent Preventive Maintenance (PM) policy, Periodic PM policy, Failure limit policy, Sequential PM policy, Repair limit policy, Repair number counting and reference time policy [17]. A basic maintenance model was presented by Marquez [18] under the constant interval replacement where the expected number of failures M(t) is estimated as:

$$M(t) = \int_0^{t_p} \lambda(t)dt \qquad (4)$$

Where λ(t) is the failure rate.

Therefore, given a MTTR for scheduled maintenance (MSMT) and a MTTR for unsheduled maintenance (MTTRu), the length of TSM (interval of preventive maintenance) will

ISBN 978-91-7583-841-0

affect the availability of the aircraft, and the objective for maintenability can be expressed as the minimization of downtime for maintenance activities (DT):

$$DT = \frac{M(T)*MTTR + \left(T/_{T_{SM}}\right)*MSMT}{M(T)+T/_{T_{SM}}} \qquad (5)$$

Where T is the total operational life, Tsm is the medium time between two scheduled maintenances, and MSMT is the Mean Scheduled Maintenance Time [6].

D. Supportability Metrics

The supportability analysis defined as an iterative analytic process by which the logistic support necessary or a new or modified system is identified and evaluated [19]. Ungar [20] in his work has addressed the economics of supportability and how the design for testability can affect its costs. Therefore, the operation and support cost should be used as a performance indicator of supportability.

Smiljanic et al [21] used for an aerospace application, parameters for supportability as turn around time (TAT) i.e., time from vehicle landing until it is ready to fly a valid mission. On the other hand, others authors[22,23] has used the Mean Time to Support (MTTS) as a measure of supportability characteristics.

In this work, it is considered the cost of support as a sum of maintenance cost (MC), inventory cost (IC) and other support cost (OSC). According to Ebeling [24] the unscheduled maintenance cost can be expressed as:

MCu = T (Cf+Cv MTTR) /MTBF (6)

Where Cv is the variable cost per hour of downtime, Cf is the fixed cost of a failure and T is the economic life in operating hours.

The preventive maintenance cost is estimated as :

MCp= T *CSM/TSM (7)

Where CSM is the average cost for the preventive maintenance.

In order to estimate the inventory cost, the author porpose the estimation of expected stock available using the Multi-Echelon Technique for Recoverable Item Control (METRIC), developed by Sherbrooke [25]. As the expected backorder can be estimated by the METRIC model, the exepcted available stock (EAS) can be expressed as :

EASi= LPi – EBOi (8)

Where EASi is the expected available stock for item i , LPi is the logistics pipeline for item i (estimated as the product between the demand for item i and the time to repair or turn arround time) and EBOi is the expected backorder estimated by the METRIC model.

Finally, the inventory cost (IC) is the product between the holding cost per unit of item i (HCi) and the expected available stock (EAS).

The other support cost can be expressed as [24] :

OSC = [Fs + PA(i,td) CsN] (9)

Where Fs is the Fixed support cost, PA represents the present value of an equal annual amount observed over d years (PA(i,td) = [(1+i)d-1] /[i(1+i)d]) , Cs is the annual support cost per unit, and N is the number of identical units.

Therefore, the support cost can be expressed as :

SC = T (Cf+Cv MTTR) /MTBF + T *CSM/TSM + [Fs + PA(i,td) CsN] + HCi*EAS (10)

E. Availability Metrics

Items which are repaired (returned to usable condition) rather than discarded are called repairable. Repairable inventory systems are typically composed of high cost, long-life goods, where is economically viable to repair an item. Repairable items are common in the military [26]. To ensure the aircraft availability, an ample supply of spare parts must be maintained. In the context of standard inventory control, stockouts can lead to unavailability of equipment whereas spare parts inventories incur holding costs [27]. The most influential model by far has been the Multi-Echelon Technique for Recoverable Item Control (METRIC), developed by Sherbrooke [25], and extensively used in the military world.

The METRIC is an interesting model due the estimation of supply availability of the system. Supply Availability values are obtained from the performance characterization of backorders at the bases via the METRIC model [25]. METRIC is really an approximation and some extensions to METRIC were developed to relax some assumptions that may be unrealistic in application. Graves [28] proposes a different approximation that uses the two-parameter negative binomial distribution to fit the distribution of the backorders at the bases and found that METRIC underestimates expected backorders, while his negative binomial approximation (VARI-METRIC) overestimates them, but, on the other hand, gave mistaken allocation of spares in less than 1% of the cases [27, 25].

It was common for failure data from individual aircraft parts to have a variance to mean ratios greater than one, and this suggested that a Poisson model may not adequately describe the variance in the failure arrival process [29]. Due this, the model VARI-METRIC is used in this work to estimate the aircraft supply availability.

$$A_s = 100 \prod_{i=1}^{I} \left\{1 - \frac{EBO(S_i)}{NZ_i}\right\}^{Z_i} \qquad (11)$$

Where EBO(Si) is the expected back-orders for item i at the stock level Si, Zi is the number of items installed i per aircraft and N is the number of aircraft.

ISBN 978-91-7583-841-0

Accordind to Minzhi [30], in order to estimate the Operational Availability it is necessary to use the expression :

$$A_o = \frac{A_s A_i}{A_s + A_i - A_s A_i} \times 100\% \qquad (12)$$

where

$$A_i = \frac{MTBF}{MTBF + DT} \qquad (13)$$

III. ANALYSIS

The optimization of multiobjective problems has several methods of solution and normally depends on the insight of Decision maker to find the final Pareto optimal solution [31].

As in this case there are some objectives to maximize and others to minimize, some useful methods can be Ɛ-Constraint Method (Bounded objective function method), Goal Programming Method and Weighted min-max method, among others [31]. Methods that provide both necessary and sufficient conditions for Pareto optimality are preferable, but there is no best method for all problems [32].

Based on the equations discussed previously, one approach is to use the Ɛ-Constraint Method (Bounded objective function method), because, often, the availability is the most important goal while the others objectives can be used as constraints.

In this work, it is suggested another approach, based on a mixed method using both the Ɛ-Constraint Method with the Goal Programming Method. In this proposal, the first step for solving four different problems using the Ɛ-Constraint Method. The first problem uses the reliability function (for example) as an objective function in order to define the maximum reliability achievable in this environment, while the maintainability, availability, and supportability functions are treated as constraints. Such constraints are considered as the minimum accepted level. This reliability found as a result of the problem will be used as reliability target for the second step.

In the second problem, another objective function is selected, as availability (for example), and again, using the Ɛ-Constraint Method, it is possible to define the maximum availability that can be reached in this circumstance, treating reliability, maintainability and supportability as restrictions. This availability found as a result in the second problem will be set as an availability target for the second step. Therefore, following this approach, the third problem defines the maintainability function as an objective function in order to define the maintainability target for the second step, and the fourth problem sets the supportability function as the objective function and defines the supportability target for the second step.

In the second step, each result found as the target in the first step is now set as a goal in the goal programming method, thus resulting in only one problem to be solved. This is shown diagrammatilly in figure 1. This final step suggests the decision variables to be addopted and the parameters related to RAMS to be used in the contract.

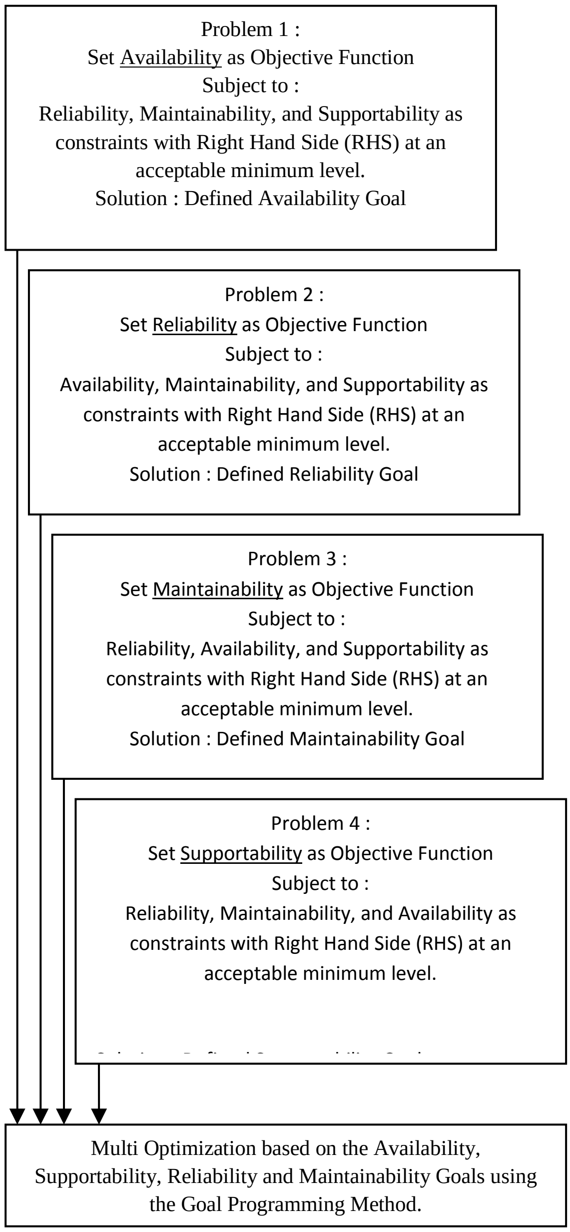


Fig.1. Diagram of the process to solve the problem.

In this work we have as decision variables the median time between two scheduled maintenances (TSM) and the inventory allocation for repairable items, while the objective functions to maximize are the reliability R(t), and the Operational Availability(A0) and at the same time the objectives to minimize are the Supportability Cost (OC+FC+SC) and the maintenance Downtime (DT).

IV. RESULTS AND DISCUSSION

In order to explore the model, a simple scenario was created based on a fleet with just one type of aircraft with ten aircraft, which one flying 1500 h per year during thirty years. It was operating on two Bases, and those two bases are supported by one depot.

For this preliminary study, it was considered three repairable subsystems, which one with different failure rate, time of repair on Base and on Depot, and fraction of repair at Bases.

It was necessary to define some maintaince inputs such as MTTR and the MSMT, and the respective cost for each one.

Considering there are no stocks of any item, and an interval between preventive maintenance of 1000 h, the results of each objective function were:

No Stock	**Objective Functions Results**			
	Oper. Availability	***Maintain.***	***Reliability***	***Support.***
	64,62 %	642 h	79,59 %	100% cost

In the first step, was established the goals for Operational Availability, Maintainability, Reliability and Supportability. The results found are showed below:

No Stock	**Objective Functions Results**			
	Oper. Availability	***Maintain.***	***Reliability***	***Support.***
	74.32 %	641.9 h	94.45 %	85.2%

These values are defined as goals in the second step, where a Goal Programming Method was used. This final result found for this instance was :

No Stock	**Objective Functions Results**			
	Oper. Availability	***Maintain.***	***Reliability***	***Support.***
	69.2 %	665.0 h	86.0 %	92.8 %

The decisions variables for this instance were :
Preventive time interval: 1319 h;
Stock level at Depot: two units for item 1;
Stock level at Base 1: 3 units for item 3;
Stock level at Base 2: 2 units for item 3.

This problem was solved using a Preemptive Method in order to compare the results. The sequence for preemptive used was availability, maintainability, reliability and supportability as the last function to be optimized. For this method the results were:

No Stock	**Objective Functions Results**			
	Oper. Availability	***Maintain.***	***Reliability***	***Support.***
	74.3 %	641.9 h	79.6 %	86.9 %

And the decision variables were :
Preventive time interval: 2000 h;
Stock level at Depot: no stocks were suggested;
Stock level at Base 1: two units for item 1, item 2 and item 3;
Stock level at Base 2: two units for item 1 and item 3, and only one unit of item 2;

Based on the previous results, it was clear that Goal programming was a better method to balance more equally all objective functions. In the preemptive method the reliability was too sacrificed in order to guarantee the availability and the maintainability.

Through this mixed method, it was able to define achievable goals without the necessity of experts' opinions.

Otherwise, this model requires a deeper knowledge about the mathematical formulation and methods for solve nonlinear objective functions, and for this reason more studies should be done to define good methods to solve more complex instances.

V. CONCLUSION

This study is limited to exploring a simple scenario and designing the methodology for the rest of the challenge presented.

In order to implement a PBL contract with consistent metrics, all parameters considered in the contract should be analyzed in an integrated way. Some decisions can influence the metrics discussed before in opposite directions, as example, a higher level of inventory will result in higher availability as discussed before, but means higher cost of supportability.

The configuration of the system, with redundancies of subsystems or components, will influence the reliability and, at the same time, the maintainability, supportability, and availability. Therefore, all the equations of reliability R(t), supportability OC (CO,i,td,), FC (MTTF, i,td, t0,,Cf), SC (i,td,,Cs) and availability A(MTTF,Si) should be simultaneously optimized based on multi criteria methods to achieve a balance of all metrics.

This approach is important to reduce the time consuming process between government and industry besides to define reasonable goals for all metrics defined. Some methods can be used, and the second approach suggested, a mixed Ɛ-Constraint Method and Goal Programming Method seems to be feasible and more reasonable compared with the first approach mentioned (simple Ɛ-Constraint Method) or with a preempitive method which needs the definition of the most important objective

REFERENCES

[1] D., Berkowitz, J.N.D. Gupta., J.T. Simpson, & J.B. Mcwilliams, "Defining and implementing performance based logistics in government", Defense Acquisition Review Journal. Vol. 11, no 3, pp. 255–267,2005.

[2] Diário Oficial da União nº 207, de 27 de outubro de 2014, Seção 3, p. 17.

[3] Devries, H.J. "Performance based logistics-barriers and enablers to effective implementation", Defense Acquisition Review Journal. 11, 243–254, 2004.

[4] K. Doerr, I. Lewis, & D. R., Eaton "Measurement issues in performance-based logistics", Journal of Public Procurement, Vol. 5, No. 2, pp. 164-86, 2005.

[5] W.S. Randall , D. R. Nowicki &T. G. Hawkins, "Explaining the effectiveness of performance based logistics: a quantitative examination", International Journal of Logistics Management. vol. 22, pp. 324-338, 2011.

[6] U. D. Kumar, D. Nowicki, D. Verma, and J. E. R Marquez, "A goal programming model for optimizing reliability, maintainability and supportability under performance based logistics", International Journal of Reliability, Quality and Safety Engineering. 14.03, pp. 251-261, 2007.

[7] Pozzetti, A., Bil, C., & Clark, G. 2013 Fuzzy Logic Application in Performance-Based Contracting Process In Concurrent Engineering Approaches for Sustainable Product Development in a Multi-Disciplinary Environment. Springer London. 303-314.

[8] A. Dell'Isola, and A. Vendittelli, "Operational availability (Ao) of warships: A complex problem from concept to in service phase", Metrology for Aerospace (MetroAeroSpace), IEEE, 2015.

[9] R. L Kirk,.& T. J. DePalma, "Performance-based logistics contracts: A basic overview", Alexandria, Virginia CNA, 2005

[10] J. L. Romeu, "Practical Reliability Engineering", vol. 45, no. 2, 2003.

[11] D. Ren, M. Hou, & H. Li, "The 19th International Conference on Industrial Engineering and Engineering Management", 19th Int. Conf. Ind. Eng. Eng. Manag. Eng. Econ. Manag, pp. 1–13, 2013.

[12] Y.X. Qin, M.D. Zhou, Y. Yong, "Reliability, maintainability, supportability studies", National Defense Industry Press, Beijing, 112, 2002.

[13] A. Elsayed, "Reliability engineering", Vol. 88, John Wiley & Sons, 2012.

[14] J. Moubray, "Reliability-Centered Maintenance", Industrial Press, Inc. 2nd ed. 1997.

[15] R. K. Sharma, & S. Kumar, "Performance modeling in critical engineering systems using RAM analysis", Reliab. Eng. Syst. Saf., vol. 93, no. 6, pp. 913–919, 2008.

[16] R. Dekker, "Applications of maintenance optimization models: a review and analysis", Reliab. Eng. Syst. Saf., vol. 51, no. 3, pp. 229–240, 1996.

[17] H. A. Wang, "Survey of maintenance policies of deteriorating systems", European journal of operational research, Eur. J. Oper. Res., vol. 139, no. 139(3), pp. 469–489, 2002 .

[18] A. C. Márquez, "The Maintenance Management Framework: Models and Methods for Complex Systems Maintenance", Springer Science & Business Media, 2007.

[19] B. S. Blanchard, "Logistics engineering and management", Prentice Hall, 2004.

[20] Ungar, L. Y., "An economics model of supportability through design for testability", AUTOTESTCON (Proceedings), pp. 74–79, 2007.

[21] Smiljanic, R. A. Y., Klevatt P. , & D. Steinmeyer, "Delta Clipper vehicle design for supportability", Aerosp. Des. Conf., 1993

[22] C. Smith & J. Knezevic, "Achieving quality through supportability - part I: concepts and principles", J. Qual. Maint. Eng., vol. 2, no. 2, pp. 21–29, 1996.

[23] C. Smith, "Achieving quality through supportability - part II – mathematical modeling", Quality, vol. 2, no. 3, pp. 37–48, 1996.

[24] C. E. Ebeling, "An introduction to reliability and maintainability engineering", Waveland Pr Inc, 2nd ed, 2009.

[25] Craig C. Sherbrooke, "Vari-Metric: Improved Approximations for Multi-Indenture, Multi-Echelon Availability Models", Operations Research Vol. 34, No. 2, 1986.

[26] V. D. R. Guide, & R. Srivastava, "Repairable inventory theory: Models and applications", Eur. J. Oper. Res., vol. 102, no. 1, pp. 1–20, 1997 .

[27] A. Díaz & M. C. Fu, "Multi-Echelon Models for Repairable Items: A Review. Decision & Information Technologies Research Works Collection", Digital Repository at the University of Maryland, 2005 .

[28] S. C. Graves, "A Multi-Echelon Inventory Model for a Repairable Item with One-for-One Replenishment", Management Science, Vol 31, n 10, pp. 1247-1256, 1985.

[29] Zamperini, M.B. & Freimer, M. 2005 A Simulation Analysis of the Vari-Metric Repairable Inventory Optimization Procedure for the U.S. Coast Guard. Proc. 2005 Winter Simul. Conf., 1692–1698.

[30] R. Minzhi, L. Yi, Li Hua, "Configuration model of partial repairable spares under batch ordering policy based on inventory state", Chinese Journal of Aeronautics, vol 27, pp. 558-567, 2014.

[31] K. Miettinen, "Nonlinear multiobjective optimization", Springer Science & Business Media, vol. 12, 2012.

[32] Marler, R. T., and J. S. Arora, “Survey of Multi-Objective Optimization Methods for Engineering.”, Structural and Multidisciplinary Optimization 26(6):, 369, 2004.

Inspection Optimization under imperfect maintenance performance

Alireza Ahmadi[1]; Iman Soleimanmeigouni[2]; Christopher Letot[3]; Jan Block[4]
[1]alireza.ahmadi@ltu.se; [2] iman.meigouni@ltu.se; [3]christophe.letot@umons.ac.be; [4]jan. block@ltu.se;
[1,2,4]Division of Operation, Maintenance and Acoustics, Luleå University of Technology, Luleå, Sweden.
[3]Machine Design and Production Engineering Unit, Research Institute for the Science and Management of Risks, University of Mons, Mons, Belgium.

***Abstract*— Scheduled maintenance and inspection development is one of the main requirements for emergency equipment and safety devices. These types of devices have hidden functions which are used intermittently or infrequently, so their failure will not be evident to the operating crew. The analytical model presented in this paper deals with the periodically tested units with overhauls (preventive maintenance) after certain number of inspections and a renewal after a series of overhauls. The cost based optimization method presented in this paper identifies the optimum interval and frequency of Failure Finding Inspection (FFI) and restoration. In the proposed model, repair due to failures found by inspection makes the unit As Bad As Old, and restoration/overhaul action rejuvenates the unit to any condition between As Good As New and As Bad As Old. As Good As New effectiveness also is considered for renewal action. It considers inspection and repair times, and takes into account the costs associated with inspection, repair, restoration, and also the cost of accidents due to the occurrence of multiple failure. The results show that when the unit is not under aging process, the optimal alternative for each inspection interval is the one with highest possible number of inspection without restoration. Finally, it is observed that when the cost of accident is quite high it is needed to perform inspections at smaller intervals to control the risk of accident.**

ISBN 978-91-7583-841-0

Stability analysis of radial turning process for Superalloys

Alberto Jiménez[1]; Fernando Boto[2]; Itziar Irigoien[3]; Basilio Sierra[4]; Alfredo Suarez[5]
[1]alberto.jimenezcortadi@tecnalia.com;
[1]Dept. of Industry and Transport, Tecnalia, Leonardo da Vinci 11, 01500 Miñano, Spain
[2]Dept. of Industry and Transport, Tecnalia, Paseo Mikeletegi 7, 20009 Donostia, Spain.
[3,4]Dept. of Computer Science and Artificial Intelligence, University of the Basque Country, 20018 Donostia, Spain
[5]Advanced Manufacturing Department, Tecnalia, Paseo Mikeletegi 7, 20009 Donostia, Spain.

[1, 2, 5] Tecnalia R&I
[3, 4] University of Basque Country
Donostia, Spain

***Abstract*—Stability detection in machining processes is an essential component for the design of efficient machining processes. Automatic methods are able to determine when instability is happening and prevent possible machine failures. In this work a variety of methods are proposed for detecting stability anomalies based on the measured forces in the radial turning process of superalloys. Two different methods are proposed to determine instabilities. Each one is tested on real data obtained in the machining of Waspalloy, Haynes 282 and Inconel 718. Experimental data, in both Conventional and High Pressure Coolant (*HPC*) environments, are set in four different states depending on materials grain size and Hardness (*LGA*, *LGS*, *SGA*, and *SGS*). Results reveal that PCA method is useful for visualization of the process and detection of anomalies in online processes.**

***Keywords*—Stability detection, Radial turning, PCA.**

I. Introduction

The common use of planes engines, are growing the demand of materials with high mechanical resistance at high temperatures, what has incremented the development of superalloys. These materials are lighter and smaller than usually used alloys, what enable to reduce the fuel consume.

Superalloys are also able to support high temperatures and they have a high mechanical resistance, what fit them perfectly in the aerospace sector.

These materials usually need to be machined and due to their strength, they are considered as hard turning materials. In this case, a radial turning process is applied to three of the wide variety of superalloys that can be founded.

Radial turning is a machining process that removes material from the outer diameter of a rotating cylindrical alloy. The tool is moved linearly parallel to the rotation axis. Turning is a complex process which involves various physical phenomes such as plastic deformation, contact friction, etc. Hard turning refers to a material with high hardness, such as superalloys, which usually are heat treated before they are performed. These materials produced bigger wear and forces during the process due to their hardness.

Industries which work with radial turning processes have always been looking forward to production optimization. Improving the tool life is one of the usual topics in this area, what is obtained by reducing tool wear. Choudhury and Srinivas [7] and M. Murua [1] predicted tool wear using some regression models, while Tugrul and Yigit [8] used also neural networks for tool wear and surface roughness, which is another prediction topic in machining processes. Tool wear also depends on the alloy hardness, cutting parameters as Sardinas [6], Sahu [3] and Bonilla exposed on their articles, the cooling conditions [4], where A.Suarez concludes that HPC produces less wear than conventional lubrication, grain size [5] [2], where Olovsjo demonstrate notch wear predominance for materials with large grains (LG) against materials with small grain (SG). Kumar [13] optimize a multi-objective process for laser cutting process of superalloys using PCA method. Parameters exposed, also affect to the cutting forces and the final quality. According to the forces, R.S.Pawade [16] demonstrates that larger cutting forces generated poor surface finish and extensive surface damage and Cedergren [17] deduce the importance of considering work material microstructure when studying cutting forces. In this paper, stability is used as a basic parameter to improve radial turning processes with experimental data.

II. Experimental Analysis

In this paper a study of the stability of a radial turning process for superalloys is done. This process is based on the forces that the ceramic tool supports during the turning against three different superalloys. All of them are Nickel-based superalloys, which differ from the others in the rest of the chemical components. These superalloys are Inconel 718, Waspalloy and Haynes.

Mentioned materials can be found in wide variety states, which are set by thermal heating and cooling processes such as annealing, which is used in this study. Annealing is a process that induces microstructural changes such as recrystallization and grain growth [11]. An alloy treated at high temperature and for big annealing periods, modifies the structure causing a recrystallization. Grain growth can also be obtained by heat treatment. This is achieved by controlling the times of heating and cooling.

Depending on the grain size, two states have been obtained for this study, which are called Large Grain (LG) and Small Grain (SG). In Fig.1 it can be shown the difference between these two states. In terms of strength, Aged (A) and Solutioned (S) are differentiated, where Aged is called to the stronger one.

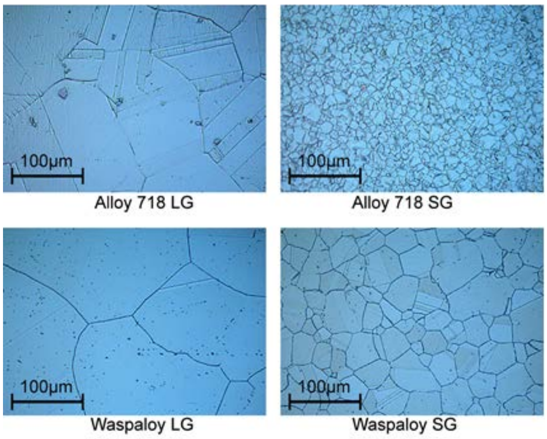


Fig. 1. Difference between LG and SG.

Superalloys are also lubricated to reduce the high temperature and forces generated during the machining process. In this case, conventional lubrication of 6 bar and High Pressure Coolant (HPC) of 80 bar are chosen to achieve that temperature reduction. In radial turning processes, test is called to a determined number of passes through the workpiece. A transition of the tool from the surface of the superalloy until the centre of it is considered as a pass.

A test is made by an accumulation of passes and on each material the number of passes is not the same. In the case of Inconel 718 and Waspalloy, 6 passes are done to complete a test, while 4 passes are needed for Haynes. In the Table I, is shown the number of test measured for each superalloy.

TABLE I. NUMBER OF TESTS

		SGS	SGA	LGS	LGA
Inconel	***Conventional***	2	2	2	2
	HPC	X	3	X	2
Haynes	***Conventional***	X	X	2	2
	HPC	X	X	1	1
Waspalloy	***Conventional***	2	2	1	1
	HPC	1	1	1	1

Other parameters are also set on this study. These parameters are the same for every material during the experiments: entering angle (91º), rake angle (0º), inclination angle (0º), nose radius (0.4 mm), cutting speed (30 m/min), feed rate (0.1 mm/rev) and cutting depth (2 mm).

While one of the passes is running, the force between the tool and the superalloy is measured, (F). Resulting cutting force breaks down into 3 components called Fx, Fy, Fz (see figure 3) and this forces are measured using sensors, which are perpendicular each other. Fy force, has the direction of the cutting speed, Fx is in the radial direction and Fz is the orthogonal direction. When a pass is finished, 2 different tool wear are also measured, Flank wear and Notch wear. The Notch wear consist on the wear that appears where the tool and the superalloy are in contact. However, Flank wear is measured in 9 different points into the tool just after the Notch one. In Fig.2 is shown how the tool seems when a pass is made.

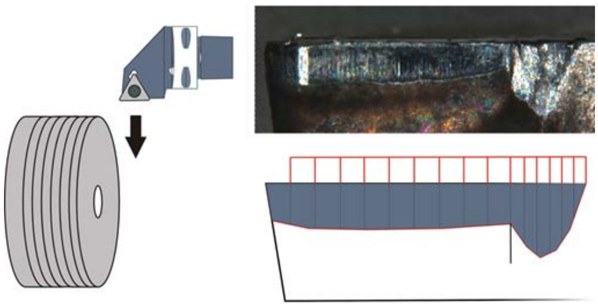


Fig. 2. Wear measurement.

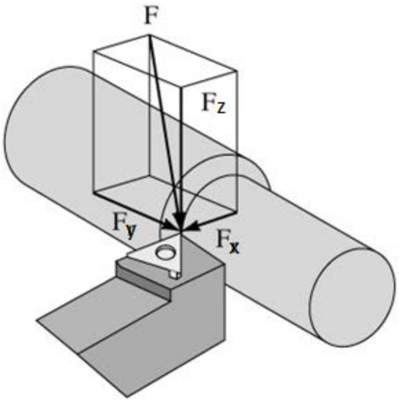


Fig. 3. Force components.

In Fig.4, forces from the 3 components are represented. These signals are a particular example taken from one pass, but in general, the signals obtained due to any of the passes has the same appearance. In this paper, force signals where analyzed to obtain the stability for each superalloy on each state and lubrication.

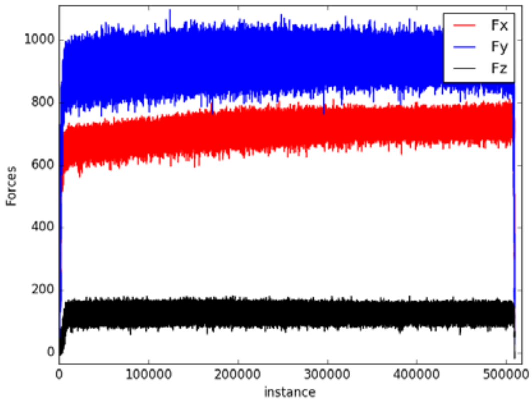


Fig. 4. Measured forces for a pass in the 3 components.

III. EXPERIMENTATION

In this section the experimentation done is exposed, which is based on the forces and achieves to classify instability for every state. A filter to the force signal is done, where the initial and the final part of the signal are deleted. This filter is made to remove the warm-up and the stop of the process, which are not going to appear in the real machining processes. Let us call xi=(x1,…,xt), yi=(y1,…,yt), zi=(z1,…,zt) the three components of the filtered signal in the ith pass, where i=(1,…,6). In figure 5, the filtered signal is shown.

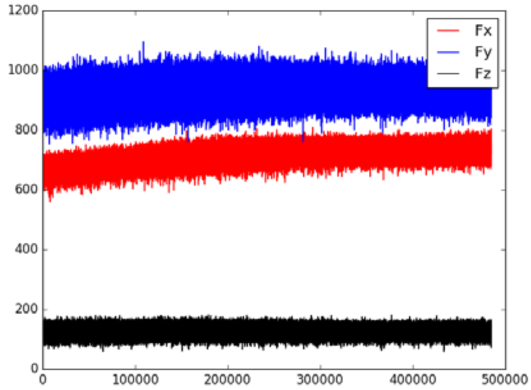


Fig. 5. Filtered forces for a pass in the 3 components

Two different methods are exposed. On one side, the first pass of every test stability is studied. Each force component is studied independently and then mixed. A robust three-sigma edit rule is used, which was proposed by Maronna [9]. This test is applicate following the next steps. Firstly median of each force is calculated, which is the center value of the sorted data Mex; Mey; Mez. Next step is to calculate a vector of the standard deviation from the median.

$$\mathbf{F}_{xi}\text{-}M_{ex}=V_x \tag{1}$$

$$\mathbf{F}_{yi}\text{-}M_{ey}=V_y \tag{2}$$

$$\mathbf{F}_{zi}\text{-}M_{ez}=V_z \tag{3}$$

Where Fzi is the ith value of the force in component z. Median is extracted from those vectors and divided by 0.6745.

$$\text{MADNx}= \text{Median}(|F_{xi}\text{-}M_{ex}|)/0.6745 \tag{4}$$

$$\text{MADNy}= \text{Median}(|F_{yi}\text{-}M_{ey}|)/0.6745 \tag{5}$$

$$\text{MADNz}= \text{Median}(|F_{zi}\text{-}M_{ez}|)/0.6745 \tag{6}$$

Finally, a quantitative value is obtained to classify the stability, which is the value of dividing the maximum of (1) with (2).

$$P_x=\text{Max}(|F_{xi}\text{-}M_{ex}|)/\ \text{MADNx} \tag{7}$$

ISBN 978-91-7583-841-0

$$P_y=Max(|F_{yi}-M_{ey}|)/ MADNy \quad (8)$$

$$P_z=Max(|F_{zi}-M_{ez}|)/ MADNz \quad (9)$$

Px, Py, Pz are then limited by an expert to expose when is considerable stable and when is unstable.

On the other side, the stability of the first pass is analyzed while the machining process is running. This achieve is obtained in three steps. Firstly, a statistic technique (PCA) is used to reduce the dimension from the 3 force component to only two of them, so that it can be seen easily. PCA is based on combining input components to obtain new ones (C1; C2) that are linearly independent between them and maintain as much original information as possible. This technique is used many times in the literature due to its easy way of programming. Some of the applications of this technique are to achieve objectives such as surface roughness [14], structural damage diagnosis[15], multi-objective optimization [13].

In this case PCA is applied to the first pass of the test to obtain a dimensional reduce which enable to represent the variables into a graphic, from 3 components (Fx, Fy, Fz) to 2 new axis(C1; C2). After representing data into the new axis the centroid of the pass is calculated.

$$O_1=\Sigma C_{1i}/N \quad (10)$$

$$O_2=\Sigma C_{2i}/N \quad (11)$$

Where O1 and O2 are the values of each axis of the centroid. After that, other passes are represented on the same principal components, so the progress of the test can be seen graphically. Instead of classifying graphically, a quantitative measure is calculated, which is the maximum distance from any of that pass point to the centroid of the first pass.

$$D=Max(\sqrt{((C_{1i}-O_1)^2+(C_{2i}-O_2)^2)}) \quad (10)$$

These distances are represented for each test, what would provide the progression of this value during the machining process. A test is considered unstable if the distance for any of the passes is 200% times the value obtained for the first pass

IV. RESULTS

As it was mentioned in section III, the first step is to filter the signal. Initial and final parts are removed. Figure 5 shows how the signal remains after removing those parts. This filter had gone through the signals of the study, which had been used after the filtering process for the rest of the methods.

Results are exposed for tests classified as stable and unstable. These tests are presented on table I. In figure 6, first pass of a test is shown.

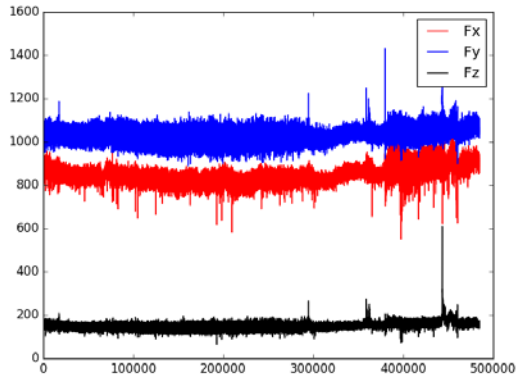


Fig.6. First pass of Waspalloy SGS Conventional.

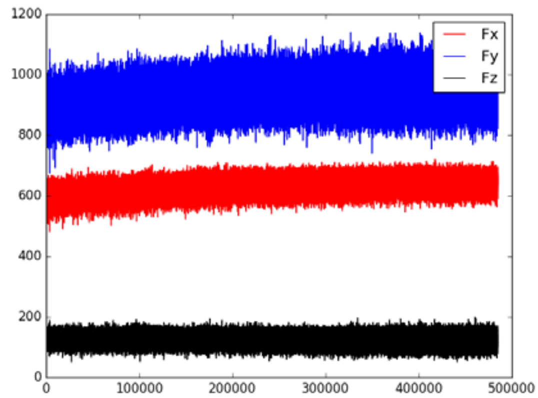


Fig. 7. First pass of Haynes LGA HPC.

A. *Stability by the force*

In this section, classification for the first pass of the test is obtained. To achieve it, some quantitative values have been taken from each of the force component (Fx, Fy, Fz). Chosen variables are the median of the filtered force, maximum distance between mentioned median and measured forces and the median value of all the distance measured. 3 values are calculated for each force component. From all the values obtained for each pass, a combination of them is made for getting a quantitative value, which classifies the tests.

The measure chosen is the mean value of the 3 components called force proportion, which is referred to the maximum distance value divided by the median distance value. This quantitative measure classifies between stable and unstable tests, where stable will be when a low value appeared an unstable when a great value is obtained. In this case, 7.33 is obtained for Haynes LGA HPC and 26.52 for Waspalloy SGS Conventional.

This results obtained confirms the hypothesis of detecting instability with the force. Validation of this method should be obtained by testing with more data. This process can also be used into the rest of the passes of each test, what could provide a good reference to determine when to stop the machining process. The main problem of this method is that this method is not able to be used into online processes. This objective is solved by using the method exposed in IV-B.

B. Stability in function of the first pass

In this section the stability of the test is studied based on its first pass. Principal Component Analysis (PCA) is applied to the first test and the centroid of the result is obtained before overleaping the rest of the passes PCA. PCA analysis has been realized to reduce the number of variables to 2 dimension, so that the result can be graphically exposed.

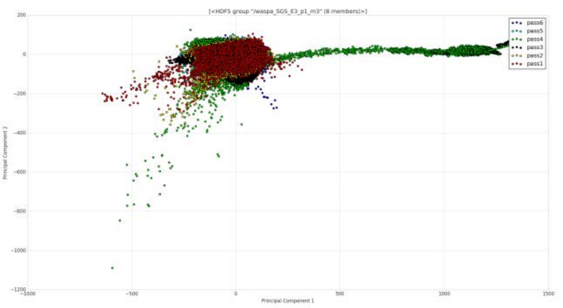


Fig. 8. Waspalloy SGS Conventional 6 passes.

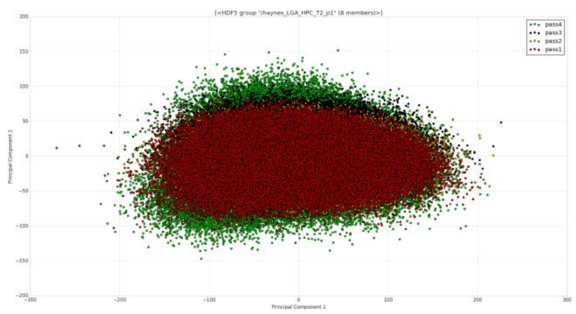


Fig. 9. Haynes LGA HPC 4 passes.

Figure 8 and figure 9 shows the PCA for both cases of Waspalloy and Haynes respectively. In both graphics, the full test in shown, where each of the passes has a different colour to be appreciated. Fixing on Figure 8 and figure 9 it will be possible to classify each test easily. Note that 4th pass of Waspalloy is gone far through the first principal component, while Haynes remains in the same space every pass. Instead of doing it graphically, a quantitative measure is calculated. Measured value consists in the maximum distance measured for each pass to the centroid of the first pass. This measure can also be obtained online when the centroid is calculated. A very useful system can be obtained with this method to detect anomalies while the process is running. When a test distance increase heavily, it will be considered that this test is instable. In figure 10 and figure 11, the maximum distance for each pass is represented.

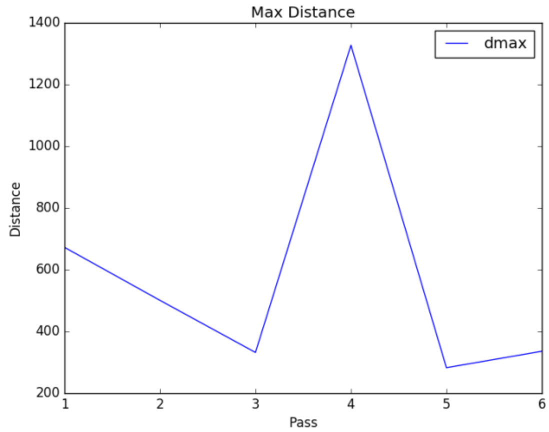


Fig. 10. Maximum distance to the centroid of the first pass for each pass in Waspalloy SGS Conventional.

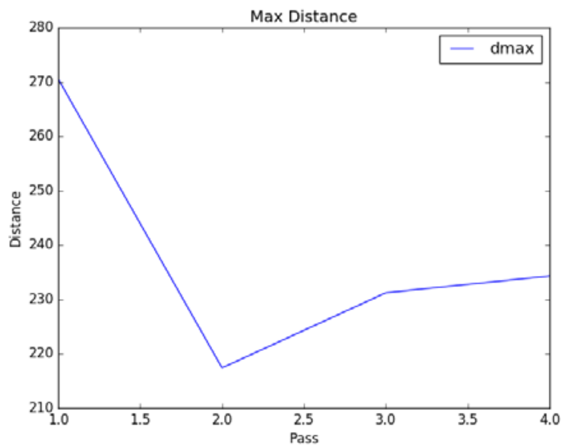


Fig. 11 Maximum distance to the centroid of the first pass for each pass in Haynes LGA HPC.

It can be seen that in this case, Waspalloy has distances between 600 and 800 while Haynes has no measure bigger than 300. This result confirms the theory of the stability for Haynes LGA HPC test and instability for Waspalloy SGS Conventional.

ISBN 978-91-7583-841-0

V. CONCLUSIONS AND FUTURE WORKS

Development of stability detection models for machining processes using forces is a difficult task due to all the factors that have impact on the force measured. In this paper, two different models have been exposed:

On the first method, the median values are calculated, what means that a range of data is needed to do it, what makes it an offline method. This method can be used not only for the first pass but also for all the passes of each test, providing a stability test when a pass is finished.

On the other method, an intuitive 2 dimension representation of forces is done, what makes easier to understand the relationship between forces in different components. The main problem of this method is that it is supposed that the first pass of each test is stable, what means that if the first pass is instable, this test could bring a stability result that will not be according to the reality.

That reason makes the development of a new method necessary, which could be a combination between both explained methods in terms of detecting stability. This will consist in the use of the first method to detect the stability of the first pass and when this stability is confirmed, apply the second method online in order to find any instability that would activate an alarm to stop the machining process. This machining process can not be stopped in any point, it is necessary to maintain machining until a specific point where stopping the process do not mean breaking the material.

In this study, two methods had been applied to two different tests that where classified previously. In order to validate these algorithms, more tests should be used, what would be done in future work when the rest of the tests are classified as stable or instable.

REFERENCES

[1] M.Murua, “Application of Advanced Regression Methods for Wear Prediction of Superalloys”, MT (2016).

[2] S. Olovsjo and A. Wretland, “The effect of grain size and hardness of wrought Alloy 718 on the wear of cemented carbide tools”, Wear (2010).

[3] Supriya Sahu and B.B. Choudhury, “Optimization of Surface Roughness using Taguchi Methodology & Prediction of Tool Wear in Hard Turning Tools”, materialstoday (2015).

[4] A. Suarez, A. Wretland, “Influence of Cooling conditions on the Carbide tools Wear in the Turning of Inconel 718”, (2015).

[5] S. Olovsjo and A. Wretland, “The effect of grain size and hardness of Waspaloy on the wear of cemented carbide tools”, The international Journal of Advanced Manufacturing Tecnology (2010).

[6] R. Sardias, M.Santana, “Genetic algorithm-based multi-objective optimization of cutting parameters in turning processes”, Engineering Aplications of Artificial Intelligence (2006).

[7] Choudhury, SK and Srinivas, P, “Tool wear prediction in turning”, Journal of Materials Processing Technology (2004).

[8] Ozel, Tugrul and Karpat, Yigit, ”Predictive modeling of surface roughness and tool wear in hard turning using regression and neural networks”, International Journal of Machine Tools and Manufacture (2005).

[9] R.A.Maronna, R.D.Martin, V.J.Yohai, “Robust Statistics. Theory and Methods”, Wiley series in probability ans Statistics (2006).

[10] S. Terashima, K. Takahama, “Recrystalization of Sn Grains due to Thermal Strain”, Materials Transaction (2004).

[11] Y.B. Lee, D.H. Shin, “Effect of annealing temperature on microstructures and mechanical properties of a 5083 Al alloy deformed at cryogenic temperature”, Scripta Materialia (2004).

[12] Hernández, A. E. B., Beno, T., Repo, J., & Wretland, A. “Integrated optimization model for cutting data selection based on maximal MRR and tool utilization in continuous machining operations”. CIRP Journal of Manufacturing Science and Technology, 13, 46-50. (2016)

[13] Avanish Kumar Dubey, Vinod Yadava, “Multi-objective optimization of Nd:YAG laser cutting of nickel-based superalloy sheet using orthogonal array with principal component analysis”, Optics and Lasers in Engineering, (2008)

[14] Gupta, M., & Kumar, S. “Investigation of surface roughness and MRR for turning of UD-GFRP using PCA and Taguchi method”. Engineering Science and Technology, an International Journal, 18(1), 70-81. (2015).

[15] Yan, A. M., Kerschen, G., De Boe, P., & Golinval, J. C. “Structural damage diagnosis under varying environmental conditions—part II: local PCA for non-linear cases”. Mechanical Systems and Signal Processing, 19(4), 865-880. (2005).

[16] R.S.Pawade, Suhas S. Joshi, P.K.Brahmankar, M Rahman“An investigation of cutting forces and surface damagein high-speed turning of Inconel 718.” Journal of Materials Processing Technology, 192-193(2007).

[17] S. Datta, G. Nandi, A. Bandyopadhyay, P.K. Pal, Application of PCA based hybrid Taguchi method for multi-criteria optimization of submerged arc weld: a case study, Int. J. Adv. Manuf. Technol. 45 (3 e 4) (2009) 276 e 286.

ISBN 978-91-7583-841-0

Chapter 6: Fleet Management

ISBN 978-91-7583-841-0

Identifying the sharing needs, problems and benefits of fleet data with the Shelo model

Lasse Metso[1]; Salla Marttonen-Arola[2]; Maaren Ali-Marttila[3]; Sini-Kaisu Kinnunen[4]; Timo Kärri[5]
lasse.metso@lut.fi; [2]salla.marttonen-arola@lut.fi; [3]maaren.ali-marttila@lut.fi; [4]sini-kaisu.kinnunen@lut.fi; [5]timo.karri@lut.fi

[1,2,3,4,5] Industrial Engineering and Management, LUT School of Business and Management, Lappeenranta University of Technology
Lappeenranta, Finland

***Abstract*—In this paper, the SHELO model is used for understanding the most critical data and information management problems and opportunities in the fleet environment. Due to the scattered nature of fleets and the data related to them, there is extensive untapped potential in processing and upgrading the accumulated fleet data into knowledge that can be used in decision making. So far inter-organizational data sharing has not been widely adopted in practice, and thus the full possibilities of fleet management are not yet known.**

In this paper, the data has been collected by interviews of people from 4 different divisions of an original equipment manufacturer, and from 3 customer companies who use the product. The first problem identified was who owns the data collected by the product. If the supplier could get this data, it could develop the product and possibly analyse the need of maintenance on the fleet level. A group of similar kinds of assets can be viewed as a fleet, and there are various advantages when the data related to the fleet of assets can utilized in asset management. Currently the supplier cannot utilize the fleet data to these purposes. The extent of data sharing is now considered case by case. There are no clear rules to sharing data, but the companies can see the potential advantages.

In order to improve fleet management practices, and information and data sharing needs, the problems and benefits are analyzed with the SHELO model. Identifying the problems systematically is an undeniable prerequisite for preventing them.

Keywords

Information management, data management, data sharing, fleet, SHELO, qualitative data analysis

I. Introduction

The purpose of paper is to identify the data sharing needs, problems and benefits in the fleet environment. A fleet can be seen as a group of similar kinds of assets. Generally, the term fleet has been associated with aviation and navy contexts, but other asset groups (e.g. industrial production machinery and equipment) can also be considered as fleets, and similar kinds of management practices can be applied [1,2]. The technical and economic data on geographically scattered fleets is vast, multifaceted, and usually fragmented to various companies. It is not feasible for each company to process all of the data by themselves. Hence, data sharing would have several positive impacts on business, e.g. through motivating collaborative decision making, increasing transparency from the provider side etc. However, companies are worried about sharing too much data.

The SHEL model has been widely used in airplane accident investigations and in aviation maintenance to identify the causes of accidents systematically. The SHELO model [3] has been developed from the SHEL model. With the SHELO model, possible problems, threats and potentials are classified in order to elicit proposals for improvements. The SHELO model has been used previously to find out the most important knowledge management problems in industrial maintenance. The main problems are information unavailability, information sharing, communication, and information integrity. The SHELO model was developed as a framework for analyzing maintenance. It allows categorizing identified problems to work out solutions to them. The SHELO model takes interactions also without human influence into account. The SHELO model has been used successfully to analyze individual assets in industrial maintenance. In this paper, the SHELO model is used to analyze maintenance problems in a fleet.

Companies have usually a view only to the fleet of assets they own. However, a manufacturer or an equipment provider has knowledge of their products but the data and information is partly fragmented to the customers who have purchased the assets. Therefore the equipment provider has rarely access to all data of the fleet of assets that they have produced. Instead of just considering assets as a singular objects, considering them as a fleet can generate certain benefits, such as fault detection, resource optimization, and product or service development [4, 5]. Although the benefits have been somehow acknowledged, there are issues that hinder the exploitation of fleet-wide data. The challenges are mostly related to the availability of the data. The data is not shared smoothly between companies, but there might be challenges in transferring the data inside a single company as well. In order to utilize the fleet data to fleet management purposes, the challenges related to data sharing need to be identified and solved.

II. Barriers and Benefits of Sharing Data

The basic hypothesis of open data is that more intensive and creative use of data can generate new value. The information is understood as given, used uncritically, and trusted without verification. However, open data could be collected or created for other purposes. Open data has potential value, but also risks for validity, relevance, and trust. Open data is context- and time-dependent. Taken out of context, open data loses meaning, relevance and usability. Data collection, management, access, and dissemination practises have an effect on the quality of data. Data quality is often used to mean accuracy, but information quality is a much wider concept. [6]

Janssen [7] have identified a great number of benefits of open data. They cluster the benefits in (1) political and social, (2) economic, and (3) operational and technical benefits. Political and social benefits have been merged because they are difficult to separate. E.g. the following benefits are recognized as political and social benefits: transparency, more participation, creation of trust, access to data, new services, and stimulation of knowledge development. Economic benefits are economic growth, stimulation of competitiveness, new innovations, improvement of processes/products/services, new products and services, availability of information, and creation of adding value to the economy. Operational and technical benefits are reuse of data, creation of new data by combining data, validation of data, sustainability of data, and access to external problem-solving capacity.

Barriers to open data have been identified at the institutional level, in the task complexity of handling the data, the use of open data, participation in the open-data process, legislation and information quality, as well as at the technical level.

Institutional barriers are:

- unclear values (transparency vs. privacy),
- no policy for publicizing data,
- no resources, and
- no process for dealing with user input.

Task complexity includes:

- lack of understanding of the potential of data,
- no access to original data,
- no explanation of the meaning of data,
- information quality,
- duplication of data,
- no index on data,
- complex data format and dataset, and
- no tools for support.

Barriers in use and participation are:

- no time,
- fees for the data,
- registration to download data,
- unexpected costs, and
- lack of knowledge to handle data.

Legislation barriers are:

- privacy,
- security,
- license and limitations to using data, and
- agreements.

Information problems are:

- lack of information,
- lack of accuracy of information,
- incomplete information,
- non-valid data,
- unclear value,
- too much information,
- information missing, and
- similar data stored in different systems yielding different results.

Technical barriers are:

- data not in a well-defined format,
- absence of standards,
- no support,
- poor architecture of data,
- no standard software,
- fragmentation, and
- no systems for publicizing data. [7]

The barriers can be naturally grouped in different ways, e.g. Saygo and Pardo [8] define barriers according to four perspectives: (1) technological, (2) social, organizational, and economical, (3) legal and policy barriers, and (4) local context and specificity. Barry and Banister [9] divide the barriers to (1) economic, (2) technical, (3) cultural, (4) legal, (5) administrative, and (6) risk-related barriers.

More similar kinds of classification can be found in the literature under slightly different names. However, the list presented by Jansen [7] covers the topic extensively.

III. Research Design

The research methods used in this paper include seven interviews for data collection and qualitative means to analyze the interview data. As shown in Figure 1, the interview data was collected from 4 different departments of an original equipment manufacturer, and from 3 customer companies who use the product. These interviews were originally conducted to identify and develop the offering of products and services. The secondary data answers were interesting, so the authors decided to analyze the answers with the SHELO model.

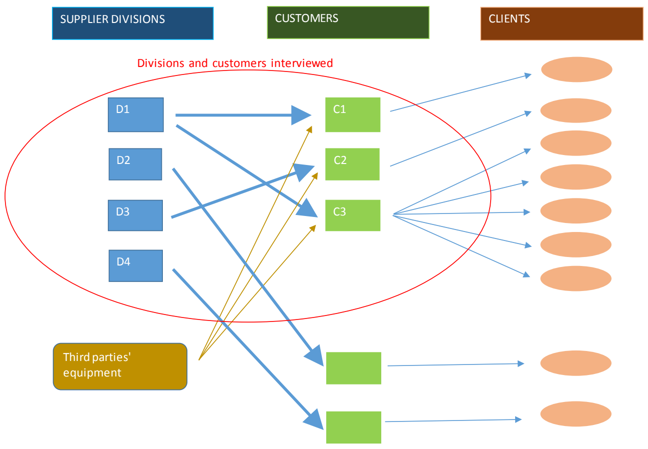


Fig.1. Overview of the fleet of main products/services.

Customer 1 uses the products bought from division 1 to operate their own equipment. Customer 2 uses equipment and services from supplier division 3 to make their own products which are sold to a limited number of clients. Customer 3 has a lot of clients to whom they sell the products. All customers have also third parties' equipment, which makes the maintenance services much more challenging. The clients and third party suppliers were not interviewed. Divisions 2 and 4 sell products mainly to other customers than the ones that were interviewed.

The interviews were semi structured theme interviews. Only the divisions and customers inside the red oval shown in Figure 1 were interviewed. The answers were coded by using the SHELO model elements listed in Table 1. The data was thematically analyzed with NVivo version 10 software. The interviews and coding were done in Finnish, and the findings were translated to English.

Table 1. Content of SHELO model elements [3].

Element	Content
S - Software	Maintenance procedures Installation instructions Plans and schedules (Automated) algorithms of condition monitoring Regulations Warranty clauses
H - Hardware	Tools Materials Objects Equipment Computers, IoT, Data Buildings/ physical infrastructure
E - Environment	Environmental context Temperature Noise Economic environment
L - Liveware	Humans (operators, maintenance technicians, managers, designers, etc.) People interactions Personal attitude Skills and education Availability of personnel
O - Organization	Organizational structure

It should be noted that software and hardware do not mean the same in the SHELO model as in computer science. These terms are used because they were selected for the original SHEL model [10].

ISBN 978-91-7583-841-0

IV. Findings – the SHELO model in the fleet

Applying the SHELO model in the interview data showed that H, H-H, H-L, H-O, L-O, and O-O themes got the most hits in the codes. There were no codes in the elements S-S, S-l, and E-E. One explanation for this can be in the interview questions, which did not ask about instructions, procedures, plans, schedules etc. Another explanation is that the persons in the interviews were managers or directors, and they do not pay attention to these matters. If there had been e.g. mechanics in the interviews, these issues would have probably been considered. Codes to the categories are presented in table 2, e.g. code H means that it is clearly a tool-related issue. Code H-H means that it is related to both tools and materials, or there can be more than one party, e.g. a maintenance service provider and a material supplier.

TABLE I. The SHELO dimensions and number of codes for each category.

		S		H		E		L		O	
S	5	S-S	0								
H	33	S-H	3	H-H	15						
E	2	S-E	1	H-E	5	E-E	0				
L	3	S-L	0	H-L	46	E-L	3	L-L	6		
O	2	S-O	9	H-O	18	E-O	4	L-O	12	O-O	21

Appendix A contains tables 3 – 19. The tables show the results that emerged when coding the interview answers to the SHELO model concepts. Tables 3 – 19 are in another file, which is linked to this document. The data is stored as a pdf file (a pdf reader is needed to open the data).

Appendix A

Findings in categories E, E-L, and E-O

Tables 3, 4 and 5 present environmental issues and possibilities. The most interesting matter in this part is the sharing economy and the companies' view that the technology is already mature enough. *"Technology is available to collect big data but standards are missing."* The sharing economy could be developed by adding transparency to data sharing and with other activities in a multi-company environment. *"In the future transparency can be seen as **sharing economy**"*. The big question is how it can be implemented in a multi-company environment with a positive attitude." The regulations of maintenance and the missing of standards to share data were presented as barriers. *"There are **barriers** for changing processes (e.g. in oil industry) because regulations specify the time between maintenance. And that's why health monitoring is not realistic to implement."*

The main **benefits or potential** of sharing data in categories E, E-L, and E-O are:

- technology
- transparency,
- support to decision making

The main **barriers** to sharing data in categories E, E-L, and E-O are:

- regulations
- missing standards

Findings in categories H, H-E, H-H, H-L, and H-O

Tables 6-10 present hardware (tools, materials, computers, data, etc.) -related codes. The most hits in codes are in these elements, which is natural because computers and data, as well as Internet of Things (IoT) belong to this part. The questions in the interviews were focused to this kind of topics. The management of big data was found to be a problem. *"The amount of process data is big, it can be used in something else than just process control."* Also data from other systems is not accurate enough and it is difficult to use. *"Data from ERP is not accurate enough."* The ownership of data was considered important, and when data sharing was needed it was done case by case. *"The ownership of data is important. The customer owns the data and wants to own it in the future."* Clear rules to share data do not exist, so a time-consuming way to share data was used. The process to decide when to share data is not defined in companies. Despite the problems in sharing data, the advantages were understood: new business models, cost savings, the advantages of big data, remote control, better maintenance services, support to decision making, development of automation systems, and combined data from different systems. *"Better data management helps in decision making and in maintaining."* Also clear fleet thinking was noticed: *"In health monitoring the decisions are made based on one equipment. There is potential to analyze the changes by comparing the whole group of the same kind of equipment."* Even inside the same company there were problems in sharing data. *"Reports in the service business are not shared in divisions. Every division has its own reports, and service data is not easy to share."* Also the basic idea of data sharing was missing: *"The barriers to share data are lack of knowledge and insufficient grounds of value added by sharing data. The **win-win** situation is not understood."*

The main **benefits or potential** of sharing data in categories H, H-E, H-H, H-L, and H-O are:

- transparency enables new business
- IoT will help data sharing
- data sharing potential is known

ISBN 978-91-7583-841-0

The main **barriers** to share data in categories H, H-E, H-H, H-L, and H-O are:

- the ownership of data
- data quality
- technical problems in data collection
- defining which data is difficult to monitor
- data architecture
- the amount of big data
- data facilitator missing
- lack of knowledge, win-win not understood

Findings in categories L, L-L, and L-O

In tables 11 – 13 there are L findings, which are related to interaction between people or their attitudes and skills. Most of the findings concern developing a new way to do something. *"At first systems and tools were sold as a product, but then IoT made it possible to sell them as a service. The demand increased a lot." "There is need to consider the value of service to the customer. Different data from divisions can be combined and new services can be offered."* There are proposals to change something or to do something in a new way, and people may need new skills to use the new methods. E.g. in a fleet, comparing all ships together may give an interesting perspective to comparing maintenance data and details. *"In the fleet the customer wants to compare all ships. Of course there is a challenge when the ships are of different ages. With new ships it is possible to compare different details between the ships." "To compare many customers' ships is interesting. Especially operation data and maintenance data are interesting things."*

The main **benefits or potential** of sharing data in categories L, L-L, and L-O are:

- IoT makes it possible to sell better services
- combining data from different systems
- big data makes it possible to compare the customer's equipment at the same time (fleet)

The main **barriers** to sharing data in categories L, L-L, and L-O are:

- limitation of ERP systems
- rules are not clear in the offerings
- co-operation with other division is difficult when the work load is heavy
- big data is shared with divisions only case by case

Findings in categories O, and O-O

Organizational findings are presented in tables 14 and 15. The main findings are related to sharing economy, risk and revenue sharing, new ecosystems, and new earning models. *"In the future open data can be seen as a 'sharing economy', which will have a positive effect on the relationships between companies and service networks."* The findings can create new business models if they can be implemented in business. Data sharing can be developed, and it will help improve the whole fleet actions, or at least help service providers create new services to the fleet e.g. in the decision support process and data analysis. *"It is important to understand that the whole network influences the customer, not only the actions of the first or last company in the network." "Clients want both support for decision making and data analysis to be used in decision making."*

The main **benefits or potential** of sharing data in categories O, and O-O are:

- discussion with clients is possible at many levels
- clients want support for decision making and data analysis, which can be done only by sharing data

The main **barriers** to sharing data in categories O, and O-O are:

- support to handle third parties' equipment is missing
- the process of contacting the "right person" is not working
- clients want to invest once but are not willing to pay for monthly services

Findings in categories S, S-E, S-H, and S-O

The findings presented in tables 16 – 19 related to procedures, instructions, regulations, etc. did not have many hits in codes because people in the interviews were at a high level in hierarchy. *"The regulations will be tighter and more accurate than now, and that will set up new demands for data collection and presentation of data."* An interesting finding was that those companies that shared emission data openly were willing to accept tighter and more accurate regulations in emission. Their products are probably more eco-friendly than those of others. *"The clients in this business are interested in environmental issues. Some clients are ready to open data, and more openness is wanted."* Another interesting finding was that in the interviewed companies it was understood that new business models need new kinds of responsibility. New business is based on data sharing and new services, which need attention to collaboration and trust in business partners. *"Rules must have been agreed on with partners beforehand."*

The main **benefits or potential** of sharing data in categories S, S-E, S-H and S-O are:

- eco-friendly solutions
- new business models can be created

The main **barriers** to sharing data in categories S, S-E, S-H and S-O are:

- it is challenging to optimize a large fleet instead of one asset
- regulations and laws are unclear/local
- suspicion that someone will understand the data better and use it for their own purposes when data is openly shared

V. Conclusions and Future Work

This paper shows that the SHELO model could be used to analyze the problems in data and information management, as well as data sharing problems in asset management at the fleet level. The identified problems could be categorized for further analysis to classified problem areas and for identifying solutions. Problems in information management could be identified by analyzing the interview data with categories contained in the SHELO model.

Data sharing has a good potential in fleet management. Clients want both support for decision making and data analysis to be used in decision making. E.g. a fault situation causes a lot of problems for the company and its clients. It would be beneficial to know beforehand when the equipment could have problems, so that the client could be informed. The results of the study showed that data is shared with the maintenance staff but not with the customer, and also combinations of data from different data sources are not used properly. Better data management would help in decision making and maintaining. Customers will give out data when the services are important to them. However, there are barriers to data sharing:

- Lack of knowledge and insufficient ground of value added by sharing data. The win-win situation in fleet management is not understood.
- Data is shared only case by case when needed.
- Every division has its own reports and service data is not easy to share.
- Data contains confidential information which it is not allowed to share.

Now data is shared and combined only case by case when needed. The ownership of data is important. The customer owns the data and wants to own it in the future. Complexity is growing and it is difficult to notice important data automatically in the very large amount of collected data. Rules to sharing and combining data are missing even though the advantages of data sharing can be seen.

In the future, open data can be seen as a "sharing economy" which will work positively between companies and fleet service networks. Transparency in data sharing will enable new business models. New ecosystems are spoken of but when creating a new ecosystem, there is a need for a lot of dialog with different parties. New models can be based on data sharing, and that is why more responsibility is needed. If "risk and revenue sharing" is the target, also the supplier needs to give more and take more risks and responsibility in order to co-operate. Customers are more interested in environmental issues than before. Some customers are ready for open data, and more openness is wanted.

The maintenance playground is fragmented, it has a large number of actors, and they have their own systems which do not work together. The different systems hinder companies' possibilities and motivation to define a common platform. So far there is no evidence that a common platform could be implemented in the near future. Transferring into platform-based business where data sharing is of major importance would be a fundamental change for many industrial companies operating with traditional business models. Most companies have been cautious in adopting practices that would take them towards a common, inter-organizational platform. However, the real value of fleet management lies in integrating and analyzing data of various assets, although comparing assets of different ages is not always straightforward. In contract business there is also third parties' equipment, and this equipment needs a support network. On the network level, standardized ways of action are needed. A new research area would be to coordinate subcontractors and clients to create a new solution or a pilot to define new rules to sharing data.

A limitation of this research was that only divisions and some of their main customers were interviewed. This was because the interviewed parties had a part in a fleet project.

Future research is needed to widen the investigation to find out what clients and third party equipment suppliers need to be able to share data or use shared data. More research is needed to investigate the root causes to solve the problems found in this research and to create new methods to develop collaboration and data sharing rules in fleets.

References

[1] Leger, J-B. and Iung, B. 2012. "Ships fleet-wide management and naval mission prognostics: Lessons learned and new issues." In Proceedings of IEEE Conference on Prognostics and Health Management (PHM), pp. 1-8.

[2] Medina-Oliva, G., Voisin, A., Monnin, M., Leger, J.B. 2014."Predictive diagnosis based on a fleet-wide ontology approach." Knowledge-Based Systems, Vol. 68, pp. 40–57.

[3] Metso, L., Marttonen, S., Thenent, N., and Newnes, L. 2016. "Adapting the SHEL model in investigating industrial maintenance", Journal of Quality in Maintenance Engineering, Vol. 22 No. 1 pp. 62-80.

[4] Kinnunen, S-K., Marttonen-Arola, S., Ylä-Kujala, A., Kärri, T., Ahonen, T., Valkokari, P., and Baglee, D. 2016. "Decision Making Situations Define Data Requirements in Fleet Asset Management." Proceedings of the 10th World Congress on Engineering Asset Management (WCEAM 2015) Part of the series Lecture Notes in Mechanical Engineering, pp. 357-364.

[5] Kortelainen, H., Happonen, A., and Kinnunen, S-K. 2016. "Fleet Service Generation – Challenges in Corporate Asset Management." Proceedings of the 10th World Congress on Engineering Asset Management

ISBN 978-91-7583-841-0

(WCEAM 2015) Part of the series Lecture Notes in Mechanical Engineering, pp. 373-380.

[6] Dawes, Sharon S. 2012. "A realistic look at open data." Center for Technology in Government, University at Albany/SUNY Available at http://www. w3. org/2012/06/pmod/pmod2012_submission_38. pdf.

[7] Janssen, M., Charalabidis Y., and Zuiderwijk A. 2012. "Benefits, adoption barriers and myths of open data and open government." Information Systems Management 29, no. 4 pp. 258-268.

[8] Sayogo, D.S. and Pardo, T.A., 2013. "Exploring the determinants of scientific data sharing: Understanding the motivation to publish research data." Government Information Quarterly, 30, pp.S19-S31.

[9] Barry, Emily, and Frank Bannister. "Barriers to open data release: A view from the top." Information Polity 19.1, 2 (2014): 129-152.

[10] Edwards, E. 1972. "Man and machine systems for safety", Proceedings of British Airline Pilots Association, London, pp. 21

Appendix A

The elements of the SHELO model are (shown in Table 1):

- S Software: Maintenance procedures, Installation instructions, Plans and schedules , Automated algorithms of condition monitoring, Regulations, Warranty clauses
- H Hardware: Tools, Materials, Objects, Equipment, Computers, Internet of Things (IoT) Data building/ Physical infrastructure
- E Environment: Environmental context, Temperature, Noise, Economic environment
- L Liveware: Humans (operators, maintenance technicians, managers, designers, etc.), People interactions, Personal attitude, Skills and education, Availability of personnel
- O Organisation: Organisational structure

Codes C1, C2, C3, D1, D2, D3 and D4 used in the tables below are shown in figure1. D stand for the divisions and C for the customers interviewed.
The following tables 3 – 19 show the results that emerged when coding the interview answers to SHELO model concepts.

Table 3. E findings.

E
The electrical network is a main issue in maintenance. If there is no electricity, there is no action. C1
Need for international standardisation in protective relay. C1

Table 1. E-L findings.

E-L
The division has a lot of substance know-how and industry-specific selection of products which offer added value to customers. D2
Service orientation is essential to fulfil customers' needs. Complex services be developed with IoT. D2
There is a need for studying the customer value of services. There is a need to make better services together with other divisions. D2

Table 2. E-O findings.

E-O
The revolution of industry was seen as a risk in business. Product 1 sells well but product 2 not so well. Maintenance in product line 1 is at maximal level (usability). In product line 2 more risks can be taken in maintenance. C1
In the future, transparency can be seen as "**sharing economy**". The big question is how it can be implemented in a multi-company environment with a positive attitude. C2
There are **barriers** for changing processes (e.g. in oil industry) because regulations specify the time between maintenance actions. That is why it is not realistic to implement health monitoring. D2
The technology is available to collect big data but standards are missing. D2

Table 3. H findings.

H
Data from the process is of good quality, and possible problems arise usually with data produced by measuring equipment. C1
The amount of process data is big, and it can be used in something else than just process control. C1
There is enough data but the problem is that the data from ERP is not accurate enough. There can be errors in feeding information to the computer and exploiting it can be difficult. C1
The potential of big data potential is interesting, as well as knowing the risks. C1
Interruptions in production or minor errors cost different amounts, so it is difficult to calculate the potential of savings. C1
The ownership of data is important. The client owns the data and wants to own it in the future. C1

ISBN 978-91-7583-841-0

Sensors as the way of measurements are considered in order to find out new services in the future. Today there are phenomena which are impossible to measure with the present sensor, but there is potential to create something new based on this in the future. C2
CBM enables performing maintenance when the machines are not used, so it saves costs because extra stops are not needed. C2
It is difficult to evaluate how much of the improvement can be calculated to ICT / IoT and process developing when they are done concurrently. C2
IoT solutions should made for critical equipment because there is most potential for development. C2
Complexity is growing and it is difficult to notice important data automatically from very large amount of collected data. C2
The problem in IoT is to create a model in which data can be analysed and give right instructions as well as guide human actions to the right direction. C2
Transparency in data sharing enables new business models. C2
The more aware the client is, the more data he/she will demand. The rights of the data user need to be defined. C2
"**Our data, our equipment**". C2
Big data and ICT possibilities are only partly known, but how can advantage from big data be taken, is the question. The amount of big data is huge and it is used on quite a low level. The target is to prevent failure situations by doing wise data management. C3
Faulty connections must be found quickly to help the operator and assembler in maintenance. C3
Maintenance has been time-based but now it is wanted to be changed to condition-based. If the system tells what needs to be done and in which order, this can prevent extra work and save costs. C3
The service plan is based on existing technology and know-how. The business view is essential when developing new service products, production is more important than one client's need. D1
Our services are connected to installed equipment. The focus is on maximizing the life time of equipment. D1
Service developing is continuing improvements and iteration. D1
The distance to the client makes services difficult to manage. D1
Service descriptions help manage services. Service descriptions should not be work instructions but general level descriptions. D1
Remote control is in focus to get enough data to offer services to clients. D1
It is a problem that there is no data available of maintenance actions made in the past and what the condition of the equipment is now. D1
Online data is not yet in use but measurement data can help recognize the need for maintenance, and as
well as point out the benefits of maintenance services. D1
When service contracts are based on the condition and in next step on data, then right services are available at the right time. D1
In data-based maintenance predictable and price models are challenges. Costs should be minimized but remote control costs a lot. D1
Defining monitoring data is difficult. D1
Putting data to a database should happen only once and the data should also be pre-selected in order to minimize mistakes. D1
Is there untapped potential available? They can be noticed by using databases. D1
New services have been developed: remote support and control, condition monitoring, health check, life cycle assessment. D4
A lot of technical solutions exist, but the architecture of the data and the service portfolio are difficult to solve. D4

ISBN 978-91-7583-841-0

Table 4. H-E findings.

H - E
Process data is not collected by relays. C1
Health data of relays is collected and used. C1
In health monitoring the decisions are made based on one equipment. There is potential to analyse the changes comparing the whole group of same kind of equipment. C1
How about intelligence relays? The data collection could be done by separate equipment, not by relay. C1
It must be possible to integrate the new solutions with all the manufacturer's equipment. C2

Table 5. H-H findings.

H - H
Relays do not collect data from equipment, they protect. Only faults are monitored online. C1
It is not known what data it is possible to collect from new relays. The data when the relay needs maintenance and fault history are needed. C1
There is no link between maintenance databases and automation systems. C1
History data is now used only for troubleshooting, but there is potential to forecast the need of maintenance and to use databases better, as well as to use life-cycle data. C1
Better data management helps in decision making and maintaining. C1
Health monitoring and measurement data are not used enough. Faults could be minimized by improving this. C1
Developing processes and automation systems can be seen as a possibility to develop data management. Now data is collected time-based online. C1
Different data in different databases are seen as a challenge or as a barrier. In the future the target is to use the data better than it is done at the moment. C1
Faults caused by relays are not recorded, more faults are caused by breakdowns in the power-distribution network. C1
Data is formatted "badly", it is on paper or difficult to automate in some other way. Manual data is difficult to use. D1
It is difficult to define which data to collect. D1
Integrated systems record data but not enough. It is impossible to see trends from insufficient data. D1
The amount of data can be very big. Only KPI data is analysed and the whole data is checked if needed when problems are noticed. D2
Integration is a challenge. How can all needed data be collected through one cable and then used? D3
Data transmission connection is used. The supplier monitors the equipment delivered to the customer. When the supplier noticed a fault in the equipment it is possible to inform the customer about this fault and give instructions for how to deal with it. D2

Table 6. H-L findings.

H – L
The biggest problem is the quality of the data in ERP systems because people can make mistakes when inputting data. C1
Faults are not recorded statistically, but the staff notices when equipment has broken more often than before. C1
The company has strategic-level support decision tools, but it expects that the service provider will offer tools for the operational level. C3
Relays have been "stupid" before but now real-time data is much more available. Relays should be used much more. C3
Data analysis and decision support are needed, as well as traffic lights to observations from data. C3

The company collects data and understands what is needed. The supplier should have connections to analyse data and give support for decision making. C3
A lot of data is available but the company does not want to give the role of the data manager to anyone else, even though support is needed to analyse big data. C3
Fault situations cause a lot of problems to the company and the company's clients. It would be better to know beforehand when the equipment might have problems, so that the client could be informed. C3
Relays are quite reliable but more analysis is needed for wider fault management in the network – what can the relay tell about the whole environment? C3
There is need to discuss not only relays but the whole automation system. C3
It is urgent to locate the faulty equipment and what exactly is broken. C3
In the underground cable network the relay could discover changes in the cable. C3
Relays could create data for maintenance staff, e.g. work order. C3
More automation – decision support proposals to the maintenance staff. C3
Customer needs are important but not all wishes can be fulfilled. Technical skills and own knowledge can limit this. D1
Data sharing has good potential. Now data is shared with the maintenance staff but not with the customer, and also combinations of data from different data sources are not properly used. D1
Online data is not available but it can be organised in an emergency. D1
Online data would offer other information but the customer does not have online data systems. D1
If fault data is available, it can be used to offer better services even when no errors occur, as well as new products to customers. D1
A wider perspective with different equipment. Is it possible to use only one database or are more databases needed? Is the combined database information too general and are there enough details? Is the information useful still? D1
How can the supplier be seen united from the customer perspective? Service based on data is challenging. The united system should be created step by step and internal services should be defined first. D1
There is potential to use better data created by equipment, at least in locating errors and doing maintenance actions faster. D1
From the customer point of view, the supplier services look different than from the supplier's view. The solution is a standardized service process. D1
Standardization of products helps also in the phase of call for bids and it standardizes offers for sale. D1
One department has know-how to model networks, but that is not put to use in maintenance. D2
IoT enables doing things more effectively, and more complex tasks can be done. Changes in the service concept and new services are needed. D2
Software and services to the core business of the customer are available. D2
The customer must realise the value of sharing data. The supplier does not want to get data in its own cloud computing, but services to data can be organised in customer servers. D2
There is potential to combine online data with process data, visualize data, store data, combine relevant data and define what is essential. D2
IoT enables better services to customers and makes remote control possible. D2
The demo environment makes it possible to simulate many different situations which are not possible in a real environment. D2
The suppliers' product groups have different variations and it is difficult to offer the same services to all the products the customer has bought. D3
Data is collected, and support to optimize the energy consumption is given. Also remote support, fault diagnosis, and health monitoring are possible because the equipment is "intelligent". D3
It is a challenge to sell data-based services because customers are used to getting also maintenance staff at the same time. D3
It is easy to share data which is collected by equipment, also analysis and reports to the customer are quite normal actions. The challenge is influencing the customer's decision making with the analysed data. D3

Data is used to find out what has been broken but there is need to prevent breakdowns by predicting. D3
Predictability is interesting to the customer because they can do maintenance actions when it is possible to do them in the right time. D3
Customers give data when the services are important to them. D3
Fleet data gives potential to process optimisation, energy optimisation and coping with quality problems. D3
Lack of technical data makes responses to the customer slow. D3
A demand for a monopoly of data is a challenge. The customer does not understand the potential of new services based on data sharing. D3
IoT gives more possibilities to offer new services to the customer even when they buy only products. D3
Divisions share their own data quite openly with other divisions because it has been understood that this helps to develop new products and services. D3
Some customers do not want to give the location of the equipment and health data. Also cloud computing is denied. D3
The barriers to sharing data are lack of knowledge and insufficient ground of value added by sharing data. The win-win situation is not understood. D3
Customers are not willing to share data because they think that the supplier will want to make the maintenance their own business. D3

Table 7. H-O findings.

H - O
Relay life cycle only 5-10 years, not worth collecting data. C1
The client owns the data and wants to own it in the future. C1
Intelligent relays may add value, but client does not want to pay more than now. C1
Health monitoring data and operation time data could be given to a selected partner. Data supports planning services better. C1
Health monitoring data could be analysed better by the supplier than what could be done in-house. Analysis service is not used now. C1
Data could be shared case by case. Production quality and product recipe data are not allowed to be shared. C1
With strategic partners data could be shared more in order to do better analysis. C1
IoT offers possibilities to optimize. How can we offer new services to our client to increase efficiency? C2
Can IoT generate new business? Are the clients satisfied with the results? C2
An aware client will need more data. C2
Who owns the data? C2
The data contains also customers' identification data and it is not allowed to share that. Other data can be shared if the advantages of sharing are clear as crystal. C3
In service business there is a common problem with a lot of "working hands". So there is a lot of variables. Product management is easier. D1
The customer is not an expert of the equipment, and they are only interested in the equipment when the devices do not work. D1
Support to the customer is given in planning maintenance and maximising the life cycle. Customers are not ready to invest in new products. D1
Is the data analysis done in order to develop the supplier's own business and processes or to create added value to customers? D1
Reports in service business are not shared in divisions. Every division has its own reports, and service data is not easy to share. D3
Remote service has developed extremely well. D4

Table 8. L findings.

L
At first systems and tools were sold as a product, but then IoT made it possible to sell them as a service. The demand increased a lot. D2
There is need to consider the value of service to the customer. Different data from divisions can be combined and new services can be offered. D2
In the spare part database, only the own country can be seen, but the division has spare parts in many countries, and the balance of those spare parts cannot be seen. D3

Table 9. L-L findings.

L - L
There is need to get suitable skills to be used in fault situations. D1
There are service contracts which include offerings of different divisions. Developing tools is an issue. ERP systems do not support this. D1
Clear rules for supplying know-how in common offerings. D1
Training is needed when business is transferred to data-based services. D1
Common offerings with other divisions are difficult when the work load is heavy. D1
The model of working is changing, which can be seen as a good thing and as a sign of development. D4

Table 10. L-O findings.

L - O
The client view is sometimes missing. If data collection and operations with critical components are in order, the other equipment maintenance can be organised as time-based. C2
Information is not used to plan marketing. “The data is this and it shows that a sales person is needed to visit the client”. C2
A sales person need tools based on data to find out the client’s need. C2
An example: “At first we sold systems and tools as products. Then we offered tools as a service and the demand increased a lot when we learned to offer our own know-how and tools as a service.” D2
Predictability interests the customer because they can schedule maintenance actions when the ship is in the harbour. D2
Service data reports are not transferred to other divisions. Every division has their own reports and documents and it is a challenge to transfer the service data reports. D3
There is available data and service to the customer on how to operate the equipment, but the customer decides how to use the data. Also analysis and data visualization services are available. D3
Automation could be added and even replace humans in condition monitoring because humans make errors. With data and sophisticated mathematics this could be done better than humans can do. D3
Big data is not shared with divisions, but the advantages of sharing data is obvious. Now data is shared and combined only case by case when needed. D3
In motors different components can be compared with the customer’s fleet. D3
In the fleet the customer wants to compare all ships. Of course there is a challenge when the ships are of different ages. With new ships it is possible to compare different details between the ships. D3
To compare many customers’ ships is interesting. Especially operation data and maintenance data are interesting things. D3

ISBN 978-91-7583-841-0

Table 11. O findings.

O
In asset management strategy the target is to maximize the life cycle of the equipment and to get as much as possible profit with it. C1
It is urgent to create and develop ways to support third parties' actions and to charge for those services. C2

Table 12. O-O findings.

O – O
Special know-how is bought from outside the company when own knowledge is not enough or there is not enough resources available in the own company. C1
We do not have a contract of maintenance with the supplier but material and technical support is bought when needed. C1
Co-operation with the supplier of the equipment is smooth, and data collected by the supplier is tried to be used e.g. to find out what the equipment life cycle is. C1
Discussions with clients take place at many levels. In the supplier's view it is important to get right information to right people in the whole fleet at the same time. C2
When dealing with a maintenance contract to a whole power plant, it is important to build support for third parties' equipment and services. C2
At the moment people know somebody who to contact if problems appear. For example, it is impossible to find the right contact with the subcontractor. There is a lot of potential to consolidate the processes. C2
The client informs the subcontractor directly, the supplier does not know anything, and everything is mixed up. C2
In the future open data can be seen as a "sharing economy", which will have a positive effect on the relationships between companies and service networks. C2
It is important to understand that the whole network influences the customer, not only the actions of the first or last company in the network. C2
Solutions must be developed with the possibility to integrate them to other systems (customers' or other suppliers' platforms). Integration and openness must be considered. C2
The maintenance playground is fragmented and it has hundreds of doers who have their own systems which do not work together. It is impossible to define a common platform. There is no evidence that a common platform will appear. C2
When you analyse data and you need more data from other sources, you need to convince the other parties about getting added value for giving the data. C2
New ecosystems are spoken of, but when creating a new ecosystem, a lot of dialog with different parties is needed. C2
There is not much discussion on what the client demands and needs are. Divisions develop products and solutions separately. C2
It would be ideal if the coordinator could get the subcontractors and clients together to create a new solution or a pilot. C2
New models need more responsibility. If **"risk and revenue sharing"** is the target, also the supplier needs to give more and take more risk and responsibility in order to get the client to come in. C2
The supplier cannot lock itself to the business model in use. Some clients want to try new models and some want to change the action only when forced. The ability to offer services to different environments is needed. C2
The supplier wants to sell a product, while the client wants to get solutions. The client has bought products and solutions from many companies, and more effective integration is needed. C2
Clients want both support for decision making and data analysis to be used in decision making. C2
The clients expect sophisticated solutions found in the world which are not yet used in Finland. C2
Customers are used to investing a lot of money once but they are not familiar with monthly payments for services. D1

ISBN 978-91-7583-841-0

Table 13. S findings.

S
The regulations and laws are unclear. Is continuous measurement of emissions needed in the marine? C2
Regulations in the marine are local. Global emission measurement is not used as widely as local. e.g. on the Baltic sea. C2
The regulations will be tighter and more accurate than now, and that will set up new demands for data collection and presentation of data. C2
The supplier has more eco-friendly solutions than others, and from their point of view tighter regulations are not a bad thing. C2
Rules must have been agreed on with partners beforehand. C2

Table 14. S-E findings.

S -E
Preparations for massive faults in the power distribution network must be organised because the regulations require it. C3

Table 15. S-H findings.

S - H
It is a challenge to optimize 60 ships instead of one ship. How can we optimize the whole fleet? Some solutions are available, but tools to optimize the whole fleet are not available. C2
As a part of sustainable development quality, recycling and eco-friendly working make it possible to develop new sources of energy. C3
The processes and practices are changing. Especially when trying to achieve big advantages, the processes could be caught in a circle of change. D2

Table 16. S-O findings.

S - O
The clients in this business are interested in environmental issues. Some clients are ready to open data, and more openness is wanted. C2
In contract business there is also third parties' equipment, and this equipment needs a support network. On the network level, standardised ways of action are needed. C2
One common platform is not realistic, because companies have different systems. C2
Optimistically, if there is no direct competition between the parties, it is possible to open data and find out new opportunities. C2
Creating new ecosystems needs a new view to look at co-operation and a lot of dialog between the
parties. C2
Many doers are afraid that someone else will have more understanding, and that will prevent the sharing of data. C2
Finding an outside facilitator whom everyone trusts could be challenging. Maybe the client can take the role and manage the whole. C2
Covering data and not sharing it can cause a situation where an outside doer takes charge of the whole business, doing it in a new way and possibly without using the covered data. C2
New models mean more responsibility. C2

ISBN 978-91-7583-841-0

A Framework for Creating Value from Fleet Data at Ecosystem Level

Sini-Kaisu Kinnunen[1]; Jyri Hanski[2]; Salla Marttonen-Arola[3]; Timo Kärri[4]
[1]sini-kaisu.kinnunen@lut.fi; [2] jyri.hanski@vtt.fi; [3]salla.marttonen-arola@lut.fi;[4]timo.karri@lut.fi
[1,3,4]School of Business and Management, Lappeenranta University of Technology
Lappeenranta, Finland
[2]VTT Technical Research Centre of Finland Ltd Tampere, Finland

***Abstract*—As companies have recently gotten more interested in utilizing the increasingly gathered data and realizing the potential of data analysis, the ability to upgrade data into value for business has been recognized as an advantage. Companies gain competitive advantage if they are able to benefit from the fleet data that is produced both in and outside the boundaries of the company. Benefits of fleet management are based on the possibility to have access to the massive amounts of asset data that can then be utilized e.g. to gain cost savings and to develop products and services. The ambition of the companies is to create value from fleet data but this requires that different actors in ecosystem are working together for a common goal – to get the most value out of fleet data for the ecosystem. In order that this could be possible, we need a framework to meet the requirements of the fleet life- cycle data utilization. This means that the different actors in the ecosystem need to understand their role in the fleet data refining process in order to promote the value creation from fleet data. The objective of this paper is to develop a framework for knowledge management in order to create value from fleet data in ecosystems. As a result, we present a conceptual framework which helps companies to develop their asset management practices related to the fleet of assets.**

Keywords—fleet data, ecosystem, framework, value, data refining, asset management

I. Introduction

Assets produced by an original equipment manufacturer (OEM) are often distributed to many customers and different locations. From the manufacturer's point of view the products or assets of fleet are often scattered to wide range of companies. Thus, the data related to fleet of assets are fragmented in an industrial ecosystem where e.g. a manufacturer has product data, an asset owner has process data and a service provider has the service data related to a certain fleet of assets. This fragmented data concerning the fleet is hindering the full exploitation of fleet data in the decision making and also in the service development.

Recently, the aim among industries has been to develop data processes in order to benefit from collected data in asset management decision making. Manufacturers are also willing to increasingly provide knowledge-based services alongside the products. Technologies have partly facilitated this movement but there are still challenges especially related to data sharing between companies in industrial network but the challenge is also to share data effectively even inside an organization. As the fleet of assets and the data related to the assets are often fragmented in different companies no one has the access to all the data concerning the fleet. In order to be able to generate fleet data based services these challenges need to be considered. The literature presents general frameworks to upgrade data into knowledge but they are lacking the perspective of company networks or ecosystems combined with the fleet management point of view. Therefore, there is a need for a framework which combines data refining process with ecosystem and fleet management perspectives. Thus, the purpose of this paper is to develop and illustrate the role of ecosystem when creating value from fleet data. The aim of this paper can be concluded into the following research question:

How can the process from fleet data to decisions in an ecosystem be illustrated?

Research question is answered by developing framework to meet the requirements of fleet data utilization in order that the value creation in ecosystem could be possible. By reviewing literature it has been acknowledged that the traditional knowledge management frameworks do not consider the development of modern ecosystem concept and the special characteristics of fleet data management. Thus, the research is conducted by developing analytically the existing data management and knowledge management frameworks. As a result a conceptual framework is developed and the results are discussed.

II. Literature

A. Ecosystems in Literature

The developments in business environments are resulting in companies and other organizations networking in increasing pace. As the significance of networking has increased, companies are trying to develop powerful partnerships in order to fare in the competition between networks. This increased interest in the subject can be noticed from the plentiful and multifaceted research conducted in the field. The subject is discussed with different terms such as industrial networks and value chains that often appear in the literature. In addition, the term of ecosystem has been used in business context as well as by several authors [1–5].

The term of ecosystem is used to represent the network and especially to highlight the interdependencies between network partners in order to achieve mutual effectiveness and survival

ISBN 978-91-7583-841-0

[6]. The term ecosystem is also utilized to symbolize the sustainability and sustainable development aspects that are aimed in ecosystem level cooperation [1, 7]. There are different kinds of views to determine ecosystems and for example the terms of business ecosystem, industrial ecosystem, innovation ecosystem, and information technology (IT) ecosystem or digital ecosystem are presented in the literature. Peltoniemi and Vuori [8] have reviewed the different views of ecosystem in detail. For instance Moore [9] defines the business ecosystem as "an economic community supported by a foundation of interacting organizations and individuals – the organisms of the business world". IT ecosystem or digital ecosystem is founded on a platform where data and applications create the basis for the value creation in the ecosystem [10]. Industrial ecosystem can be defined as "a regional collection of industrial actors that cooperate in each other's waste material and waste energy utilization" [4]. Therefore industrial ecosystem can be regarded as an environmental ecosystem with the circle of material, energy and information. Despite the accurate term, the ecosystem can be concluded to refer to an interconnected population of organizations which can be small companies, large corporations, universities, research centers, public sector organizations, and other actors who influence the system [8].

As the definition for the ecosystem does not appear to be fully unambiguous and none of the definitions meets the requirements that we have when considering the ecosystem in the fleet context, we are regarding the ecosystem as the combination of three different ecosystem concepts: business ecosystem, IT ecosystem, and industrial ecosystem. In the Figure 1 the relation between these three definitions is presented. We define the value ecosystem around the fleet to contain the properties of business ecosystem, such as strong interdependencies between the actors of ecosystem and the aim of mutual value creation. The concept of industrial ecosystem highlights the importance of sustainability aspects which are significant as well for the fleet value ecosystem. The sustainability refers to the point that the ecosystem functions in a way where each actor is benefitting and no one's position in the ecosystem is indefensible. As the fleet data is the starting point for the value ecosystem around the fleet, the features of IT ecosystem, such as data and platform-centered approaches, are essential. Consequently, we define the value ecosystem around the fleet to be a combination of three subsystems including features of business ecosystem, IT ecosystem and industrial ecosystem. The ecosystem is formed around the fleet and basing on fleet data platform or corresponding information technology solutions. With the aid of information technological solutions a group of interconnected organizations are benefitting from fleet data and creating value in a sustainable way.

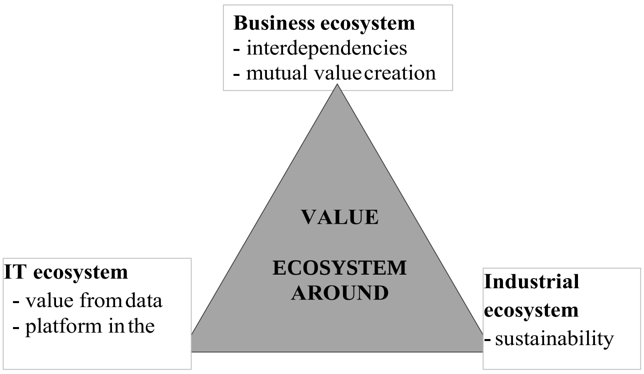


Fig. 1. The concept of value ecosystem around the fleet as a combination of different definitions of ecosystem.

Ecosystem around the fleet is formed by several different actors which have different roles in the ecosystem interaction. Companies in the ecosystem may have roles such as equipment provider, customer or asset owner, and various service providers who all have certain relation to the fleet of assets and are involved in the fleet data based value creation. Especially, when it is a question about data refining in the ecosystem, the role of IT service providers is emphasized. Different actors in ecosystem are complementing the whole ecosystem and they have their role in the data refining process in order to create value from fleet data. The aim of value ecosystem around the fleet is the value creation for the whole ecosystem. The functionality of ecosystem is based on mutual trust and benefitting all the actors of ecosystem [11]. However, this characterization is representing the ideal ecosystem, and the common value creation and benefitting all the actors in ecosystem are more like the ambition than reality. There is still plenty to do before this kind of ecosystem could function as it is supposed and before the companies can create value for ecosystem around a fleet.

In order to get closer to the ambition state, the first step is to understand the roles of actors in ecosystem around a fleet. As the ecosystems and their interdependencies are often complex, this sets requirements for data acquisition and data sharing as well as for upgrading the data into valuable business knowledge for decision makers. These issues become relevant if companies in the ecosystems are willing to benefit from fleet-wide data and as the data can be owned by different companies they need to understand their role in the fleet data refining process. Figure 2 is presenting simply the roles of ecosystem actors in fleet data generation.

ISBN 978-91-7583-841-0

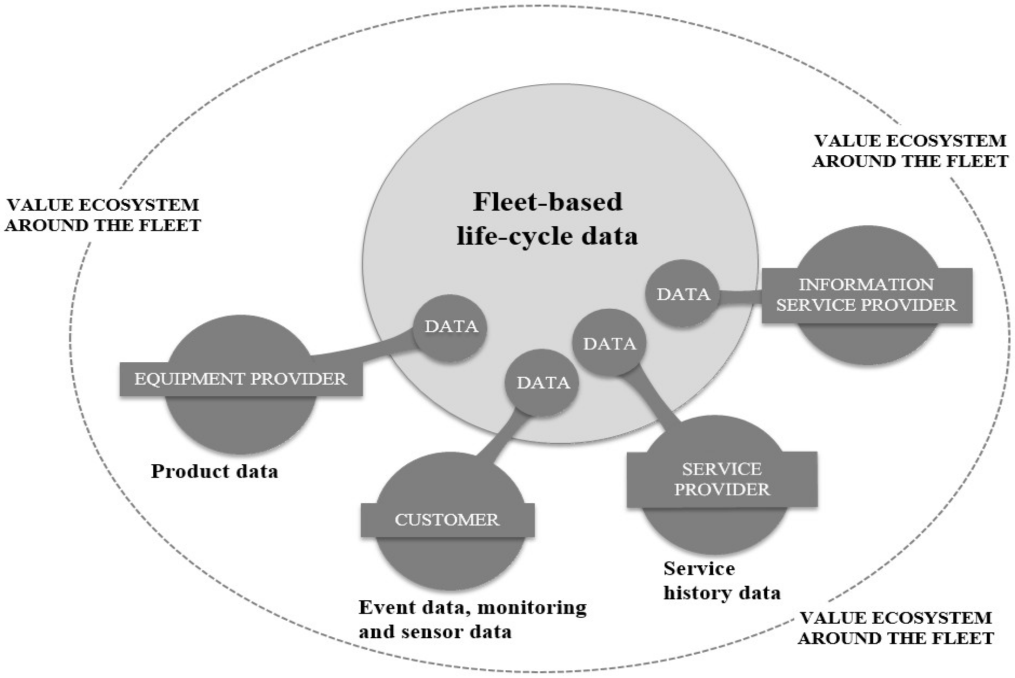


Fig. 2. Ecosystem around the fleet - the impact of ecosystem actors on fleet data.

B. Information and Knowledge Management Models for Ecosystems to Manage Fleet Data

In the literature, general models for data management and data refining process are presented often in the fields of information and knowledge management research. General models and frameworks for knowledge management are presented by noted researches e.g. Nonaka and Takeuchi [12] as well as Davenport and Prusak [13]. When considering the process from data to knowledge the classifications for the data refining levels, also known as knowledge hierarchy, often appears in literature [14]. Knowledge hierarchy divides the levels of data, information, knowledge and wisdom. Data is regarded as unprocessed data or symbols, information is regarded as processed data that can be used, knowledge is refined from data and information, and wisdom refers to understanding. This kind of classification is essential when discussing the data to decision process.

Although the literature presents a large amount of models and frameworks for information and knowledge management, there is still a need for more specific frameworks in different business contexts and different levels of business. In other words, there are needs for the models for information management related to just a certain process, for the models related to information management at organizational level, and when the business networks and ecosystems are increasing, there is a need also for ecosystem level information models. Within the research program Service Solutions for Fleet management [15] researchers such as Kunttu et al. [16] have applied the data models to the knowledge-intensive service development by creating a framework (Figure 3) for information management in a single firm case. They present the framework for data-to-decision where the manufacturer manages the information flows from external and internal sources. The framework consists of six phases: data collection, data pre- treatment, descriptive data analysis, data modelling, soft and hard data combination and the comparison of decision options. The sequential phases result in the various levels of understanding to make the data useful for decision-making i.e. data, information, knowledge and wisdom [16].

ISBN 978-91-7583-841-0

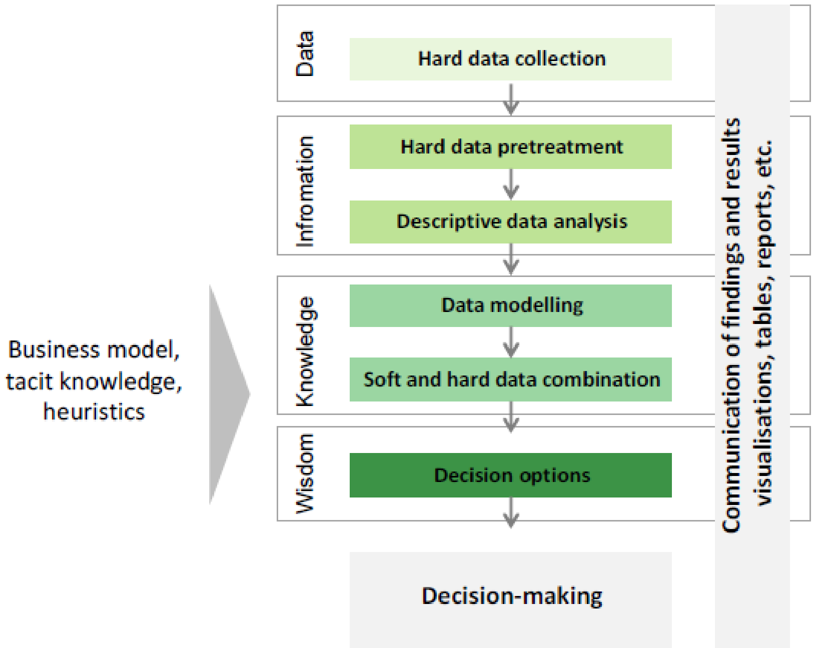


Fig. 3. Framework for information management and the relationship of data, information, knowledge and wisdom [16].

When starting to develop the framework for fleet data management at ecosystem level, the data-to-decision framework presented by Kunttu et al. [16] is a good starting point. The framework presented by Kunttu et al. [16] illustrates the data refining process from data to decisions and the framework functions as a tool to develop knowledge-intensive services. However, the framework considers that the process is handled by a single company but it does not consider that the process from data to decisions is not always mastered by a single company. The process from data collection to decision making may be affected by several companies in ecosystem. Especially, when we are considering fleet-wide data, even the phase of data collection is executed by multiple companies as was presented in figure 2. In addition, data pre-treatment and other data processing is often provided by information service providers. Another important aspect which is related to the ecosystem view is the value creation through data refining process. There is a need to clarify the roles of companies in the ecosystem around the fleet when creating value from fleet-wide data. Thus, who is benefitting or should we maximize the value for the whole ecosystem? The understanding of the roles in ecosystem is a step forward to create new business as well as sharing benefits and risks in ecosystems. Framework (figure 3) could be developed further in a way which takes the role of collaboration in the ecosystem into account and considers challenges related to costs, benefits and information sharing.

III. Framework for Creating Value from Fleet Data at Ecosystem Level

Existing knowledge management models which generally are known in information management context have been the basis for the development of the new framework in this paper. The general information and knowledge management frameworks presented in literature have now been integrated with IoT, ecosystem and fleet management viewpoints as a part of ongoing research program. Prior research, the research work during the research program and the collaboration with companies within the program, including workshops, have been the basis for the development work of the framework. Data-to- decisions framework developed by Kunttu et al. [16] is also a result of the research program and there are still possibilities to develop the ideas of data-to-business-knowledge process further. Some ideas for further development were discussed in section 2.2.

In figure 4, we are presenting the new framework which has influences also from the data-to-decision framework developed by Kunttu et al. [16]. The main need to develop the framework further is to clarify the roles of actors in data-to-decision process at ecosystem level. In other words, to clarify the process of how the fleet data can be turned into value in ecosystem. As there are several actors involved in the ecosystem, it is vital to be able to create value for the ecosystem as an entity but to create value for each actor in ecosystem as well. The actors in the ecosystem have different roles in the data refining process and thus in value creation. Figure 4 describes a swim lane flowchart where each actor has their own lanes describing their participation in the data-to-decision process. The black arrows are representing information flows between data refining phases and actors. It can be noticed that some of the actors have smaller roles in the process while the others might have important role in multiple phases in the process. In addition, in the top part of the figure, the stacked bars describe how the costs and benefits are generated through the process. Costs and benefits can be observed at actor level, as each actor has their own green and orange colors, and at the ecosystem level when the total costs and benefits can be observed. The value for ecosystem can be evaluated as the difference or ratio between discounted benefits and costs.

ISBN 978-91-7583-841-0

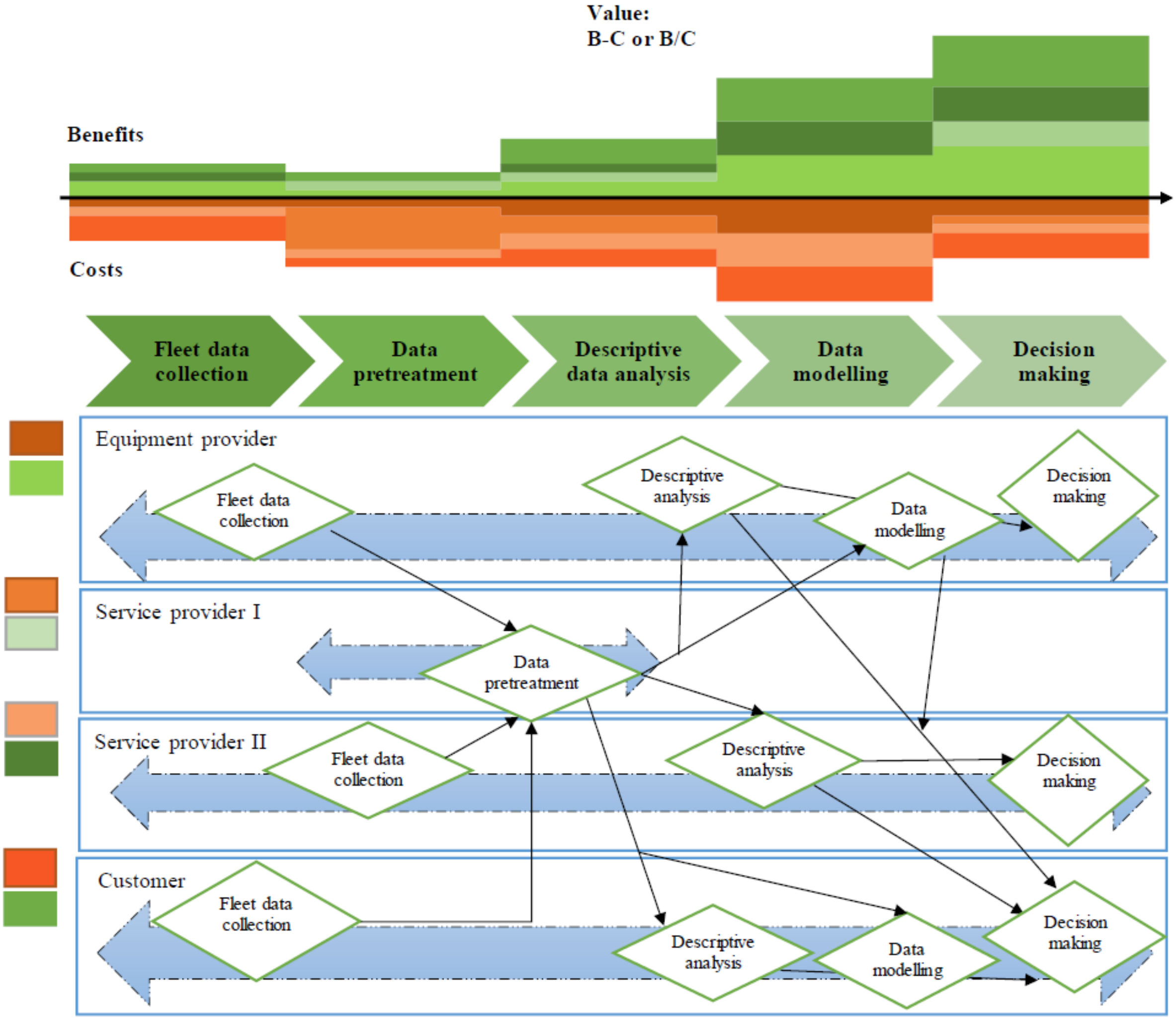


Fig. 4. Framework for exploiting fleet data at ecosystem level

Figure 4 is representing an example how the process from data to decision in the ecosystem around fleet can be illustrated. However, the situation is often that each actor is managing the process from data collection to decisions by themselves inside the boundaries of company, i.e. companies are staying in their own swim lanes. However, this may lead to the situation where all the data is not available as fleet data is often fragmented to several actors in ecosystem. Therefore, it would be reasonable if the whole ecosystem was pursuing to benefit from the fleet data gathered by different actors. However, this requires that the actors of ecosystem are willing to cross the boundaries of their swim lanes and consider the roles of actors in data refining process. The mobility of data between actors in ecosystem is essential for fleet data utilization at ecosystem level.

Naturally, the whole process and each phase from data collection to decision making are not the core business for all the actors. Some actors might be specialized to some phases while others are mastering the other phases. It could be beneficial if the roles for different data refining phases were considered based on the core competencies of companies. This requires that the current situation in ecosystem can be illustrated and then developed and managed in order to create more value from fleet data for the ecosystem. Figure 4 is representing a suggestion for the data refining process in ecosystem where data are shared in ecosystem and each actor has their own roles in the process. For example, service provider I is taking care of data pretreatment collected by multiple actors and other actors are utilizing this data. It can be noticed as well that equipment provider and

ISBN 978-91-7583-841-0

service provider II are providing analysis and models to support their own businesses but to support the customer’s business as well. The costs and benefits are generated through the process for each actor and for the whole ecosystem. For example, different phases are causing different amount costs to each actor and the amounts of benefits are varying as well. Inspecting the value aspect is important as none of the actors should be in an indefensible position while others are gaining all the value. It is not beneficial either for the ecosystem. The ambition of ecosystem is to create value for each actor in ecosystem but for the whole ecosystem as well.

Figure 4 is a simplified description of an ecosystem. The purpose of the framework is to demonstrate how the actors could cross the boundaries of their own company and utilize the fleet data collected by other actors in order to create more value for the whole ecosystem. There could be more actors in real ecosystem and the situation is often more complex. The framework can be applied to different cases and the illustration needs to be done based on the case. Based on the illustration, the process from fleet data to decision making can be developed and managed at ecosystem level.

IV. DISCUSSION AND CONCLUSION

The potential to utilize fleet-wide data, which have been fragmented inside and outside organization, has been acknowledged and the need for understanding how to better manage the fleet data is recognized. This brings into discussion the data utilization at ecosystem level where the ecosystem is founded on the data of asset fleets. The value ecosystem around the fleet is founded on fleet data which highlights the IT ecosystem perspectives, but at the same time the interdependencies and value creation of business ecosystem definition are present, as well as sustainability considerations from industrial ecosystem approach are essential. Value from fleet data should be created in a way which benefits all the actors and the ecosystem as a whole. To respond this and the research question, a new framework is developed as a result of this paper. The framework is suggesting that the phases from fleet data collection to decision making could be realized by utilizing the core competencies of each actor and sharing the data between the actors in order to create value for each actor and for the whole ecosystem.

The framework can be used in many managerial purposes such as a tool of service development but also as a tool in fleet management related to asset management and as a help in information system descriptions where the information management model combined with ecosystem can be valuable. The framework can be used as a tool to evaluate the ecosystem around a fleet and the roles of actors in the data refining process. Companies can model their ecosystem around the fleet with the aid of the framework, and develop the data-to-decision process at ecosystem level in order to increase value creation. Companies can analyze the ecosystem and data refining process in order to recognize if there are overlapping processes which could then be improved by clarifying the roles of each actor. In addition, as the framework considers also value creation as the difference or ratio between discounted benefits and costs, it can also be used as a tool to develop the performance management of ecosystem.

The presented framework needs to be developed further and it needs to be tested with case ecosystem. The further research is focusing on the calculation of the costs and benefits of actors and on modelling the value of fleet data for ecosystem.

ACKNOWLEDGMENT

The authors gratefully acknowledge DIMECC (Digital, Internet, Materials & Engineering Co-Creation) for organizing Service Solutions for Fleet Management program (S4Fleet), the Finnish Funding Agency for Technology and Innovation for funding the program and the companies involved in the research.

REFERENCES

[1] Y. Geng and R. Côté, “Diversity in industrial ecosystems”, International Journal of Sustainable Development and World Ecology, Vol. 14, No. 4, pp. 329-335, 2007.

[2] G. K. S. Gossain, “Reinventing value: The new business ecosystem".Strategy & Leadership, Vol. 26, No. 5, pp. 28-33, 1998.

[3] M. Iansiti and R. Levien, “Strategy as Ecology”, Harvard Business Review, Vol. 82, No. 3, pp. 68-78, 2004.

[4] J. Korhonen, “Four ecosystem principles for an industrial ecosystem”, Journal of Cleaner Production, Vol. 9, No. 3, pp. 253-259, 2001.

[5] J. F. Moore, “Predators and Prey: The New Ecology of Competition”, Harward Business Review, Vol. 71, No. 3, pp. 75-83, 1993.

[6] M. Iansiti and R. Levien, ”The Keystone Advantage: What the New Dynamics of Business Ecosystems Mean for Strategy, Innovation and Sustainability”, Harvard University Press, Harvard, MA. 304 p, 2004.

[7] W. S. Ashton, “The Structure, Function, and Evolution of a Regional Industrial Ecosystem”, Journal of Industrial ecology, Vol. 13, No. 2, pp. 228-246, 2009.

[8] M. Peltoniemi and E. Vuori, ”Business ecosystem as the new approach to complex adaptive business environments”, In Proceedings of eBusiness research forum, pp. 267-28, 2008.

[9] J. F. Moore, “The Death of Competition: Leadership and Strategy in the Age of Business Ecosystems”, New York, NY: HarperBusiness, 1996.

[10] K. Karhu, A. Botero, S. Vihavainen, T. Tang ans M. Hämäläinen, ”A Digital Ecosystem for Co-Creating Business with People”, Journal of Emerging Technologies in Web Intelligence, Vol. 3, No. 3, pp. 197-205, 2011.

[11] M. Heikkilä and L. Kuivaniemi, “Ecosystem Under Construction: An Action Research Study on Entrepreneurship in a Business Ecosystem”. Technology Innovation Management Review, Vol. 2, No. 6, pp. 18-24, 2012.

[12] I. Nonaka and H. Takeuchi, “The knowledge-creating company: How Japanese companies create the dynamics of innovation”, Oxford university press, 1995.

[13] T. H. Davenport and L. Prusak, “Working knowledge: How organizations manage what they know”, Harvard Business Press, 1998.

[14] J. Rowley, “The wisdom hierarchy: Representation of the DIKW hierarchy”, Journal of Information Science, Vol. 33, No. 2, pp. 163-180, 2006.

[15] DIMECC S4Fleet (Service Solutions for Fleet management) program, avaiable: <http://www.dimecc.com/dimecc-services/s4fleet/>, [referred 01.11.2016].

[16] S. Kunttu, T. Ahonen, H. Kortelainen, and E. Jantunen, ”Data to decision– knowledge-intensive services for asset owners”. In Proceedings of EuroMaintenance 2016, to be published.

Tapping the value potential of extended asset services – experiences from Finnish companies

Helena Kortelainen[1]; Jyri Hanski[1]; Pasi Valkokari[1]; Toni Ahonen[1]
[1]helena.kortelainen@vtt.fi; [1]jyri.hanski@vtt.fi; [1]pasi.valkokari@vtt.fi; [1]toni.ahonen@vtt.fi
[1]VTT Technical Research Centre of Finland
Tampere, Finland

***Abstract*— Recent developments in information technology and business models enable a wide variety of new services for companies looking for growth in services. Currently, manufacturing companies have been actively developing and providing novel asset based services such as condition monitoring and remote control. However, there is still untapped potential in extending the service delivery to the long-term co-operative development of physical assets over the whole lifecycle. Close collaboration with the end-customer and other stakeholders is needed in order to understand the value generation options. In this paper, we assess some of the asset services manufacturing companies are currently developing. The descriptions of the asset services are based on the results of an industrial workshop in which the companies presented their service development plans. The service propositions are compared with the Total Cost of Ownership and the closed loop life cycle frameworks. Based on the comparison, gaps that indicate potential for extended asset service concepts are recognised. In conclusion, we argue that the manufacturing companies do not recognise the whole potential for asset based services and for optimizing the performance of the end customers' processes.**

***Keywords*— asset, fleet, extended asset services**

I. Introduction

Companies operating in the manufacturing sector typically have a large quantity of different physical assets, such as machinery, equipment and infrastructure. These assets are managed in order to achieve the best possible short and long-term asset performance. The modern industrial environment involves a number of organizations as key stakeholders including asset operators and owners, regulatory and statutory bodies, service providers, engineering contractors, technology developers, equipment manufacturers, spare part vendors and logistic providers [1]. The asset performance can be assessed with direct, indirect, financial and non-financial measures, and from the economic, social and environmental perspectives [2]. Because of the multiple performance dimensions and stakeholders involved, the assessment and the improvement of the asset performance are complex tasks.

Manufacturing assets typically have long life cycles and major changes may occur in all the external and internal factors on which the investment calculations have been originally based [3]. Eventhough it is a well-known fact that the major part of the costs incur over the life-cycle, the acquisition price drives decisions in the investment phase [4, 5]. The companies make efforts to maximise asset productivity. Asset management calls for approaches where localised resources and capabilities are blended together with external resources and capabilities [1]. In order to stay competitive, manufacturing companies need to better utilise the data from their supply chain, stakeholders and other external sources. An active engaging of network partners will be needed for innovations to occur [6] since a wide collaboration assures that experiences, know-how and knowledge of various stakeholders can be used and combined [7]. Combining knowledge allows collaborating parties to achieve levels of knowledge and to create outcomes, which individual by themselves are not capable of [8].

Implementation of IoT platforms is expected to result in a series of benefits for manufacturing operations and asset management, for instance, increasing visibility of the manufacturing operations and across the supply chain, improved efficiencies, automation of workflow, optimized energy consumption, improved preventive maintenance, and real-time information exchange among manufacturing facilities and across supply chain [9]. Physically distributed resources and abilities controlled by different parties are made available to the companies that need those resources through a cloud service [10, 11]. In addition, companies may have an access to data from the installed base of machines and infrastructure located anywhere [12]. This data may be used for assessing the performance of a single machine compared to the current and previous performance of the entire fleet [13].

Currently, manufacturing companies have been actively developing and providing asset services such as condition monitoring and remote control that help to improve asset performance. In our opinion, there is still untapped potential in extending the service delivery to the long-term co-operative development of physical assets over the whole lifecycle in close collaboration with the end-customer and other stakeholders. The goal of this paper is to identify the opportunities for extending the service offering beyond the current delivery.

In this paper, we assess some of the asset services that the manufacturing companies are currently developing. The paper is collected in an ongoing Finnish nationally funded research project "S4Fleet – Service solutions for Fleet management". The descriptions of the asset services are based on the results of a company workshop, where the companies presented their service development plans. The services are compared with the total cost of ownership and a closed-loop life cycle frameworks. Based on the comparison, gaps for potential extended asset service concepts are recognised.

II. Extended Asset Services

In this chapter, the most crucial terms for this study are defined. Firstly, the terms asset and asset management are defined based on ISO 55000 [2].

Asset is "an item, thing or entity that has potential or actual value to an organization. The value will vary between different organizations and their stakeholders, and can be tangible or intangible, financial or non-financial."

Asset management "involves the balancing of costs, opportunities and risks against the desired performance of assets, to achieve the organizational objectives. It enables an organization to examine the need for, and performance of, assets and asset systems at different levels. Additionally, it enables the application of analytical approaches towards managing an asset over the different stages of its life cycle."

To support the asset management, services can be provided by several agents such as the owner of the asset, the provider of the asset, a service provider or another stakeholder. When a service is fully or partially based on the data that originates from assets, or it supports the operation and/or the development of the assets, these services are defined as asset services in the context of this study. Asset services can be, for instance, remote control, condition monitoring or product use based services.

According to ISO 55000 [2] assets should be managed during their whole life cycle with analytical approaches using multiple decision criteria and objectives. Additionally, asset management is executed at different organizational and system levels. In order to answer these requirements, companies delivering asset services need to establish long-term customer relationships and understand the whole life cycle of the managed assets from the perspective of all the relevant actors and stakeholders. In this study, we call the services needed to fulfill these requirements extended asset services.

III. Methodology

The empirical research was carried out in co-operation between researchers and companies. During our research, industrial companies were asked to present their development goals and plans related to data-based industrial services in a structured workshop. The industrial participants are experts from different branches and they represented technology, service and IT providers, and software companies. The participating companies are listed in Table I. During the workshop the researchers analysed the presentations and collected the data dealing with the service concepts and their expected benefits to the potential customers. Especially, the descriptions and prospects of the asset management related services were recorded.

TABLE I Industrial partners participating in the study.

Company Identifier	**Company description**	**Role in the IoT ecosystem**	**Company size**
A	Equipment and service provider	Asset service	Large
B	Equipment and service provider	Asset service	Large
C	Technology and service provider	Asset service	Large
D	Equipment and service provider	Asset service	Large
E	Technology and service provider	Asset service	Medium
F	Information service provider	Asset service	Large
G	Information service and infrastructure provider	Asset service enabler	SME
H	Information service and infrastructure provider	Asset service enabler	Large
I	Information service and infrastructure provider	Asset service enabler	Medium
J	Information service provider	Asset service	SME
K	Information service and infrastructure provider	Asset service enabler	Medium

A. *Total cost of ownership model*

Services that the companies described during the workshop are assessed against two frameworks: the Total Cost of Ownership (TCO) and closed loop life cycle framework. The selected frameworks represent important future development pathways for extending asset services; monetizing the benefits and costs, and enhancing the sustainability and circular economy practices of asset management services. In our analysis we aim to identify which framework phases or areas are addressed by services and which phases or areas offer space for extended asset services.

According to Ellram [14] Total Cost of Ownership (TCO) is a purchasing tool and philosophy which is aimed at understanding the true cost of buying a particular good or service form particular supplier. In addition to the acquisition price, TCO may include such elements as transportation, inspection, replacement, downtime caused by failure, disposal costs and so on. A standard model for TCO calculation hardly exists [14, 15] but some cost drivers are more universal than others and will appear in many TCO valuation models. As our case companies provide investment goods and related services we choose a TCO-model developed by Keys and Chen [5] for heavy equipment. Fig. 1 contemplates the breakdown of the Total Cost of Ownership (TCO) during the life cycle of a product or service. Additionally, it points out the potential asset management value creation options.

ISBN 978-91-7583-841-0

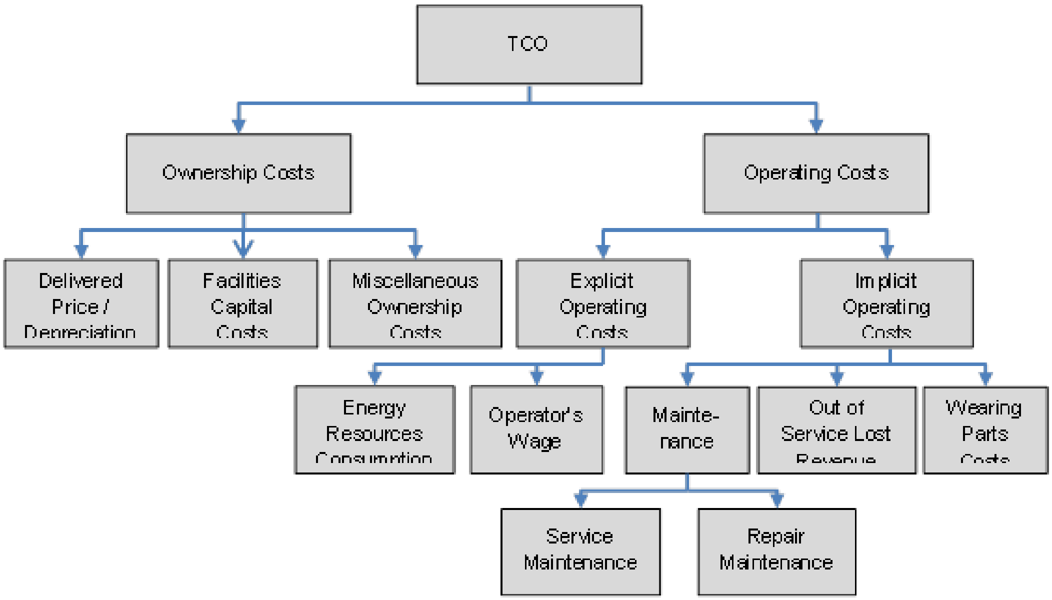


Fig.1. Total cost of ownership framework according to Keys and Chen [5].

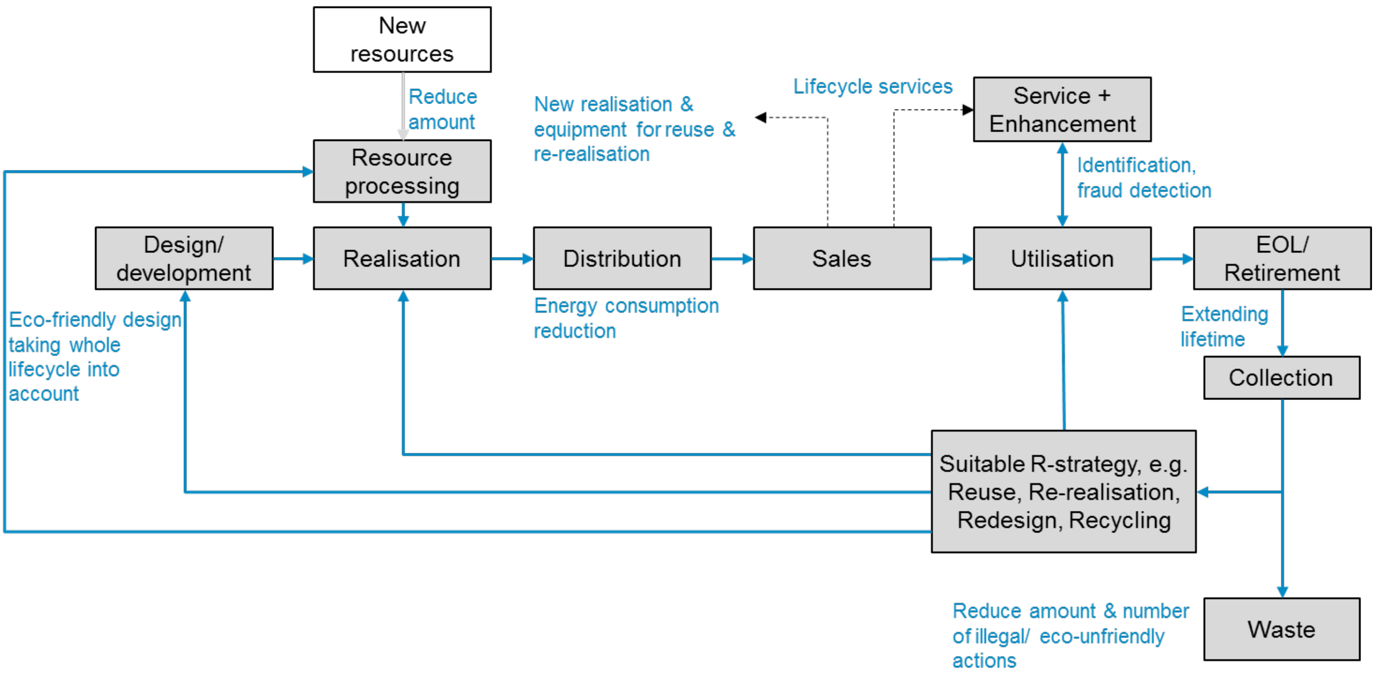


Fig.2. Closed loop life cycle framework [16].

ISBN 978-91-7583-841-0

The economic perspective as described in TCO framework is, however, not sufficient to describe the performance of asset management. Asset management should be a key driver for improving the sustainability of companies [17]. Taking the social and environmental perspectives into account in addition to the economic perspective gives a more complete view on asset management.

B. Closed loop life cycle framework

In comparison to the TCO framework, the closed loop life cycle framework (Fig. 2) represents a circular model of a life cycle where technical and biological resources such as products, machinery, equipment, material and energy are returned to the cycle after their first life cycle. Circular economy is “restorative and regenerative by design, and aims to keep products, components, and materials at their highest utility and value at all times” [18]. The closed loop life cycle supports sustainable product and service development. It complements the traditional life cycle models by including the material and information flows related to the manufacturing, realisation, distribution, utilisation and end-of-life of a product or service.

The closed loop life cycle contains several feedback loops which enable new kinds of asset based services. These asset based services are enabled by the development of the Internet of things technologies that makes it possible to keep track of the valuable smart products, services and material much more economically than earlier [16]. The development of ICT has brought forth opportunities especially for implementing new R-strategies and waste management practices [16].

IV. RESULTS

A. Service Concepts

Table II describes shortly the service concepts as expressed by the case companies. The service concepts in the case companies are classified into two groups – the asset based services and the ICT services enabling them. These categories are rough but the classification helps to understand the role of the company in the service ecosystem.

B. Assessment of the service concepts

Table III presents the life cycle cost elements in the TCO and the phases in the closed loop life cycle framework. The described elements/phases have been used for the analysis of the service offering summarized in Table II.

TABLE III. THE PHASES IN THE TCO AND THE CLOSED LOOP LIFE CYCLE FRAMEWORKS.

<table>
<tr><th>TCO framework cost elements</th><th>Phases in the closed loop life cycle framework</th></tr>
<tr><td rowspan="4">1. Ownership costs
a. Delivered price
b. Facilities capital costs
c. Miscellaneous ownership costs</td><td>1. Design and development</td></tr>
<tr><td>2. Realisation
a. Resource processing
b. New resources</td></tr>
<tr><td>3. Distribution</td></tr>
<tr><td>4. Sales</td></tr>
<tr><td>2. Explicit operating costs
a. Energy
b. Operator´s wages</td><td rowspan="2">5. Utilisation
a. Service + Enhancement</td></tr>
<tr><td>3. Implicit operating costs
a. Maintenance - service
b. Maintenance - repair
c. Out of service lost revenue
d. Wearing parts cost</td></tr>
<tr><td></td><td>6. End-of-Life or retirement
a. Collection
b. Suitable R-strategy
c. Waste</td></tr>
</table>

Table IV visualises in which phases of the TCO model and the closed loop framework the service concepts of the case companies provide support. Additionally, the goal of the analysis is to highlight the potential for completely new services. The evaluation is based on the expert opinion of the authors.

TABLE IV. COMPARING THE SERVICE CONCEPTS WITH THE TCO-MODEL AND THE SUSTAINABILITY FRAMEWORK.

Company	TCO framework	Closed loop life cycle framework
Asset based services (A)	3a,b	5
Asset based services (B)	3a,b	5
Asset based services (C)	1-3	All phases
Asset based services (D)	3a,b	5
Asset based services (E)	-	2-5
Asset based services (F)	3a,b	3-5
Asset service enabler (G)	2,3	2-6
Asset service enabler (H)	2,3	5 (-6)
Asset service enabler (I)	3a,b	5
Asset based services (J)	1a, 3	1,5
Asset service enabler (K)	3b	5

The companies offering asset based services seem to concentrate their offering development especially to maintenance services with the aim to improve the predictability and efficiency of maintenance actions. Only one provider (Company C) expressed the intention to extend the offering towards full life cycle services. The closed-loop framework yields the same finding: the service focus is in the utilisation phase. None of the asset service providers mentioned wearing parts. The applied TCO model was coarse and for this reason the services delivered by the logistics company (Company E) could not be classified.

ISBN 978-91-7583-841-0

TABLE II. DESCRIPTION OF THE DEVELOPED SERVICE CONCEPTS.

Service type	Service concept	Service concept details
Asset service (A)	- Service for analysis of maintenance, failures and lifetimes	- to identify the possible over or under maintenance, to improve maintenance effectiveness, lifetime of products, subsystems and components, and failure probability estimates
Asset service (B)	- Services for predicting equipment failures, predictions for unit's performance, maintenance and defining best practices	- to predict equipment failures and unit's performance and to define best practice by combining data
Asset service (C)	- Service for optimizing operations and maintenance activities, and estimating total life cycle costs.	- the optimization of operations using multiple data sources and advanced data analysis, defining best maintenance practices through benchmarking different customer segments.
Asset service (D)	- Services for predictable and guaranteed failure free run to the customer based on using machinery and equipment related data.	- to improve the maintenance services, the understanding of the production environment and its causes and effects, and the capabilities for selecting correct maintenance options. - to complement the own data by external data from the customers.
Asset service (E)	- Logistics services and material stream analyses for improved logistic processes.	- to improve logistics services and material stream analyses, and providing a plan for every part in the supply chain. - utilise new opportunities for comparing and analysing logistics processes.
Asset service (F)	- Service manager view to integrated fleet level and customer profiling information	- to make important information available to field service personnel and maintenance management to support their decision-making.
Asset service enabler (G)	- Platform and technical means for IoT solutions	- IoT solutions that increase production output, eliminate breakdowns, predictive maintenance modelling, reduction in downtime, maintenance and service costs, optimizing logistics services, enabling new services
Asset service enabler (H)	- Analytics and platform for predictive maintenance and asset optimization solutions for fleet management	- to support predictive maintenance, asset optimization and advanced analytics in customer companies to, for instance, reduce costs and optimise operations - predictive maintenance and asset optimization solutions for fleet management. - big data analytics
Asset service enabler (I)	- Offering collaboration platforms which combine data from different sources	- to combine maintenance information from various systems, improving the validity - services for ensuring data quality in the customers' information systems.
Asset service (J)	- Helping customers to focus development efforts to improve OEE. Using software and working practice to manage reliability and RAMS requirements.	- to support design for reliability, risk assessment, maintenance optimization decisions and maintenance planning decisions
Asset service enabler (K)	- Platform/infrastructure service for extending the existing service from measuring the asset level to the fleet-level.	- to provide remote monitoring and asset control for supporting asset management decisions and benchmarking. - Predictability information of fleet (e.g. KPIs)

ISBN 978-91-7583-841-0

One software company (Company J) offered services for design and development and utilisation phases that correspond the ownership costs and implicit operating costs in the TCO-model. The companies offering enabling technologies (Companies G, H, I and J) focus also in supporting the utilisation phase and corresponding cost elements in their development work. However, the offered technologies may have much broader application area.

The analysis seems to confirm the assumptions that the manufacturing companies concentrate their service offering development to the utilisation phase asset performance with the emphasis on reducing maintenance costs. This endeavour is supported by enabling ICT technologies (asset service enablers). Less activities are addressing the ownership costs and explicit operating costs, or to the emerging service options in the end-of-life management. A lot of feedback loops in the closed loop model are not covered by the services such as those connected to design and development, realisation and end-of-life or retirement. There is a lot of untapped service potential and extending the service delivery beyond current asset services may help the companies to answer to the recognised service needs.

V. CONCLUSIONS

Manufacturing companies have been actively developing and providing asset based services such as condition monitoring and remote control that help to improve asset performance at the customer's production sites. IoT platforms are important enablers that are needed to offer novel services also to distributed asset fleets and to ensure real-time information exchange across the supply chain. However, close collaboration with the end-customer and other stakeholders is needed to understand the ever-changing customer needs, business and operation environment, and value generation options.

In this study, we used two general frameworks to illustrate customer needs, namely the Total Cost of Ownership (TCO) model and a closed loop life cycle framework. Selected frameworks represent important future development pathways for extending current asset services; monetizing the benefits and costs, and enhancing the sustainability and circular economy practices of asset management services. Thus, the models and frameworks help the technology and service providers to better understand what actions, task and processes the customers carry out, and what cost and value elements drive their actions.

The analysed descriptions for the development of asset based services and the ICT services enabling them seem to confirm the assumptions that the manufacturing companies concentrate their service offering development to the utilisation phase asset performance with the emphasis on reducing maintenance costs. When comparing the service delivery with the TCO model and closed loop life cycle framework it revealed gaps in their service offering. It seems that service providers have not yet recognized the whole growth potential when designing new services as they stick mainly on the data that originates from assets and aim to supports the operation and/or maintenance of the assets rather than co-developing the process with the customer or other stakeholders. Based on the analysed material, extended asset service concepts currently do not exist, however, they are made possible by the asset service enablers.

The service offering gaps indicate potential for extending the service delivery and creating new service concepts together with the customers. Manufacturing companies seem not to recognise the whole potential for asset based services and optimizing the performance of the end customers' processes. In our study, extended asset services refer to the extension of the service delivery to the long-term co-operative development of physical assets over the whole lifecycle. Close collaboration with the end-customer and other stakeholders is needed in order to understand the value generation options of the extended asset services. There is a lot of untapped service potential and extending the service delivery beyond current asset services may help the companies to answer to the recognised service needs.

This study focused on seven asset services and four services that enable asset services to be provided. Larger amount of service concepts should be analysed to provide more accurate insights about the asset services and service development in companies, and the usefulness of the proposed assessment approach.

ACKNOWLEDGMENT

The authors gratefully acknowledge DIMECC (Digital, Internet, Materials & Engineering Co-Creation) for organizing Service Solutions for Fleet Management program (S4Fleet), the Finnish Funding Agency for Technology and Innovation (Tekes) for funding the program and the companies involved in the research.

REFERENCES

[1] J.P. Liyanage "Smart Engineering Assets through Strategic Integration: Seeing Beyond the Convention," In: van der Lei, T., Herder, P., Wijnia, Y. Asset Management: The State of the Art in Europe from a Life Cycle Perspective. Springer Netherlands, 2012.
[2] ISO 55000 "Asset management - Overview, principles and terminology, Standard, 2014.
[3] K. Komonen, H. Kortelainen, and M. Räikkönen "Corporate Asset Management for Industrial Companies: An Integrated Business-Driven Approach," In: van der Lei, T., Herder, P., Wijnia, Y. Asset Management: The State of the Art in Europe from a Life Cycle Perspective. Springer Netherlands, 2012.
[4] B.S. Blanchard and W.J. Fabrycky "Systems engineering and analysis," (3rd ed). Eaglewood Cliffs, NJ. Pretice Hall, 2000.
[5] L. Keys and S. Chen "A cost analysis model for heavy equipment," Computers & Industrial Engineering 56, pp. 1276-1288, 2009.
[6] I. Miles "Service innovation: coming to age in the knowledge-based economy," International Journal of Innovation Management, Vol. 4, No. 4, pp. 371-389, 2000.
[7] T. Ahonen, M. Reunanen, O. Pajari, V. Ojanen, and M. Lanne "Maintenance communities - A new model for the networked delivery of maintenance services," International Journal of Business Innovation and Research, Vol. 4, No. 6, pp. 560-583, 2010.
[8] L. Wiseman, and G. McKeown "Bringing out the best in your people," Harvard Business Review, May, pp. 117-121, 2010.
[9] R.F. Babiceanu and R. Seker "Big Data and virtualization for manufacturing cyber-physical systems: A survey of the current status and future outlook," Computers in Industry, 2016.
[10] B. Esmaeilian, S. Behdad and B. Wang "The evolution and future of manufacturing: A review," Journal of Manufacturing Systems, Volume 39, April 2016, Pages 79–100, 2016.
[11] F. Tao, L. Zhang, V.C. Venkatesh, Y. Luo and Y. Cheng "Cloud manufacturing: a computing and service-oriented manufacturing model," Proc Inst Mech Eng B: J Eng Manuf, 225 Aug (10), pp. 1969–1976, 2011.
[12] J. Hanski, H. Kortelainen, T. Uusitalo "The impact of digitalization on product-service system development in the manufacturing industry – an

interview study," Manuscript sent to International Journal of Services Technology and Management, 2016.
[13] J. Lee, B. Bagheri and H-A. Kao "A Cyber-Physical Systems architecture for Industry 4.0-based manufacturing systems," Manufacturing Letters, Vol. 3, pp.18–23, 2015.
[14] L. Ellram "Total Cost of Ownership. An analysis approach for purchasing," International Journal of Physical Distribution & Logistics Management. Vol. 25. No.8. pp. 4-23, 1995.
[15] B. Ferrin amd R. Plank "Total Cost of Ownership Models: An Explaratory Study," Journal of Supply Chain Management. 2002 Summer, 18-28, 2002.
[16] P. Valkokari, N. Tura, M. Martinsuo, K. Dooley, J. Hanski, J. Jännes, J. Kivilä, K. Palomäki, M. Reunanen, I. Sukanen and K. Valkokari "Sustainable business - Case studies from Finnish forerunners," VTT. 50 p. ISBN 978-951-38-7447-6. Available: http://www.vtt.fi/inf/julkaisut/muut/2016/Sustainable_business_case%2 0studies%20from%2 0Finnish%20forerunners.pdf. [Accessed 23.5.2016], 2016.
[17] D.R. Marlow "Sustainability-Based Asset Management in the Water Sector," In: Amadi-Echendu, JE., Brown, K., Willett, R., Mathew, J. (Eds.) Definitions, Concepts and Scope of Engineering Asset Management. Volume 1 of the series Engineering Asset Management Review pp. 261-275, 2010.
[18] Ellen MacArthur Foundation "Definition of circular economy," website of Ellen MacArthur Foundation. Available at:http://www.ellenmacarthurfoundation.org/circular-economy/overview/concept. [Accessed August 30 2016], 2015.

Chapter 7: New Technology and Solutions

ISBN 978-91-7583-841-0

Processing mining for maintenance decision support

Adithya Thaduri[1]; Stephen Famurewa[2]
[1]adithya.thaduri@ltu.se; [2] stephen.famurewa@ltu.se;
[1,2]Division of Operation, Maintenance and Acoustics, Luleå University of Technology,
Luleå, Sweden.

***Abstract*— Process mining is gaining importance for the classification, clustering, workflow models, process discovery, predictions and planning and scheduling in a process or events in especially business oriented fields. On the other hand, there are several events that are required to perform a maintenance action in various industries. There is a need to understand the process flow of events to reduce the delays to increase the performance of the maintenance action. This paper applies the concept of process mining to understand the events in a typical maintenance action (repair or replacement,). We implemented the process mining for administrative, logistic and repair delays for one section in Swedish Railway. We identified the bottlenecks in this process for different subsystems for productive feedback to the railway industry.**

ISBN 978-91-7583-841-0

Ergonomics Contribution in Maintainability

Kiumars Teymourian[1], A.M.N.D.B.Seneviratne[2], Diego Galar[3]
[1]kiumars.teymourian@ltu.se; [2]dammika.seneviratne@ltu.se; [3]diego.galar@ltu.se
[1,2,3]Luleå University of Technology, Department of Civil, Environmental and Natural Resources Engineering, Division of Operation, Maintenance and Acoustics, Luleå, Sweden

Abstract:—**The objective of this paper is to describe an ergonomics contribution in maintainability. The economical designs, inputs and training helps to increase the maintainability indicators for industrial devices. This analysis can be helpful, among other cases, to compare systems, to achieve a better design regarding maintainability requirements, to improve this maintainability under specific industrial environment and to foresee maintainability problems due to eventual changes in a device operation condition. With this purpose, this work first introduces the notion of ergonomics and human factors, maintainability and the implementation of assessment of human postures, including some important postures to perform maintenance activities. A simulation approach is used to identify the critical posture of the maintenance personnel and implements the defined postures with minimal loads on the personnel who use the equipment in a practical scenario. The simulation inputs are given to the designers to improve the workplace/equipment in order to high level of maintainability. Finally, the work concludes summarizing the more significant aspects and suggesting future research.**

Keywords: ergonomics, maintainability, human posture, human factors, ALBA simulation

I. INTRODUCTION

Technologies for automating manufacturing systems and processes played a key role in manufacturing facilities in the last decades; however, it is impossible to remove human involvement in some of the manufacturing processes and still requires manual handling due to the flexibility and the skill of human operators. Some of these handling tasks deal with heavy physical loads or uncomfortable postures, which might result in stress or overload in the muscles and joints, and further generate potential risks of musculoskeletal disorders (MSDs) [1,2]. In the manufacturing facilities, the design of complex mechanical systems must be carried out easing the tasks of operators who assemble and maintain them. To achieve these objectives, there is a need of detailed set of working instructions, ensuring an effective manufacturing process and a safe work environment.

Digital Human Modelling (DHM) techniques have been introduced to test, validate and improve the working instructions, improve both the design of workers' task and of the product, taking human as the center of the work design system [3–6,7]. A human centric approach allows validating the workspace design, assessing the accessibility of an assembly design, reducing the production cost, and the risk of MSDs as well. Human centred product design [8, 9] is considered an effective means to fulfil the customization trend and it should be conducted through the life cycle as much as possible. In particular in the early stage of product development like Design for Manufacturing (DFM) [10, 11] or Design for Assembly (DFA) [12, 13] ergonomic issues must be seriously taken into account.

During the product design, designers mostly focus on the functionality of their product. These products (industry and private consumers) have an interaction with the intended users at the moment when they are in function or /and when they are in maintenance operations in order to keep them in the function. Nowadays, industrial products are so complex and complicated that a group of designers (electrical, mechanical, hydraulic, etc.) will be engaged only for one product.

In order to have high quality, durability, reliability and ease of use for each product it depends on up to what extent designer contemplated the end users' physical and mental abilities as well as end user limitations. Fulton Suri, (2000) [14] highlighted that today's designers work at a distance from their widely diverse communities of users. In many cases, they are expected to rely upon other specialist functions, such as market research and ergonomics, to act as interpreters of peoples' needs and desires. It is not expected products designer should have a thorough knowledge regarding the end users abilities and limitations. These areas are a domain or knowledge base of ergonomist. Haslegrave and Holmes (1994) [15] argued that it is important for ergonomists to understand the main aspects of engineering design, both related to process, product and business constraints, as well as it is important for design engineers to get some formal education in ergonomics, so that both professions understand each other's approach to design problems.

User centred system-product design logic makes an important conceptual distinction between purely technical design and ergonomically design. So, any divergence or distance from this concept make end users to adapt themselves more to the system or product functions rather than design engineers together with ergonomist try to adapt their system or products to the end users abilities' characteristics.

O'Neill [16] described one of the maintainability aspects during the design process is involvement of the safety engineer in the maintainability management.

ISBN 978-91-7583-841-0

Maintainability in general is a procedure in the process for the design of the system or product in which designers need to go through with the aim of having more maintainable and reliable, high quality, easy to use and higher durable functionality of their design in order to meet intended user requirements.

The content flow of this manuscript is arranged as follows. After an introduction, in the second part a brief literature review is presented, including the definition of the main concepts, which are later used in the paper. Afterwards, in Section 3, the maintainability indicators and maintenance levels are presented. Then, Section 4 the methodology to assign the maintainability attributes from the device design perspective, maintenance staff and work conditions perspective and logistics support perspective is illustrated. Consequently, in Section 5, the implementation of the methodology is explained and the corresponding results are also presented. Section 6 discusses the results obtained from the analysis. Finally, the work concludes summarizing the more significant aspects and suggesting future research.

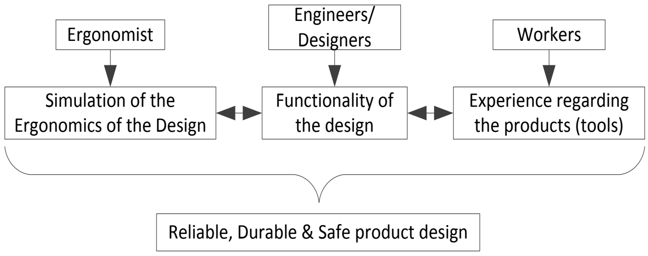


Fig.1. Product design work flow

II. ERGONOMICS AND HUMAN FACTORS

Human factors or ergonomics stands as a multidisciplinary science. It applies for distinction between human abilities concerning physical as well as mental and limitations at the time when human is used or being involved in system operation or use of manufactured products.

Because of being multidisciplinary science Human Factors and Ergonomics Society introduce five different definitions [17];

1) Definition from Professional Societies,

2) Definition from Scientific Literature,

3) Definition from Government Agencies,

4) Definition from Industry;

5) Definitions from open Sources.

All these definitions are shared in the fundamental principle that ergonomic (or human factors) is a method for investigations of interactions between humans and system in order to evaluate compatibility of: design, task, products, technologies and system to the human biological, physiological, psychological and social characteristics. They are also shared in optimizing human performance as well as enhancing health and safety in the environment they are engaged.

Ergonomics deals with human capacities by considering of their work environment. It deals with fitting the task to the man not vice versa as Wickens (1984) [18] defined. There are several tools in ergonomics that can be used in order to evaluate human capacities to the work system requirements. Among them is participatory ergonomic. Brown, (2002) [19] describes; participation and participatory practices are the principal methodologies in the design and analysis of the work system. Cotton (1993) [20] defines the term "employee involvement" as a participative process to use the entire capacity of workers, designed to encourage employee commitment to the organizational success. Wilson and Haines [21] pointed out participatory ergonomics can be regarded as philosophy, an approach or strategy, a program, or a set of techniques and tools. They defined it as the involvement of people in planning and controlling a significant amount of their own work activities, with sufficient knowledge and power to influence both process and outcomes in order to achieve desirable goals.

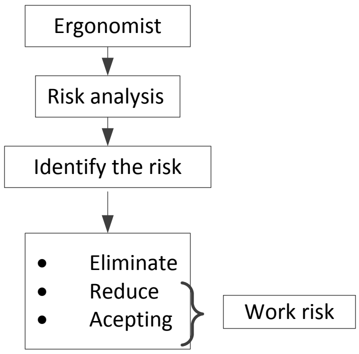


Fig.2. Role of ergonomist participation

III. MAINTAINABILITY

Dhillon [22] define; Maintainability refers to the measures taken during the development, design, and installation of a manufactured product that reduce required maintenance, man-hours, tools, logistic cost, skill levels, and facilities, and ensure that the product meets the requirements for its intended use.

O'Neill [16] "The relative ease and economy of time and resources with which an item can be retained in or restored to a specified condition when maintenance is performed by personnel having specified skill levels, using prescribed procedures and resources, at each prescribed level of maintenance and repair. In this context, it is a function of design." He stated maintainability and reliability test and analysis usually follow performance analysis in the design process. One of the maintainability aspects during the design process is involvement of the safety engineer in the

ISBN 978-91-7583-841-0

maintainability management. The concept of “Safety is first” is believed in all branches.

In Handbook of Department of Defence [23]” In designing for maintainability, the maintainability engineer must be constantly aware of the relationship between maintainability and safety, also maintainability engineer must collaborate with human factors engineer in order to consider human factors during design efforts. It is also mentioned maintainability is included as a subset of human engineering. Safety includes designing the product and maintenance procedures to minimize the possibility of damage to the product during servicing and maintenance, and to minimize the possibility of harm to maintenance and operating personnel.”

In the many industries design of products is for private and/or industrial consumers. For both, designer in European Countries follows the CE (Conformity marking/ Conformite’ Europe’enne) marking in order to clarify their products comply with Safety Directive for intended users.

SIS-ISO/TS 16949:2009 [24], is the standard that supplier for car industries should follow it in order to be Certified as a car parts supplier. The shortage of that cause deviation or in case of major deviation it can be a result of cancelling Certification.

ISO 9001:2008, Quality management systems-Requirement which refers to work environment defines; “the organization shall determine and manage the environment needed to achieve conformity to product requirements”, in that the term “work environment relates to those conditions under which work is performed including physical, environmental and other factors (such as noise, temperature, humidity, lighting or weather). In this standard there is specifically required; “personnel safety to achieve conformity to product requirements as: product safety and means to minimize potential risks to employees shall be addressed by the organization, especially in the design and development process and in manufacturing process activities”.

As it reported in “Fatal Injuries Among Grounds Maintenance Workers --- United States” [25], a total of 1,142 grounds maintenance workers (GMWs) were fatally injured at work during 2003--2008, an average of 190 each year. A study by AFIM [26] (French association of maintenance engineers) on a population of maintenance workers shows an occupational disease rate 10 times higher than for other workers.

Even though designers following all standards for their products or systems, the above reports reveals maintenance people are more in danger compare with other workers. This indicates the designer unintentionally trap in a Black Hole concerning to safety aspects in their design, that is “They do not know what they do not know”.

In order to minimize or eliminating the risks as it mentioned earlier using participatory ergonomics as a tool in the design and development process, it is not only improving safer work environment also will result the increasing of a safety culture among designers. Participators can be; designers, representative of workers union, skilled operators and ergonomist or human factors engineer.

As maintainability designers use different simulation’s programs for testing the functionality of their future product(s), ergonomics engineers can do necessary simulations concerning physical workload (products heaviness, posture taken, calculating biomechanical forces and moments in different part of body), inventing of risks (fall from height, cutting fingers, pinching finger under assembly or/and disassembly of part(s), slippery floor, electrical shock). Through pre-simulation, participators can start to develop a Standard Operating Procedure (SOP) as described by Ali Rastegari [27]. He stated, “An SOP is a written document or instruction detailing all relevant steps and activities of a process or procedure”.

For each operation of task this group should provide a standardized working the process for maintenance operators in a way that where to start and how to end the work. Standardized work provides great benefits such as: stability in process, clear stop and start points for each process, organizational learning, audit and problem solving, employee involvement, Kaizen and training operators, as described by Pascal Denis [28] in his book “Lean Production Second Edition”.

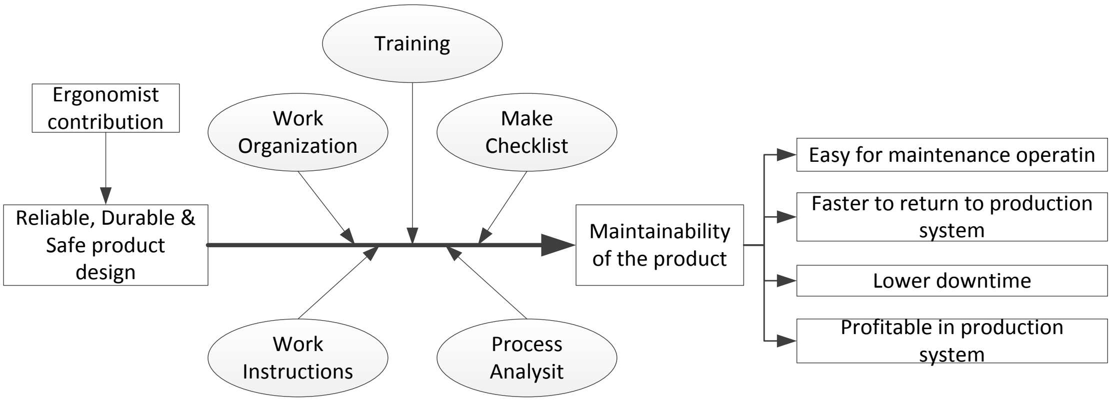


Fig.3. Ergonomics contribution in maintainability

IV. METHODOLOGY

When this process (maintainability design) carried out, the new risk analysis should be done and it should be compared with the simulation phases whether they discover new risk or not. Each identified risk should delegated to responsible person(s) with due date. Responsible person(s) have three alternative; eliminating risk, minimizing risk or accepting the risk as it is. In the situation of second and third alternative relevant personal protective equipment and safe work instruction must be prepared. Regarding physical workload is the same, ergonomist should find technical lifting aids, other aid equipment or redesigning work cell structures.

Concerning physical workload at different taken postures, it is necessary to calculate biomechanical forces and moment to the most critical parts of the body.

One way during the design process in maintainability is that ergonomist use different simulation program which among them is a ALBA biomechanical analysis program. This program is developed at Linköping University in Sweden in 1994. ALBA has different functions and has eight countries anthropometrical data both for women and men. Among its anthropometric data two of them concern with body segment weight and their center of mass locations. Chaffin, Andersson and Martin in “Occupational Biomechanics [29] describe how to calculate body segment mass which is a product of:

$$D = m/V = (W/g)/V \qquad (1)$$

Where D is mass per unit volume (g/cm3), m is the mass of body segment (g or kg), V is the volume of water displaced (g/cm^3), W is the weight of the body segment (N) and g is the gravitational acceleration constant (m/sec^2).

Segment mass = Segment Volume (cm^2) x Segment Density (g/cm^3). (2)

Knowing these two parameters (body segment weight and its centre of gravity) it helps to calculate the biomechanical stress (forces and moments) in some critical parts of the body. These critical parts are; elbow, shoulder, L5S1 (the lowest of the lumbar spine’s of five vertebrae and the first vertebrae of the sacrum), hip, knee and ankle.

V. IMPLIMENTATION AND RESUTS

In ALBA compendium it is stated if the compression in spine shows the force between 2500-4500 Newton it increase the risk of back injury and significantly increased risk of back injury when the compression exceeds over 4500 Newton.

At first, the existing working conditions are considered. Figure 1 shows a simulation without any hand load in situations; Squat and stoop postures. In these simulations it assumed an asymmetry angle in the sagittal plane is 0. In the ALBA anthropometries data, body segments weight for head, neck, hand and trunk is 63.5% of the total body weight. For below simulation, English men at 50 percentile were selected. In figure 2 and 3 it simulated hand load for 5 and 10 kg for the same postures. The results in table 1 show even there is no load in hands based on only body segments weight having stoop posture is in risky zone and significantly increasing stress on moments on L5S1 and back compressions when hand load is 5 and 10 kg respectively.

Table 1 shows the existing taking squat posture compare to stoop posture maintenance operators have less stress moment on L5 S1 (Nm) and back compression (N) in all three simulation phases.

Squat posture Stoop posture

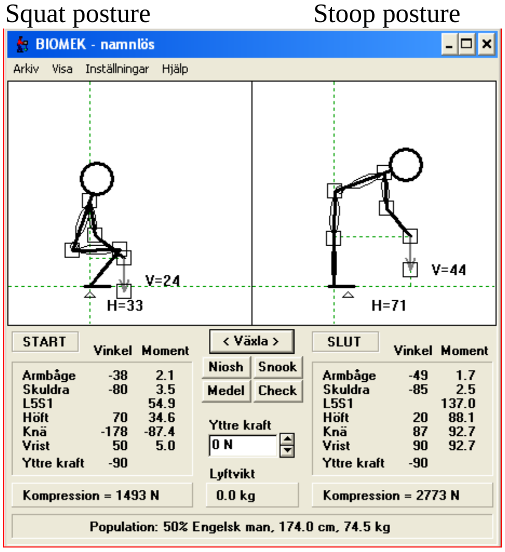


Fig.1. Lift object is 0 kg

Squat lift posture Stoop lift posture

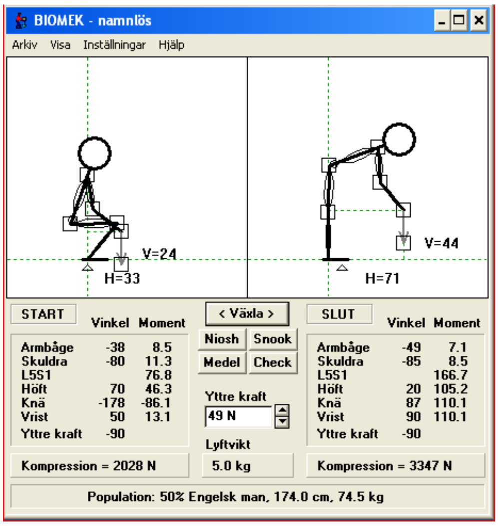


Fig.2. Lift object is 5 kg.

ISBN 978-91-7583-841-0

Squat lift posture Stoop lift posture

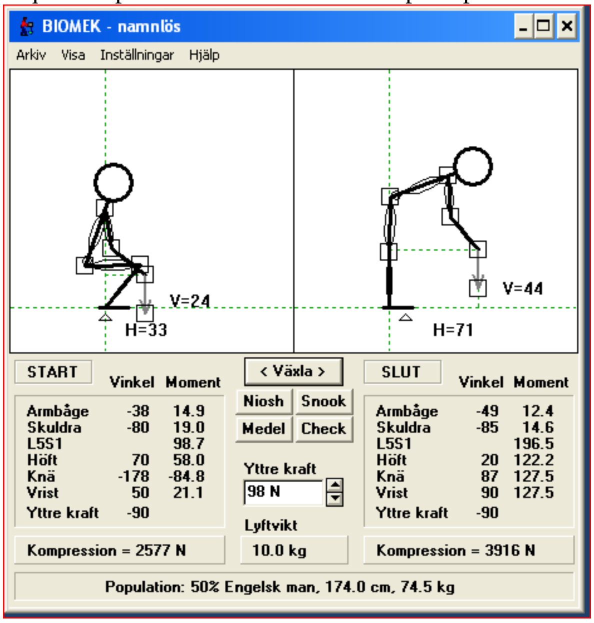


Fig.3. Lift object is 10 kg.

Squat lift posture Stoop lift posture

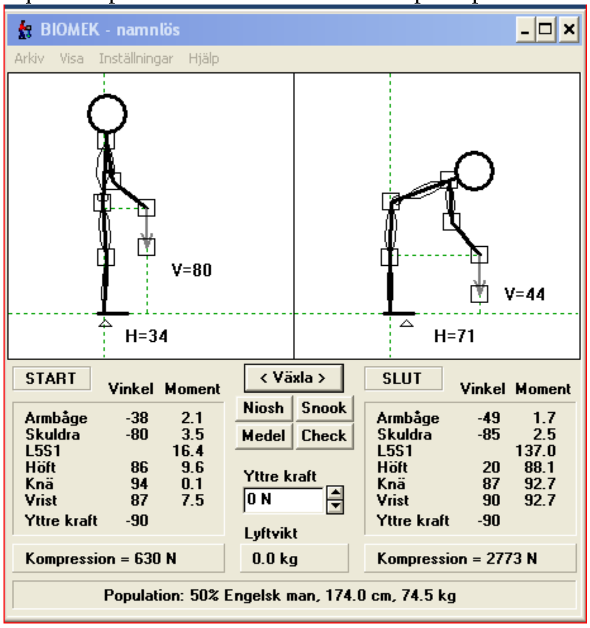


Fig.4. Lift object is 0 kg (new posture)

TABLE I. EXISTING STRESSES FOR LOADING CONDITIONS

	Squat posture			Stoop posture		
Hand load weight	0 kg	5 kg	10 kg	0 kg	5 kg	10 kg
L5 S1 (Nm)	54,9	76,8	98,7	137	166,7	196,5
Back compression (N)	1493	2028	2577	2773	33477	3916

In the shop floor the existing working conditions at the working place were observed and better arrangement of working place with a better positioning is suggested. The improved work place environment is designed in a way that operators can have standing posture instead of squat situation the stress moment and back compression can be reduced. The simulated results of the new working environment with the new posture for the stresses with different loading conditions are shown in figure 4, figure 5 and figure 6. The table 2 summarise the stress conditions for the new posture.

Squat lift posture Stoop lift posture

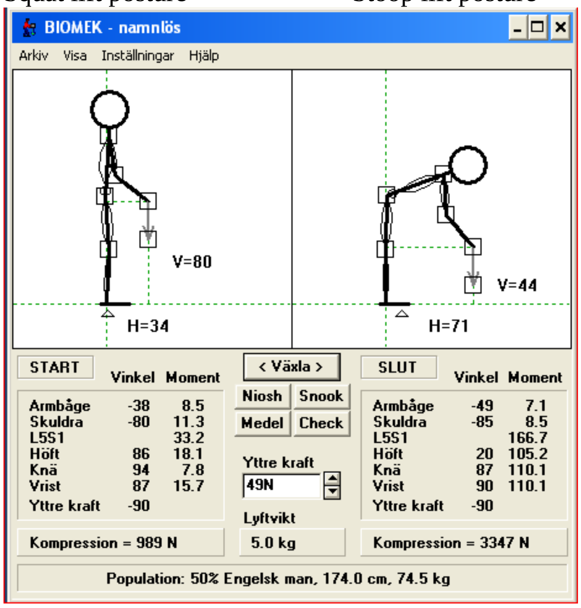


Fig.5. Lift object is 5 kg (new posture)

Squat lift posture Stoop lift posture

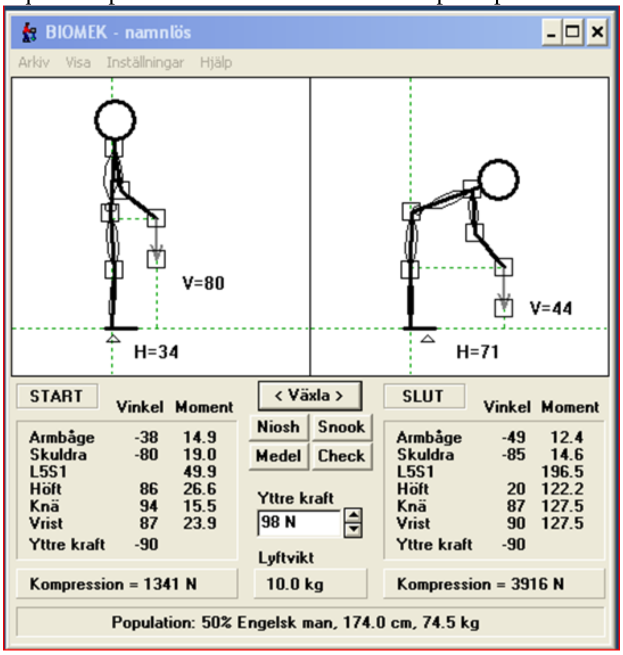


Fig.6. Lift object is 10 kg (new posture)

TABLE II. IMPROVED LOADING CONDITIONS

	Standing posture			Stoop posture		
Hand load weight	0 kg	5 kg	10 kg	0 kg	5 kg	10 kg
L5 S1 (Nm)	16	33,2	49,9	137	166,7	196,5
Back compression (N)	630	989	1341	2773	3347	3916

VI. DISCUSSION AND CONCLUTIONS

The newly introduced “Squat lift posture” reduces the stress levels (L5S1 and back compression) of the workers by 50% (approximately). Therefore, the newly designed workplace has improved the working levels, improving the maintainability aspects.

With the purpose of optimizing human performance in maintainability design procedure, establishing a group of designer, ergonomist and skilled operators who will have interaction with products is key of success to have a good designed product. Designers solve problem by technical manual(s) and aids while ergonomist and skilled operators prefer analytical and technical way base on their knowledge and experience.

Ergonomist contribution in maintainability design process can be in two platforms; Micro and Macro Ergonomic. Micro ergonomic deals with technical aspects of design; workplace, tools, software, while Macro Ergonomics deals with instruction or regulation of production system, work organization, organizational design (complexity, formalization and centralization) and function allocation.

In the maintainability design process both designer and ergonomist need to understand each other more in order to solve both technical and human limitation problems. Successful design needs collaboration between maintainability designer and ergonomist.

This collaboration leads higher adaptability and flexibility of designing a product to the intended users, lower cost for maintenance operation, more efficient maintenance can result faster return to operation or service consequently decreasing downtime, and lower cost of ownership over the product’s life cycle.

REFERENCES

[1] Colombo, G.; et al.: Virtual ergonomics to design auxiliary equipment for commercial refrigeration, Proceedings of TMCE 2012, May 7–11, 2012, Karlsruhe, Germany. Karlsruhe (Germany), 7–11 May 2012, Voorschoten: Emerald Eye R&C, 383–392.

[2] Li G.; Buckle, P.: Current techniques for assessing physical exposure to work-related musculoskeletal risks with emphasis on posturebased methods, Ergonomics, 42(5), 1999, 674–695.

[3] Chaffin, D.B.: On simulating human reach motions for ergonomics analyses, Hum Factors Ergon. Manuf., 12(3), 2002, 235–247.

[4] Chaffin, D.B.: Human motion simulation for vehicle and workplace design. Hum Factors Ergon. Manuf., 17(5), 2007, 475–484.

[5] Colombo, G.; Cugini, U.: Virtual Humans and Prototypes to Evaluate Ergonomics and Safety, Journal of Engineering Design, 16(2), 2005, 195–207.

[6] Colombo, G.; Facoetti, G.; Rizzi, C.: Virtual testing laboratory for lower limb prosthesis, Computer-Aided Design and Applications, 10(4), 2013, 671–683.

[7] Mavrikios, D.; et al.: An Approach to Human Motion Analysis and Modeling, International Journal of Industrial Ergonomics, 36(11), 2006, 979–89.

[8] Baek, S.Y.; Lee, K.: Parametric Human Body Shape Modeling Framework for Human-Centered Product Design, Computer Aided Design, 44(1), 2012, 56–67.

[9] Maguire, M.: Methods to Support Human- Centred Design, International Journal of Human Computer Studies, 55(4), 2001, 587–634.

[10] Kuo, T.C.; Huang, S. H.; Zhang, H.C.: Design for Manufacture and Design for ’X’: Concepts, Applications, and Perspectives, Computers and Industrial Engineering, 41(3), 2001, 241–60.

[11] Skander, A.; Roucoules, L.; Klein Meyer, J. S.: Design and Manufacturing Interface Modeling for Manufacturing Processes Selection and Knowledge Synthesis in Design, International Journal of Advanced Manufacturing Technology, 37(5–6), 2008, 443–54.

[12] Stone, R. B.; McAdams, D. A.; Kayyalethekkel, V. J.: A Product Architecture-Based Conceptual DFA Technique, Design Studies, 25(3), 2004, 301–25.

[13] De Lit, P.; Delchambre, A.; Henrioud, J. M.: An Integrated Approach for Product Family and Assembly System Design, EEE Transactions on Robotics and Automation, 19(2), 2003, 324–34.

[14] Fulton Suri, J. (2000b). (1) Inclusive design through individual insight. XIVth congress of

[15] Haslegrave, C. M. and Holmes, K. (1994). (2) Integrating ergonomics and engineering in theTechnical design process. Applied Ergonomics 25(4): 211-220.

[16] O'neill, Gary. "Maintainability: Theory and Practice." System Health Management: With Aerospace Applications (2011): 309-317.

[17]http://www.hfes.org/Web/EducationalResources/HFEdefinitionsmain.html

[18] Wickens, C.D. (1984). Engineering Psychology and Human Performance (Columbus, OH: Charles E. Merrill).

[19] Brown, O., Jr. (2002), Macroergonomic methods: participation, in Macroergonomics: Theory, Methods, and Applications, Hendrick, H.W. and Kleiner, B.M., Eds., Lawrence Erlbaum Associates, Mahwah, NJ, pp. 25–44.

[20] Cotton, J.L. (1993), Employee Involvement, Sage, Newbury Park, CA.

[21] Haines, H.M. and Wilson, J.R. (1998), Development of a Framework for Participatory Ergonomics, Health and Safety Executive, Sudbury, Suffolk, U.K.

[22] B.S. Dhillon, Engineering Maintainability: How to Design for Reliability and Easy Maintenance, Publisher: Elsevier Science & Technology Books

[23] Department of defense handbook designing and developing maintainable products and systems volume i. Superseding mil-hdbk-470 12 june 1995 mil-hdbk-471 12 june 1995.

[24] http://www.sis.se/en/management-system/quality-management-systems/sis-iso-ts-169492009

[25] Fatal Injuries Among Grounds Maintenance Workers --- United States, 2003—2008, Weekly May 6, 2011 / 60(17);542-546, http://www.cdc.gov/mmwr/preview/mmwrhtml/mm6017a3.htm

[26] https://oshwiki.eu/wiki/Why_is_maintenance_a_high_risk_activity%3F

[27] Ali Rastegari, Master Thesis for Volvo Powertrain, 2012-10-20. Strategic Maintenance Management in Lean Environment.

[28] Pascal Denis, Lean Production Second Edition ISBN 978-1-56327-356-8.

[29] Don B. Chaffin, Gunnar. B. J. Andersson and Bernard J. Martin. Occupational Biomechanics Fourth Edition, ISBN 978-0-471-72343-1.

An approach to Symbolic Modelling: A Railway Case study for Maintenance Recovery Level Identification

Mahdieh Ahmadi[1]; A.M.N.D.B.Seneviratne[2]; A.H.S. Garmabaki[3]

[1]mahdiehahmadi@yahoo.com; [2]dammika.seneviratne@ltu.se; [3]amir.garmabaki@ltu.se;

[1]Department of Industrial Engineering, Mazandaran University of Science and Technology, Babol, Iran

[2,3]Division of Operation, Maintenance and Acoustics, Luleå University of Technology, Luleå, Sweden.

***Abstract*— Increasing demand for quality and reliability of the asset is progressively seen as a motivation for improved maintenance procedure and management. Always the role of qualitative maintenance data is neglected in the maintenance recovery level identification. Human factor parameter in the maintenance and qualitative technical data, for instance, maintenance experience, maintenance knowledge, training, quality before maintenance, number of previous maintenance, maintenance documentation and environmental condition can be collected and evaluated to increase the accuracy of maintenance recovery estimation. This information always expressed linguistically and considering their effect in the recovery model is challenging. The aim of this study is to propose a symbolic model to capture the effect of above qualitative factor on maintenance recovery level. Fuzzy inference systems are applied to qualitative expert knowledge to extract the percentage effect which can be incorporated in the recovery level model. The tamping railway case study is considered to validate the model. The results show that the maintenance experience and environmental condition are playing main role in maintenance quality. The application of above method can be extended to asset condition assessment in combination with data driven and physical model.**

ISBN 978-91-7583-841-0

ISBN 978-91-7583-841-0

Organized by

LULEA UNIVERSITY OF TECHNOLOGY
DIVISION OF
OPERATION AND MAINTENANCE ENGINEERING

Sponsored by

ScAIEM: Scandinavian Academy of Industrial Engineering and Management

Division of Operation and Maintenance Engineering
Luleå University of Technology, SE– 97187, Sweden
Tel: +46920491000 Fax: +46920491935
Website: www.ltu.se

ISBN 978-91-7583-841-0