DEGREE PROJECT

Improving Availability of the Pelletization Process

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Industrial and Management Engineering, master's level
2022

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Preface

This master's thesis has been conducted to finalize our five years of higher education in the subject of Industrial Engineering and Management at Luleå University of Technology. The thesis project was conducted in collaboration with LKAB in Kiruna, Sweden. The thesis focused on quality management in a high-volume industrial setting and was conducted in the spring of 2022.

The assistance received from the employees at LKAB and especially from our supervisor, Mattias Orava, has been essential for the thesis' workflow and its result, for which we want to express our graduate. We also want to seize this opportunity to express our appreciation to our peer reviewers, Albin Genberg, Mattias Roos, Eleonore Höddelius, and Martin Johansson, for their expertise and valuable feedback influenced the thesis' outcome in the most positive manner. Lastly, we would like to thank our instructor from Luleå University of Technology, Erik Vanhatalo, for his constant support and guidance throughout the spring, which have been great assets for us to rely on during its procedure.

Luleå, June 22, 2022

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Abstract

The Grate-Kiln-Cooler process is a commonly used method of sintering during iron ore pelletization, where the pellets are formed, dried, and hardened. The pellets are oxidized in the rotating Kiln, turning magnetite (Fe_3O_4) to hematite (Fe_2O_3), making the pellets attain suitable metallurgical attributes for further processing. The process is constantly exposed to thermal and mechanical stress, causing equipment degradation and thus unwanted production stops due to internal process disturbances. A suitable maintenance policy is required to cope with the risk of equipment degradation causing these production stops. Predictive maintenance (PdM) is the most current maintenance policy, utilizing a substantial amount of production data to foresee breakdowns and thus indicating the need for maintenance efforts to prevent them from occurring.

The global supplier of iron ore products, Loussavaara-Kiirunavaara Aktiebolag (LKAB), operates three pelletization plants in Kiruna. One of these pelletization plants experiences availability below desired levels. This hampers the plant from fulfilling its yearly production goals, resulting in lost revenue. This master's thesis aimed to increase the understanding of which causes influence the Grate-Kiln-Cooler process' availability. When these causes were identified, the aim was to develop a method of monitoring these to predict the need for maintenance (i.e., incorporating a PdM policy) to mitigate the risk of production stops. The work has been conducted by utilizing the systematic problem-solving DMAIC methodology.

The refractory material was identified as the primary contributor to the low availability in the investigated plant. Using principal component analysis (PCA) and statistical process control (SPC), a Hotelling T^2 chart based on principal components was established to monitor the refractory material's condition. In this context, the combined usage of PCA and SPC highlighted three possible tendencies in the Kiln that potentially damaged the refractory material, causing production stops. The observed tendencies with the possibility of damaging the refractory material were; abnormally high refractory material temperatures, periods where the pellets' temperature exceeded the refractory material's temperature, and sporadic heat fluctuations in the refractory material.

The utilized Hotelling T^2 chart provided a current state evaluation of the refractory material's condition and thus indicated the need for maintenance efforts. However, it was impossible to predict breakdowns by identifying patterns in either the T^2-statistics or the individual charts. The inability to predict stops was derived from obstacles related to lacking documentation, deficient data, and that the time for breakdown is difficult to determine accurately. These obstacles hinder the prediction of breakdowns and, therefore, need to be dealt with to facilitate the implementation of a successful PdM strategy.

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1 Introduction

The following chapter presents a background where central themes regarding the subject are brought up alongside a problem description. The purpose of the master's thesis will then be presented followed by the limitations of the study.

1.1 Background

The Grate-Kiln-Cooler process is one of the most commonly used pelletization processes of iron ore (G. Singh et al., 2015). Pelletization in this context is a process where pellets consisting of bindings and magnetite concentrate are formed, dried, and hardened (Kawatra & Ripke, 2003). It is performed for the pellets to obtain strength to survive transportation and to acquire the right metallurgical attributes for further processing (Kawatra & Ripke, 2003). It is crucial for the pellets to keep their shape and not break into smaller pieces called fines (Eisele & Kawatra, 2003). Fines could create a nonpermeable bed of material in further processing, which decreases the quality of the final product (Eisele & Kawatra, 2003). Formed pellets travel through the Grate to lower their moisture level by gradually increasing the heat in sections while the pellets move through it (Thurlby, 1988). The hardening process is performed through oxidation which starts in the later stages of the Grate and accelerates when the pellets reach the rotating Kiln (Stjernberg et al., 2015). The process of oxidizing magnetite is called sintering and turns magnetite (Fe_3O_4) to hematite (Fe_2O_3) and simultaneously fuses the individual particles into a solid (Kawatra & Ripke, 2003). After the sintering process, the pellet's temperature decreases in the Cooler until they reach a temperature that allows them to be stored and then transported to the customer (A. Rönnebro, personal communication, 18 Jan 2022).

Varying temperatures and constantly moving components expose the equipment in the Grate-Kiln-Cooler to thermal and mechanical stress, which causes degradation of machine components (Malfliet et al., 2014). The process involves many different components at risk for degradation that could cause production stops. Unplanned production stops affect the total amount of produced pellets and lead to waste when the plant is shut down. Maintenance efforts are needed to ensure the process's performance to avoid component failure that could cause unexpected stops (Çınar et al., 2020).

Maintenance of machinery can reduce production costs and increase profits by increasing equipment's lifetime and hindering production stops (Sharma et al., 2005). In recent years, the significance of maintenance management has become vital as organizations today allocate more resources in terms of workforce and financial means in favor of their maintenance efforts (Garg & Deshmukh, 2006). Cost of maintenance stands for a large part of producing organization's overall operating costs (Garg & Deshmukh, 2006), and according to Han and Yang (2006), it accounts for about 15 to 40% of organizations' total operational-related costs. Poorly managed maintenance efforts could increase this portion to become even more substantial (Salonen & Deleryd, 2011). Maintenance management can be defined as the combination of technical and administrative tasks utilized to retain or restore a system to its normal functional state (C.-H. Wang & Hwang, 2004). C.-H. Wang and Hwang (2004) further mentions that the objectives of a maintenance management program are to ensure system lifetime, safety, and function.

For organizations to benefit from the objectives presented by C.-H. Wang and Hwang (2004), a maintenance strategy is needed (Parida, 2007; Murthy & Hwang, 1996). Different strategies fit different situations (Nezami & Yildirim, 2013), and the different strategies are generally divided into two categories; preventive- and corrective maintenance (Li et al., 2006). According to H. Wang (2002), subcategories within the preventive maintenance domain consist of policies with the general objective to perform maintenance before failures occur, often based on systematic measurements and inspections to assess the equipment's condition. Corrective maintenance, in contrast, aims to perform actions solely when failure is a fact (H. Wang, 2002). Preventive maintenance strategies are considered more demanding due to their need for data and subsequent analysis to manage the maintenance and thus avoid the negative consequences that emerge when the process stops (Carvalho et al., 2019). If operations succeed with acquiring and utilizing this data, it enables them to predict and schedule when maintenance is needed and thus, avoid breakdowns, reduce costs, increase effectiveness, and improve reliability (Hashemian, 2010). Predictive maintenance (PdM) is the most current policy that utilizes these large quantities of data to foresee potential breakdowns and signal when early signs of failures emerge (Selcuk, 2017). Besides preventing system failure, PdM fosters efficient use of resources (Selcuk, 2017).

1.2 Problem discussion

Luossavaara-Kiirunavaara Aktiebolag (LKAB) is a global supplier of refined iron ore products. LKAB's operation in Kiruna consists of mining and refinement of iron ore. The iron ore is mined underground and later processed above ground into different products and then shipped to customers. The refinement operation in Kiruna consists of a sorting plant, three concentrating plants, and three pelletizing plants, see Figure 1.

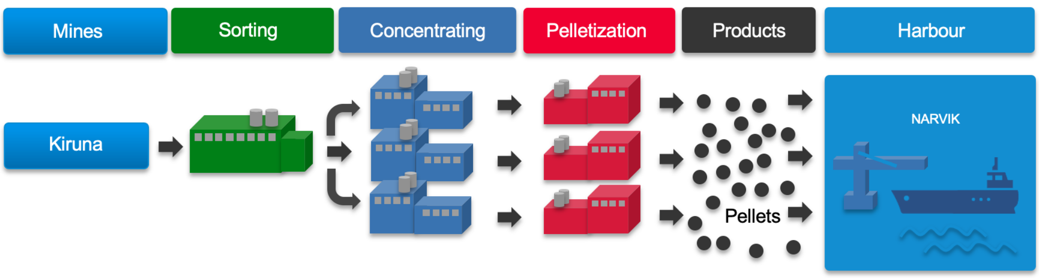

Figure 1: *LKAB's supply chain*

The pelletization process can be divided into two major parts, the cold and the warm. The cold part involves creating the right mixture between binders and raw material and forming the pellets. The warm part consists of the Grate-Kiln-Cooler process, which sinters and cools the pellets. LKAB experiences challenges with an availability below satisfactory levels in one of the pelletization plants, which has made the plant unable to fulfill its yearly production goal. The investigated plan is also less reliable than the others in regards to yearly produced pellets due to a more considerable year-to-year variation, see Figure ??. Today, the causes of this problem and their effect on the plant's availability are unknown. However, LKAB believes it could stem from deviations within the warm part of the process (A. Rönnebro, personal communication, 18 Jan 2022).

The pelletizing plant's performance is mainly evaluated through three Key performance indicators (KPIs), which constitute LKAB's Overall Equipment Efficiency (OEE) (M. Orava, personal communication, 18 Nov 2021). The purpose of the OEE value is to highlight areas with potential for improvement and thus provide fact-based support to foster development (Nakajima, 1988). According to Nakajima (1988), the OEE is determined as the product of the factors; availability, operational efficiency, and quality rate. Thus, the OEE value can be defined as follows:

$$OEE = \ Availability \quad \mathbf{x} \quad Operational\ efficiency \quad \mathbf{x} \quad Quality\ rate \tag{1}$$

According to Parida et al. (2014), low OEE industry averages are today's most prominent existing industry issue. Ylipää et al. (2017) who researched the average OEE of 98 Swedish companies, concluded it to be approximately 50%, which is coherent with Ingemansson (2004) estimations. The two main contributors to the low OEE values in the research by Ylipää et al. (2017), were the average operational efficiency (67,1%) and the average availability (78,9%).

LKAB defines availability as the fraction of the time the pelletization plant produces pellets out of the total available time (M. Orava, personal communication, 01 Feb 2022). Factors determining the availability are internal disturbances (y) and preventive maintenance efforts (z). External disturbances (e.g., downtime due to supplier shortages) and scheduled downtime (t) do not influence the availability as these factors do not evaluate equipment condition. All factors are measured in terms of hours. It is thus possible to calculate the daily availability value (A) as:

$$A = \frac{24 - y - z - t}{24 - t} \quad ; \quad 0 \leqslant y,\ z,\ t \leqslant 24 \tag{2}$$

The availability of the investigated plant is 86-87%, while the others both have an availability of 88-89%. It suggests that potential for improvement exists due to the goal of 93% availability. The potential for improvement is further strengthened by the fact that the plant is the latest plant and that it should be able to be at least or more efficient than the other plants. According to LKAB, it costs the organization around 1 million SEK in lost revenue per hour when the plant is experiencing failure (i.e., production stops)[1]. Failure is defined as the termination of an item's ability to perform a required function (Swedish Standard Institute,

[1]The lost revenue is a rough estimation from two senior engineers at LKAB. Important to mention is that the iron ore price heavily influences the loss, where this estimation is based on the prizes of 2021.

2010). LKAB's aim is that the availability should be greater or equal to the other pelletizing plants as this would have a positive financial impact. All of LKAB's pelletizing plants use similar processes and raw materials, which indicates that the availability could increase (M. Orava, personal communication, 27 Jan 2022). With these factors being similar, a hypothesis is that the divergence stems from internal disturbances unique to the investigated plant.

1.3 Purpose

The purpose of this thesis is to contribute to increased availability in one of LKAB's pelletization plants in Kiruna. The aim is to increase the understanding of what is affecting the availability in order to monitor these causes by developing a model to predict when maintenance is needed. This aim could be divided into the following two sub-aims;

- identify causes of process disturbances,
- develop a method of monitoring these identified causes to predict the need of maintenance.

1.4 Delimitations

The project will investigate only one of the pelletizing plants in Kiruna. The plant needs to increase availability in order for the plant to achieve its long-term goal of increased production rate. Availability is the only KPI out of the OEE measurements which will be investigated. The parts of the process included within the scope are limited to the Grate-Kiln-Cooler process, which LKAB deem has caused much downtime in recent years. Only internal disturbances will be taken into account as it is a factor that heavily affects the availability.

2 Methodology

The following chapter presents the research method with a motivation for why it has been chosen to fulfill the master's thesis purpose. Further, how data was gathered and analyzed is explained and motivated, followed by a discussion regarding the reliability and validity of the study.

2.1 Investigative approach

This thesis project was conducted in collaboration with LKAB to identify the causes of low availability at the investigated plant. An exploratory approach was adopted because of the need to find what could have been the cause's origin of the problem. Data was gathered through access to LKAB's maintenance software (Plant performance) and production software (Process Explorer), which contained data regarding internal stops and multiple production parameters. It was decided to explore the problems and recognize patterns throughout the project in different ways, which is explained for each step. Therefore, the study utilized a quantitative research approach using secondary data, which saved time in the data collection and enabled a significant amount of historical data to be analyzed. The analysis was conducted to generate hypotheses of possible causes, which were subsequently tested. This approach which moves back and forth between data and theory is referred to as an abductive approach (Saunders et al., 2007), which is a suitable approach when one desires to develop an understanding of what could have caused an unanticipated event (Van Maanen et al., 2007). The abductive approach was appropriate as it is a combination of the inductive and deductive approach (Dubois & Gadde, 2002). An abductive approach allowed the continuous increase of knowledge during the workflow to be obtained simultaneously by observations and existing literature. This approach became beneficial as it allowed the results to be based on a fusion of current theory and empirical observations, increasing the probability of novel findings.

To fulfill the purpose of the thesis, the problem-solving methodology DMAIC was used, which is a part of the Six Sigma framework. DMAIC is a systematic approach for solving problems divided into different steps and is a widely used procedure in quality and process-related improvements (Mehrjerdi, 2011). The framework is often related to the quality of a process's outcome but could also be used as a tool to improve process quality (S. Kumar et al., 2011). The authors further mention that utilizing the DMAIC methodology in a project could eliminate errors and disturbances that affect the process's output. When the problem is defined and quantified, data could be used to clarify it, which enables analytic tools to trace the problem to its root causes (S. Kumar et al., 2011). The operation is then subjected to a control stage to monitor future behavior to prevent the recurrence of the problem. In the context of LKAB, the output were the availability. The DMAIC approach were used because the causes of the stops had to be identified in order to achieve the project's purpose. The DMAIC methodology contains five steps: *Define, Measure, Analyze, Improve, and Control* which objectives, according to Montgomery (2017), are presented in Table 1, where the actions taken to fulfill the steps are presented.

Table 1: *The steps of the DMAIC methodology and their content*

Step	Content presented by Montgomery (2020)	Actions
Define	Identify and map the involved processes and define critical requirements for the process. When an opportunity for improvement is identified, it is essential to validate the improvement's possible impact on the business performance.	The Grate-Kiln-Cooler process was mapped together with employees at LKAB through meetings and a tour of the pelletizing plant in Kiruna. A literature review complemented the gathered knowledge, which enabled an investigation regarding how to increase availability. The causes of disturbances were examined, and their impact on the availability during recent years was later evaluated. The results later laid the ground for deciding what cause to examine further in future steps. Also, the impact of the business performance were approximated by a calculation of the potential savings.
Measure	Determining what to measure, how to collect data, and assessing the current state of the process performance.	The current performance was evaluated for the whole process and its constituting parts. An investigation regarding whether autocorrelation was present for the initial availability screening was conducted to ensure validity. Furthermore, the project presents and discusses how quantitative and qualitative data were gathered and utilized.
Analyze	Analyzing obtained data to identify causes of variation by investigating hypotheses.	The seasonal effect on the availability was investigated. Production data was analyzed through both univariate and multivariate methods to explain as much variation as possible. Further, a method to monitor the process's performance was developed.
Improve	Propose suggestions based on the previous steps aimed to fulfill the project's purpose. Finally, verify the final solution to gain approval.	Findings gathered from previous steps were used to present suggestions that would fulfill the thesis's aim. The proposed solution's merits and limitations were further discussed. The proposed findings were validated with LKAB to ensure their relevance to fulfill the thesis's purpose.
Control	Propose a method in order to sustain the gained benefits thanks to the earlier presented improvements.	The section proposed how the solution can be used into LKAB's daily operations. The need to update the model was also presented with critical factors that have to be considered when updating the model in the future.

The project was constructed in three phases, with different objectives. The phases aimed to; identify internal disturbances, identify causes of these disturbances, and finally develop a way of monitoring critical factors that will indicate the need of maintenance. The initial phase aimed to fulfill the thesis's first part of the purpose regarding identifying process disturbances. The two following phases aimed to fulfill the second part of the purpose regarding developing a model with the ability to indicate when maintenance is needed. How the steps of the DMAIC methodology were divided among the phases and which specific activities were concluded in each phase are presented in Figure 2.

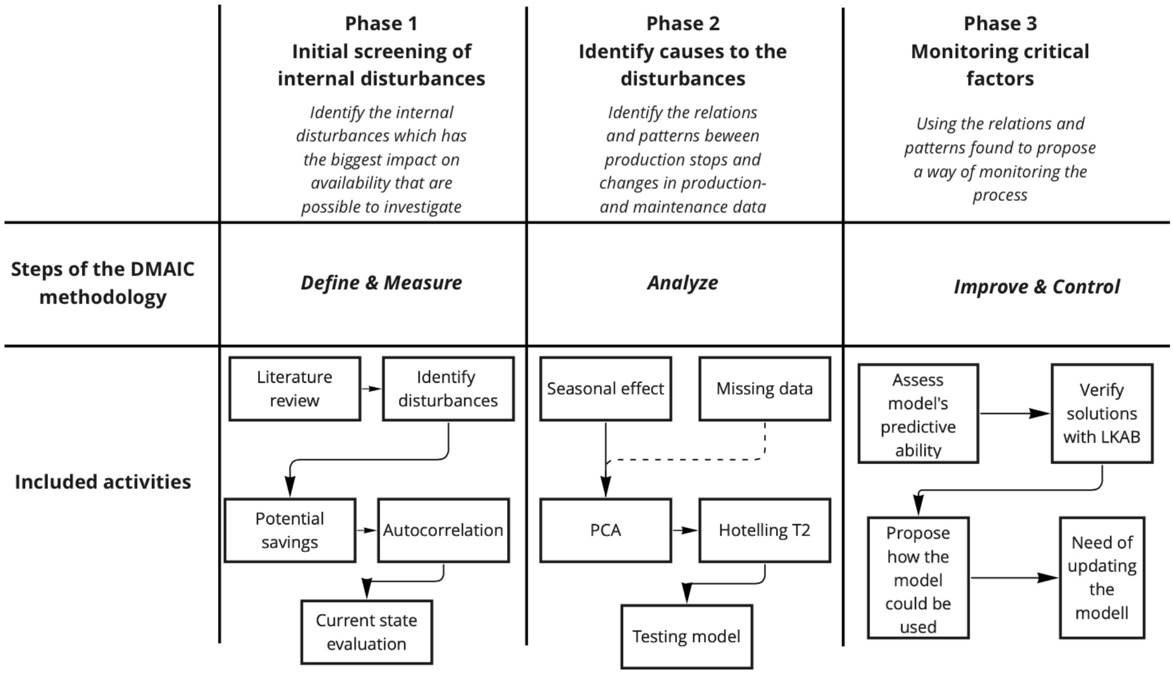

Figure 2: *Executed activities in the different project phases*

2.1.1 Literature review

A literature review was conducted during the first phase of the project. The literature review was performed to increase the understanding of maintenance efforts in the Grate-Kiln-Cooler process. The gathered knowledge did also act as a foundation for the project's last phase. Peer-reviewed scientific articles published in journals were primarily used to gather information and knowledge. Books were also used to find information but less frequently. For a book to be perceived as valid literature to be included in the theoretical background, it needed to previously be frequently cited in other peer-reviewed scientific papers to verify its scientific validity. However, books were only used when needed, and if there existed the possibility to use a scientific article instead, the scientific article was used. The databases Google Scholar and Scopus were used to obtain literature. During the search for appropriate literature, the search results were filtered based on the number of citations to increase the probability that the obtained literature was relevant. Some of the keywords and the number of hits the keyword generated during the search for relevant literature are presented in Table 2.

Table 2: *Keywords used in Google Scholar and Scopus*

Database	**Keywords**	**Date of retrieval**	**No. Hits**
Scopus	Predictive maintenance AND availability AND increase	February 2022	126 hits
Google Scholar	SPC AND OEE AND monitoring	February 2022	1500 hits
Google Scholar	Grate-Kiln AND pelletization AND performance	March 2022	407 hits
Google Scholar	Grate-Kiln AND refractory material	March 2022	254 hits
Google Scholar	Grate-Kiln AND monitoring	March 2022	249 hits

The literature review included research regarding appropriate maintenance strategies to increase plant performance and current methods for production performance evaluation. Further, literature were reviewed regarding how monitoring of processes could be conducted. Literature regarding the Grate-Kiln-Cooler process was also gathered to gain a deeper understanding of how it operates and which generic internal disturbances it is prone to. The review enabled the identification of possible causes for process failure.

2.2 Define

The define step aimed to identify and validate the potential improvements of the Grate-Kiln-Cooler process. To gain an initial understanding of the pelletization process, three meetings were arranged during the first week of the project, where process engineers presented the process in detail. The company's site in Kiruna was further visited to understand the manufacturing process. The literature review was extended with literature about the Grate-Kiln process with the purpose of complementing the received information from LKAB.

Maintenance data regarding causes of stops were reviewed to identify the causes which had the most significant impact on the availability. Data were gathered from LKAB's maintenance software (Plant Performance) was limited to the last three years (2019-2021) during the initial determination of the plant's performance. The limited time frame was chosen to focus on the present causes of failure and not be heavily affected by historical data. The identified causes' effect on the availability were evaluated, which was the main deciding factor on what to continue to analyze in the next phase. The data set contained the following information regarding internal disturbances for the investigated plant:

- stop time due to internal disturbance,
- start time after the internal disturbance is fixed,
- duration of internal disturbance,
- object that caused the internal disturbance,
- cause of the internal disturbance.

The data included information about production stops for the entire plant but was limited to the Grate-Kiln-Cooler process in the analysis. The limitation resulted in 229 stops representing 2081 hours caused by disturbances in either the Grate, Kiln or Cooler. To investigate which specific causes had the most significant effect on availability (i.e., caused the most production stop hours), three causes for each part of the process were extracted. It resulted in nine causes divided between the three parts, representing approximately 90% of the total 2081 hours of stops the Grate-Kiln-Cooler had experienced during the investigated period of time. Before it was decided which causes were chosen to investigate further, they were validated together with LKAB to assure their feasibility. The frequency of occurrence for each cause of failure was also evaluated to eliminate causes with too few appearances. These would have made it difficult to show statistical significance in later analysis.

2.2.1 Potential savings

Based on the information of what an hour of stop in the plant cost LKAB in lost revenue, potential savings were calculated regarding the chosen cause of stop. It was done by multiplying the lost revenue per hour by the number of hours it occurred. The number of stops was then used to estimate what a single stop represents in lost revenue to understand better how years with varying stops affect it. From this, an annual loss could be calculated even if large fluctuations existed on a year-to-year basis. Fluctuations in the iron ore price also affected the estimation, where the estimation was based on the ore prizes of 2021.

2.3 Measure

The measure step was conducted in the first phase of the project with the primary aim of explaining the current situation of the plant to benchmark its present operational capacity. Therefore, an initial screening of the Grate-Kiln-Cooler process was conducted to fulfill its purpose. Primary data needed to be gathered to investigate the process's current performance. Both qualitative and quantitative data were gathered to ensure a valid result. The qualitative data was gathered from discussions and meetings with employees at LKAB. The scope of the meetings varied, but the general reasoning for them to be conducted was to either questions or validate hypotheses that emerged during the project's progress. The meeting's content depended on which step of the DMAIC methodology the workflow was dealing with, for example, meetings in the earlier steps contained more general questions to establish a foundation for the thesis's later steps. The conducted meetings and their content are presented in Table 3.

Table 3: *Conducted meetings for each step of the DMAIC methodology*

Date	**Respondent**	**Scope**	**Duration**	**Step**
18/11/2021	Supervisor at LKAB	Defining thesis scope	25 min	Define
17/01/2022	Process engineer	Presentation of the sorting, concentrating and pelletizing plants	60 min	Define
17/01/2022	Lean Coach	Presentation of the mining process	60 min	Define
18/01/2022	Maintenance manager	Defining availability, elucidating present performance and potential savings	60 min	Define /Measure
18/01/2022	Process engineer	Presentation of the investigated pelletizing plant	60 min	Define
24/02/2022	Supervisor at LKAB	Presentation of the investigated pelletizing plant	60 min	Define
24/02/2022	Supervisor at LKAB	Discussion and validation of the result in Phase 1 and discussion regarding Phase 2	30 min	Measure
07/03/2022	Process engineer	Validate which parameters will be included in the analyze step	45 min	Analyze
10/03/2022	Technician	Discussion regarding the Kiln and the refractory material	65 min	Analyze
11/03/2022	Refractory material specialist	Data collection and explanation regarding the refractory material	45 min	Analyze
11/03/2022	Supervisor at LKAB	Validation of which parameters to include in the analysis step	25 min	Analyze
10/05/2022	Supervisor at LKAB	Validation of the proposed solution's relevance and fit within the project's scope	40 min	Improve

The quantitative data included information regarding production stops, temperatures in Kiruna, and production parameters for the Great-Kiln-Cooler process. Data regarding production stops and the production parameters are gathered through various sensors. Table 4 presents where the utilized data in the project was gathered and how it was used. The gathered quantitative data were analyzed and illustrated through the use of the software program *Statgraphics*[2].

[2]Statgraphics centurion, version 19. https://www.statgraphics.com

Table 4: *Gathered quantitative data during the project*

Data	***Source***	***Subject of investigation***	***Time frame***	***Step***
Production stops	Plant performance	Potential savings	2019-2021	Define
Production stops	Plant performance	Initial screening	2019-2021	Measure
Production stops and temperature in Kiruna	Plant performance and (och Hydrologiska Institutet, 2021)	Potential seasonal variation	2010-2021	Analyze
Production parameters	Process Explorer	Monitoring of refractory material	2014-2021	Analyze

2.3.1 Initial screening of present performance

The initial screening was constructed to generate an understanding of the plant's present performance and the impact the disturbances had on the availability. To do this, a variable to assess current performance was established; the fraction of unavailable time (FUT). The FUT variable represented the time when the process was not able to produce output out of the total amount of available time on a monthly basis. Autocorrelation was investigated using the FUT variable to determine if potential autocorrelation was present. If autocorrelation were present, the general assumption that an arbitrary observation could be modeled by equation (3) would be invalid. In equation (3), μ indicated the process's mean and ε_i the sequence of random, independent variables from the same distribution. This was done both for the parts of the Grate-Kiln-Cooler process individually and the entire process.

$$x_i = \mu + \varepsilon_i \tag{3}$$

The initial screening was further complemented by investigating the FUT between 2019-2021 using Shewhart control charts and Moving-range-charts. The control charts provided information regarding which parts of the process performed the worst and how the fraction of available time altered between different months for each part of the process. The Shewhart chart, sometimes referred to as an individual chart, was used because the sample size was equal to one (Montgomery, 2020). It was impossible to derive the standard deviation from the intragroup variation when the sample size was one. The MR-chart was thus used as a determinate of dispersion to overcome this challenge. For a brief explanation of how the control limits for the charts were calculated, see Appendix A.

When using Shewhart charts and Moving-range-charts, the Grate-Kiln-Cooler process was divided into separate components to analyze them in isolation to examine which part of the process had the most significant influence of the process' availability. The entire process was also investigated to examine its current performance and compare the result against desired levels. The entire process was constructed as a series constituted by the Grate, Kiln, and Cooler. The potential autocorrelation among the observed months was investigated to ensure that the initial screening results were valid due to the Shewhart charts sensitivity to autocorrelation. If autocorrelation were present and positive, it would influence the initial screening result because the standard deviation estimate would be underestimated, making the control limits too narrow (Montgomery & Mastrangelo, 1991). If the control limits were estimated too narrow, it would increase the risk of false alarms, increasing the risk of an incorrect interpretation of the process performance. The investigation regarding the potential presence of autocorrelation was essential since autocorrelation has a substantial effect on the Shewhart chart's performance (Maragah & Woodall, 1992).

2.4 Analyze

2.4.1 The season's effect on the availability

Potential seasonal variations regarding the availability were investigated for the pelletizing plants. The analysis investigated if the outside temperature in Kiruna influenced the plant's respective availability. Data for the outside temperature was gathered from och Hydrologiska Institutet (2021), which contained the daily temperatures in Kiruna. Only measured temperatures from 2010 until 2021 were considered because of the limitation that Plant Performance data only existed for this period for the plants. The reason for choosing the most amount of data possible was to achieve statistical significance in the results. The daily temperatures were aggregated to a monthly average temperature for each month of the year. Months with an average temperature below zero were classified as a cold month, and months with an average temperature above zero were classified as a warm month. Therefore, each year could be divided into two seasons, a warm season consisting of all the months classified as warm and a cold season constituted of all the cold months. The average unavailable time for the respective season was calculated by dividing each season's total unavailable time by the number of months the season included. It was necessary to use the average unavailable time since the cold season included more months than the warm season. A hypothesis test and confidence interval were established to investigate if the season influenced the availability.

2.4.2 Missing data for the process parameters

After the process parameters from Process explorer were obtained, cases with missing data values existed. The data ranged from 2014 to 2021, where data were measured with a frequency of one hour. The missing data values were scattered, meaning that a case did not exist where two missing data values appeared consecutively. The missing data values were linearly interpolated to enable further analysis. Because these missing data values could not be traced to any disturbances in Plant performance, the production was perceived not to be stopped. The linear interpolation was constructed in accordance with what Liston and Elder (2006) suggests; which proposes that during the condition where missing data values are measured hourly and do only appear single-handed, one can approximate the missing values as the average of its values one hour before and after the missing data value. Figure 3 presents a general illustration regarding how the missing data values were interpolated, where T_1 represents the missing data value during observation n_i.

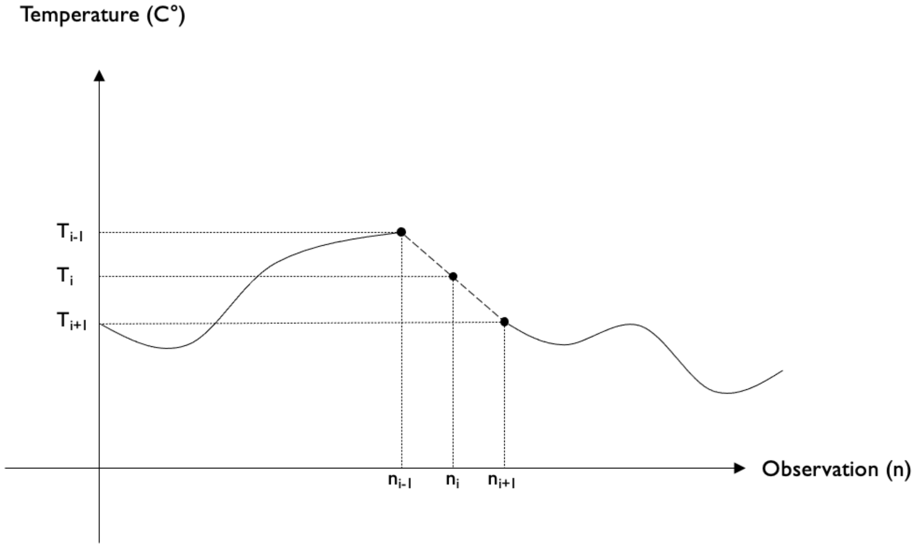

Figure 3: *Illustration of how the missing values were approximated*

2.4.3 Principal component analysis

Principal component analysis (PCA) is a multivariate analysis technique that describes data by several inter-correlated quantitative components (Mishra et al., 2017). The objective of PCA is to reduce the dimensionality of a data set by aggregating variance onto a new set of orthogonal variables referred to as principal components (z_i). The established principal components are thus uncorrelated and explain a significant amount of the existing variation (Mishra et al., 2017). PCA was primarily used in this project because of its features of reducing dimensionality. The principal components are constructed as linear combinations of the process variables (x_i). The process variables are obtained a component weight (c_{ij}), highlighting its influence to determine the principal component's value for each observation. The linear combination for an arbitrary principal component can thus be described as follows:

$$z_i = [c_{i1}, c_{i2}, \dots c_{in}] \cdot \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \tag{4}$$

The principal components are ordered by how much variation they account for, meaning that the first principal component explains most of the data's variation. The eigenvalue (λ_i) for each principal component corresponds to the amount of variation the principal component accounts for; thus, the first principal component's eigenvalue is higher than the second principal component (Montgomery, 2020). The relationship between the established principal component's eigenvalues can be stated as:

$$\lambda_i \geq \lambda_{i+1} \geq \lambda_{i+2} \geq \dots \geq \lambda_n \geq 0 \tag{5}$$

The decision regarding how many principal components to use needed to be made with caution. More variability from the original data would be retained as additional principal components are included. However, the complexity of interpreting the result would have increased if more principal components were added (Montgomery, 2020), which resulted in a trade-off between additionally explained variability and increased complexity of interpreting the results. Because the data was unstandardized, it was impossible to select the numbers of principal components to include depending on if their respective eigenvalues were greater than one or not (Todorov et al., 2018). Therefore, a threshold (i.e., a certain percentage of the original variation) was selected. Principal components were thus added until their total explained variability reached or exceeded the selected threshold. In this project, the threshold was set at 70%, meaning that principal components were added until at least 70% of the original variation could be explained.

2.4.4 The Hotelling T^2 control chart

The multivariate control chart Hotelling T^2 is a widely used monitoring technique (Mahpouya et al., 2022). A multivariate control chart is used when more than one parameter is monitored (Ahsan et al., 2018). Further, the Hotelling T^2 is able to monitor production processes and detect when outliers during production becomes present (Montgomery, 2020). Because several independent variables were included in this project to monitor the process' performance, the Hotelling T^2 was used. Because several production parameters aimed to be monitored, in combination with large quantities of observations to consider, the computational time became an issue. To cope with this challenge, Ahsan et al. (2018) proposes the usage of principal components when constructing the model for the Hotelling T^2. The benefits of utilizing PCA when constructing the Hotelling T^2 stems from its ability to reduce data dimensionality and thus decrease the number of variables to monitor, which increases the chart's effectiveness and decreases the computational time (Ahsan et al., 2018). Therefore, the Hotelling T^2-statistic was based on principal components. Each observation in the control chart obtains a value based on the principal components. The obtained value is referred to as the T^2-static and can be defined according to Ahsan et al. (2018), as follows:

$$T^2 = \sum_{i=1}^{k} \frac{(y_i - \mu_i)^2}{\lambda_i} \tag{6}$$

The k refers to the total number of included principal components, y_i is the value for the principal component i, and μ_i is the respective mean. λ_i is the eigenvalue corresponding to principal component i. When the model for the Hotelling T^2 was constructed, the mean vectors and the covariance matrices from the principal components were used. The means and covariance matrices were established from a training set consisting of 641 observations of the Kiln, where the process was determined to be in steady-state production during the first quarter of 2019. Steady-state was estimated based on the most frequent range of values that the production speed and the independent variables obtained during the observed period. The previously saved means and covariance matrices were used as parameters for a new Hotelling T^2, which included observations for the entire time frame (i.e., the testing data set). The entire time frame spanned from 2014 until the end of 2021, where sequences prior to stops only due to the refractory material were considered. To enable a prediction regarding what has caused each stop, 100 observations prior to each investigated stop were included. However, stops during 2019 were not included in the test data set because it was previously used for the training data set. Figure 4 illustrates how the training data set were used to develop a model for monitoring the process.

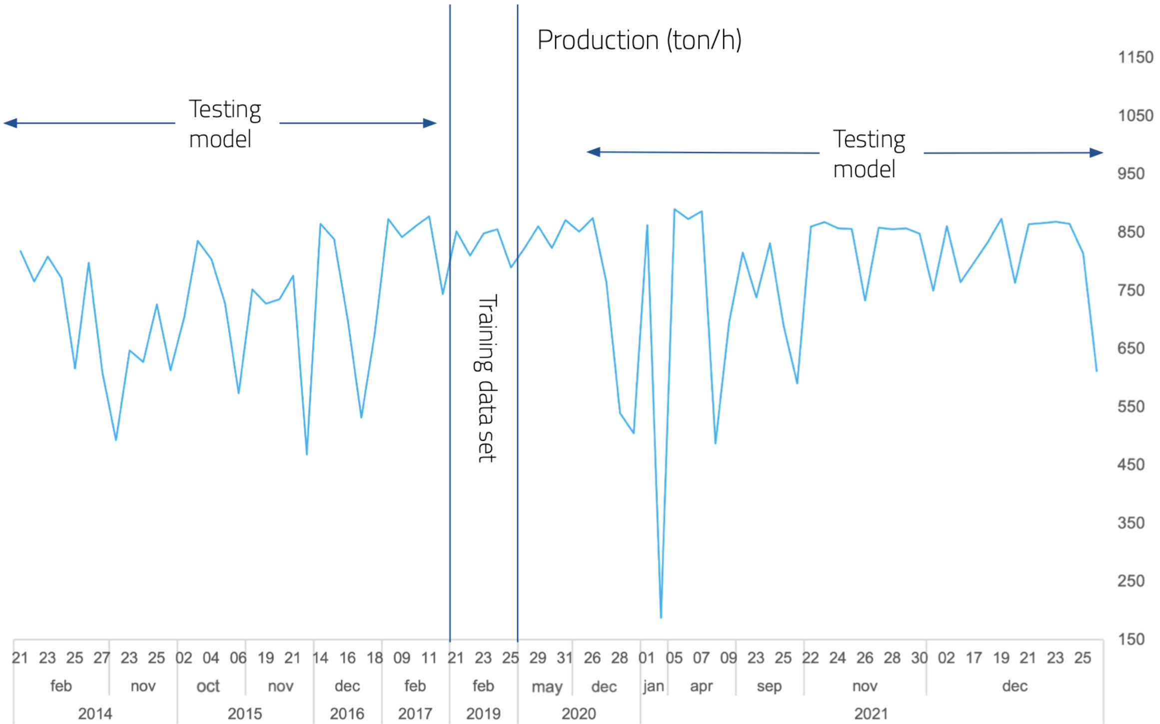

Figure 4: *Illustration of how the training data set were used to monitor the entire time frame*

The alpha risk (i.e., the risk of a false alarm originating from pure chance) was chosen to 0,0054 for the Hotelling T^2 because the chart is one-sided and its control limit aimed to reflect three-sigma-levels. If the upper-control limit of the control chart is surpassed, resulting in an alarm, it will indicate abnormalities in any of the principal components. The Hotelling T^2 chart was thus able to simultaneously monitor all the included independent variables. During the diagnostics regarding which parameter contributed to a specific alarm, Lowry and Montgomery (1995) suggest univariate control charts to be used for the chosen independent variables. Thus, were the multivariate control chart (i.e., Hotelling T^2) established to monitor the process, with additional individual control charts to enable a more straightforward diagnostic procedure. Because the pelletization plant's production speed has increased during the test data period (i.e., 2014-2021), the univariate chart's control limits were recalculated every 200th observation. The control limits for the individual parameters needed to be reevaluated because their values increased as the production speed increased during the period. If the control limit were determined not to be recalculated, the risk of false alarms in the independent charts would increase.

2.5 Improve

The findings of the analysis step resulted in that it was impossible to isolate the root causes of refractory material breakdowns. Because of this issue, the improve stage's approach needed to be altered. Thus, instead of proposing strict recommendations to solve the root causes, the improve step adopted a general approach to discussing the analysis' findings. Therefore, the improve section aimed to discuss how the project's findings from the analysis related to fulfilling the project's stated purposes by combining the gathered insights from the analysis and the obtained knowledge from the conducted literary review. The findings from the analysis are discussed, where the model's merits and delimitations are highlighted. The section further emphasizes how the model should be utilized in LKAB's daily operations to increase its availability. The section further initiated the discussion regarding which prerequisites must be addressed to further improve the model's predictive ability.

2.6 Control

The last section within the DMAIC methodology, control, mainly revolved around what LKAB in the future has to do to maintain the merits of this project. As a consequence of not being able to propose distinct recommendations in the previous step, the control step's content also needed to be altered. Thus, the control step adapts a general approach, focusing on how future initiatives to solve the issues regarding the refractory material shall be evaluated. The earlier constructed measure of evaluating the process' performance in the measure step (i.e., the FUT measurement) was proposed to assess the issues regarding the refractory material. The section proposes how and with which frequency the evaluation could be conducted. Suggestions for maintaining the model's merits regarding the need to update the model was also proposed, where similar aspect as with the discussion regarding the FUT measurement are discussed.

2.7 Reliability and Validity

To assess the level of quality a research methodology yields, reliability and validity are two commonly used parameters (Forza, 2002). The level of reliability refers to which degree its results are repeatable, i.e., the probability of the same results being achieved when using the identical methodology in a future attempt to answer the same research question (Forza, 2002). The validity, in contrast, is instead a measurement regarding if the right concept has been observed (Forza, 2002). The reliability and validity are not two separate measurements because if the validity is perceived as low, the reliability is also low. However, the validity can still be perceived as high even if the reliability is low.

There was no need to collect new data in this project since it was already obtained from LKAB's different databases, which could be seen as a factor that would increase the reliability. However, due to the authors not being able to collect the data by themselves, the knowledge regarding the measurement system's margin of error is unspecified. The fact that the DMAIC methodology was used is perceived as a factor that could have increased the reliability because of the methodology's systematic approach, which according to S. Kumar et al. (2011), could eliminate errors and disturbances which could have affected the result. How the DMAIC methodology was utilized in the project, presented in Table 1, is an additional factor that the authors perceive to strengthen the reliability. The reasoning behind this is because Table 1 provides a holistic presentation of which methods were used for each step within the methodology, which could increase the method's repeatability in future replicates of the project.

During the initial period of the project, the entire Grate-Kiln-Cooler process was in consideration as the potential cause for low availability in plant before narrowing the scope to solely examining the refractory material in the Kiln. The substantial decrease in scope could influence the reliability in both a positive and negative fashion. The reliability could have been decreased as the wrong section of the process was examined due to an insufficient method when deciding which part of the process would be further investigated. On the other hand, the reliability could have been increased as the narrower scope enabled a more in-depth analysis of the refractory material.

In this project, the production speed was used to evaluate if the process was experiencing a stop or not. This assumption was based on the fact that production speed is a fair measurement of process performance. The assumption was perceived to be appropriate in many cases, for example, if a stop is present, the production speed will be equal to zero. Because the production speed is continuous, periods of deviating or unstable values in the process parameters could be observed when the production speed deviates from steady-state production. Even though the production speed in many cases provides a fair evaluation regarding whether a stop is present, it likely exists periods in the examined data set where the production speed is not an accurate translation. Due to the risk of the assumption not always being valid, the project's validity was perceived to be hampered.

Even though it existed aspects during the project's execution that could have hampered the project's reliability and validity, the quality of the project's method is still perceived as adequate. The reliability and validity are perceived as adequate enough to yield similar outcomes if an external party replicates the project.

3 Theoretical background

The following chapter presents an overview of the current literature regarding the main topics of this master's thesis. The chapter begins with a brief presentation of different maintenance policies. Further, a selection of literature regarding process monitoring is followed by how monitoring is performed in the Grate-Kiln process and what disturbances could emerge. The chapter concludes with other studies that have researched the prediction of breakdowns.

3.1 Maintenance strategies

Maintenance managers need to be careful when deciding which maintenance strategy to incorporate due to its complexity (Sharma et al., 2005). The lack of adequate estimations regarding which factors deserve the most attention during the decision of appropriate strategy distorts the decision-making process (Sharma et al., 2005). Preventive and corrective maintenance are the two main categories of maintenance management (Li et al., 2006), where further sub-categories within both domains exist. These sub-categories make up maintenance policies that organizations exercise, which are; Run-to-Failure (R2F), Preventive maintenance (PvM), Condition-based maintenance (CBM), and Predictive maintenance (PdM) (Sharma et al., 2005; Susto et al., 2012; Garg & Deshmukh, 2006). How these are divided into the two categories is presented in Figure 5.

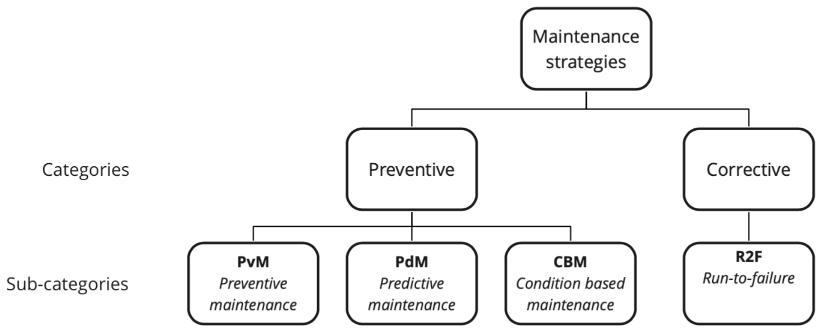

Figure 5: *Categories of maintenance strategies and its subcategories using categories proposed by Li et al. (2006)*

The R2F strategy is the most elementary maintenance strategy as maintenance efforts only are executed during equipment failure (Carvalho et al., 2019). The strategy is a sub-category within the corrective maintenance domain, meaning that actions are only made when needed (Hao et al., 2010). R2F is the least resource-efficient maintenance strategy as interventions, and its associated downtime after failure is usually more substantial compared to other strategies (Susto et al., 2014). In contrast to a reactive maintenance approach like R2F, PvM instead utilizes a proactive approach (Hao et al., 2010). The PvM strategy proposes maintenance efforts to be scheduled based on the equipment's age and the number of performed iterations (Susto et al., 2014; Dekker, 1996). The main objective of PvM is to mitigate the risk of frequent and sporadic system failures (Gits, 1992). Even though PvM reduces the risk of system breakdown (Dekker, 1996), unnecessary maintenance actions are sometimes performed, resulting in an insufficient use of resources and increased operational costs (Susto et al., 2014). The third policy CBM was introduced with the ambition to solve the shortcomings with PvM (Ahmad & Kamaruddin, 2012). A CBM system is consistently monitoring specific equipment parameters and, with the gathered information, deciding if maintenance is needed or not (Ahmad & Kamaruddin, 2012).

It does not exist a universal agreement if CBM and PdM are synonyms or two different practices (Fernandes et al., 2021; Selcuk, 2017). The connection between the two practices is strong and according to (Hashemian, 2010), is it possible to perceive CBM as PdM and vice versa. One similarity is that both policies measure and analyze specific parameters of an asset, and from that, evaluate its condition (L. Wang et al., 2007; Bashiri et al., 2011). One difference, on the other hand, is that CBM usually only presents a short-term measurement of the asset's health in contrast to PdM that enables a long-term prediction of the asset's condition (Levitt, 2003; Chebel-Morello et al., 2017). Furthermore, PdM is also capable of recognizing behavior patterns to determine when maintenance efforts are needed (Lee et al., 2006). Predictive tools are used based on historical data, statistical methods, integrity factors (i.e., visual aspects, wear, and other apparent physical deviations), and machine learning (ML) (Susto et al., 2014; Selcuk, 2017).

3.2 Process monitoring

Statistical process control (SPC) is used to monitor a process through various control charts (MacCarthy & Wasusri, 2002). SPC utilizes statistical methods to determine when deviations from normal occur (MacCarthy & Wasusri, 2002). Traditionally, SPC has its domain within quality assurance-related issues but is currently also used as means for fault detection and diagnostics (Woodall, 2000). The objectives with SPC and PdM are not identical as SPC is used to monitor critical quality parameters rather than indicating when maintenance is required. Even if the general motivators to adopt SPC and PdM are different, Panagiotidou and Tagaras (2010) recommended a joint treatment because the two concepts complement each other, thanks to the following two reasons.

Firstly, the two concepts share the same central issue; the configuration of the monitoring mechanism. It is challenging to decide which parameters should be monitored, how they should be measured, and when corrective actions should be performed. Some parameters indicate both the level of equipment condition and product quality, making it possible to combine SPC and PdM to obtain additional information about the process. By that, knowledge gathered primarily for maintenance purposes can explain SPC-related concerns and vice versa. Combining these two concepts thus mitigates the risk of information loss due to improper configuration of the monitoring system. (Panagiotidou & Tagaras, 2010).

Secondly, SPC is primarily used to monitor critical quality parameters. If the control charts indicate deviations from the target value, it could stem from the equipment operating in adverse conditions, making it more prone to failure. For example, if vibrations of the machine extend healthy rates, it will damage the equipment. However, the extended vibrations will be detected in the control charts as the monitored quality parameters probably will deviate from normal. Therefore, it is possible to utilize the close relationship between equipment condition and shifts in quality to foresee potential breakdowns. (Panagiotidou & Tagaras, 2010)

Thanks to the possibility to combine PdM and SPC in order to monitor parameters that have an effect on equipment condition, it could be used as a tool within PdM. It is illustrated in Figure 6 as an add-on to Figure 5. In Figure 6, CBM could also be perceived as PdM as it is closely connected and difficult to differentiate (Hashemian, 2010).

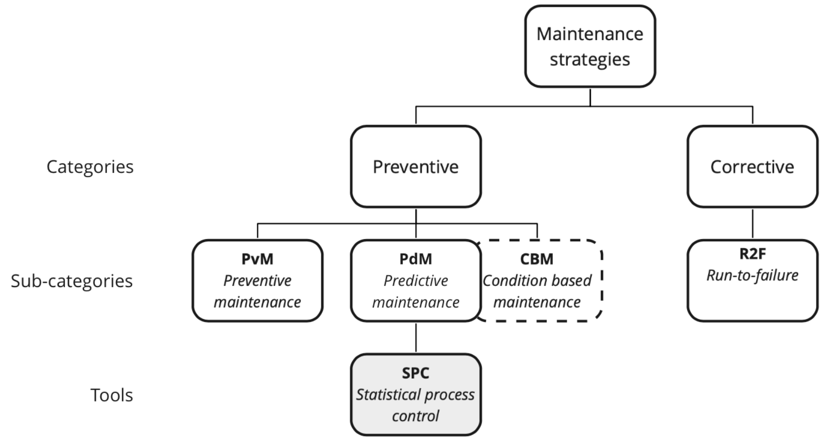

Figure 6: *Categories of maintenance strategies presented in Figure 5 with the addition of SPC*

When monitoring a system's condition, there is a need to use various sensors and other tools to obtain necessary data (Hashemian, 2010), which in practice is not done with ease Panagiotidou and Tagaras (2010). Selcuk (2017) proposes that the first step for organizations intending to implement PdM successfully is to identify which components to be monitored. The second step is to determine which parameters indicate the degradation of the asset by influencing the identified critical component. Lastly, Selcuk (2017) deems that organizations have to choose appropriate PdM techniques to analyze and monitor the parameters with. Hashemian (2010) suggests some generic parameters to monitor, which will provide data that enables an assessment of the equipment's condition. These proposed parameters were; rate of vibration, humidity, ambient temperature and pressure, acoustic level, and temperature. Commonly used measurement techniques to measure the generic parameters are; vibration, lubrication analysis, ultrasonic, acoustic emission, and high-frequency vibration (Hutton, 1996). When appropriate monitoring techniques are combined with SPC, it will enable continuous improvements (Azizi, 2015). The usage of SPC thus both acts as a mean of monitoring the process and evaluating its performance (Panagiotidou & Tagaras, 2010; Woodall, 2000), which according to Azizi (2015), are factors that could enhance production performance, hence increasing OEE.

3.3 The influence of maintenance strategy on OEE

Performance measurement (e.g., KPIs and OEE) is a fundamental tool in management because it provides a quantitative evaluation for where improvements are possible (Velmurugan & Dhingra, 2015). The three pillars that constitute the OEE (i.e., availability, operational efficiency, and quality rate) act as a foundation for organizations to enrich productivity, flexibility and decrease unwanted expenses (S. Singh et al., 2021). Within each part of the OEE measurement, sub-dimensions exist, referred to as the *Six big losses*, which all influence at least one of the OEE's constituting parts (Wudhikarn, 2011). According to Wudhikarn (2011), the six big losses are; equipment breakdowns, set-ups and adjustments, minor stops, reduced speed of production, defect or needed rework, and start-ups losses. The availability is affected by the two first mentioned losses (Azizi, 2015). The three main components of the OEE are all heavily affected by how well the maintenance efforts are orchestrated, meaning that OEE is partly influenced by the maintenance efforts (Juuso & Lahdelma, 2013). However, it is essential to determine OEE correctly, as an improper evaluation of OEE hampers the implementation of future maintenance initiatives (J. Kumar et al., 2014). To evaluate the OEE correctly is unfortunately a complex issue because it is hard to evaluate the quality rate because of its intangible elements (Parida & Kumar, 2009). Therefore, OEE acts as a measurement of equipment performance, and indicator of which maintenance policy to adopt in future maintenance initiatives, see Figure 7. Effects of maintenance efforts are vital to evaluate because maintenance performance depends on how well maintenance-related KPIs align with other business objectives (Swanson, 2001).

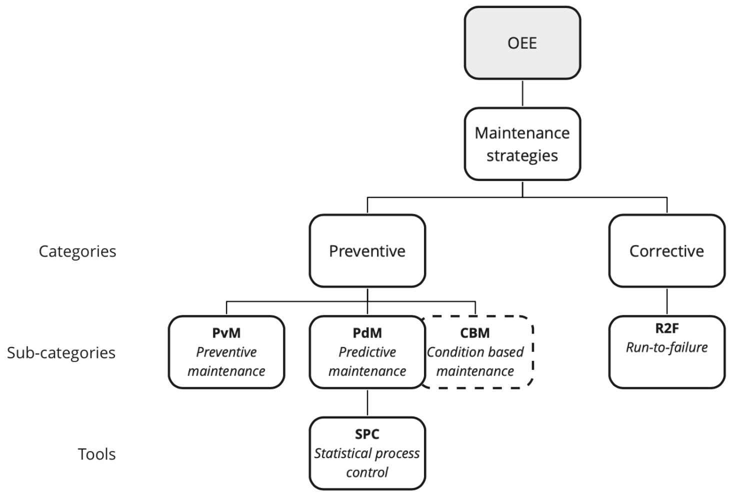

Figure 7: *Categories of maintenance strategies presented in Figure 5 with the addition of OEE*

One of the objectives of all maintenance policies is to improve OEE; however, various maintenance policies yield different results. PdM and CBM are perceived as more effective policies in this regard compared to PvM and R2F (Christou et al., 2020; Sullivan et al., 2010; Christou et al., 2022). Çınar et al. (2020) mention that organizations who adopt an R2F policy only could obtain an OEE at most of 50%. Çınar et al. (2020) further state that a PvM policy could acquire an OEE between 50-70% but utilizing PdM results in the highest increase of OEE where it is possible to obtain a level above 90%.

3.4 The Grate-Kiln process

The pelletization process of iron ore produces a uniform and firm pellet with high iron purity, which is suited for further processing in either blast furnaces or through direct reduction (G. Singh et al., 2015). There are different processes and technologies for pelletization where the Grate-Kiln process is the most commonly used for sintering (G. Singh et al., 2015). There exist different varieties of the Grate-Kiln process (G. Singh et al., 2015). However, at LKAB's pelletizing plant the process consists of a straight traveling Grate with a rotating Kiln. Grate-Kiln processes are well suited for producing pellets with consistent quality using minimal amounts of energy thanks to the recycling of hot gases created in later stages of production (Stjernberg et al., 2015). Gases from the cooling stage are pumped to the drying and pre-heating sections which result in less thermal losses (Stjernberg et al., 2015). The Grate-Kiln process is applicable in different metal ore refinement processes and is not restricted only to iron (Stjernberg et al., 2015). Even though there are differences in specific components, Stjernberg et al. (2015) states that the process involves the same significant three steps. Pre-heating in a Grate, hardening in a Kiln, and then a Cooler. The Grate generally consists of four main sections where the temperature increases gradually as the product proceeds through the sections; updraught drying (UDD), downdraught drying (DDD), tempered pre-heating (TPH), and pre-heating (PH) (Y. Wang et al., 2012). The Kiln, in contrast, is a continuous process where the pellets from the PH come to reach their final mineral composition and structural densification through sintering (Fan et al., 2012). It is achieved by exposing the pellets to high temperatures through a burner that uses either coal, gas, or oil (S. Wang et al., 2018). From the Kiln, the pellets proceed to the Cooling stage, divided similar to the Grate until they are cold enough for transport.

3.4.1 Disturbances in the Kiln

In the case of the sintering of iron ore, the oxidation process of magnetite to hematite is an exothermal reaction, meaning that thermal energy is released during the process (Stjernberg et al., 2015). Fluctuations in the pellet condition thus affect the production circumstances due to different amounts of thermal energy being released (Fan et al., 2012). The authors mentions that stable thermal regulation is critical in achieving a high-quality pellet, making this a challenge for pellets producers. Heat fluctuations do affect not only the quality of the pellets but also equipment condition (Stjernberg et al., 2015). Thermal stress is one of three factors that Malfliet et al. (2014) found affecting the equipment of the sintering process in copper production, together with chemical and mechanical stress. Malfliet et al. (2014) emphasize that specific degradation mechanisms could differ between furnaces, making it challenging to generalize specific mechanisms but state that these three main factors are the ones that affect equipment lifetime. The same classification could also be seen on the mechanisms affecting mechanical degradation at LKAB presented by Stjernberg et al. (2015), which advocates that it could be generalized for iron ore processing as well.

A common source of failure in the Grate-Kiln process is problems regarding the lining inside the Kiln, also referred to as refractory material (Stjernberg et al., 2015). Problems related to refractory material wear in Kiln are connected to high costs of maintenance and defaulted production (Weinberg et al., 2016). The refractory material's purpose is to protect the metal casing of the Kiln from thermal stress, chemical degradation, and mechanical wear (Malfliet et al., 2014). The material often contains high levels of alumina (Al_2O_3) and silica (SiO_2) together with other oxides and carbides containing aluminum, magnesium, or silicon (S. Wang et al., 2022). There are mainly two categories of problems regarding the lining; degradation of the material and the formation of deposits on the material (Stjernberg et al., 2012). The authors state that these causes are often linked, for example, when formations are removed or come loose, the material could be damaged in the process. The lining consists of a more resistant material than the surrounding metal, however, it is also worn out by the conditions in the machine (Stjernberg et al., 2015). When being exposed to high temperatures, the lining expands, which causes mechanical stress as it interacts with surrounding material as well as chemical stress from interaction with the pellets (Shubin, 2001). The stress is substantial when starts and stops are made in the process due to fluctuating temperature, which has been seen causing refractory material to fall off as a result of spalling (Shubin, 2001). Spalling is the process were irregularities in the lining appear, small cracks, which increase its adhesion for deposit formations (S. Wang et al., 2018). In the Kiln, reactions between unburnt carbon and pulverized pellets create these deposits, which stick to irregularities in the surface of the lining (S. Wang et al., 2018). Formations are often observed when the burner of the Kiln uses coal as fuel which creates ash consisting of unburnt coal which bonds to the pulverized pellets (Stjernberg et al., 2015; S. Wang et al., 2022).

3.4.2 Monitoring the Kiln

The Kiln is a relatively closed system because the goal to minimize thermal losses and prevent heat fluctuations (Y. Wang et al., 2012). As a result of this, process monitoring of what is happening inside the system becomes challenging during steady-state production, which is further complicated by the high temperatures of the sintering process (Fan et al., 2012). The growing demand for monitoring the Kiln has increased the demand for sensors able to monitor the closed and complex process (Y. Wang et al., 2012; Fan et al., 2012). As fluctuation in the raw material condition affects the released thermal energy, monitoring of the process becomes essential to ensure both product quality and equipment health (Fan et al., 2012).

To effectively control the Grate-Kiln-Cooler process, two parts are needed. Firstly, an expert system to detect and respond to abnormal conditions, and secondly, a model designed to describe relations and interactions between all production parameters and how these affect output (G.-m. Yang et al., 2016). Each of these two parts consists of multiple steps which need to be functional for the process to be controlled effectively (G.-m. Yang et al., 2016). Figure 8 presents the included steps that G.-m. Yang et al. (2016) highlights to be considered during the configuration of the expert system. When the parts are integrated, the authors state that it can be managed to achieve a more stable production which is economically beneficial.

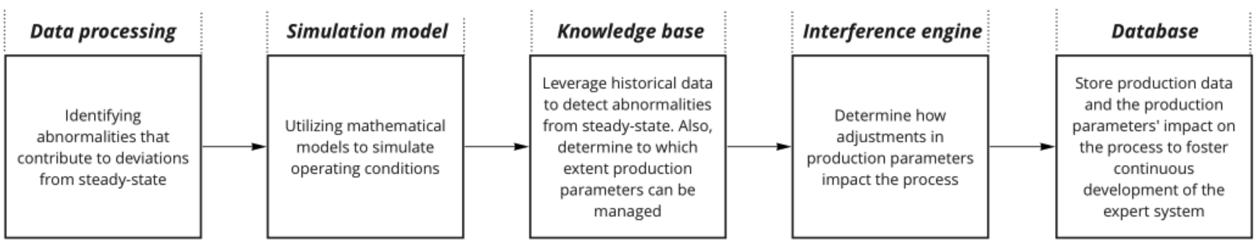

Figure 8: *The constituting components of an expert system for the Grate-Kiln process based on the article by Y. Wang et al. (2013)*

The purpose of an expert system according to Y. Wang et al. (2013) and G.-m. Yang et al. (2016), align with what Hashemian (2010) mentions being the aim of process monitoring. Hashemian (2010) mention that a central part of process monitoring is to choose a set of variables that could be analyzed to assess the condition of process equipment. Therefore, one could argue that monitoring could be seen as part of an expert system for process control, with the difference that monitoring alone lacks the possibility of making adjustments to the system. Since developing a fully functional expert system is out of the project's scope, focus will be on the first component, *Data processing*, where the aim of monitoring is to detect process shifts from steady state. The monitoring of equipment's condition could hence be seen as a way of determining when maintenance efforts are needed for the equipment to go back to steady-state, which make it fall within a PdM strategy (Lee et al., 2006). Determining the state of equipment require an dependent variable which according to Liu et al. (2015) could be an indicator of equipment health based on different input variables. An effective way to monitor equipment condition in PdM is to combine it with SPC (Panagiotidou & Tagaras, 2010), which utilizes statistical methods to detect abnormal deviations from steady-state production (MacCarthy & Wasusri, 2002). As a result, it is suitable to utilize SPC as a first step in the development of a control system to achieve a more stable production process, which Stjernberg et al. (2015) state would be favorable for equipment health.

3.4.3 Monitoring degradation of refractory material in the Kiln

Manufacturing companies often produce large quantities of equipment data used to detect disturbances in production (Luo et al., 2008). The authors mention that manufacturing companies tend to store production data for long periods of time and that a common problem occurs when companies work with interpreting the data. Finding patterns that could indicate future equipment failure could help to make proactive decisions regarding when preventive maintenance are needed to avoid critical breakdowns (Luo et al., 2008). The complexity of industrial environments has out-competed the human capability to analyze much of the data by itself and is therefore in need of more complex analysis tools (Luo et al., 2008). Another thing that also affect the complexity of the analysis are the scope, if the degradation model are monitoring on equipment level or component level (Weiss & Hirsh, 1998). The author state that monitoring on equipment level are much more complex due to the fact that equipment consist of many different components that could be affected by degradation. In the work of building a model for predicting equipment failure at a test bed company by Luo et al. (2008), the authors were faced with a number of issues which they mentioned needed to be handled before the model could be useful. These were problems regarding standardization of production stop documentation, finding useful events to train the model with and to find patterns in the data.

There are many different ways to detect patterns where many are based in machine learning which use algorithms to build models that could be trained to identify reoccurring patterns (Mohammadi & Wang, 2016; M.-C. Yang et al., 2018). Even though there exist different methods to detect patterns, many follow the same basic problem formulation. The target events (E_t) has to be chosen and timestamped (Weiss & Hirsh, 1998), which in the case of breakdowns in the refractory material is when a large enough fall-out of refractory material cause a production stop. From these, a chosen time leading up to that point makes up the monitoring time (M), which in turn are divided into a prediction period (P) and warning period (W) (Weiss & Hirsh, 1998; Luo et al., 2008), see Figure 9. The duration of these could differ between situations and together they make up a sequence of separate monitoring times M, (Weiss & Hirsh, 1998). During the prediction time P, patterns are being searched for in the values of the chosen variables (M.-C. Yang et al., 2018).

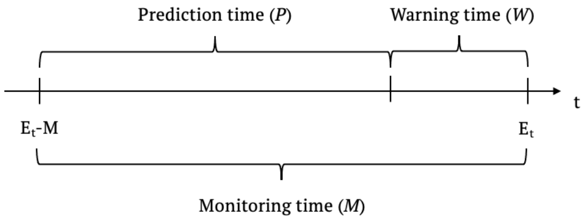

Figure 9: *Timeline of how the monitoring time are divided*

M.-C. Yang et al. (2018) developed a monitoring system that could detect large fall-off of refractory material in a cement Kiln, which they further claimed could be generalized in other similar situations. M.-C. Yang et al. (2018) found two things that could indicate when this occurred; when the drive amp of the Kiln motor increases sharply and when the temperature quickly drops in the burning zone in the Kiln. The sudden increase in drive amps were derived from an increase of material moved in the Kiln, which were the case when large fall-outs happened. As a result of the fall-outs, the temperature may drop for a short period due to the increased energy loss to the environment before it returns to its stable state. In that case, the outer layer of the Kiln will be exposed to higher temperatures, which could be observed as red spots on the Kiln mantle. These signs could be harder to detect if the fall-out is rather small, but in that case, adjustments may not always be needed. These two indicators could be used together to detect refractory material fall-outs to achieve a more reliable monitoring (M.-C. Yang et al., 2018).

4 DMAIC

The following chapter presents the result for the stages in the DMAIC methodology in chronological order. The first two sections (i.e., Define and Measure) aims to describe and evaluate the causes of process disturbances. Further, the developed method of monitoring these causes is presented in Analyze, followed by an explanation of how to utilize the method to fulfill the purpose of the study presented in Improve. Lastly, the Control stage discusses which management efforts are needed to sustain the result's merit.

4.1 Define

The sintering process of iron pellets consists of three main steps; Grate, Kiln, and Cooling. Formed pellets from earlier processing are transported to the Grate and then passed through the other steps in the mentioned order to end up as finished products after exiting the cooler. For a visual overview of the three-step process, see Figure 10.

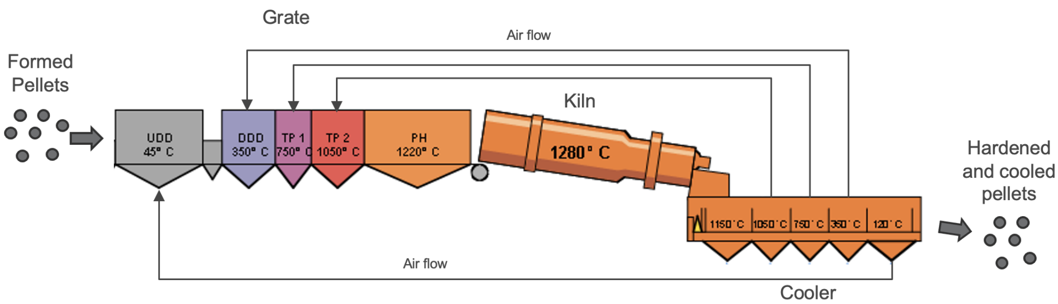

Figure 10: *Overview of the Grate-Kiln-Cooler process*

Production time is divided into three categories at LKAB: the time the plant is available, time for preventive maintenance efforts, and time of internal disturbances. The plant is scheduled to run almost all the time, making up around 730 hours each month, resulting in over 8800 hours of production time every year. Time for external disturbances and planned downtime is not included in the production time due to the inability to control these. Therefore, assuming that the plant will be in production every hour is not plausible.

The production goal is to reach a maximum of 4% of preventive maintenance efforts and 3% of internal disturbances out of the total production time (M. Ryytty, personal communication, 21 Feb 2022). Table 5 and Figure 11 show the outcome and goals for the three categories of production time during 2019-2021. Figure 11 highlights that both preventive maintenance efforts and internal disturbances exceed the target values, which results in lower availability than expected. Preventive maintenance efforts are included in the calculation because it is a parameter that could be controlled. Preventive maintenance efforts should not be mistaken for planned maintenance executed during the planned downtime. Preventive maintenance efforts are actions to repair and stop breakdowns from reoccurring. It is not reasonable to assume that there will be no breakdowns; therefore, the availability could never archive the value of 100%.

Table 5: *Scheduled vs actual outcome*

	Preventive maintenance efforts (%)	**Internal disturbances (%)**	**Availability (%)**
Goal	4,00%	3,00%	93,00%
Outcome	7,72%	9,79%	82,47%

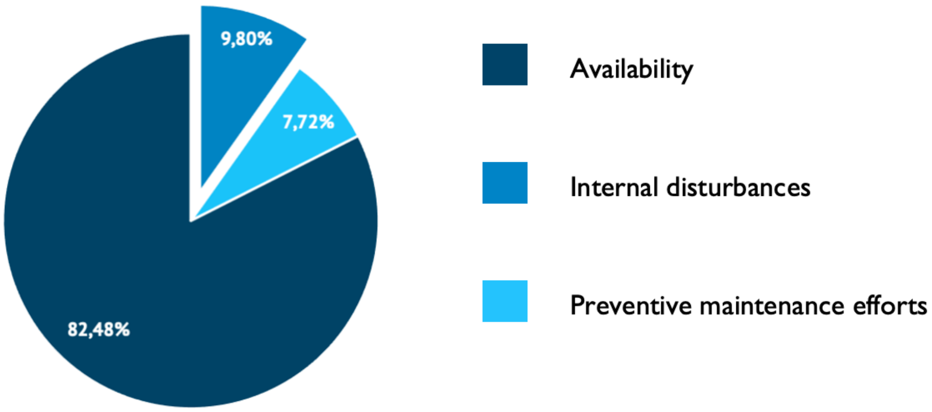

Figure 11: *Time distribution of the plant, 2019-2021*

The total time of production stops during the selected period makes up the highlighted slice in Figure 11 called *Internal disturbances*. The analysis of stops resulted in differing causes of failure for each part of the Grate-Kiln-Cooler process. The three most significant causes of production stop for each part are presented in Figure 12 together with the number of times (n) they occurred. It was done as an initial screening to explore which cause to move forward within the analysis. The distribution and duration of the stop causes is also presented in the Pareto diagram in Figure 13. The result shows that stops caused by refractory material have the most significant negative effect on availability, representing around 63% of all downtime during the investigated period.

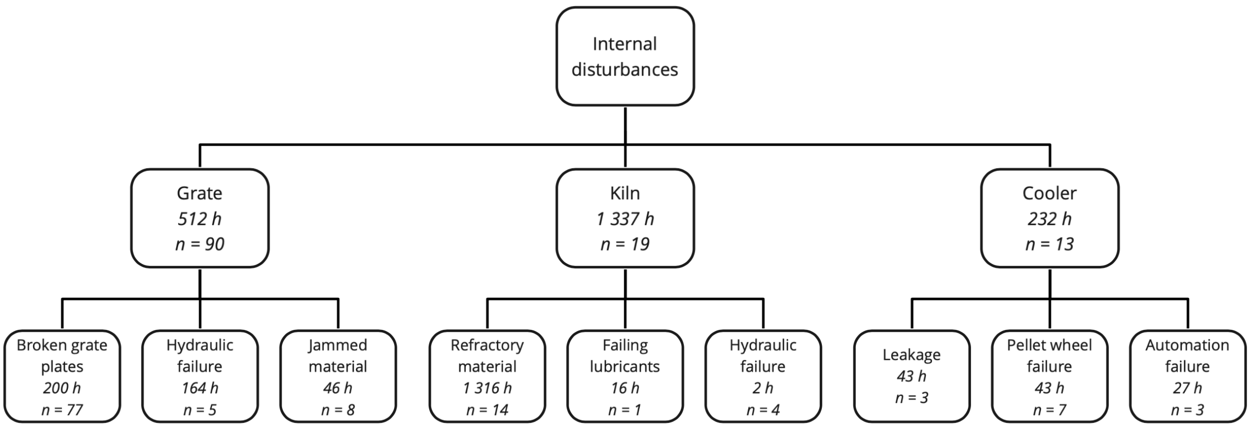

Figure 12: *Causes of production stop, duration of stop (hours) and number of stops (n), 2019-2021.*

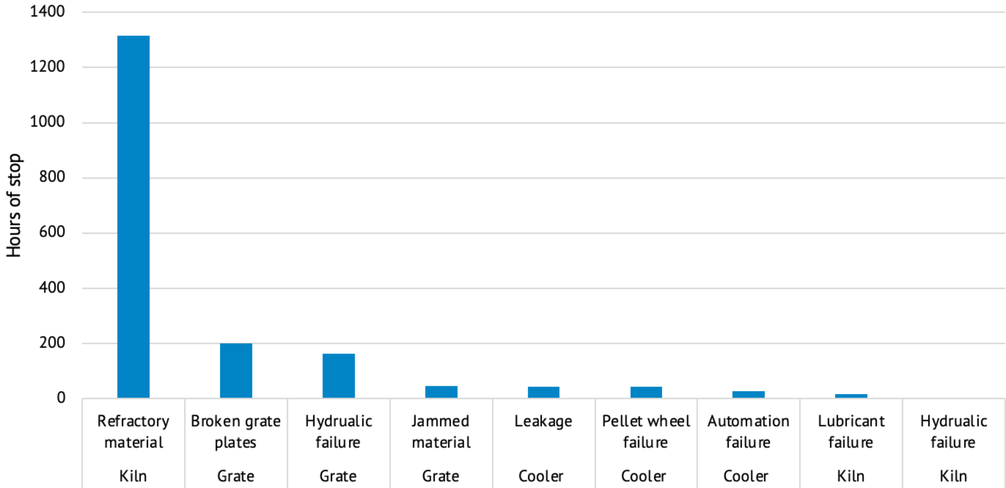

Figure 13: *Causes of production stop and their duration (hours) 2019-2021.*

The initial investigation of what caused the disturbances in the Grate-Kiln-cooler process resulted in the decision to further investigate refractory material breakdowns due to the potential impact if the number of stop hours could be decreased. As illustrated in Figure 14, the refractory material could be found inside the Kiln and acts as a protection for the Kiln mantle against thermal and mechanical stress. The material comprises multiple separate bricks, which together make up the component referred to as the refractory material.

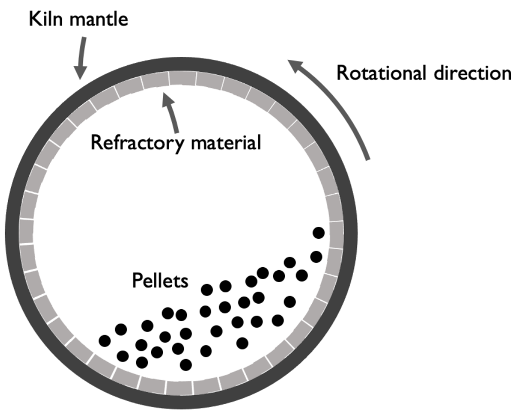

Figure 14: *Visualization of the Kiln's cross-section*

4.1.1 Potential savings

Stops as a result of refractory material represented a total of 1 316 hours, accounting for 63% of the total time of internal disturbances in the plant during the sample time as seen in Figure 12. With 14 stops during 2019-2021, the average stop lasts for 94 h, which is the longest average stop among all disturbances. Every hour of stopped production represents approximately 1 million SEK in lost revenue. Based on this estimation, lost revenue due to the refractory material during the past three years exceeds 1 300 million SEK. The calculation was based on the assumption that the demand for iron ore exceeded the supply, i.e., every additional ton of produced iron ore would be sold. The project will thus focus on reducing the number of stops which, based on the data from 2019-2021, means that reducing one stop could increase revenue by around 94 million SEK. On the other hand, increasing annual availability by 1% represents an increase of 88 hours, which represents around 88 million SEK. The estimations have to be taken with caution due to additional costs of maintenance that may be needed to prevent stops, which are not included. Also, the loss of revenue per hour is an estimation that is difficult to estimate precisely.

According to Fan et al. (2012); Stjernberg et al. (2015), there could be a possible correlation between stops, meaning that reducing one stop could prevent other production stops as well, which aligns with what production engineers at LKAB mentioned. With this reasoning, the financial impact of reducing the number of stops could be even more significant than the linear relation discussed above.

4.2 Measure

A variable to assess current performance was established during the measure step, the fraction of unavailable time (FUT). Shewhart charts and moving-range charts (MR-chart) highlight how the FUT varies between months. Potential autocorrelation had to be investigated to ensure that the assumption of independent observations in time is reasonably fulfilled to use these charts.

4.2.1 Investigation of autocorrelation

While investigating whether autocorrelation was present, the partial autocorrelation function (PACF) and autocorrelation function (ACF) were used. It was done for the Grate, Kiln, and Cooler individually and for the entire combined process. The probability limits were established using a 95% confidence interval for both the PACF and ACF. The result showed that none of the four investigations showed any tendency for its data to be autocorrelated in either the PACF or ACF. The result is presented in Appendix B, C, D, and E.

4.2.2 The entire process

When measuring the current performance of the entire process combined using control charts, it becomes evident that the process today does not perform at a satisfactory level. The Shewhart chart that was conducted is presented in Figure 15. The goal that internal disturbances should not exceed 3% for the entire process is currently not met. The control charts highlights that both the dispersion and mean increase over time, which means that the Grate-Kiln-Cooler process performed better in 2019 than 2021. The months 28 and 34 represent the worst performing, as the FUT exceeded the upper six sigma control limit of 42%. The MR-chart, presented in Figure 16 highlights that the average moving range of the internal disturbances from one month to the next is 13%, measured in absolute terms. The MR-chart further indicates that the variability of the FUT seems to increase over time.

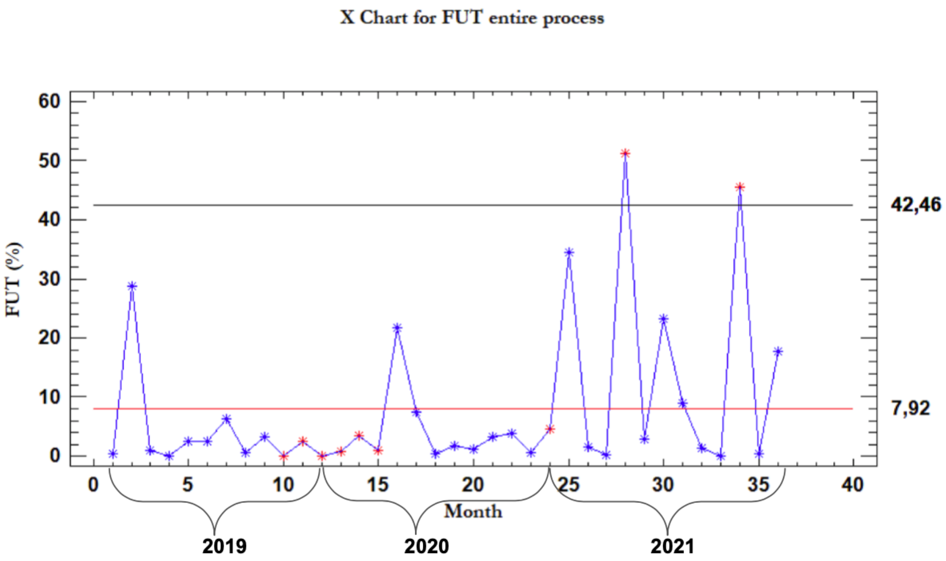

Figure 15: *FUT for the entire process*

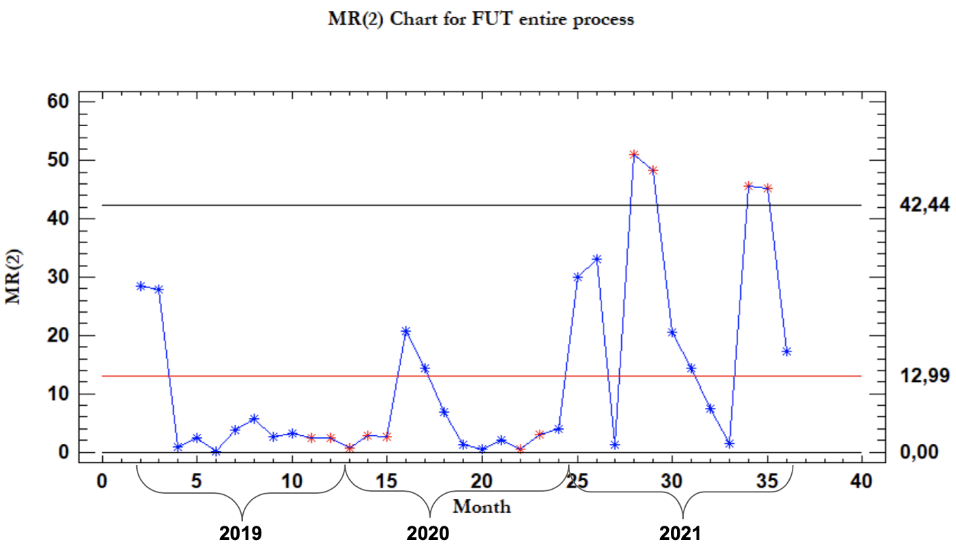

Figure 16: *MR-chart of the FUT for the entire process*

4.2.3 Kiln

The investigation of the Kiln provided insights regarding its performance were the established control charts presented in Figure 17 and Figure 18, highlights that the performance of the Kiln was more satisfactory in 2019 compared to 2021. The Shewhart chart has a mean FUT of 5%, while a possible shift of the mean may exist after month 24 until the end of 2021. After month 24 (i.e., the end of 2020), the availability fluctuated heavily between months. The FUT has exceeded the upper control limit three times (i.e., 26, 28, 34). Due to recent fluctuations, the mean of 5% is perceived as invalid for the Kiln today. Observing the months after month 24 in isolation, a FUT mean of 20% is perceived to be more representative as a measurement of its current performance. Thus, the Kiln's performance has degraded during the investigated period.

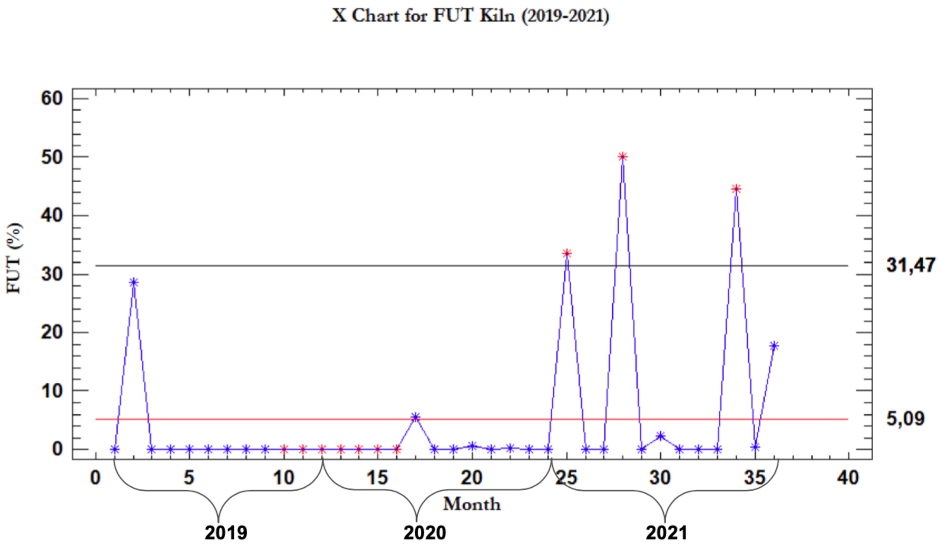

Figure 17: *FUT for the Kiln*

The MR-chart conducted for the Kiln showed that its average moving range is 10% between months. The MR-chart alarmed due to its upper control limit being exceeded at months 25, 26, 28, 29, 34, and 35. By analyzing the control charts for the Kiln, it is possible to claim that the Kiln does not appear to be in statistical control, at least in recent time. A similar inspection of the Grate and Cooler has been conducted and is presented in Appendix F and Appendix G. Based on the initial inspection of Kiln's performance during recent years, in combination with previous findings regarding the refractory material's impact on the availability; the refractory material was chosen to be further analyzed.

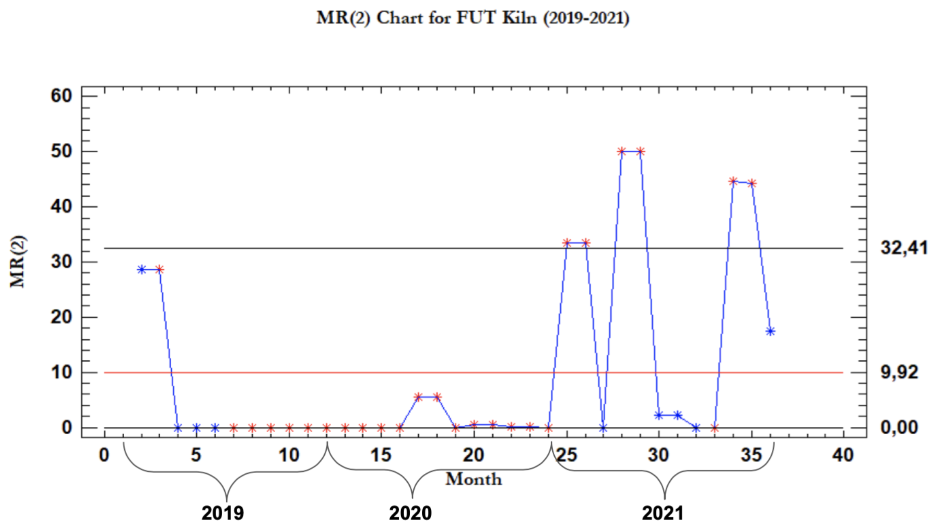

Figure 18: *MR-chart of the FUT for the Kiln*

4.3 Analyze

4.3.1 The seasonal effect on the availability

The null hypothesis for the hypothesis test was that the availability was independent of the current season. The second generated hypothesis was that season affected the availability. The confidence interval was established to validate the results from the hypothesis test and provide further information regarding the potential difference's proportion. The difference between the two seasons was calculated for each year by subtracting the average time of unavailable hours during the cold season (A_{ci}) with the average time of unavailable hours during the warm season (A_{wi}) (i.e., A_{ci}-A_{wi}). The final test variable denoted as ΔA_i, reflects the difference in availability, measured in the unit of hours between the two seasons for each observed year. Table 6 presents how the test variable was constructed:

Table 6: *The construction of the test variable*

i	1	2	3	...	12
Cold	A_{c1}	A_{c2}	A_{c3}	...	A_{c12}
Warm	A_{w1}	A_{w2}	A_{w3}	...	A_{w12}
Difference	ΔA_1	ΔA_2	ΔA_3	...	ΔA_{12}

A test to investigate if the final test variable ΔA_i stemmed from a normal distribution was conducted because both the hypothesis test and the confidence interval are based on the assumption that data is normally distributed (Endo et al., 2015). The constructed test for normality (i.e., The Shapiro-Wilk test) is presented in Appendix H. The final test variable was determined to stem from a normal distribution, as the Shapiro-Wilk test could not reject the normality assumption at the 5% significance level.

The season's effect on the availability was significant for investigated plant. The hypothesis test highlighted that it is possible to reject the null hypothesis with a 95% confidence. Because the null hypothesis could be rejected, it implies that the season's influence on the availability can be perceived as significant. The hypothesis test provided the following result:

Hypothesis test for ΔA_i
Sample mean = 29,78
Sample standard deviation = 40,00

t-test
$Null\ hypothesis\ (H_0) : mean = 0$
$Alternative\ hypothesis\ (H_1) : mean \neq 0$

Computed t-statistic = 2,5795
P-value = 0,026
Reject the null hypothesis for $\alpha = 0{,}05$

The confidence interval was later established to examine the season's magnitude of influence on the availability. The confidence interval was constructed with a confidence level of 95%. The confidence interval showed that the cold season has a higher average unavailable time (μ) compared to the warm season. The difference in average unavailable time among the seasons is with 95% probability within the range presented in the confidence interval.

Confidence interval for ΔA_i
95% confidence interval for μ: [4,37; 55,19]
95% confidence interval for σ: [28,33; 67,91]

The final test variable was the average unavailable time for each observed cold season minus the respective warm season. The difference in hours of average unavailable time, measured in absolute numbers, was highlighted in the confidence interval and determined with 95% confidence to be within the range [4,37; 55,19]. Because the constructed confidence interval does not include zero and solely includes positive numbers implies that the cold season has a higher rate of unavailable time.

4.3.2 Monitoring of refractory material

A total of seven independent variables were included in the calculation of the T^2 statistic. The production parameters were selected based on discussions with process engineers at LKAB and gathered knowledge from the literature review. Both sources of knowledge frequently highlighted that temperature had an important influence on the refractory material health. Thus, the common denominator among all the selected production parameters is their ability to influence temperature in the Kiln. The selected independent variables are presented in Table 7. Production parameters that were perceived to create redundancy were not included. Like the two production parameters *oil flow* and *coal flow*, which act as fuel for the burner, hence influencing the amount of energy it uses. Because the production parameter *power of burner* already was included, the parameters *oil flow* and *coal flow* were perceived as redundant and thus not included.

Table 7: Selected independent variables

Production parameter	Unit	Frequency
The temperature of refractory material	Celsius (C°)	Hourly
The temperature difference between refractory material and the pellet's temperature	Celsius (C°)	Hourly
Kiln rotation	RPM	Hourly
Power of burner	Megawatt (MW)	Hourly
Speed Cooler	Percent (%)	Hourly
Gas flow in upper PH	Millimeter water pillars (mmVP)	Hourly
Gas flow in lower PH	Millimeter water pillars (mmVP)	Hourly

Three principal components were extracted, which explained approximately 79% of the total variability. The component's weights are presented in Table 8. The first principal component is heavily influenced by the speed of the Cooler and the rotational speed of the Kiln. Thus, the first principal component will obtain a high value if these two independent variables obtain high values. In contrast, the gas flow for the upper and lower part of PH (pre-heating section of the Grate) decreases the first principal component value; hence if PH upper and lower obtains a high value, it will decrease the first principal component's obtained value. The second principal component is positively influenced by the temperature of the refractory material and the temperature difference. On the other hand, Kiln's rotation and the Cooler speed will negatively influence the second principal component. Lastly, is the third component positively influenced by the gas flow in upper PH and negatively influenced by the burner's power.

Table 8: Component weights for the three constructed principal components

Independent variable	PC1	PC2	PC3
The temperature of refractory material (C°)	0,34	0,51	0,23
The temperature difference between refractory material and material (C°)	0,04	0,70	-0,05
Kiln rotation (RPM)	0,52	-0,12	0,26
Power of burner (MW)	0,18	0,41	-0,20
Speed Cooler (%)	0,53	-0,19	0,19
Gas flow in upper PH (mmVP)	-0,22	0,04	0,88
Gas flow in lower PH (mmVP)	-0,50	0,20	0,16

The principal components were further used to diagnose the internal disturbances due to refectory material fall-outs in the established Hotelling T^2. Observing to what extent a single principal component contributed to an observation's T^2-statistic makes it possible to understand which production parameter contributed to the s in the Hotelling T^2. Since each principal component is constructed as a linear combination of the independent variables and their respective component weights, it is possible to know which independent variable significantly influences the T^2-statistic. The higher the absolute value of the component weight, the bigger its influence is on determining the principal component's value. The information gathered from the principal components was validated through the established univariate control charts to ensure the diagnostics' validity.

4.3.3 The first investigated stop

Due to the observations being measured hourly, there were a lot of data to be analyzed due to the available data consisting of many years of measurements. That made it hard to visually assess the process performance for the entire time frame through the Hotelling T^2. Nevertheless, it was possible to only focus on the production stops by using the Hotelling T^2 and its corresponding univariate charts. Therefore, the need existed to examine each stop in isolation to reduce the amount of data and thus enable a visual assessment of the process's behavior towards failure. Out of the existing stops during the entire period, two stops were of greater interest. The two selected production stops were chosen because they did not have a significant amount of noise in the data prior to stop. Only stops due to refractory material fall-outs were of interest, meaning that other internal disturbances for the Kiln were ignored. The time period of interest for each investigated stop was 100 hours prior to it. The first examined stop occurred at observation 523 (December, 2016), and the Hotelling T^2 were able to highlight this production stop as presented in Figure 19. The T^2 chart was able to signal when the stop became present, as the upper control limit was notably surpassed. Before the stop, the T^2-statistic is below the control limit indicating steady-state operation.

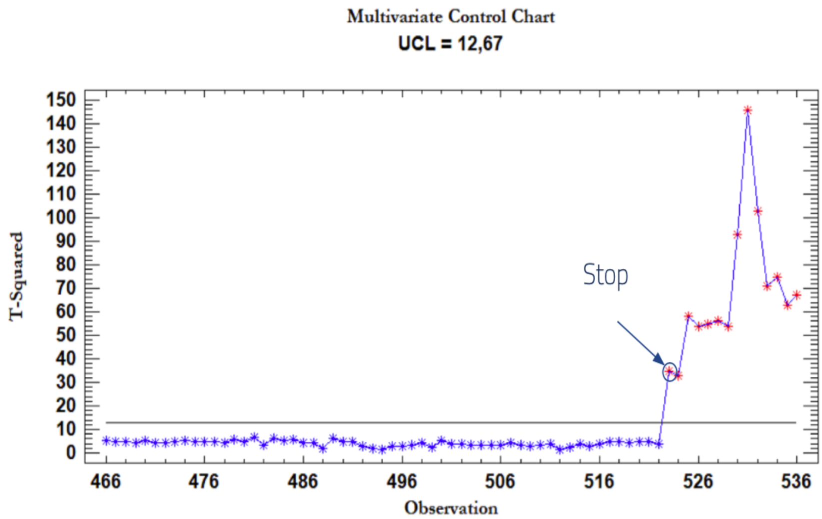

Figure 19: *Hotelling T^2 chart for the first selected stop, occurring during observation 523*

It was difficult to diagnose the cause for the stop by using the principal component's relative contribution. All the individual charts for the stop therefore had to be examined to find what could have been the cause of the stop. The individual chart regarding the temperature of the refractory material was the only parameter that showed any possible deviating behaviors, see Figure 20.

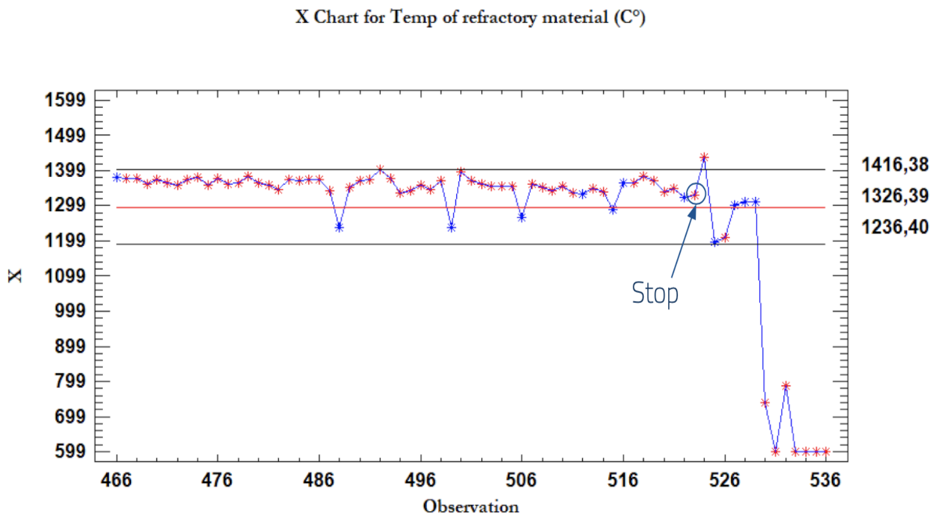

Figure 20: *Individual chart for the temperature of the refectory material for the stop during observation* 523

The temperature of the refractory material was high compared to the centerline in the chart prior to stop during the entire investigated period. The three observations where the temperature rapidly decreased (i.e., 488, 499, and 506) were of interest as the temperature decreased much during a short amount of time. This occurred even though the burner did not highlight a significant drop in power during these three observations making it noticeable. Because the temperature for the refractory material was of interest, the temperature difference was also investigated. In Figure 21, the difference in temperature is presented where the similar patterns occurred for the three observations where the temperature dropped (i.e., observations 488, 499, and 506), see Figure 20.

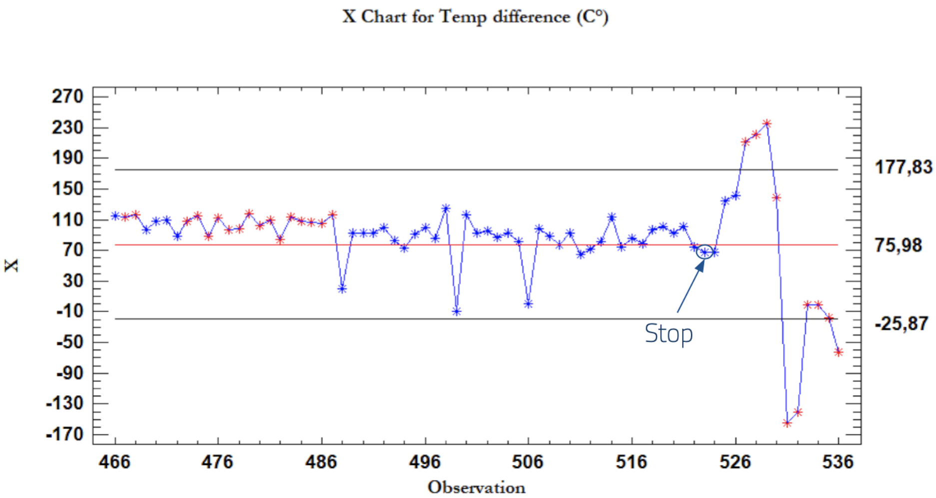

Figure 21: *Individual chart for temperature difference of the refectory material for the stop during observation* 523

4.3.4 The second investigated stop

The second investigated stop occurred at the beginning of 2017, during observation 669 in Figure 22, and lasted for 178 hours. In Figure 22, the constructed Hotelling T^2 is presented. In the Hotelling T^2, the T^2-statistic experienced two spikes (i.e., observations 592 and 635) before the stop. The production did not experience a stop during either observation 592 or 635. After observation 635, it is possible to detect a slight shift of the T^2-statistic, which continues until the stop becomes present.

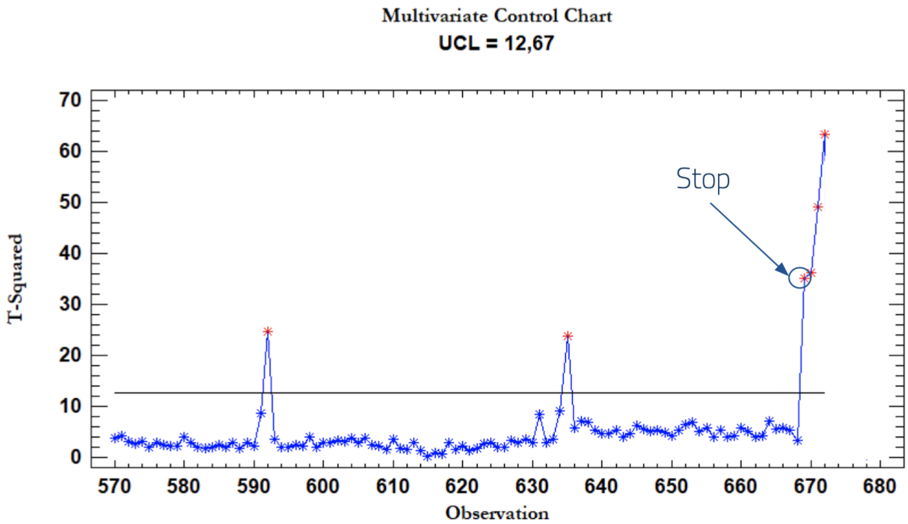

Figure 22: *Hotelling T^2 chart for the second stop, occurring during observation* 669

The principal component's relative contribution to the T^2-statistic was investigated to understand what caused the two alarms during observations 592 and 635. The T^2-statistics and the principal component's relative contribution are presented in Table 9. According to the table, the second principal component were the main contributor to the observed T^2-statistics during the two investigated observations. As mentioned earlier, the second principal component's value is heavily determined by the refractory material's temperature and the temperature difference. Their univariate charts were thus investigated to understand what could have caused the two spikes and the production stop.

Table 9: T^2-statistics and principal component's relative contribution

Observation	T^2-statistic	PC1	PC2	PC3
592	24,677	0,378	24,190	0,331
635	23,785	0,389	23,757	0,004

The individual chart illustrating the temperature of the refractory material during the second stop is presented in Figure 23. The control chart highlights that the refractory material experienced temperatures above the control chart's centerline before the stop occurred for 36 consecutive hours (i.e., from observation 593 until observation 629). The refractory material's temperature experienced two temperature drops during observations 592 and 635. The two temperature drops thus caused the two observed alarms in the Hotelling T^2 chart. Right after the two temperature drops occurred, the temperature increased the following hour rapidly while no significant changes were observed in the burner's effect. A few hours before the stop occurred, a minor trend of increasing temperature for the refractory material can be observed.

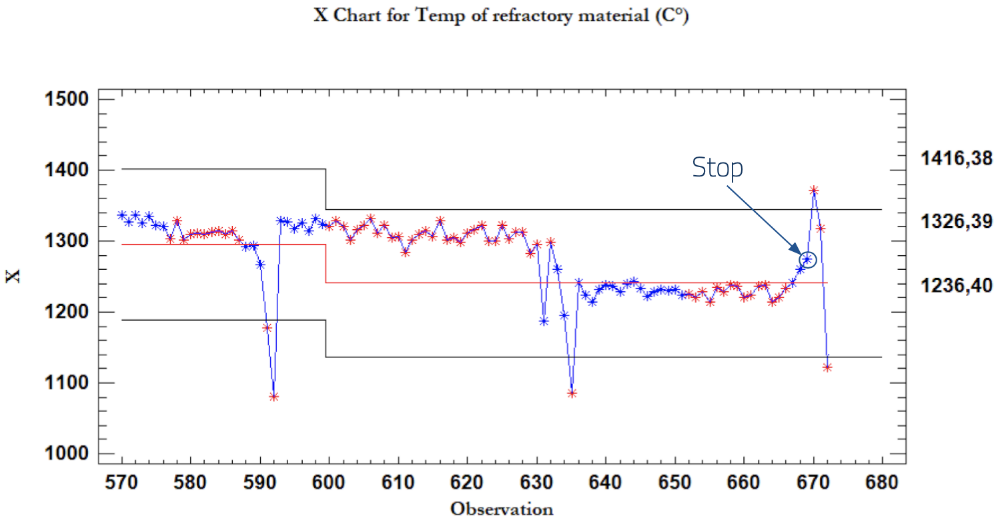

Figure 23: *Individual chart for the temperature of the refectory material during observation* 669

The individual chart regarding the temperature difference between the pellets and the refractory material was further investigated, which is presented in Figure 24. Before the stop occurred, the temperature difference was negative as the discrepancy was below the lower control limit for most observations. A negative temperature difference value implies that the refractory material's temperature was lower than the pellet's temperature. The trend of negative temperature differences continued for 39 hours (i.e., from observation 628 until observation 667). Similar to the first investigated stop, the direction of the temperature drops indicates that the cause for the temperature change stemmed from the refractory material.

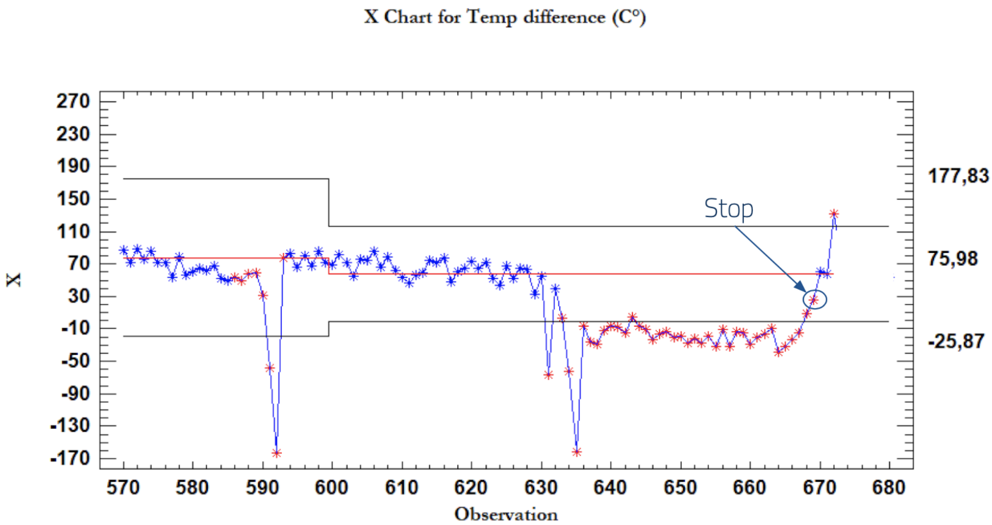

Figure 24: *Individual chart for the temperature difference during observation* 669

4.3.5 Summary of analysis

The analysis highlighted that the Kiln process is more prone to failure during the cold season. In addition to the literature review and discussions with employees at LKAB, this insight initiated a hypothesis that temperature variations influence the Kiln's health. The Hotelling T^2 chart was constructed using three principal components to monitor the Kiln's performance prior to production stop. For the second examined stop, the principal components highlighted that the second principal components obtained deviating values prior to breakdown. Individuals charts for the temperature of the refractory material and difference in the material temperature were investigated further in both cases. Their respective charts highlighted abnormal high temperatures for the refractory material with several sudden drops in temperature. The sudden drops in temperature in the refractory material resulted in periods of negative temperature difference between the refractory material and the pellets. Through investigating the individual charts for the two selected stops one could observe a tendency that the temperature of the refractory material and the temperature difference affect the Kiln's health. If the tendency is valid, it would suggest that Kiln's health is negative influenced by at least one of the following:

- Periods of high temperatures in the refractory material.
- Temperature drops in the refractory material which appears sporadic.
- Negative difference in temperature between the refractory material and the pellets.

Please note that the analysis only brought up two stops as these were the ones that showed the most significant results. The tendencies were more distinct for the two selected stops compared to others, like the ones presented in Appendix I and Appendix J, where the tendency was not as prominent. Therefore, it still exists a need to validate the observed tendencies additionally.

4.3.6 The shortcomings of the developed Hotelling T^2 chart

The analysis proposes that the constructed Hotelling T^2 chart's performance to predict breakdowns could have been distorted. In order to examine which shortcomings could have hampered the chart's predictive abilities, the autocorrelation for the included production parameters and the T^2-statistic was investigated. The autocorrelation was examined for the model's training data. The training data were used instead of the test data because the test data includes production stops, which contribute to autocorrelation as the production parameters obtain trends due to the production parameters deviating before a stop. The autocorrelation test is present in Appendix K, and highlights that all production parameters, except *Kiln rotation*, were indeed autocorrelated to some extent. Consequently, since autocorrelation was indeed present, it hampered the Hotelling T^2 chart's monitoring ability because positive autocorrelation leads to an overestimation of the upper control limit, decreasing the chart's ability to signal when shifts occur (Vanhatalo & Kulahci, 2015). To cope with the challenge of autocorrelated data in a multivariate setting, Vanhatalo and Kulahci (2015) proposes the usage of the residuals attained from a suitable vector autoregression model (VAR) to construct the Hotelling T^2 in order to erase the hazards which emerge when autocorrelation becomes present.

An alternative approach to cope with autocorrelated data would be to utilize an autoregressive AR-model to erase autocorrelation for the individual charts (Montgomery & Mastrangelo, 1991). Figure 25 illustrates how the individual chart regarding the temperature of the refractory material in Figure 20 would differ if an AR-model of the second-order (i.e., AR(2)-model) were leveraged to erase the autocorrelation. If the autocorrelation is considered, the control limits widen, resulting in a decreased number of false alarms and a more accurate diagnostics procedure. When autocorrelation is considered, the individual chart's upper control limit increases by approximately 1% compared to when autocorrelation was neglected.

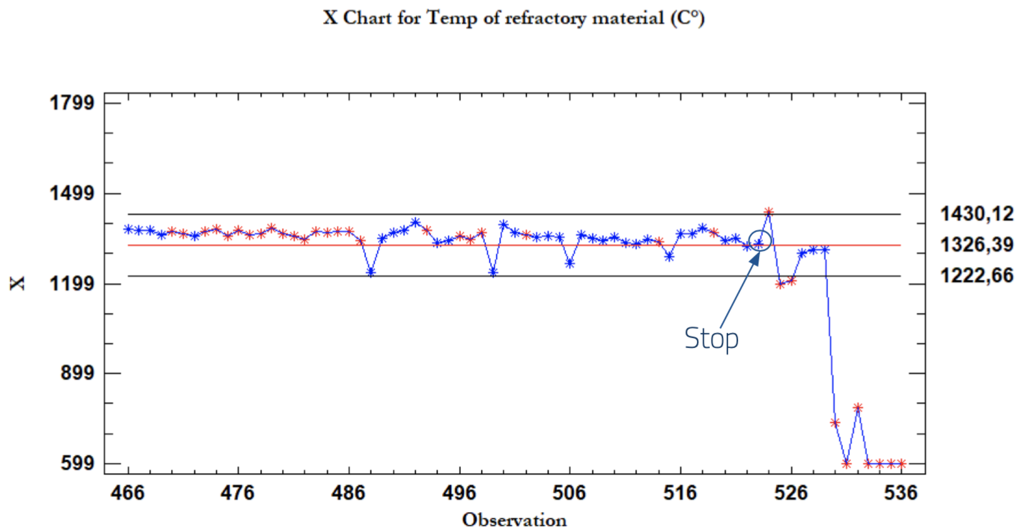

Figure 25: *Individual chart for the temperature of the refectory material for the stop during observation* 523 *when an AR(2)-model is utilized*

A test for normality was also conducted to examine which shortcomings could have distorted the Hotelling T^2 chart's predictive ability. The test for normality was conducted for the production parameters regarding the refractory material's temperature, the temperature difference, and the established T^2-statistics, which are presented in Appendix L. The training data used during the investigation was similar to the case when the potential autocorrelation was investigated. The reason why not all production parameters' probability distribution were investigated was based on the fact that the analysis proposes that only the parameters regarding the refractory material's temperature and the temperature difference influence the stop, implying that it is most valuable to examine their potential violation against the assumption to be normally distributed. If the T^2-statistic was normally distributed or not was examined to investigate how the production parameter's respective distribution affected the Hotelling T^2 chart. Normal distributed T^2-statistics are preferred as the upper control limit otherwise run the risk of being overestimated and hence become misleading (Borror et al., 1999). All examined tests for normality concluded that the assumption of the data to stem from a normal distribution could be rejected with 95% confidence.

4.4 Improve

Based on the analysis step, the Hotelling T^2 chart is perceived as a suitable method for monitoring multiple parameters simultaneously to evaluate the equipment's health. As mentioned in multiple literature sources, monitoring equipment health could be beneficial in a production environment as it could indicate when maintenance is needed and therefore increase availability. Today, no multivariate analysis tools are used to monitor the process in the investigated plant. If multivariate tools are implemented correctly, it could help to detect interrelationships between variables that could be lost when only using univariate tools (Montgomery, 2020).

4.4.1 Monitoring of equipment health

To be able to determine the refractory material's health in the Kiln, a variable representing the state of the equipment is needed Liu et al. (2015). By constructing a model of the steady-state production as done in the Hotelling T^2 chart, we create a way of monitoring the equipment by using the T^2-statistic as the variable representing equipment health. The recommendations to LKAB will be to use the same methodology used in this project to monitor the equipment's condition to indicate when maintenance is needed.

Using the Hotelling T^2 chart makes it possible to monitor multiple production parameters at once to detect if any of these deviate from normal operating values. Suppose any parameters deviate significantly, the T^2-statistic will increase, which would indicate that something has happened in the process. A situation without any operational decisions being executed to change the process along with a large T^2-statistic would indicate that something is wrong or no longer operates as it should. Therefore, it would indicate that maintenance is needed to mitigate the risk of breakdowns. Using a Hotelling T^2 chart based on principal components also enables the identification of possible causes of the disturbances, which is essential to allocate suitable corrective maintenance efforts where it is needed.

To understand how movements in the Hotelling T^2 chart could be derived from behaviors in different production parameters, an example from a stop caused by refractory material in the beginning of 2017 in Figure 26 is used. In the figure, two spikes, marked with 1 and 2, could be observed in the Hotelling T^2 chart. The analysis of the T^2-statistics showed that the two spikes were derived from the second principal component, which is heavily weighted by the parameters temperature difference and refractory material temperature. Therefore, the individual charts for those two parameters were investigated, which showed distinctive patterns for the same observations. On occasions 1 and 2, drops in the temperature were observed, causing the spikes in the Hotelling T^2 chart. Occasion 3 was instead explained by a shift in the average temperature difference, stretching over several observations.

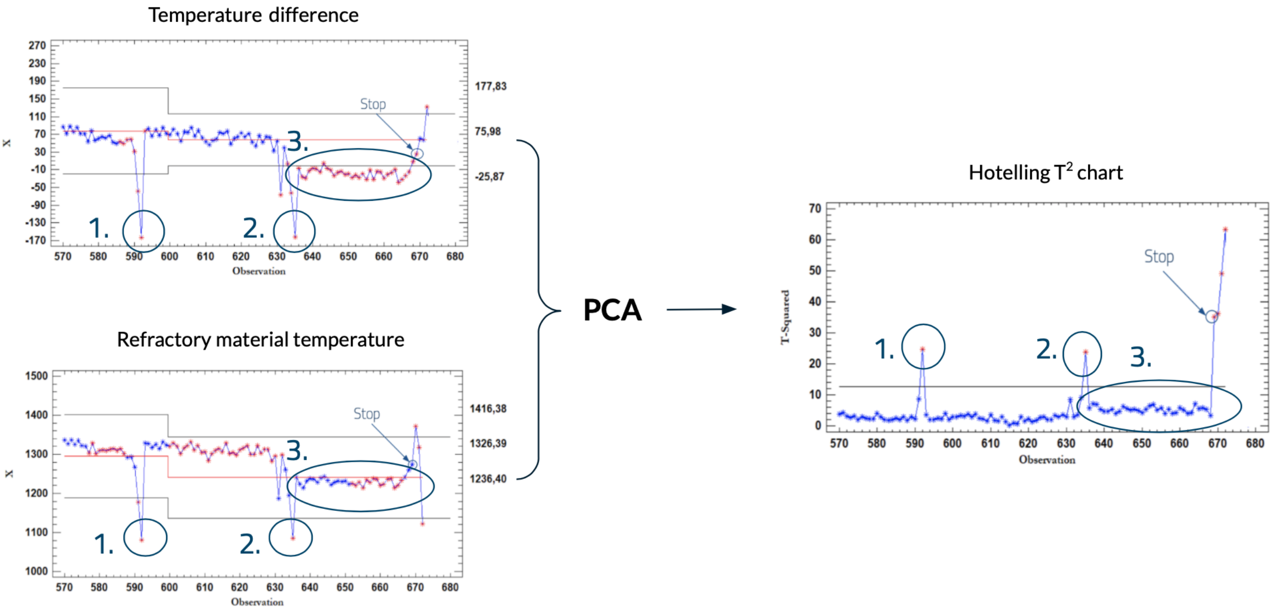

Figure 26: *Visualization of how movements in the individuals charts are reflected in the Hotelling* T^2 *chart*

4.4.2 The need to search for patterns in data

The analysis results show that monitoring only the T^2-statistic as a categorical variable, being in control or not, is not enough to decide if maintenance is needed. It could be seen that only because the T^2-statistic exceeds the upper control limit at a single moment in time, there could not be assumed that maintenance is needed. An example of this could be seen in Figure 27, where the T^2-statistic exceeds the upper control limit during several observations before returning to steady-state before a production stop occurs.

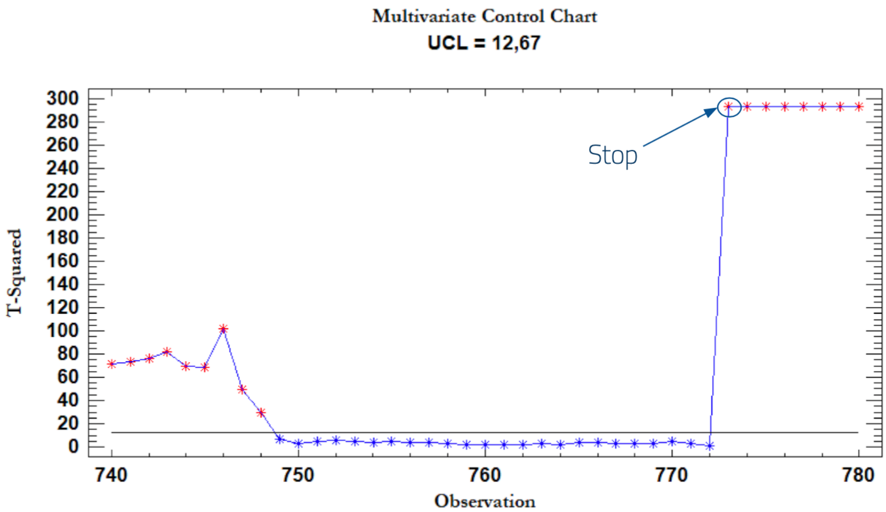

Figure 27: *Hotelling* T^2 *chart during a stop caused by refractory material in May 2020*

The risk of a sequence of observations above the control limit in the Hotelling T^2 chart is low, and for this to happen by chance for multiple subsequent values is highly unlikely. Therefore, it could be assumed that it could be derived from abnormal behaviors in any production parameters making the process deviate from steady-state. Deviating from steady-state therefore does not solely indicate that a breakdowns will appear in the near time meaning that the deviation could depend on other factors. The result of the model not being able to signal exclusively in situations before breakdowns occur indicates that we cannot solely look at the T^2-statistic as the determinant for when maintenance is needed, which Ahmad and Kamaruddin (2012) would define as a CBM strategy. However, observing T^2-statistics exceeding the upper control limit could be useful to detect abnormal behaviors in the process. To more accurately determine the need for maintenance, we recommend that the Hotelling T^2 chart also should be used to find patterns in the data which could indicate changes in equipment health which, according to Chebel-Morello et al. (2017); Lee et al. (2006) fall within the PdM strategy domain. As seen in Figure 26, there exist some patterns in the data which indicate that there would be of great interest to explore further if patterns like this would be possible to prove significant before stops.

4.4.3 Improve monitoring accuracy

Movements in the T^2-statistics were not always derived from such apparent changes in the production parameters as in Figure 26. The issue of identifying these could be assumed to be the result of different things. One of those things could be the Kiln's position in the production process, which makes it challenging to analyze in isolation due to being a part of the critical production line. Therefore, disturbance from other plant processes could cause production to diverge from steady-state and cause movements in the Hotelling T^2 chart. The second reason connects to what Weiss and Hirsh (1998) mentions, that it is more complex to monitor equipment than individual components. The Kiln consists of many different components where the refractory material could be seen as one. However, counting the refractory material as one component is misleading because it covers the whole inside of the over 40m long Kiln, which has a diameter of 8m. The third relate with the Kiln's size and concerns the different measurements of the process parameters. Having only one sensor providing measurements to describe the whole refractory material temperature may not reflect all variations making the measurement a poor representation. The lack of sensors providing data for monitoring is seen as one of the potential improvements to better represent the refractory material's health. Additional sensors could better represent the current state of the process, but as more data is collected, the risk of deficient data increases correspondingly. In addition to this, the increasing the frequency of the measurements is also recommended because it could yield an even better representation and increase the ability to detect small changes in the process.

Accurately deciding when maintenance efforts are needed could contribute to increased availability. To achieve this, predicting breakdowns would be beneficial because, if accomplished, maintenance efforts could be applied when a breakdown is predicted. The method developed in the analysis step could only indicate the equipment condition. The T^2-statistic is recommended to act as a signal for when maintenance is needed, but more accurate ways of deciding when maintenance is needed could be achieved by predicting breakdowns. Therefore, it is recommended to not solely base the decision of future maintenance efforts on the Hotelling T^2 chart's ability to signal when the process is deviating from steady-state. It is the first step toward utilizing a predictive maintenance strategy. The next step is to develop a method to find statistically significant patterns in the data before it stops. A recommendation for how LKAB should move forward with this will be further presented in section 5.

4.5 Control

To assess if future improvements solve the issues regarding the refractory material, LKAB is recommended to reevaluate the Kiln's performance through a similar procedure as in the measure step. By reevaluating the FUT, it will contribute to an understanding of how future initiatives influence the availability. The reevaluation of the FUT measurement is recommended to be conducted monthly in order to detect potential trends or shifts among observations. Since this project's findings revolve around the refractory material, the present calculation of the FUT should only include downtime due to the refractory material. By only including the associated downtime in the Kiln due to the refractory material, it will become easier for LKAB to trace how the issue varies between months. Further, the construction of a FUT measurement evaluating the current performance regarding the refractory material will enable an assessment of future improvement initiatives' impact on solving the issues related to the refractory material. Because of how the FUT measurement has been constructed, a decrease will be perceived as an improvement and vice-versa.

4.5.1 The need to update the model

The model needs to be updated in the future as the production speed is planned to increase. Consequently, the production parameters' steady-state will change accordingly, making the current model outdated. If the model is not updated, the risk of false alarms would be increased since the principal component's means would no longer represent the actual mean of the principal components during steady-state production. How often the model should be updated is difficult to determine exactly. By observing to which degree the production speed increases between different years, we recommend updating the model at least every year due to the small yearly change. When the model aims to be updated, the most current obtainable steady-state production values are recommended to be used when developing the model.

The decision regarding which production values are perceived as steady-state production and thus used to develop the model is crucial since it regulates the model's sensitivity to process disturbances. If the range of values perceived as steady-state production is too wide, the model cannot signal when deviations occur, hence not being able to detect emerging stops. In contrast, if the range of perceived steady-state values is too narrow, the model will likely result in many false alarms.

5 Improving the ability to determine the need for maintenance

The following chapter presents the improvements the project recommends to complement the developed method of monitoring equipment health presented in previous chapters. First, the discovered obstacles for developing a method of predicting breakdowns are presented. Furthermore, the challenges to incorporating the method into the daily operations are discussed with a suggested implementation plan.

5.1 Obstacles for predicting breakdowns

In the project's third phase, the Improve and Control steps of the DMAIC methodology, improvements to more accurately determine when maintenance is needed were identified. Predicting breakdowns was identified as a way to achieve this, which was attempted during the analysis by finding patterns before production stops. During the analysis step, statistically significant patterns in the data could not be established. The reason for this was identified as being the result of four obstacles. These obstacles need to be handled in a way that makes it possible to avoid their negative impact on pattern-finding. Therefore, solving these issues becomes complementary recommendations to those earlier presented to enable future prediction of breakdowns through pattern finding. Solving these obstacles is also seen as having a positive impact on monitoring equipment health, thanks to the possibility of increasing the quality of available maintenance data. The obstacles were the following:

- **Not enough documentation about the stop**
- **Deficient data**
- **The actual breakdown time has to be known**
- **Breakdowns that satisfy pattern finding are rare**

5.1.1 Not enough documentation about the stop

When analyzing past production stops, the quality and quantity of documentation vary between stops. For some stops, documentation exists in addition to the information automatically generated by various sensors. The additional documentation comes from the operator's observations. It is the piece of information that is needed to better understand and analyze changes in the production in historical data. A consequence of this issue was the difficulty in differentiating what kind of stop (i.e., alarms from sensors, operators pushing emergency stop, or decisions from plant managers) caused the production stop in Plant performance. The problem of not being able to connect movements in data from actual events in the Kiln or if its decisions made by employees is seen as the biggest obstacle to finding reliable patterns in data. Therefore, additional documentation is needed to distinguish the changes influenced by production decisions and those resulting from actual process fluctuations. The problem regarding documentation could be derived from a lack of standardization of the documentation process resulting in different operators having different documentation routines in connection with production stops. This obstacle complicated the analysis of stops, and the shortage of documentation proved to be a common denominator for all encountered obstacles in the search for patterns. Therefore, more documentation about the stops is perceived as a prerequisite that needs to be addressed to predict breakdowns.

5.1.2 Deficient data

Deficient data was a problem that was present throughout the whole project. The obstacle consisted mainly of observations that obtained values significantly deviating from values immediately before and after the specific value in Plant performance. This problem was the case for all production parameters, which disturbed the search for patterns and made the T^2-statistics obtain misleading values. One of the identified reasons for this could be that measurements of different production parameters are taken at different timestamps every hour. That means measurements taken for the same observation could theoretically differ by up to 59 minutes, making measurements of production parameters an unfair representation of separate hours. For example, if there were a short stop during ten minutes, this stop would only be reflected in those measurements taken during that period. However, the other production parameters may not indicate any disturbances. Another thing that was observed was parameters that took on the same value for multiple measurements in a row. It often appeared in combination with production stops causing significant movements in the T^2-statistics, which aggravated the search for patterns in connection with stops. The obstacle was further complicated because many of these cases were untraceable when looking at the maintenance data due to the lack of documentation from operators.

An example of how the deficient data could appear is presented in Table 10. The abnormal observation during observation 417 resulted in a spike in the Hotelling T^2 chart, which could not be explained in hindsight when analyzing the data. The production parameters indicate that the process could either have been stopped, a measurement error has occurred, or something in the process had changed. These behaviors must be addressed if any conclusions can be drawn from observations like these, highlighting the need to handle these deficient data values.

Table 10: Example of a situation with deficient data

Row	**Production speed (Ton/h)**	**Temperature of refractory material (C°)**	**Temperature difference refractory material and material (C°)**	**Kiln rotation (RPM)**	**Speed Cooler (%)**	**Power of burner (MW)**	**Gas flow upper PH (mmPV)**	**Gas flow lower PH (mmPV)**
416	857,3	1387	118	2,3	23,68	47,74	-6,4	-210,58
417	841,7	1369	100	**0,62**	**0**	35,61	-6,86	-221,68
418	842,2	1412	139	2,25	27,76	43,01	-8,62	-259,32

5.1.3 The actual breakdown time has to be known

When production stops caused by refractory material are initiated, it often depends on how long it takes operators to detect a breakdown. Because these stops are substantial and often stretch over long periods, there is a policy that production engineers have to decide if a production stop should be initiated. The timestamp documented in Plant performance as the breakdown moment is the time for initiating the stop, not the actual time for the breakdown. The time from identification to production stop could further vary due to decisions to keep production going for different amounts of time. There is no documentation of when the actual time for breakdowns could have occurred or how long it took to decide when to initiate the stop. Therefore, it is difficult to know with certainty when a breakdown has happened by looking at historical data. Therefore, it makes finding patterns before production stops in an attempt to predict breakdowns difficult because the time of breakdown is untraceable as of today.

According to LKAB, it is confirmed that a difference could exist between the actual time of the breakdown and the time of production stop. The problem is visualized in Figure 30 based on the problem formulation presented by Weiss and Hirsh (1998). Assigning a too-late timestamp to a breakdown results in looking at the wrong prediction time (P_1) when searching for patterns instead of the actual prediction time (P_0). The problem is further complicated due to the difference in time (ΔE) between the actual breakdown (E_1) and the production stop (E_0), which varies between stops since it could take different amounts of time to detect the stop for operators and make a decision if the stop should be initiated. Because of that, it becomes difficult to find consequent and accurate patterns when assessing prediction rules for breakdowns due to different time intervals being analyzed.

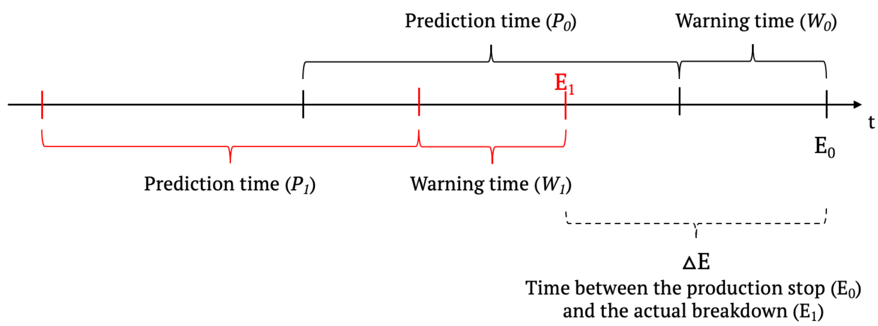

Figure 28: *Timeline of how the the predicting time differ when the wrong time for breakdown is used based on the model of Weiss and Hirsh (1998).*

In the second stop in the analysis, a slight shift in the Hotelling T^2 chart was observed, which was derived from a change in the temperature difference between the refractory material and the pellets, see Figure 29. One hypothesis is that the shift could result from a breakdown, which occurred somewhere between observation 630-640 instead of the marked production stop at observation 669. The reason for the production stop being initiated much later could either be the result of the breakdown not being identified directly or from a decision to keep production going. The importance of documenting details in situations like these is needed in order to improve the model and to be able to find patterns in the data to predict breakdowns.

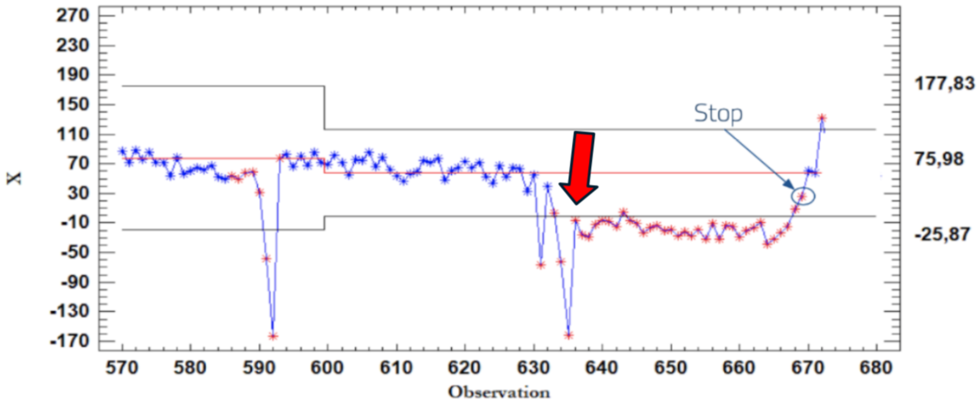

Figure 29: *Individual chart regarding the temperature difference for the second stop during observation* 669

Identifying and rectifying the breakdown early could limit the maintenance efforts needed to repair the equipment. As mentioned by Fan et al. (2012), the Kiln is challenging to monitor due to high temperatures and because it is a closed system which contributes negatively to identifying these timestamps accurately. Even though operators can look inside the Kiln through a camera located at the end of the Kiln close to the burner, it is difficult to see fall-outs throughout the whole Kiln. Apart from the limited visual inspection on the inside, operators also could inspect the Kiln mantle externally by searching for red spots.

In the article by M.-C. Yang et al. (2018) where they try to indicate refractory material fall-outs in a Kiln, they identified three indicators of when fall-outs of refractory material appear. M.-C. Yang et al. (2018) used a combination of; a heat sensor that analyzed the Kiln mantle for red spots, monitoring of the drive amps of the Kiln motor, and identified sudden drops in the Kiln temperature to identify fall-outs. Measurements were done with short sample times, which enabled them to be used together to determine when a fall-out occurred more accurately. These methods could be valuable to investigate further if these could contribute to solving the problem by more accurately determining the time for a breakdown.

5.1.4 Breakdowns that satisfy pattern finding are rare

Even though production stops caused by refractory material represent most stop time in the Grate-Kiln-Cooler process, there are not many production stops yearly. Cases that satisfy pattern searching are even rarer because, before some stops, there are often large fluctuations in the production parameters. Further, the mentioned obstacles also disrupt the ability to find patterns by creating noise in the data. The result is that the number of stops that could be analyzed and used to determine prediction rules is scarce, making it challenging to find statistically significant patterns.

This obstacle is closely connected to the problem of deficient data. It could be the case of occasional or multiple subsequent deficient observations and is further complicated due to missing documentation. Some production stops happen in combination with other stops, such as during the start-up process from another stop without reaching steady-state production in between. A visualization of this are presented Figure 30 for two stops in September 2021. The T^2-statistic never reaches steady-state again (i.e., under the upper control limit) before the next stop occurs.

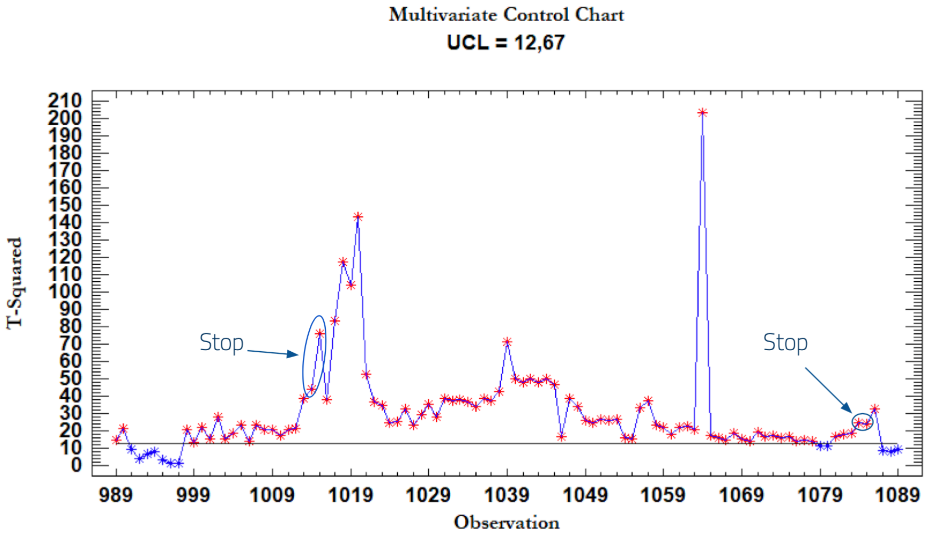

Figure 30: *Hotelling T^2 chart for 22-26 of September 2021*

The several T^2-statistics above the upper control limit could be interpreted as unsatisfactory equipment health, and thus, maintenance is required. In the example in Figure 30, however, the T^2-statistics could be derived from a lower production rate than usual, resulting in all individual production parameters deviating from steady-state. The reason why production was not settled back to steady-state between these stops could not be answered by the information in Process explorer. Documentation would be needed if these kinds of stops will ever be able to contribute with information about breakdowns.

5.2 Tuning the Hotelling T^2 model

In addition to the obstacles which need to be solved, the model's ability to indicate when maintenance is needed could benefit from adjustments to improve its monitoring accuracy, for example, which operational values are perceived as steady-state. The analysis findings further propose the need to evaluate which parameters to include in the model, in addition to the parameters regarding the refractory material's temperature and the temperature difference, which showed a tendency to influence the refractory material's condition. Selecting a different set of variables to be included in the model could increase the capability of predicting equipment health more accurately. Hashemian (2010) propose a set of generic variables, where the rate of vibration, ambient temperature, and pressure are perceived as variables that could be considered in the future development of the model. The ambient temperature could be of great interest as this project's findings propose that the weather temperature influences the Kiln's performance.

The decision if the Hotelling T^2 should be based on principal components or not is a further factor that could influence the model's performance. The principal components provide the benefit of reducing the data set's dimensionality (Mishra et al., 2017), which is advantageous if an extensive amount of data that needs to be handled. If the number of included parameters is high in combination with many observations during the model's development, principal components are considered beneficial. However, if the model solely aims to monitor a few variables, the usage of principal components could be unnecessary. A reason to consider neglecting the idea of using principal components in the case of a few included parameters is the increased complexity of interpretation, which becomes more challenging when using principal components (Montgomery, 2020). The increasing complexity of interpreting the result will make diagnosing the cause of the T^2-statistic's behavior more challenging, increasing the risk of misallocated maintenance efforts.

5.3 Incorporating the improvements in the daily operations

For the model to create value for LKAB, it must be effectively incorporated into its daily operations. Challenges to configuring the model into existing digital systems and establishing ways of working are essential aspects that need to be addressed. Educating the employees on how the model's results should be interpreted and utilized is also important. This does not mean that the usage of the model should replace all diagnostics of equipment health that are already in place. LKAB has a lot of knowledge and ways of handling breakdowns based on years of experience, an asset that should not be neglected. Therefore, the presented method should complement existing ways of working to enable a faster recognition of the need for maintenance and more accurately describe their causes.

Additional systems may be needed in the future as a part of the pattern-finding before stops which may need algorithms to detect trends in the data. The literature also highlights that a connected system for monitoring the Kiln to assess its condition could yield higher productivity, often referred to as an expert system Y. Wang et al. (2013), where the first step towards developing a fully functional expert system is to establish a way of monitoring a process to detect abnormalities. This project could be perceived as the initial step towards developing an expert system, personalized for monitoring the Kiln G.-m. Yang et al. (2016).

5.4 Implementation plan

Once the obstacles have been handled and the decision on how the model should be tuned, an implementation plan, as presented in, Figure 31, is required for LKAB to incorporate a PdM strategy successfully. The implementation plan highlights the need first to address the current obstacles, which act as a prerequisite to facilitating the model development. The prerequisites should be addressed according to the implementation plan, which proposes the obstacle of insufficient documentation to be solved first due to its close connection to the other obstacles. In which sequence the prerequisites are addressed is important since interconnection exists among them. For example, if the problem regarding insufficient documentation is solved, the issues concerning deficient data will be less challenging. The implementation plan's previous steps regarding the prerequisites will facilitate the model development phase. The development and evaluation of the model will be an iterative process, which will continue until the model is perceived as adequate to be incorporated into the daily operations. The last phase of the implementation plan regarding the integration of the model in the daily operations revolves around the infrastructure and ways of working needed to seize the model's generated value.

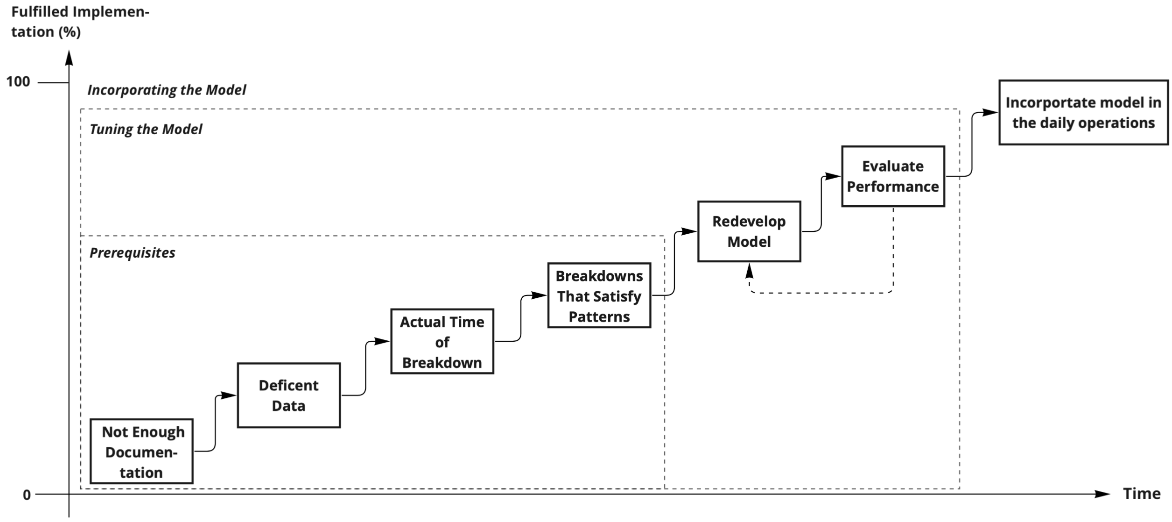

Figure 31: *Implementation plan of how to incorporate the model into the daily operations*

6 Discussion

The following chapter presents a brief discussion, mainly focusing on the utilized method and assessing its attained level of reliability and validity. Suggestions of alternative methods for future projects that strive to continue the journey towards incorporating a PdM strategy are proposed.

6.1 Method discussion

The systematic problem-solving methodology DMAIC was a critical success factor during the scope reduction of the project. Initially, the entire Grate-Kiln-Cooler process was investigated, which then was limited to examining the refractory material. Exploring which internal disturbance had the most significant impact on availability was vital. The utilization of the DMAIC methodology increased the likelihood that the right part of the process was targeted after the narrowed scope since the methodology stressed the importance of properly defining the problem.

The art of deciding which production parameters to monitor and which range is determined as steady-state production is aspects of the project that needs to be further investigated. A more suitable method of deciding these needs to be identified and exercised because the current methods are inadequate since assumptions were necessary which could have influenced the results (e.g., the range perceived as steady-state for the production parameters might not reflect the actual steady-state).

The Kiln's position in the production line increased the complexity of investigating which parameters truly affect the refractory material. Therefore, the authors propose that isolating the Kiln during analyses would be beneficial to ensure that observed disturbances stem from the included production parameters and not from other parts of the production line. Additionally, the extensive amount of data handled in the project has been seen as an asset and a liability. It enabled hypotheses to be tested and verified quantitatively but also caused confusion on several occasions, resulting in rework.

This project used statistical methods such as the Hotelling T^2 chart based on principal components to indicate whether maintenance efforts are needed. However, it is possible that other mathematical modeling techniques could have been more suitable to indicate the system's need for maintenance (e.g., various classification methods). Further, the possibility of utilizing other predictive methods as machine learning approaches to detect when maintenance is needed could also be of relevance. Nevertheless, independent of which predictive method is the most suitable to detect the need for maintenance, the non-satisfied prerequisites, as issued earlier, have to be attained first.

6.1.1 The ability to increase availability using SPC

The question remains if SPC is the most suitable method to improve the plant's availability. Monitoring using the Hotelling T^2 will not prevent degradation of the refractory material. Degradation will always be present due to the limited lifetime of the refractory material, which usually lasts 1-3 years. However, it is known from the literature that stable operating conditions favor the lifetime of the refractory material. Monitoring the equipment's health using the Hotelling T^2 chart detects when the process operation deviates from stable conditions (i.e., steady-state). It would provide the benefit of indicating when adjustments may be needed to stabilize the process and improve operational conditions, which could decrease the degradation rate and potentially result in fewer breakdowns during the refractory material's lifetime. When the T^2-statistic is observed taking on large values, the process deviates from steady-state, which otherwise could be difficult to detect due to the complexity of monitoring the Kiln. These deviation does not solely need to be the result of breakdowns. However, it indicates that something has changed in the process and needs to be investigated. As of today, breakdowns often are addressed as operators observe them, which could take time, making the process operate for hours with defective components. Therefore, monitoring could enable earlier detection of breakdowns limiting the impact of the breakdown and thus, minimizing the maintenance needed and accordingly increasing availability.

However, if the availability will increase due to the monitoring method developed in this project, is difficult to know beforehand. The data used for the development of the model is the data that is available from the sensors in place today. Knowing if these are causal with the deterioration of the refractory material to provide any early signs of breakdown is unlikely and needs more investigation. The risk is that the chosen production parameters used in the model's development cannot be used to describe the deterioration, meaning that there could be a need to explore new parameters or other occurrences that would indicate breakdowns. If the parameters are not chosen correctly, the risk is that the consequences of breakdowns are monitored rather than the occurrences leading up to them, preventing increased availability by the proposed monitoring method.

The monitoring may become unnecessary since the Kiln today can operate for several hours without any noticeable consequences for the end products. Suppose the decrease of maintenance hours due to early identification of breakdown through monitoring does not exceed the lost production hours due to stopping the process early; monitoring will not yield a positive financial outcome. Thus, it would indicate that other approaches within the realm of PdM perhaps would be more suitable from a financial standpoint. The final decision criteria depend on whether the advantages of utilizing a specific PdM approach exceed the increased use of resources it entails.

6.1.2 The robustness of the results

Autocorrelation was present for the vast majority of the included production parameters, which resulted in challenges regarding the constructed Hotelling T^2 chart's monitoring ability. Autocorrelation caused the upper control limit in the chart to increase, which poses an issue because it impaired the monitoring system's ability to detect shifts, consequently decreasing its monitoring performance. In addition, the issue concerning the unfulfilled assumption that data were normally distributed was also perceived to impair the monitoring system's performance.

The authors perceive the presence of autocorrelation, which were unconsidered during the model development, as an issue that needs to be considered in future attempts to monitor the refractory material. However, the authors have reasons to believe that the negative effect of autocorrelation on the project's result could have been hampered since the issued obstacles, regardless of whether autocorrelation is present, make it impossible to predict emerging breakdowns effectively. Furthermore, when breakdowns were identified in the Hotelling T^2 chart, the T-statistic obtained values notably above the upper control limit, suggesting that the utilized model's ability to detect shifts once they occurred was not decreased. The individual chart presented in Figure 25, where autocorrelation was considered and erased through the usage of an AR(2)-model, further suggests that the initial individual charts (i.e., when autocorrelation was neglected) might be misleading as the control limits are to narrow. Nevertheless, the initial individual charts still enable visualization of how its respective parameters alter as time progresses, enabling detection of abnormalities and possible trends before breakdowns. In addition, when considering the slight relative increase in the upper control limit (i.e., 1%) compared to when autocorrelation were neglected, suggesting that the conclusions drawn from the charts does not differ significantly from when autocorrelation is accounted for.

The issue that the investigated parameters did not stem from a normal distribution impacted the project's results. The production parameters measuring the refractory material's temperature and the temperature difference between the refractory material and the pellet's temperature were non-normally distributed. This resulted in the assumption of normality being violated, increasing the risk of falsely interpreting the individual charts while monitoring the system. However, when the monitoring system is incorporated into the daily operation, the individual charts are intended to be interpreted through a qualitative approach to diagnose the cause of the deviating T-statistics. A qualitative approach refers to employees utilizing existing knowledge of the system to decide when abnormalities occur in the individual charts instead of solely reacting when the upper control limit is surpassed. The negative consequence of the data being non-normally distributed, and the sample size is one, is that according to Chou et al. (2001), the upper control limit becomes overestimated. The hazard that arises when the upper control limit is overestimated is that the Hotelling T^2 chart's ability to detect shifts will be hampered, decreasing its proficiency in monitoring the process. To solve the issues regarding the violation of the normality assumption in the individual charts, Borror et al. (1999) proposes the usage om of an exponentially weighted moving average (EWMA) chart, which is a more robust approach to non-normally distributed data. Further, Borror et al. (1999) mentions the EWMA chart's adequate ability to detect shifts in the process mean, resulting in it being a beneficial control chart to consider in the case of non-normally distributed data.

6.2 The reliability and validity of the result

As issued earlier, the normal operational condition for all independent variables was unknown. Consequently, the operational condition highlighting steady-state needed to be estimated, which influenced the model's ability to monitor the process accurately. The production speed was used to decide which periods were perceived as steady-state production. If the normal operating conditions for each included production parameter were known, these would be used to determine steady-state, increasing the model's probability of monitoring the process more accurately. Therefore, the lack of knowledge regarding which operational condition reflected steady-state hampered the project's reliability. Furthermore, the reliability was also perceived to be hampered by deficient data in the Process explorer data set as it increased the risk of examining the concept incorrectly.

In terms of the project's validity, several factors could have influenced it during the project's execution. Which production parameters that finally were chosen to be included in the model in order to monitor equipment health was perceived to influence the validity. In which fashion is nevertheless hard to determine. The included parameters were chosen based on current literature and discussions with employees at LKAB, which would initially suggest the validity to be strengthened. However, the results from the analysis propose the opposite, i.e., that the parameters could be wrongly selected because of the model's inability to predict breakdowns, which instead suggests the result's validity to be decreased.

The validity could have been strengthened thanks to the several meetings held with the supervisor at LKAB to ensure that the workflow and the findings prior to the meetings were within the project's scope and of relevance to LKAB. The meetings also provided the opportunity to benchmark the current finding's credibility, thus increasing the validity.

To what extent the presented findings in the thesis can be generalized is according to Lucas (2003), referred to as the study's external validity. Even though the findings presented in the thesis can be perceived to only apply to the Kiln for the investigated plant, one could argue that the production parameters affecting the health of the refractory material are generic. As the production parameters can be perceived as generic, it implies that the possibility exists that the findings could be generalized for similar Kiln processes. Furthermore, the currently non-satisfied prerequisites identified could be perceived to some extent also be generalizable for similar processes. The fact that similar research, for example, by (Luo et al., 2008), identified similar obstacles further strengthens that the prerequisites could be applicable for other Kiln processes.

7 Conclusion

The following chapter presents the conclusions which answer the master's thesis stated purpose. Beginning with the first part, which aimed to identify the causes of process disturbances, followed by the second part regarding the chosen method of monitoring the critical causes identified in the first part.

This thesis has contributed to understanding what affects availability in the Grate-Kiln-Cooler process in one of LKAB's pelletization plants. Refractory material breakdowns in the Kiln are the most significant disturbance causing a majority of the downtime in the plant and thus, preventing LKAB from reaching its production goals and missing out on a substantial amount of revenue. Stops caused by refractory material are rare, and there could be many months between them. Nevertheless, the disturbance still represents the most significant influence on low availability because these stops often are present for over a hundred hours. It means that either preventing stops from happening or limiting the maintenance needed to correct them could substantially impact the availability. Therefore, monitoring the refractory material is assumed to be favorable for detecting future disturbances and preventing them from happening.

An appropriate way of monitoring the refractory material is perceived to be through the usage of a Hotelling T^2 chart. It enables multiple production parameters to be monitored simultaneously to construct a quantification of the equipment health in the form of the T^2-statistic. The model on which the Hotelling T^2 chart is based on using steady-state values for the included production parameters. The T^2-statistic will therefore represent how far these parameters are from their steady-state, which indicates if production is unstable. In that case, the principal components could then be used to assess which production parameters have deviated and may need maintenance. The main contribution of this master's thesis will be its used methodology to determine the need for maintenance. Providing the right maintenance efforts as soon as needed could prevent and ease the impact of future breakdowns. Determining the need for maintenance by investigating a variable representing equipment health has been beneficial in previous literature. However, the findings suggest that the method could lack precision and that the ability to predict breakdowns through identifying patterns in the data before stops could help to determine this more accurately.

The Hotelling T^2 chart and its constituting parameters were investigated in an attempt to find patterns before stops. Unfortunately, stops caused by refractory material could not be predicted by analyzing the T^2-statistics. However, some patterns were observed in the process parameters. The individual charts regarding refractory material temperature showed some tendencies which caught the authors' attention. It resulted in a hypothesis that changes in the temperature could be a valid indicator of when a breakdown is about to occur. Only a few production stops caused by refractory material had occurred during the observed period, combined with noisy data, making it difficult to conclude the tendencies' statistical significance. Therefore, further investigation is recommended about how refractory material temperatures are connected to the need for maintenance and if patterns could indicate an upcoming breakdown. In addition, there is also a need to develop the model further and evaluate if the current way of collecting and handling data needs to be developed to achieve a more accurate representation of the equipment's health and improve the ability to predict future stops through pattern finding.

The ambition of this project is that the findings alongside the developed methodology could create a fundamental understanding of what could be included in a predictive maintenance strategy. The understanding is perceived not only limited to the examined process in this project; thus, it could be generalized to other similar Kiln processes. However, the impact of implementation, independent of which process the method will be applied to, will depend on the model's ability to reflect the process and distinguish patterns in data proceeding stops. Therefore, further development of the model is essential for a successful predictive maintenance strategy.

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8 Appendices

8.1 Appendix A - Control limits for the univariate control charts

The average moving range $\overline{\text{MR}}$, based on two observations, were calculated as follows:

$$\overline{\text{MR}} = \frac{\sum_{i=1}^{n} |x_i - x_{i-1}|}{n} \tag{7}$$

Thus could the centerline (CL) and the upper- and lower control limit (UCL and LCL) for the Shewhart chart be calculated as follows:

$$UCL = \mu + 3\frac{\overline{\text{MR}}}{d_2} \tag{8}$$

$$CL = \mu \tag{9}$$

$$LCL = \mu - 3\frac{\overline{\text{MR}}}{d_2} \tag{10}$$

Where μ is the process mean, and d_2 is a constant whose value depends on the number of observations used to determine the $\overline{\text{MR}}$. This case was based on only the previous observation, meaning that two observations were used to determine the $\overline{\text{MR}}$. Therefore, d_2 obtained the value $d_2 = 1,128$ (Montgomery, 2020). The CL, UCL, and LCL for the MR-chart were later calculated, which used Montgomery (2020) definition, as follows:

$$UCL = D_4\overline{\text{MR}} \tag{11}$$

$$CL = \overline{\text{MR}} \tag{12}$$

$$LCL = D_3\overline{\text{MR}} \tag{13}$$

Where $\overline{\text{MR}}$ is the average moving range, and D_4 and D_3 are two constants depending on how many observations were used to determine the $\overline{\text{MR}}$. Because only two observations were used to determine the $\overline{\text{MR}}$, D_3 became equal to zero (Montgomery, 2020), meaning that the LCL obtained a value of zero for all the conducted MR-charts.

8.2 Appendix B - Investigation of potential autocorrelation for the Great

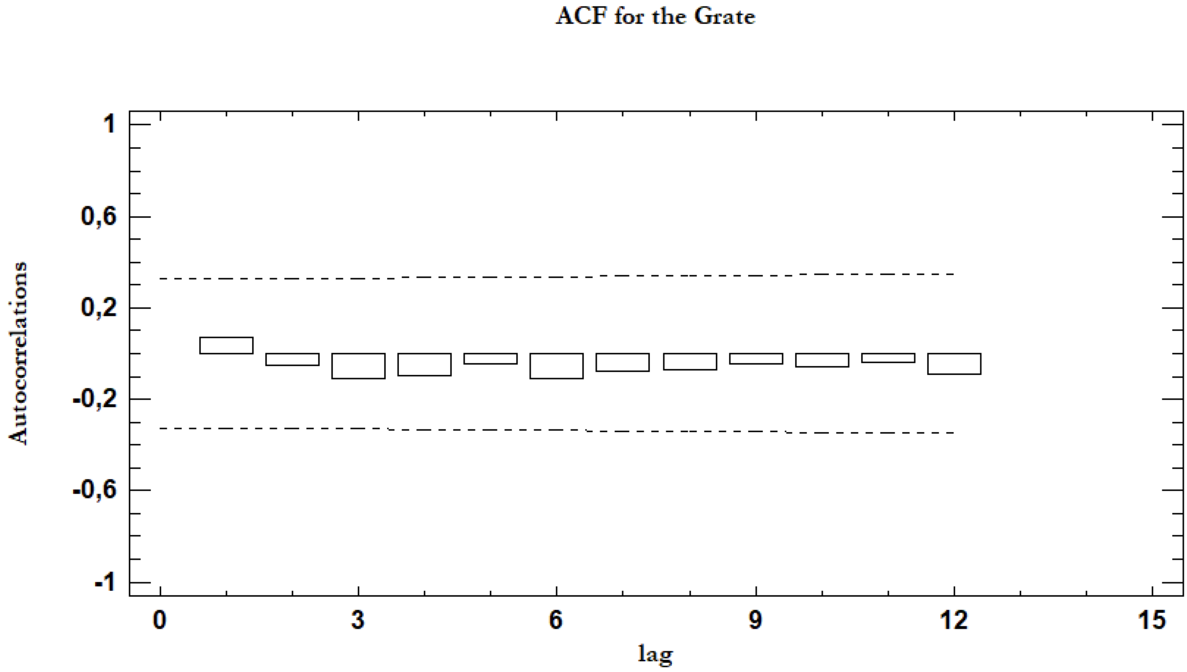

Figure 32: *Autocorrelation functions for the Grate*

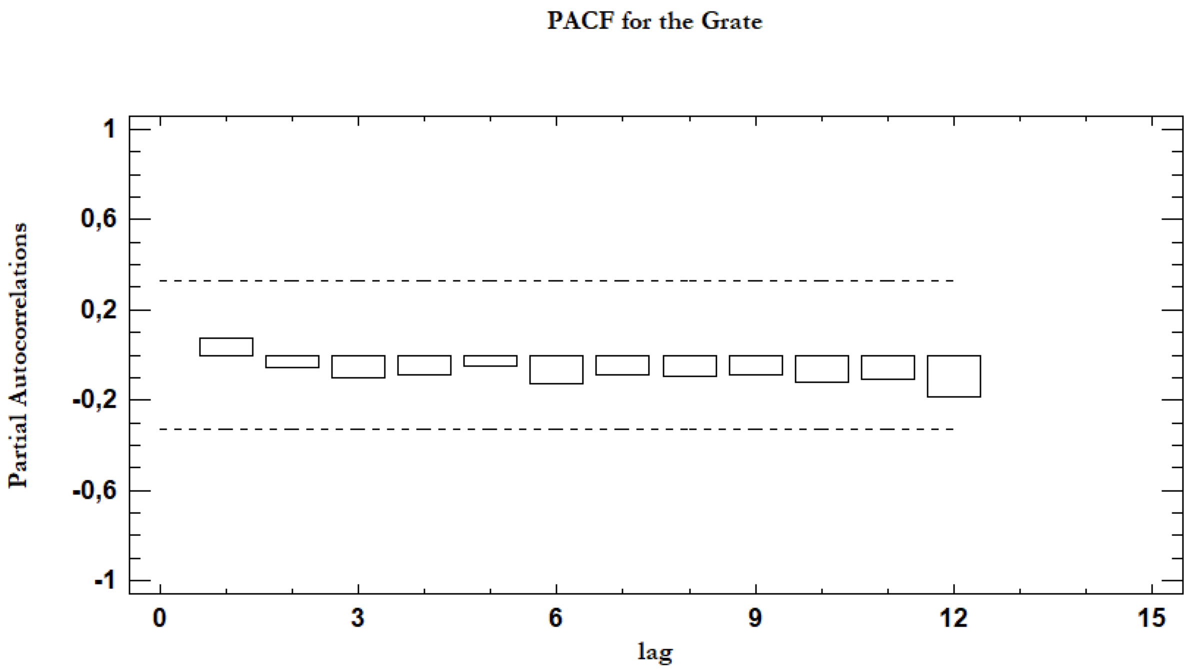

Figure 33: *Partial autocorrelation functions for the Grate*

8.3 Appendix C - Investigation of potential autocorrelation for the Kiln

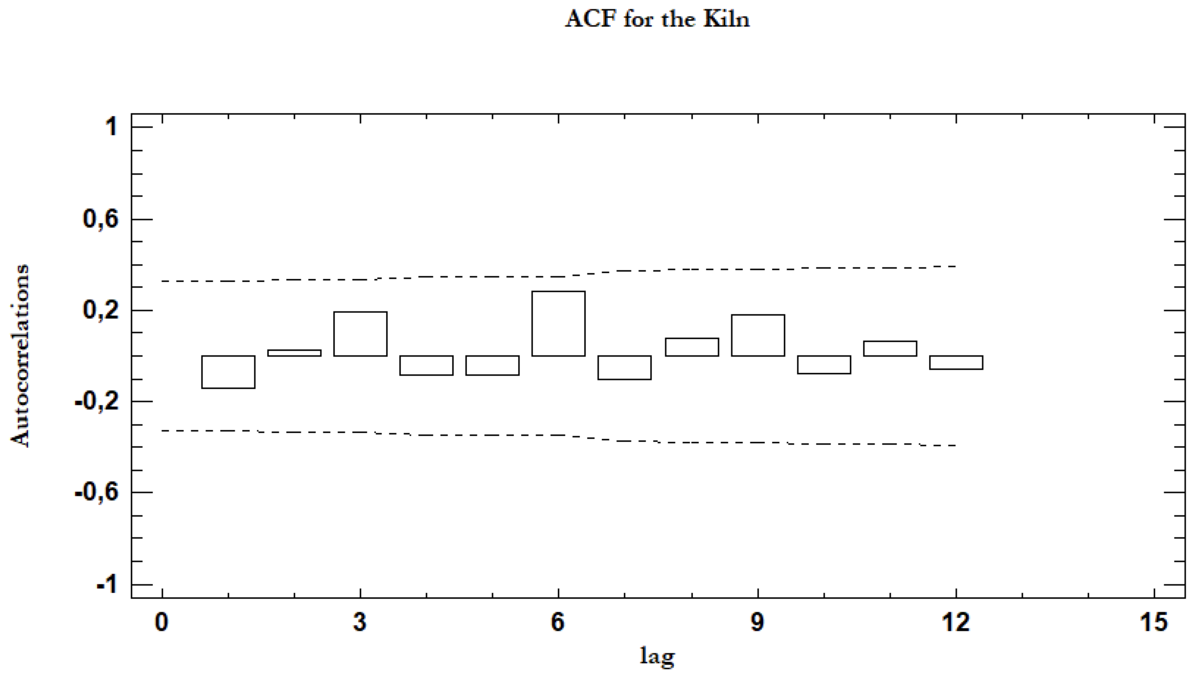

Figure 34: *Autocorrelation functions for the Kiln*

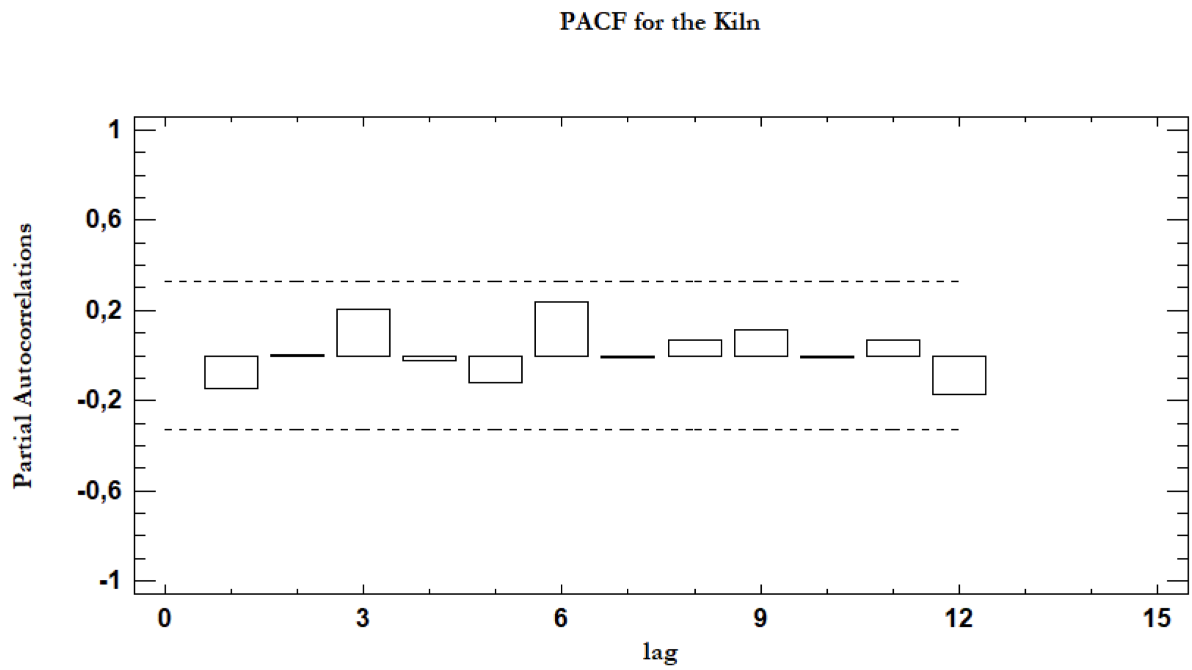

Figure 35: *Partial autocorrelation functions for the Kiln*

8.4 Appendix D - Investigation of potential autocorrelation for the Cooler

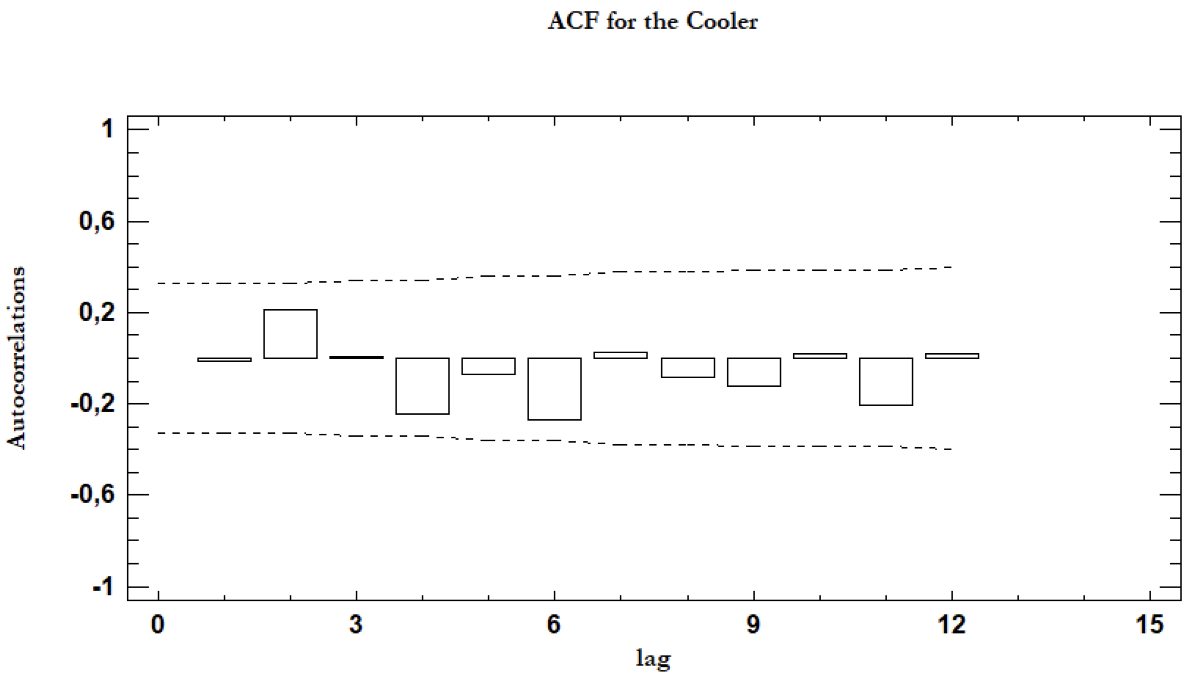

Figure 36: *Autocorrelation functions for the Cooler*

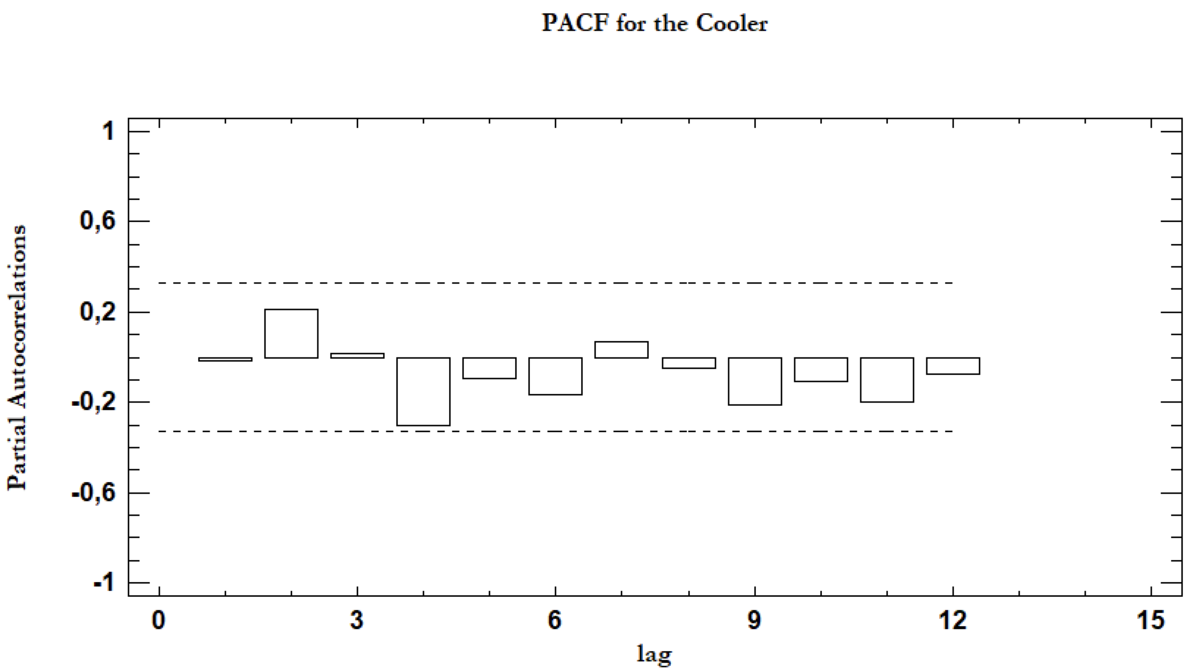

Figure 37: *Partial autocorrelation functions for the Cooler*

8.5 Appendix E - Investigation of potential autocorrelation for the entire process

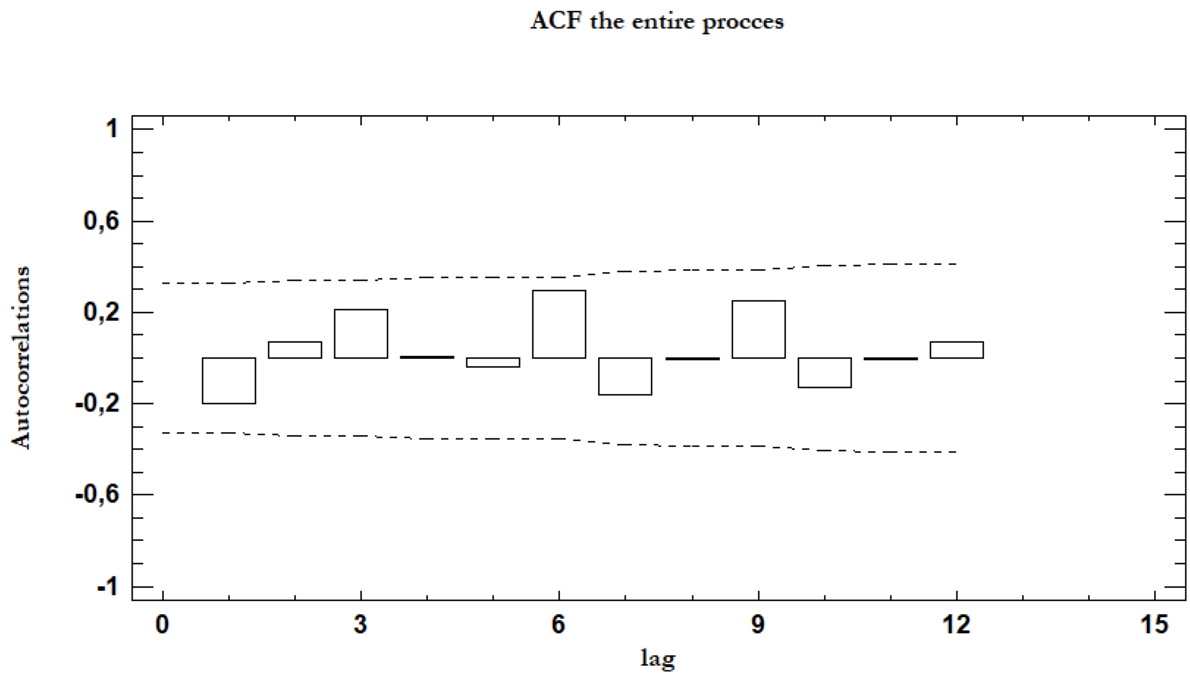

Figure 38: *Autocorrelation functions for the entire process*

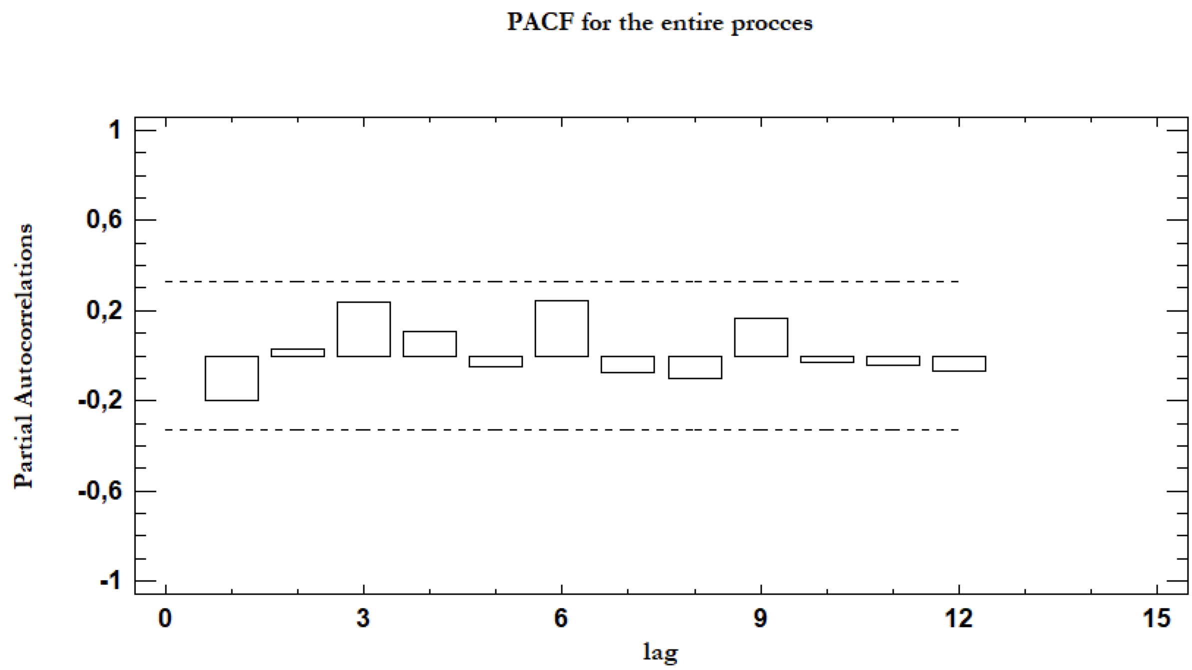

Figure 39: *Partial autocorrelation functions for the entire process*

8.6 Appendix F - Initial screening for the Grate

The established control chart highlight that Grate's performance varies heavily during the selected time frame. However, the mean is at 2%, meaning that, in general, the process's availability is satisfactory under the assumption that the remaining components of the process are available the entire time. The Shewhart chart presented in Figure 40 highlight the volatility of the process. The alarms in the control chart for months 16 and 30 are of special interest as the availability was extraordinarily low. The corresponding MR-chart for the Grate in Figure 41, highlights that the average moving range was 3%. Further, the MR-chart posits that four months exceeds the upper control limit, which stems from the two spikes at months 16 and 30 in the Shewhart chart. As both control charts include alarms more frequently than the amount that would be present only due to pure chance, it is possible to claim that the process is not in statistical control.

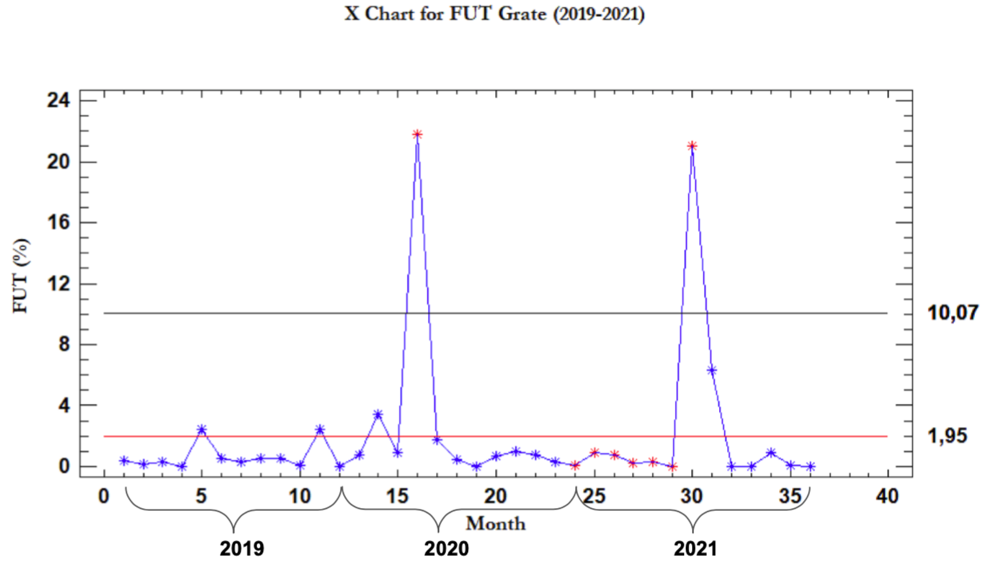

Figure 40: *FUT for the Grate*

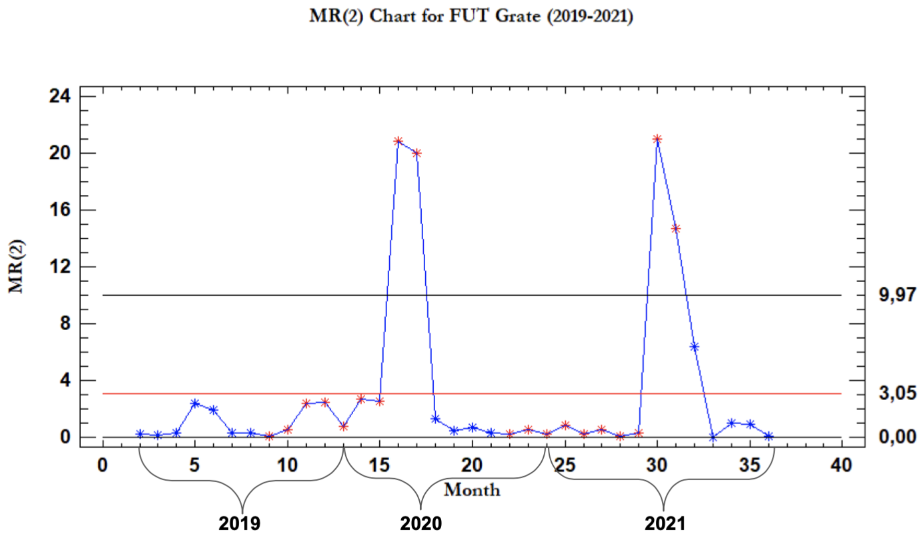

Figure 41: *MR-chart FUT for the Grate*

8.7 Appendix G - Initial screening for the Cooler

The Cooler as the last component in the process were as well analysed by the usage of a Shewhart and an MR-chart, which is presented in Figure 52. The Shewhart chart highlights that the mean of the Cooler is 1%, which is the lowest identified mean among the three process steps. It is not possible to identify a shift or a trend in the Shewhart chart. The upper control limit was exceeded once, which was at the month 7. The MR-chart show that he average moving range of the cooler is 1% and the upper control limit is exceeded once. The cooling process could be perceived to be in statistical control as none of the two examined charts imply the contrary.

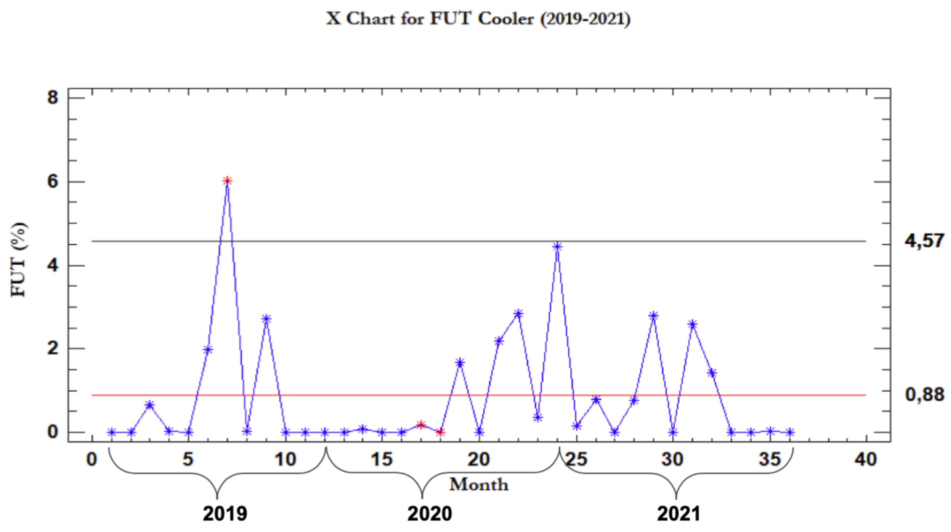

Figure 42: *FUT for the Cooler*

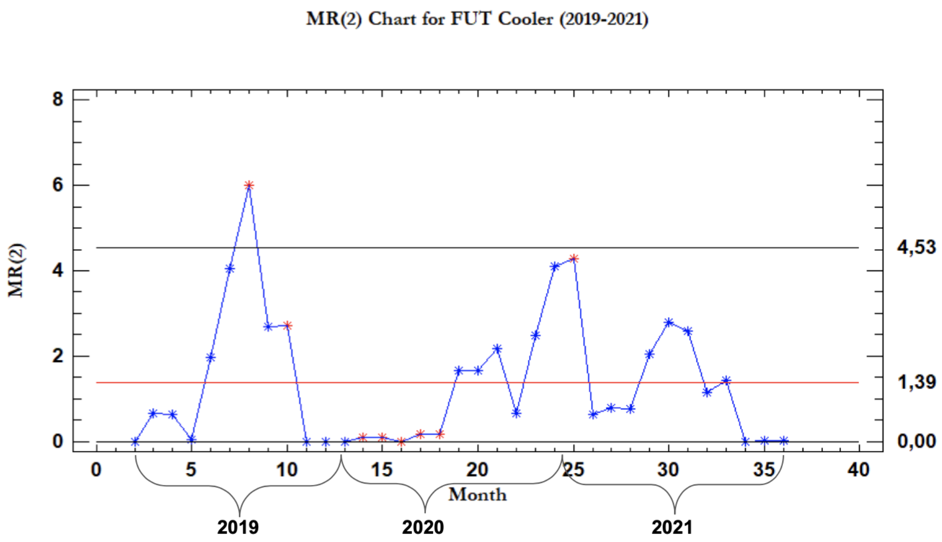

Figure 43: *MR-chart FUT for the Cooler*

8.8 Appendix H - Test for normality

Tests for Normality for Cold-Warm

Test	*Statistic*	*P-Value*
Shapiro-Wilk W	0,980831	0,986737

The StatAdvisor

This pane shows the results of several tests run to determine whether Cold-Warm can be adequately modeled by a normal distribution. The Shapiro-Wilk test is based upon comparing the quantiles of the fitted normal distribution to the quantiles of the data.

Since the smallest P-value amongst the tests performed is greater than or equal to 0,05, we can not reject the idea that Cold-Warm comes from a normal distribution with 95% confidence.

Figure 44: *Test for normality for the final test variable*

8.9 Appendix I - The first contradicting stop

The investigated production stop appeared in observation 1192. In the Hotelling T^2 chart, there is no prominent trend apart from a slightly increasing positive trend. The individuals charts, presented in Figure 46 and Figure 47 indicated high temperatures for the refractory material prior to stop. The temperature difference increased during the selected time frame. The temperature difference was still not big enough to be perceived as a deviation. However, it existed hours before the stop when the temperature difference was negative.

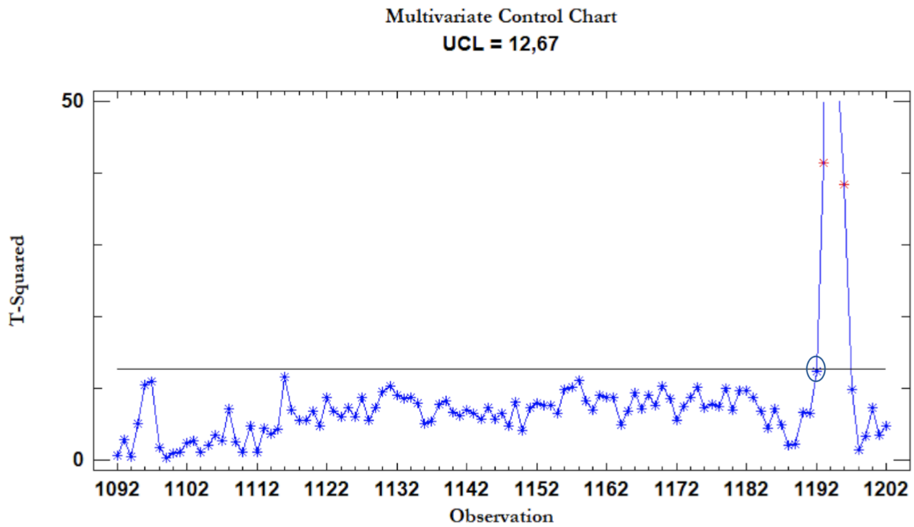

Figure 45: *Hotteling T^2 chart for the stop during observation 1192 in November 2021*

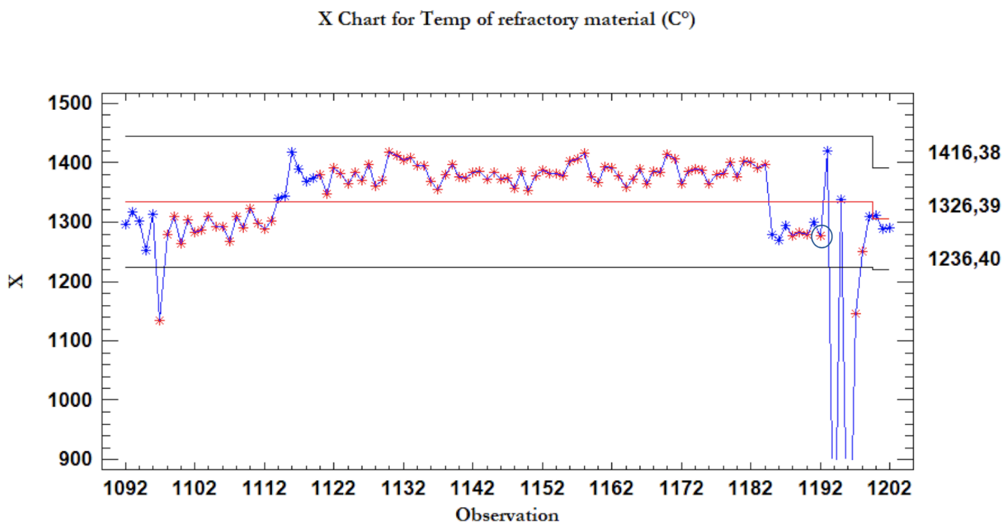

Figure 46: *Individual chart for the temperature of the refractory material during observation 1192 in November 2021*

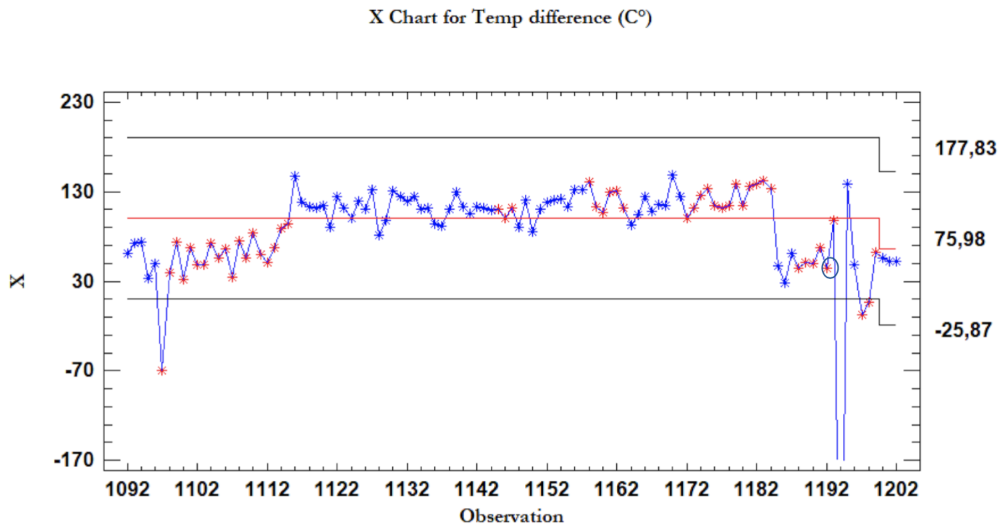

Figure 47: *Individual chart for the temperature difference during observation 1192 in November 2021*

8.10 Appendix J - The second contradicting stop

The production stop, which occurred at the end of 2021, is presented in Figure 48. The Hotelling T^2 chart highlight steady-state production with no visible trend. Its respective individual charts, presented in Figure 49 and Figure 50 also highlights steady-state production. Because the individual charts did not show any deviations or strange behavior, one could argue that these two variables were not the cause of the production stop. Stops, where this phenomenon occurred were why it is impossible to conclude that the refractory material's temperature and temperature difference are the only factors influencing equipment health. The stop during observation 1569 rather suggests that other variables influence equipment health.

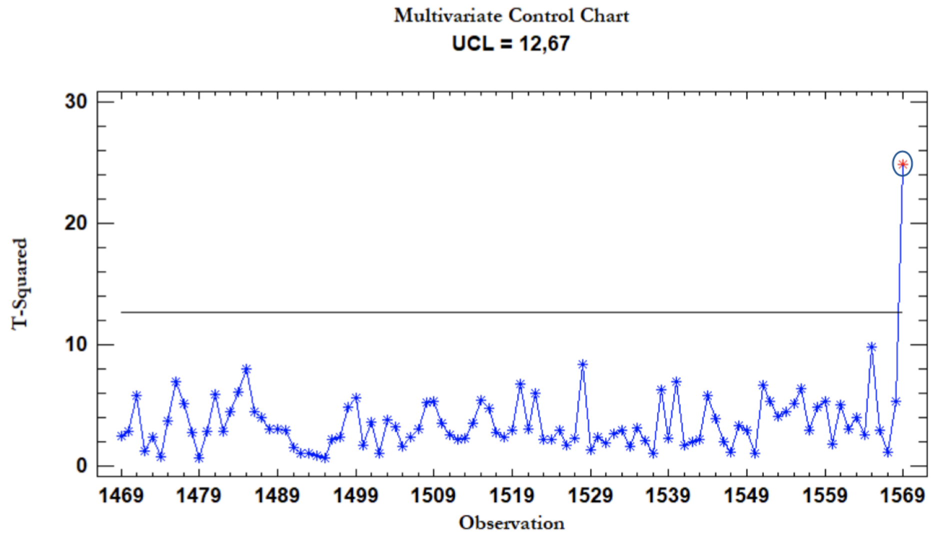

Figure 48: *Hotteling T^2 chart for the stop during observation 1569 in December 2021*

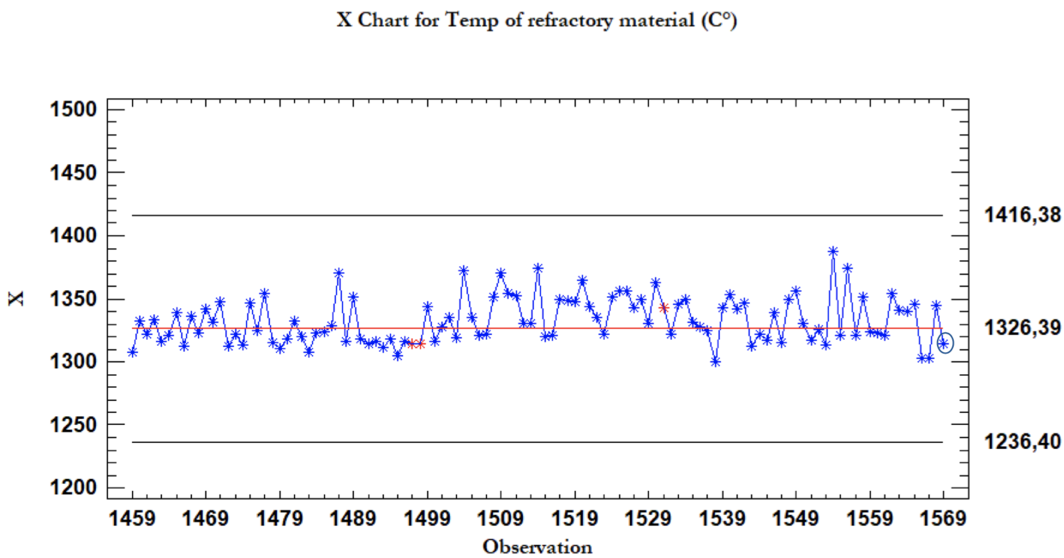

Figure 49: *Individual chart for the temperature of the refractory material during observation 1569 in December 2021*

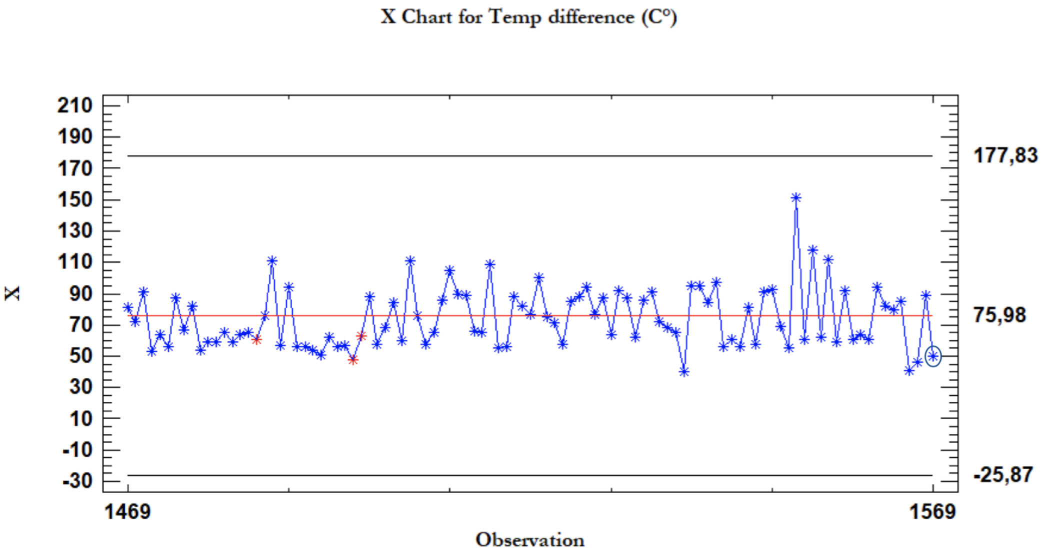

Figure 50: *Individual chart for the temperature difference during observation 1569 in December 2021*

8.11 Appendix K - Test for autocorrelation among production parameters and the T^2-statistic

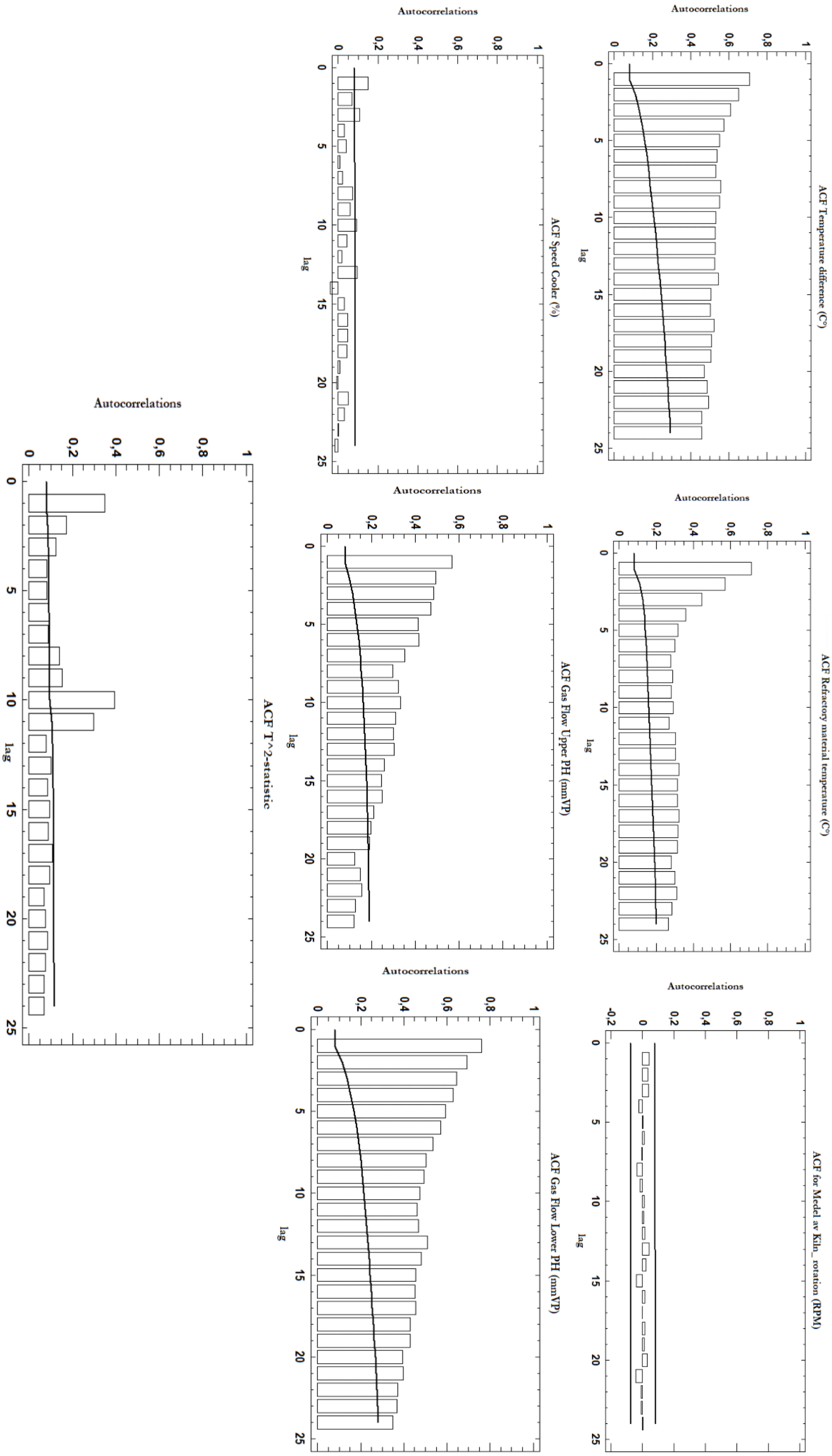

Figure 51: *Autocorrelation function for the investigated production parameters and the T^2-statistic from the training data set*

8.12 Appendix L - Test for normality for the influencing parameters and the T^2-statistic

Tests for Normality for TSQUARED

Test	Statistic	P-Value
Chi-Square	1668,13	0,0
Shapiro-Wilk W	0,307649	0,0
Skewness Z-score	19,9962	0,0
Kurtosis Z-score	16,4736	0,0

The StatAdvisor
This pane shows the results of several tests run to determine whether TSQUARED can be adequately modeled by a normal distribution. The chi-square test divides the range of TSQUARED into 50 equally probable classes and compares the number of observations in each class to the number expected. The Shapiro-Wilk test is based upon comparing the quantiles of the fitted normal distribution to the quantiles of the data. The standardized skewness test looks for lack of symmetry in the data. The standardized kurtosis test looks for distributional shape which is either flatter or more peaked than the normal distribution.

Since the smallest P-value amongst the tests performed is less than 0,05, we can reject the idea that TSQUARED comes from a normal distribution with 95% confidence.

Tests for Normality for Temp refractory material (C°)

Test	Statistic	P-Value
Chi-Square	101,356	0,00000731222
Shapiro-Wilk W	0,845754	0,0
Skewness Z-score	11,7855	0,0
Kurtosis Z-score	13,554	0,0

The StatAdvisor
This pane shows the results of several tests run to determine whether Temp refractory material (C°) can be adequately modeled by a normal distribution. The chi-square test divides the range of Temp refractory material (C°) into 50 equally probable classes and compares the number of observations in each class to the number expected. The Shapiro-Wilk test is based upon comparing the quantiles of the fitted normal distribution to the quantiles of the data. The standardized skewness test looks for lack of symmetry in the data. The standardized kurtosis test looks for distributional shape which is either flatter or more peaked than the normal distribution.

Since the smallest P-value amongst the tests performed is less than 0,05, we can reject the idea that Temp refractory material (C°) comes from a normal distribution with 95% confidence.

Tests for Normality for Temperature difference (C°)

Test	Statistic	P-Value
Chi-Square	82,0109	0,00118481
Shapiro-Wilk W	0,991719	0,0012016
Skewness Z-score	1,45607	0,145372
Kurtosis Z-score	0,96037	0,336867

The StatAdvisor
This pane shows the results of several tests run to determine whether Temperature difference (C°) can be adequately modeled by a normal distribution. The chi-square test divides the range of Temperature difference (C°) into 50 equally probable classes and compares the number of observations in each class to the number expected. The Shapiro-Wilk test is based upon comparing the quantiles of the fitted normal distribution to the quantiles of the data. The standardized skewness test looks for lack of symmetry in the data. The standardized kurtosis test looks for distributional shape which is either flatter or more peaked than the normal distribution.

Since the smallest P-value amongst the tests performed is less than 0,05, we can reject the idea that Temperature difference (C°) comes from a normal distribution with 95% confidence.

Figure 52: *Test for normality for the influencing parameters and the and the T^2-statistic from the training data set*