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A Survey on Control Configuration Selection and New Challenges in Relation to Wireless Sensor and Actuator Networks

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Abstract: This survey on Control Configuration Selection (CCS) includes methods based on relative gains, gramian-based interaction measures, methods based on optimization schemes, plantwide control, and methods for the reconfiguration of control systems. The CCS problem is discussed, and a set of desirable properties of a CCS method are defined. Open questions and research tracks are discussed, with the focus on new challenges in relation to the emerging area of Wireless Sensors and Actuator Networks.

1. INTRODUCTION

The design of a control system for a multivariable process usually involves the following tasks (Manfred Morari, 1980; van de Wal and de Jager, 2001):

1. Formulation of control goals by relating process variables to production targets.
2. Modeling of the process.
3. Control Structure Design.
4. Synthesis of the controller parameters using an adequate control strategy (i.e. PID, MPC, LQG, ...).
5. Evaluation of the closed-loop system by simulations or experiments.
6. Implementation of the controller in the real plant.

Iterations in this procedure are often required, since a simulation or plant experiment might indicate unsatisfactory performance and the controller has to be redesigned.

In general, the Control Structure Design (CSD) is divided in two parts: a) the Input-Output (IO) selection and the Control Configuration Selection (CCS)[1]. The IO selection has been defined by van de Wal and de Jager (2001) as selecting suitable variables to be manipulated by the controller (control actions) and suitable variables to be supplied to the controller (measurements). The CCS consists of establishing the measurements, which are used in the calculation of each control action. These two steps are usually done considering different criteria on the controllability and observability of the resulting structure as well as its potential to achieve the previously formulated control goals.

Since the CCS task has a combinatorial nature, its difficulty is mostly determined by the topological complexity. Topological complexity increases with the number of process variables, and with the intricacy of the pattern of interconnections between them. An example is the usual reuse of discarded material in long production processes, which is often fed to other sub-processes, or even fed back to the original process directly or after a recovering step. Topological complexity can be quantified using different structural or functional criteria. Structural complexity refers to the amount of variables and interconnections between them, and can be quantified using graph theory concepts (Jiang et al., 2007). Functional complexity refers to the pattern of correlations between variables, and its quantification comprises both the concept of segregation ins subsets which behave more or less independently, and the concept of integration of the segregated units in a coherent behavior Sporns and Tononi (2001). In topologically complex systems, local actions or decisions can derive in unexpected consequences and failures in other parts of the interconnected structure. Therefore, even if it is possible to introduce hierarchies for decomposing, analyzing and structurally designing a complex control system, a holistic perspective has to be contemplated.

For the actual framework of process control, there exists a vast host of methods for CCS. However, the large gap between research, education and industry application (Bettayeb et al., 1995) implies that, control engineers in current process industry still make use of a strongly empirical approach to CCS, basing their decisions in know-how or common sense principles and experience, which results in ad-hoc solutions (van de Wal and de Jager, 1995).

This situation is gradually changing, with an increasing number of courses with content in CCS, and the apparition of dedicated course books. To name a few examples, a chapter on CCS has been dedicated in the course book by Skogestad and Postlethwaite (2005), and two full focused books have recently been published by Khaki-Sedig and

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[1] Additionally, the term Control Structure Selection (CSS) is used by many authors. It is sometimes used as synonym of CSD and sometimes used to refer to the CCS. Another term used to refer to the CCS task is *input-output pairing*, which often refers to the special case in which sensor-actuator pairs are selected for being later connected by Single-Input-Single-Output controllers (full decentralized structure).

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Moaveni (2009) and Wang et al. (2008). In addition, the software tool ProMoVis has been recently introduced by Birk et al. (2014), with the goals of being a platform for the technology transfer of state of the art research results in CSD to industry application, as well as a research platform for the comparison of different CSD methods.

The volume of research articles in CCS has significantly increased in the last decade (see Fig. 1), especially with respect to the modern gramian-based Interaction Measures (IMs) introduced by Conley and Salgado (2000) and with respect to the use of (convex) optimization techniques. This background indicates that CSD is an emerging field, with a large progress in the last decade that motivates the survey conducted in this article, since the latest survey on the field dates from 2001 by van de Wal and de Jager (2001).

The survey work in this paper additionally targets the discussion of research trends within CCS. Special focus has been placed on the new opportunities and challenges opened by the use of Wireless Sensor and Actuator Networks (WSAN). In order to advantage from the opportunities given by WSAN, a rethink of existing automation concepts is required. Opportunities arise from the increased flexibility, which allows for example the deployment of novel inline miniaturized wireless sensors that move with the material flow and are being able to transmit from the process internal dynamics. To make an opportunistic use of these local measurements, the existing control scheme should be able to be reconfigured in accordance to their availability. Additionally, some of the existing challenges in CCS obtain an special relevance on the WSAN scenario. One example is the challenges on CCS for time-delayed systems, which is a direct intrinsic property of WSANs and thus novel theoretical concepts and tools should be also developed and surveyed towards this direction.

The structure of the paper is as follows. The traditional CCS problem is discussed in Section 2, and the desirable properties of a CCS tool are described in Section 3. The surveyed methods are classified in the following sections: i) the IMs based on Relative Gains are given in Section 4, ii) the gramian-based IMs are given in Section 5, iii) the CCS methods based on optimization schemes are given in Section 6, iv) the methods for plantwide control are given in Section 7, v) the methods for controller reconfiguration are given in Section 8. In Section 9, new opportunities and challenges on CCS given by WSAN are discussed. General research topics are discussed in Section 10. Finally the conclusions are given in Section 11.

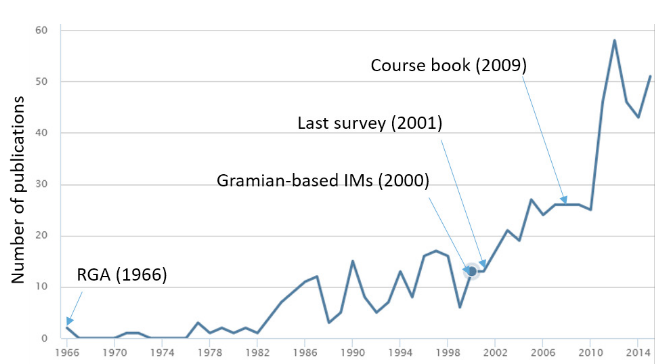

Fig. 1. Number of publications in CCS listed by Scopus using keywords related to Control Configuration Selection.

2. PROBLEM DISCUSSION

Interaction analysis plays an important role in the design of control configurations for multivariable processes. The design of a control configuration which is neglecting important process interconnections is likely to lead to large loop interaction and significant performance degradation as direct consequence. Relevant studies on the nature of interactions have been performed by Zhu and Jutan (1996) and by Grosdidier and Morari (1986).

CCS is usually done by selecting a reduced model which is formed by the elementary models of the most important input-output channels. If the elementary model for the input-output channel connecting the plant input u_j (actuator) to the plant output y_i (measurement) forms part of the selected reduced model, then the control configuration should use the measurement of y_i to compute the control action u_j.

In a topological complex system, simple configurations are preferred for being easier to design, implement and maintain, as well as more robust to plant failures (Šiljak, 1996). The complexity of a configuration can be quantified by counting the number of interconnections between measurements and actuators which exist in the controller. Or in other words, by counting the number of times that any measurement is used in the calculation of the control actions. For the configurations represented in Figures 2, 3, 4, this is equivalent to counting the number of non-zero (shaded) elements in the controller matrix.

The simplest closed-loop configuration which can be derived for a process is the fully decentralized configuration. In this configuration, inputs and outputs are grouped in pairs, being the control action on each input calculated considering its corresponding output pair (see Fig. 2). For the design of decentralized control structures, the RGA was introduced in Bristol (1966), and is currently the most widely used method for CCS.

When scalar (SISO) controllers are used to track the references on a multivariable control system, then a change on a single reference will affect the system in two ways: (1) the controller attempts to bring the referenced output to the desired value (2) the controller will influence other

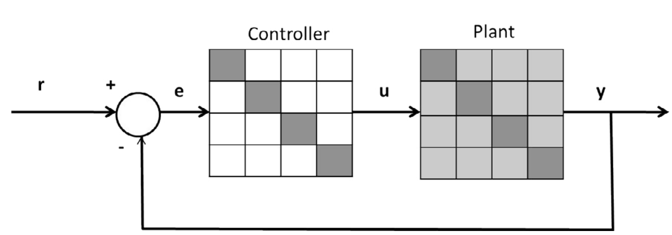

Fig. 2. Fully decentralized control configuration. The shaded elements in the controller matrix represent SISO controllers. The considered input-output channels in the reduced model of the plant are represented in dark gray.

loops of the control system forcing them to respond as well, which may further influence the original loop Zhu and Jutan (1996). The so-called two-way interaction is present when a reference change creates a loop perturbation which influences the original loop. Significant two-way interactions often require the use of multivariable (block) controllers. The so-called one-way interaction is present when a reference change creates a perturbation on other loops which does not return to the original loop. Significant one-way interactions are often compensated with feedforwards of the loop perturbation.

Decentralized configurations become inadvisable as the degree of segregation of the process decreases. This led to the introduction of new CCS methods like the BRGA (Manousiouthakis et al., 1986), which can be used to design control configurations in which multivariable controllers are designed independently for segregated units composed by a reduced number of inputs and outputs (see Fig. 3).

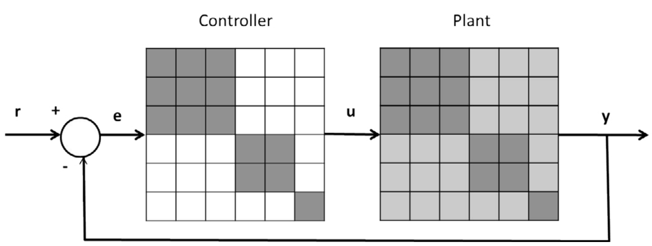

Fig. 3. Block diagonal control structure. In this case, the process is assumed to be composed by three segregated subsystems which are independently controlled by each of the blocks in the controller.

Therefore, the use of relative gains results in control configurations which decompose the considered process in segregated subsystems for which controllers are designed independently. Such a configuration presents potential problems when the significance is large for any of the input-output channels which are not belonging to any of the segregated units. This implies interactions between the segregated control units, with the consequent performance loss depending on the level of interaction. The IMs using relative gains are surveyed in Section 4.

As an alternative to the use of relative gains, the more modern gramian-based IMs were introduced. With these tools, the resulting reduced model is not restricted to be composed of segregated units (see Fig. 4). The structure of the resulting controller matrix is the transpose of the structure of the resulting reduced model. The gramian-based IMs are surveyed in Section 5.

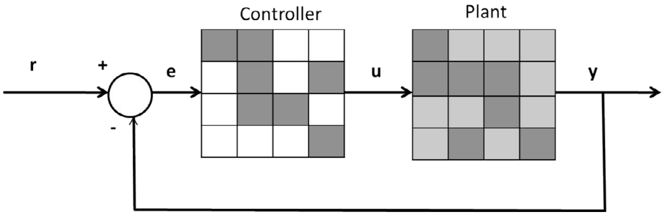

Fig. 4. Sparse control configuration.

The combinatorial nature of the CCS problem makes the CCS methods hard to apply to large scale systems, and in these cases the CCS is usually preceded by a step where manipulated and controlled variables are grouped into subsystems where the number of variables is reduced to no more than approximately a couple of dozens. The resulting subsystems are composed by variables with strong mutual interconnections. The control configurations are designed within the subsystem boundaries, and the resulting controllers for the subsystems have to be appropriately combined (Manfred Morari, 1980). Methods for such a decomposition have been proposed by Sezer and Šiljak (1986); Zečević and Šiljak (2005); Pothen and Fan (1990).

In addition to this decomposition, the design of control structures for complex systems usually involves the use of hierarchies to represent different time scales of the process. As interface between hierarchies, the output of a controller often becomes the setpoint for another controller at a faster scale, deriving in a cascade structure. A possibility is to decompose the system in different hierarchies to which IMs are applied (Leonard, 1998).

Recently, many efforts have been placed in the development of methods which can design control configurations based on an optimization scheme. The resulting cost function expresses a trade-off between performance and complexity of the controller. The main difference of these methods with the IMs is that their interpretation is more obscure, and the resulting control configuration is presented as the result of an optimization criterion, being harder for the control engineer to integrate acquired know-how in the design of the control configuration. The methods based on optimization techniques are surveyed in Section 6.

An alternative is the concept of plant wide control (PWC) which was initiated in 1964 by the work of (Buckley, 1964), and has received much more attention in recent years. These methods target the complete design of control structures including the IO selection and the CCS, and aim to be applied to large scale systems. The methods for PWC are surveyed in Section 7.

Another scenario to consider is the reconfiguration of a control system which is functioning with unsatisfactory performance due to large loop interaction. This loop interaction may be the consequence of a deficient configuration. In these cases it is desired to commit to small changes in the controller configuration which derive in a significant performance. The methods for such reconfiguration are surveyed in Section 8.

3. DESIRABLE PROPERTIES OF A CCS TOOL

This section discussed a set of desirable properties of a CCS method [2] which have been synthesized by analyzing the strengths and weaknesses of the existing CCS methods, as well as by analyzing the studies by van de Wal and de Jager (2001).

P1. **Well-founded**. The method must have a strong and sound theoretical base, considering concepts like control-

[2] Some of these properties may enter in compromise with each other. For example, methods which are applicable to a large class of systems are of interest but at the same time it is of interest to have methods which can be applied to only DC-gains for the cases when very limited plant information is available.

lability and observability, stability or closed-loop performance.

P2. **Generally applicable**. The method has to be applicable to a large class of systems. Usual limitations of existing methods are:
- *The applicability to only systems with a reduced number of process variables.* An increase in topological complexity hinders the CCS problem due to: i) the combinatorial nature of the problem, ii) the effect of process/model uncertainty, iii) the effect of appropriate scaling on some CCS methods.
- *The need of linear process models.* When most of the existing CCS tools are applied to non-linear processes, a prior calculation of a linearized model around an operating point is often required.
- *The application to time-delayed systems might derive in inappropriate results.* This is due to the fact that some methods are either insensitive to time-delays or fail to address time-delays in an appropriate way.

P3. **Computational efficiency**. The computation is to be attained in a reasonable time lapse. This is not fulfilled by some of the existing CCS tools, since they are based on evaluating a performance criteria for all of the possible control configurations. This is not an efficient approach, since the number of possible configurations increases enormously with the number of process variables as illustrated in Table 1.

Size of the system	Number of configurations
2×2	9
3×3	343
4×4	50625
5×5	$\sim 29 \cdot 10^6$

Table 1. Number of candidate control configurations depending on the size of the system. Candidate control configurations are restricted to consider at least one element in each row of the reduced model.

P4. **Quantitative**. Qualitative methods for CCS analyze the interconnected system using concepts like structural controllability and observability. These methods can be very useful when limited model information is available, since they only require the knowledge of which interconnections between the process variables exist. However, assuming that a complete dynamic model is available, the applied CCS method has to be quantitative in order to quantify the strength of the process interconnections and not merely their existence.

P5. **Informative**. An study of the current design environment in process industry was done in Downs (2012). The analysis concluded that the design environment drives the CSD question more towards the use of heuristics than to rigorous approaches. The market requirements imply that control decisions have to be taken in a short time horizon, and the control strategies will frequently have to be adapted. For this reason, there might not be time to fully develop optimal process conditions, being preferred to use strategies which are straightforward and easy to understand. The support of a running control system can depend upon the simplicity of the strategy and its understandability. Control configurations in industrial processes are traditionally designed based on extensive process knowledge. It is of interest to combine previously acquired know-how with the indications given by the CCS tools. These indications have to therefore be provided in an intuitive way, e.g. by visualizing the strength of the process interconnections using graphs for an increased comprehension (Castaño and Birk, 2012).

P6. **Independent from pre-defined structures**. Some tools assume a pre-defined structure of the configuration, like the RGA which assumes that decentralized control is to be used. The assumptions of the control structure to be used have to be as scarce as possible.

P7. **Incremental**. This means that, increment the complexity of the controller does not take out existing interconnections in the control system. When a configuration candidate is evaluated, the designer often considers slight increases/decreases in its complexity. Often a configuration is tested in experiments and/or simulations and its complexity is increased if the achieved performance is not satisfactory. For some CCS tools, increasing the achievable performance results in a configuration which doesn't necessary include the input-output interconnections of the original one. CCS tools with this counter-intuitive property hinder the design of configurations and the maintenance of the control system.

P8. **Robust**. Traditional methods for CCS are evaluated on nominal process models. This might result in inappropriate results as the process behavior deviates from the nominal conditions. The CCS tools have to integrate tools to handle model uncertainty and allow the design of robust control structures.

P9. **Data-driven**. The usual need of parametric process models for the computation of CCS tools is an important limitation in their practical use. Since the complexity of the modeling task increases largely with the number of inputs and outputs, it is of desire to be able to calculate the tools for CCS from process data, thereby removing the need of parametric process models.

P10. **Applicable on limited plant knowledge**. Due to the cost of generating process models, it is of interest to create CCS methods which can give indications based on limited plant knowledge like DC-gains or bandwidths. This is a major reason for the popularity of the RGA, since DC-gains can be estimated from simple process experiments.

4. INTERACTION MEASURES BASED ON RELATIVE GAINS

The work on IMs was initiated by Mitchell and Webb (1960), where the *interaction quotient* was introduced for the design of decentralized control configurations for 2×2 systems, and which was later applied to distillation columns by Rijnsdorp (1965).

A large amount of literature on IMs has been published since Bristol introduced the Relative Gain Array (RGA) in 1966 (Bristol, 1966) as an indicator based on steady-state gains for choosing input-output pairings in decentralized control structures. Some limitations of the RGA have been addressed by introducing variants of the RGA, like the Block RGA for block diagonal structures

(Manousiouthakis et al., 1986). Other limitations have been resolved by introducing extensions of the RGA concept to e.g. analyze systems with pure integrators.

The RGA can provide feasible candidates for decentralized control structures, and its indications are usually combined with the later introduced Niederlinski Index (Niederlinski, 1971), which provides a necessary condition for the stabilizability of the closed-loop system under integral control and can be used to discard unstable configurations (Grosdidier et al., 1985).

Other tools for the design of decentralized control structures are: i) the μ Interaction Measure (Grosdidier and Morari, 1986) which can be used to predict the stability of diagonal or block diagonal structures and reveal the performance loss associated to the structure, ii) the Directed Nyquist Array (DNA) (Rosenbrock, 1969) and iii) the Gershgorin bands (Chen and Seborg, 2001) which are graphical approaches to analyze the dominance of the diagonal input-output channels and provide a generalized stability criteria for multivariable systems.

4.1 Relative Gain Array (RGA)

The RGA of a continuous process $G(s)$ with equal number of inputs and outputs is defined as:

$$RGA(G) = G(0) \otimes G(0)^{-T}$$

where $G(0)^{-T}$ is the transpose of the inverse of $G(0)$, and $\otimes$ denotes element by element multiplication.

The main properties of the RGA are: i) it is normalized so the sum of all the elements of each row or column add up to one, ii) it is scaling invariant. iii) RGA of a triangular or diagonal matrix is the identity.

For interpreting the RGA we will use the definition of RGA used by Bristol in Bristol (1966). For each input-output pairing u_j, y_i, the DC gains in a multivariable system have to be evaluated in two extreme cases:
- Case 1. All the other loops opened, with all the other inputs $u_k, \forall k \neq j$ kept constant. This is equivalent to obtain the dc gain of the plant $G(s)$ from the G_{ij} element.

$$\left(\frac{\partial y_i}{\partial u_j}\right)_{u_k, \forall k \neq j} = g_{ij}$$

-Case 2 All the other loops closed, with all the other outputs $y_k, \forall k \neq i$ kept constant under perfect integral control. A change in the input u_j will yield to a changed in y_i, but also to a change in all the other outputs which are controlled under perfect control; the other inputs $u_k, \forall k \neq j$ will also change in order to compensate the variation of the outputs $y_k, \forall k \neq i$, and this will lead to a new change in the observed output y_i due to interaction. Then, we evaluate:

$$\left(\frac{\partial y_i}{\partial u_j}\right)_{y_k, \forall k \neq i} = \widehat{g}_{ij}$$

The element λ_{ij} of the RGA is then defined as

$$\lambda_{ij} = \frac{g_{ij}}{\widehat{g}_{ij}} = \frac{((\partial y_i)/(\partial u_j))_{u_k, \forall k \neq j}}{((\partial y_i)/(\partial u_j))_{y_k, \forall k \neq i}}$$

Based on the RGA definition, the following pairing rules have been formulated:
- Pairings with values of λ close to 1 are preferred. A value of 1 in λ_{ij} means that the gain g_{ij} is not affected by closing the other loops, so there is no two-way interaction effects in the pairing $u_j - y_i$.
- A value of λ_{ij} close to 0, means that the input u_j should not be used to control the output y_i. These values are related to a large relative increase in the absolute value of the gain g_{ij} when the rest of the loops are closed.
- Pairings with negative values of the RGA should be avoided. A negative value in λ_{ij} means that the gain of the subsystem formed by the j^{th} input and the i^{th} output changes its sign when all the other loops are closed, leading to instability and/or integrity issues. As given by a theorem introduced by Grosdidier et al. (1985), a pairing with an element $\lambda_{ij} < 0$ indicates that at least of the following holds: a) the closed loop system is unstable, b) the loop formed by $u_j - y_i$ is unstable when all the other loops are opened, c) the closed loop system is unstable when the loop formed by $u_j - y_i$ is brought out of operation.
- Pairings with large numbers in the RGA should be avoided. As stated by Chen et al. (1994), large RGA numbers are related to ill-conditioned plants. Additionally, large RGA values would indicate proximity to singularity of the inverse of the plant, which indicates problems with the use of inverse-based controllers.

Some relevant observations on the RGA are:
-The RGA is based on DC-gains and therefore is adequate for the cases where limited plant information is available. If dynamic models are available, the RGA is not able to capture process dynamics in the decision making. To deal with this limitation, several variants of the RGA have been introduced, including the methods DRGA, ERGA and RNGA described below.
- The RGA is not directly applicable to systems with pure integrators, since these systems have an infinite DC-gain. It was suggested in Woolverton (1980) to use the derivatives of the integrating state variables as the controlled variables, so that the steady-state RGA could be defined. Other alternatives for integrating systems have been proposed by McAvoy (1998); McAvoy and Miller (1999); Arkun and Downs (1990). The RGA for systems with differentiators was defined by Hu et al. (2010).
- The RGA is captures the so called two-way interactions, and is unable to capture one-way interactions, e.g. in triangular systems.
- There are time-domain performance limitations derive from the RGA as discussed by Goodwin et al. (2005).
- There is a relationship between non-minimum phase transmission zeros and the sign change of the RGA elements calculated at steady state and infinite frequency. This relationship has been proven by Skogestad and Hovd (1990).
- The RGA is invariant to the scaling of inputs and outputs. This favors its simplicity in practical applications.
- The application of the RGA for unstable plants have been discussed by Hovd and Skogestad (1994).
- The RGA for nonsquare plants (NSRGA) can be calculated with the use of the pseudo inverse. The NSRGA can be useful to square down the plant when there is a different number of sensors and actuators. The properties and interpretation of the NSRGA are slightly different than those of the RGA, since perfect control at DC is not possible when the plant has more sensors than actuators

and the NSRGA is defined in terms of the minimization of steady state errors in a least square sense. For more information on the NSRGA, the reader can refer to the publications by Reeves and Arkun (1989) and Chang and Yu (1990).

4.2 Dynamic Relative Gain Array (DRGA)

Several authors created indicators under the name Dynamic RGA in order to obtain indications in the frequency domain based on relative gains. We discuss the DRGA introduced by Witcher and McAvoy (1977), which is straightforward approach of evaluating the RGA in the frequency domain, and can be used to design decentralized control at any desired frequency . The DRGA of a continuous process described by a transfer function $G(s)$ is:

$$DRGA(\omega) = G(j\omega) \otimes G(j\omega)^{-T}$$

The DRGA is a complex number and has a more obscure interpretation than that of the RGA: it is usually preferred to use its magnitude as indicator due to the gain interpretation, however only the sums of the rows or columns of the resulting complex array (or its real part) add up to 1. Moreover, by evaluating the magnitude alone, the sign of the DRGA is lost as an indicator, which is often used to rule out certain input-output pairings. Additionally, the calculation of the DRGA assumes perfect control at all frequencies, but this is only possible at low frequencies. More details on the use of the DRGA can be found in the publication by Skogestad and Hovd (1990).

4.3 Effective Relative Gain Array (ERGA)

The ERGA was introduced by Xiong et al. (2005). In its calculation the DC gain matrix is substituted by a matrix with the integral of the magnitudes of the SISO transfer functions with respect to the frequency.

The ERGA is very convenient for consider process dynamics in practical applications where limited plant information is available. The integral of the magnitude can be roughly approximated by the product of the gain and the bandwidth, which can both be estimated from e.g. a simple step response.

4.4 Relative Normalized Gain Array (RNGA)

First introduced by He et al. (2009). It aims to improve the analysis performed by the RGA by also weighting information in frequency domain. The RNGA of a MIMO system G(s) is computed as:

$$RNGA = K_N \otimes K_N^{-T}$$

where K_N is:

$$[K_N]_{ij} = \frac{G_{ij}(0)}{\tau_{ar,ij}}$$

where $\tau_{ar,ij}$ is the average residence time of the input-output channel (i,j), which is a measure of the response speed of the controlled variable y_i to manipulated variable u_j (see Astrom and Hagglund (1995)). The average residence time is calculated as:

$$\tau_{ar,ij} = \int_0^{\infty} (\bar{y}_{i,j}(\infty) - \bar{y}_{i,j}(t))dt$$

where $\bar{y}_{i,j}(t)$ is the step response of the normalized subsystem $\bar{y}_i = \bar{G}_{ij}(s) \cdot u_j$. The normalized subsystem satisfies $\bar{G}_{ij}(0) = 1$.

This information considers the accumulative error to step response of each input-output channels. In the RNGA, the gains are therefore scaled by the average residence time of its input-output channel, which is a measure of the response speed of the controlled variable y_i to manipulated variable u_j (see Astrom and Hagglund (1995)).

4.5 Other relevant RGA variants

- The Relative Interaction Array (RIA) was introduced by Zhu (1996). It is directly related with the RGA as $RIA_{ij} = RGA_{ij}^{-1} - 1$. The RIA is a more linear indicator than the RGA and is more robust to process uncertainty.
- The Block Relative Gain Array (BRGA) was introduced by Manousiouthakis et al. (1986) for the design of block configurations.
- The Relative Disturbance Gain Array (RDGA) introduced by Chang and Yu (1992) is used for the design of control configurations for disturbance rejection.
- The Partial Relative Gain (PRG) has been introduced by Häggblom (1997a,b) for systems under partial control, and provide necessary conditions for integrity.

4.6 Niederlinski Index (NI), stabilizability and integrity

Assuming diagonal pairing, and denoting $\hat{G}$ as the matrix formed by the diagonal entries of G with zeros in the off-diagonal. NI was defined by Niederlinski (1971) as:

$$NI = det(G(0))/det(\hat{G}(0))$$

From a theorem introduced by Grosdidier et al. (1985), a necessary condition for the stability of the diagonal decentralized configuration is that $NI > 0$. This means that NI can be used to screen unstable configurations.

Within this framework, integrity is an important property of decentralized control systems, which relates to the ability of the control system to remain stable when loops are brought in and out of control. A stronger requirement than integrity is the Decentralized Integral Controllability (DIC) introduced by Skogestad and Morari (1992). To satisfy DIC, a closed loop system under integral action must remain stable for arbitrary detuning the loop gains. Necessary conditions for integrity and DIC can be derived from NI and RGA, and surveys of these conditions can be found in the publications by Skogestad and Postlethwaite (2005) and Campo and Morari (1994). Additionally, conditions for integrity can be derived from the PRG (Häggblom, 1997b). A recent contribution by Eslami and Nobakhti (2016) is the proof that the necessary conditions for integrity based on DC-gains also hold for time-delayed systems.

5. GRAMIAN-BASED INTERACTION MEASURES

Relative gain arrays provide selection methodologies which are limited to decentralized control or block decentralized control. Depending on the level of interaction in the multivariable system, a decentralized controller or block decentralized one may not be sufficient to achieve set control targets. The obvious question is then how a so called sparse controller can be selected. A sparse controller will make use of system interconnections which are not necessarily belong to a block decentralized structure and is less complex than a fully centralized controller.

In this context of selecting sparse controllers, it is of interest to analyze the controllability and observability properties of a multivariable system with the use of the gramians.

Khaki-Sedigh and A.Shahmansourian (1996) presented an early contribution in the field of gramian-based IMs with an input-output pairing matrix based on the cross-gramian matrix introduced by Fernando and Nicholson (1983). This pairing matrix was later classified as an IM and named Dynamical Input-Output Pairing Matrix (DIOPM) by Moaveni and Khaki-Sedigh (2008). Despite the early contribution by of Khaki-Sedigh and A.Shahmansourian (1996), the term *gramian-based IMs* became popular after the publication from Conley and Salgado (2000), where the Participation Matrix (PM) was first introduced. The Hankel Interaction Index Array (HIIA) was later introduced by Wittenmark and Salgado (2002). The HIIA turned to be equal to the DIOPM, but reinvented using the largest Hankel Singular Value instead of the largest singular value of the squared cross-gramian matrix, being both values equal. Later Birk and Medvedev (2003) introduced the gramian-based IM denoted as Σ_2.

5.1 Introduction to Gramians

Assume a stable continuous-time MIMO system with n inputs and m outputs, represented in state space form by

$$\dot{x}(t) = Ax(t) + Bu(t)$$
$$y(t) = Cx(t)$$

with $A \in \Re^{pxp}, B \in \Re^{pxn}, C \in \Re^{mxp}$, where p is the number of states. The controllability gramian (P) and observability gramian (Q) are obtained by solving the following continuous-time Lyapunov equations (Skogestad and Postlethwaite, 2005):

$$AP + PA^T + BB^T = 0$$
$$A^T Q + QA + C^T C = 0$$

The controllability gramian quantifies the ability to control the system states from the system inputs, and the observability gramian quantifies the ability to observe the system states from the system outputs. This is reflected by the following properties (Antoulas, 2002):

- The minimal energy required to transfer the states of the system from 0 to x_f is $x_f^* P^{-1} x_f$.
- The maximal energy of the output obtained by observing a system with initial state x_0 is $x_0^* Q x_0$.
- The states which are difficult to reach are in the span of the eigenvectors of P which correspond to small eigenvalues, and the states which are difficult to observe are in the span of the eigenvectors of Q which correspond to small eigenvalues.

Accordingly, the eigenvalues of P quantify the ability to control the system states from the system inputs, and the eigenvalues of Q quantify the ability to observe a system state from the system outputs.

Consequently, gramians can be used to quantify the significance of the input-output channels and select viable control structures which present an acceptable level of loop interaction. The use of different gramian-based operators to quantify this significance gives raise to the different gramian-based IMs.

5.2 Gramian-based Interaction Measures as Index Arrays

The gramian-based IMs use different gramian-based operators to quantify the significance of the dynamics of the input-output channels in a multivariable process. They are defined as an Index Array (IA) including the significance of each input-output channel divided by the total sum of the significance of all the input-output channels.

$$IA_{ij} = \frac{[G_{ij}(s)]_p}{\sum_{k,l=1}^{m,n} [G_{kl}(s)]_p}$$

where $[\cdot]_p$ denotes the operator used by the gramian-based IM. The use of distinct operators differentiates the various gramian-based IMs.

Note that, due to the normalization, all the elements of a gramian-based IM add up to 1. Therefore the larger elements in the IM identify the input-output channels which have a larger contribution in the process dynamics. The gramian-based IMs are used to derive a simplified model formed by a reduced subset of the process input-output channels. This model will be used for the controller design and has to capture most of the process dynamics. The sum of the contributions IA_{ij} of all the considered input-output channels indicates the ratio of the total process dynamics that the reduced model is considering.

The gramian-bsed IMs concentrate the frequency domain properties of the system in a real valued array, and therefore it is traditional to restrict the range of frequencies of interest with e.g. the use of pre-filters (Birk and Medvedev, 2003). The frequency limited gramians can be used as an alternative to the filters, being both alternatives equivalent with the use of perfect filters (Gawronski and Juang, 1990). Additionally, the gramians are not defined for systems with pure integrators but they can be analyzed by restricting the range of frequencies (Castaño et al., 2015).

5.3 Control Configuration Selection using gramian-based Interaction Measures

Gramian-based IMs are sensitive to the scaling of the inputs and outputs, and therefore an appropriate scaling has to be applied prior to their computation. Usual values for scaling are the allowed or expected variation of the process variables (Skogestad and Postlethwaite, 2005), or the standard deviation of the signals (Castaño and Birk, 2012).

The resulting IA from calculating a gramian-based IM has to be interpreted by the designer in order to select an appropriate control configuration. The following heuristic rules have been formulated in Salgado and Conley (2004) for the use of the PM, and are currently applied for selecting the most significant input-output channels with the use of any gramian-based IM:

Rule 1. The simplest control configuration whose total contribution exceeds an arbitrary threshold τ is selected as candidate. This configuration considers the input-output channels with largest significance while considering at least one input-output channel in each row. Control configurations designed with $\tau \leq 0.7$ are likely to derive in satisfactory performance.
Rule 2. In a hypothetical process with r input-output channels where all the channels have the same contribution, this contribution will be equal to $1/r$. This suggests that in a more heterogeneous scenario there is no benefit from considering those input-output channels for which $IA_{ij} << 1/r$. The converse is also true, and the those input-output channels with $IA_{ij} >> 1/r$ present a significant contribution in the process dynamics.

The usual procedure for CCS using gramian-based IMs is derived from these rules and is formulated as follows:
Step 1. Find the configuration which can derive a contribution larger than τ and considers the minimum possible number of input-output channels with the condition that the matrix representing the reduced model has full structural rank. This is often done by starting with a full decentralized configuration designed using relative gains and adding channels in crescent order of significance until the threshold τ is reached.
Step 2. The resulting control configuration has to be reviewed using *Rule* 2. This is done by adding or removing input-output channels which are suspected to present a significant or insignificant contribution respectively. In both cases the designer has to judge if the increase or decrease of the complexity of the configuration is justified by the increase or decrease in the total dynamic contribution.
Step 3. To obtain additional evidence to take a heuristic decision on the configuration, it is recommended to use the indication of more than one gramian-based IM. In case of indecision between configurations, a simple configuration is often selected and tested, and the complexity of the configuration is increased if the obtained performance is not satisfactory.

5.4 Participation Matrix (PM)

PM was introduced by (Conley and Salgado, 2000), and uses $trace(P_jQ_i)$ as gramian-based operator:

$$PM_{ij} = \frac{trace(P_jQ_i)}{\sum_{k,l} trace(P_kQ_l)} = \frac{trace(P_jQ_i)}{trace(PQ)}$$

where P_j denotes the controllability gramian related to the j^{th} input and Q_i denotes the observability gramian related to the i^{th} output. The trace of PQ is also known as the Hilbert-Schmidt norm (HS-norm). A major advantage of PM is the opportunities given by the different ways of calculating the HS-norm, which include:
- The HS-norm is equal to the area enclosed by the Nyquist diagram divided by π (Hanzon, 1992). This suggests that depicting the Nyquist plot of the input-output channels of a multivariable system provides visual information on which input-output channels have the largest contribution on the process dynamics, since the larger the area of the Nyquist plot of an input-output channel, the larger its quantified contribution in the PM. This relationship with the frequency domain has been used by to calculate uncertainty bounds on PM and also used by Castaño and Birk (2011) to estimate PM using taylored excitations.
- The HS-norm equals the sum of the squared Hankel Singular Values.
- The HS-norm can be calculated from the impulse response $h(\tau)$ as $trace(PQ) = \int_0^\infty \tau h(\tau)^2 d\tau$. This calculation has been used to estimate PM from time-domain data by Salgado and Yuz (2007) and Castaño et al. (2011).
- The HS-norm can be calculated form the eigenvalues or trace of the cross-gramian matrix.

A significant disadvantage of PM is that it gives erroneous information on time-delayed systems. An increase of the time delay on an input-output channel will imply an increase of its associated value of $trace(P_jQ_i)$.
Lemma. For SISO system G with gramians P and Q, an addition of a time delay d will increase the value of trace(PQ) by $d \cdot ||G||_2^2$.
Proof Denote by $\hat{G}$, $h(\tau)$, $\hat{P}$ and $\hat{Q}$ the transfer function, impulse response and gramians resulting from adding the delay d to the system G.

$$trace(\bar{P}\bar{Q}) = \int_0^\infty \tau \cdot \bar{h}(\tau)^2 d\tau = \int_{k=0}^\infty (\tau + d) h(\tau)^2 d\tau = \underbrace{\int_0^\infty \tau \cdot \tau(k)^2 d\tau}_{trace(PQ)} + d \cdot \underbrace{\int_0^\infty h(\tau)^2 d\tau}_{||G(s)||_2^2}$$

□

5.5 Hankel Interaction Index Array (HIIA)

HIIA has been defined by Wittenmark and Salgado (2002) as:

$$[HIIA]_{ij} = \frac{||G_{ij}||_H}{\sum_{k,l} ||G_{kl}||_H} = \frac{||G_{ij}||_H}{||G||_H}$$

HIIA uses the Hankel norm as gramian-based operator, which is calculated as

$$||G||_H = \sqrt{\lambda_{max}(PQ)} = \sigma_1^H$$

Thus, the Hankel norm is the largest singular value of the Hankel operator of the dynamic system G.

An alternative definition of the Hankel norm is as follows. Assume that a stable SISO system $G(s)$ is excited with an input $u(t)$ up to $t = 0$, and the output $u(t)$ is measured for $t > 0$. The Hankel norm is then obtained by finding the input $u(t)$ which maximizes:

$$||G(s)||_H = \max_{u(t)} \frac{\sqrt{\int_0^\infty ||y(\tau)||_2^2 d\tau}}{\sqrt{\int_{-\infty}^0 ||u(\tau)||_2^2 d\tau}}$$

This definition of the Hankel-norm has energy interpretations in terms of the maximum ratio of energy which can be obtained from the past inputs to the future outputs. A comprehensive illustration of this interpretation of the Hankel-norm using an analogy with a swing is given by Skogestad and Postlethwaite (2005).

The Hankel norm of the time delayed system $G_d(s) = G(s) \cdot e^{-t_d}$ is higher or equal than that of $G(s)$. For the

$$||G_d(s)||_H = \max_{u(t)} \frac{\sqrt{\int_0^\infty ||y(\tau - t_d)||_2^2 d\tau}}{\sqrt{\int_{-\infty}^0 ||u(\tau)||_2^2 d\tau}} = \max_{u(t)} \frac{\sqrt{\int_{-t_d}^0 ||y(\tau)||_2^2 d\tau + \int_0^\infty ||y(\tau)||_2^2 d\tau}}{\sqrt{\int_{-\infty}^0 ||u(\tau)||_2^2 d\tau}} \leq \max_{u(t)} \frac{\sqrt{\int_0^\infty ||y(\tau)||_2^2 d\tau}}{\sqrt{\int_{-\infty}^0 ||u(\tau)||_2^2 d\tau}} \quad (1)$$

same input sequence $u(t)$, $G(s)$ will present an output $y(t)$ and $G_d(s)$ will present as output $y(t-t_d)$. The increase of the Hankel norm with time delays is then proven in Equation (1)

Therefore, HIIA fails to address time delay systems in a similar way than PM.

A relationship between the HIIA and PM has been stated by Halvarsson et al. (2010).

5.6 Σ_2 Interaction Measure

Σ_2 was introduced by Birk and Medvedev (2003) and uses the $\mathcal{H}_2$-norm as gramian-based operator:

$$[\Sigma_2]_{ij} = \frac{||G_{ij}||_2}{\sum_{k,l} ||G_{kl}||_2}$$

The $\mathcal{H}_2$ norm has a strong connection with the controllability and observability gramians. In the case that the process is given by state space description $(A, B, C, 0)$, and if the input-output channel (A, B_j, C_i) is stable and strictly proper, its $\mathcal{H}_2$-norm can be computed as:

$$||G_{ij}(s)||_2 = \sqrt{C_i P_j C_i^T}$$

where P_j is the controllability gramian of the SISO subsystem, and C_i the i-th row of C. This relationship gives a first interpretation of the $\mathcal{H}_2$-norm as a measure of the output controllability of the process (Halvarsson, 2008).

In addition, the $\mathcal{H}_2$-norm is suitable for quantifying the importance of the input-output channels due to its different interpretations as transmitted energy from the input to the output:
- The squared $\mathcal{H}_2$-norm of each elemental SISO subsystem can be interpreted as the coupling in terms of the energy transmission rate between the past inputs and the current output.
- The squared $\mathcal{H}_2$-norm is the energy observed at the output when the input is excited with a unitary impulse.
- The squared $\mathcal{H}_2$-norm is also from a stochastic perspective, the power conversion rate between input and output when the input is excited with white noise.

6. CONTROL CONFIGURATION SELECTION METHODS BASED ON OPTIMIZATION SCHEMES

When using optimization techniques, a cost function is first chosen which should be minimized over all the possible configurations. Such a cost function should express a trade off between the achievable performance of the resulting structure and its complexity:

$$\Theta_s = \underset{\Theta \in S}{arg\ min}\, \Gamma(\Theta, G) + \lambda \cdot \Pi(\Theta)$$

where G represents the plant. Θ represents the controller structure and is a binary connectivity matrix with $\Theta_{ij} = 1$ when $K_{ij}(s) \neq 0$. $\Gamma(\Theta, G)$ is a function quantifying the achievable performance of the configuration Θ. The function $\Pi(\Theta)$ is a quantification of the complexity of the control structure Θ. The discrete feasibility set S includes all the possible binary combinations of the connectivity matrix Θ. Different values of the regularization parameter λ result in different Pareto-optimal configurations which describe the Pareto frontier depicted in Fig. 5. This Pareto Frontier starts at the best fully decentralized configuration represented by Θ_d and finishes with a full multivariable controller which uses all the available n^2 interconnections (assuming n inputs and outputs). The full multivariable controller would be the controller with the best achievable performance Γ_{min}. The solution Θ_s would be a trade-off between the complexity of the controller and the achievable performance.

Ideally, this formulation is independent from the parametrization of the controller K. However, the calculation a closed-loop performance function Γ requires the design of the controller parameters. A possible solution is to choose a standardized approach to close the loop for a given connectivity matrix Θ using fixed-structure design methods.

Due to the discrete nature of the feasibility set S the solution to this problem is of combinatorial nature. Several authors proposed methods using mixed integer programming for evaluating the achievable performance of each of the possible configurations. This results in an NP-hard problem with lack of practical use, since the number of alternative control configurations grows extremely rapidly as the topological complexity of the system to be controlled increases (van de Wal and de Jager, 1995). An approach to reduce the computational complexity is the previous use of IMs to screen the set of candidate structures (Cai and Marlin, 2004). It is of interest to pursue an investigation on the maximum size of the systems that would derive in acceptable computational time using modern computers.

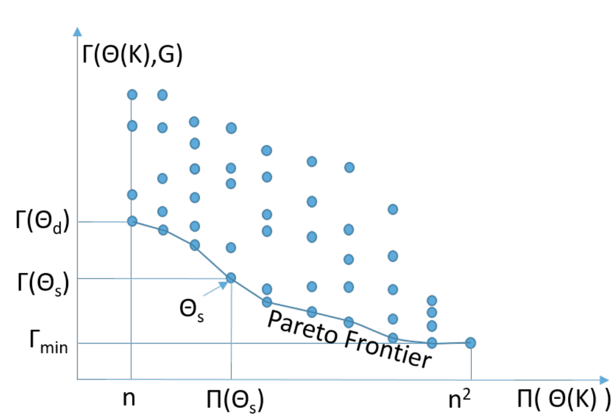

Fig. 5. Illustration of the Control Configuration Selection problem as an optimization scheme.

It is expected that this limit would be around 5×5 systems, where the number of possible combinations is in the order of $29 \cdot 10^6$.

With the reckoning of approximations, the problem can be formulated in a convex form by the Reduced Structure Control (RSC) method introduced by Nobakhti et al. (2007) and later extended by Nobakhti (2010). However, some of the limitations of this method are: i) starts from a decentralized structure which has to be previously designed, ii) the performance function Γ is based on the open-loop transfer function iii) it is not informative (see P5) and has obscure interpretation, since the resulting configuration of the optimization scheme is directly presented to the designer who has at this moment little insight on the reason for considering or neglecting the input-output channels.

Additionally, the CCS methods using optimization techniques are subject to the paradox that the control configuration resulting from solving the problem for an increase of the controller complexity does not necessarily contain the previous configuration (see P7).

7. PLANTWIDE CONTROL

A review of plantwide control methods was published by Larsson and Skogestad (2000), although a few years later it was pointed by Skogestad (2004) that the industrial approach to plantwide design was still very much aligned with the methods given by Buckley (1964).

Two are perhaps the most popular methods for plantwide control which have received increasing attention: the nine-step method proposed by Luyben et al. (1997, 1998) and the more recent self-optimizing control (SOC) procedure by Skogestad (2004).

The SOC aims at creating a systematic method for CSD which is partially automated, providing a systematic tool for CSD with the advantage of producing tractable results in contrast with the results provided by the RSC method. Another important advantage of this method is the introduction of economic factors in the design of the control structure. The SOC has been evaluated on realistic large scale systems (Zhang et al., 2010).

A generalization of SOC is discussed in Ye et al. (2015). where a tractable solution for the controlled variable selection problem is suggested considering nonlinear models as well as uncertainties.

A shortcoming of the PWC methods was pointed out by Downs (2012), which stated that the likelihood of a complex plantwide strategy becoming unworkable is high. The reason is that control strategies must often be changed from the original design, and these changes may need to be done by third parties without the adequate training in plantwide strategies. Recent results by Ye et al. (2017) aim at the practical use of the SOC by discussing a retrofit which allows to update a SOC-based control system with a new SOC layer on the top of the existing one. Preliminary results on the retrofit SOC were based on the Tennessee Eastman process (Ye et al., 2016).

8. RECONFIGURATION OF CONTROL SYSTEMS

A large scale system can be understood as a system which is composed of a large number of subsystems. Each of the subsystems in itself might be a multivariable system. Such large systems do undergo changes, willfully or not, and thus should not be treated as fixed over time. While control configurations are selected the first time a control system is put into place, it is not practically possible to replace a complete control system for a large scale system with another one when changes have occurred.

Reconfiguration therefore addresses the problem of determining an updated control configuration based on the one which is already in place.The trigger for a reconfiguration can be the addition or removal of sensors or actuators, a performance loss of the closed loop system due to hardware degradation, or a change in the performance requirements for the closed loop system. In this paper reconfiguration due to failures in the context of fault tolerant control is not considered. The interested reader is referred to Blanke et al. (2016) for more information on this topic.

When new sensors or actuators are becoming available in a large scale system, it is a natural step to re-evaluate the current control configuration. Here, the concept of *Plug & Play control* as proposed in Stoustrup (2009) presents ideas and challenges that need to be addressed to enable system reconfigurability, where the current controller is re-used in the new control configuration. This means that the complexity of the control scheme is increased, but not reduced.

A similar concept was proposed in Birk (2007), where the complexity of a control configuration is increased by considering neglected dynamics in the control configuration. There, a factorization of the sensitivity transfer functions is used to identify the significant parts of the neglected dynamics, with the opportunity to consider model uncertainty. This approach creates block diagonal structures, which rapidly increase in complexity, which is a disadvantage in comparison with the method given by Stoustrup (2009) . More details on the approach and how it can be applied in real life is given by Birk and Dudarenko (2016).

The *Plug & Play Control* concept is then developed into a complete methodology and presented in Bendtsen et al. (2013). A that point it has to be noted that the disadvantage of not being able to reduce complexity is still present in the methods. In that paper the authors also apply the concept on two case studies which are highly relevant.

In the recent paper Bodenburg et al. (2016) the work by Stoustrup is extended such that the controller complexity can also be reduced. It is also worth while noting that the concept is now extended to plug-in and plug-out of subsystems in a large scale system, while guaranteeing I/O stability and global performance characteristics of the closed loop system.

One important aspect when addressing large scale systems is the model uncertainty, or in other words the limited model information that is available. Robustness of a reconfiguration approach is therefore very important, if the methods should be applied in real-life, see Bodenburg et al. (2016).

9. CHALLENGES ON CONTROL CONFIGURATION SELECTION FOR WIRELESS SENSOR AND ACTUATOR NETWORKS

There is a tendency from companies offering control system architectures to offer WSAN services. Such architectures are already implemented in the current industry, like in the froth flotation process in Boliden, Sweden.

According to the plenary talk by Johansson (2006), removing cables saves installation and maintenance costs, but often the real gains lie in the radically different design approach that wireless solutions permit. In order to fully benefit from wireless technologies, a rethink of existing automation concepts and the complete design and functionality of an application is required. We explore in this section the rethinking of the CCS problem in relation to WSAN.

The new WSAN architectures lead to a potential to for a dramatic change by being able to close local control loops over wireless multihop networks. The fixed hierarchical centralized systems which are inherent of cabled systems can be restructured using WSAN for a more flexible and distributed system where computations and decision making can potentially be moved from dedicated computers to sensors and actuators.

A major opportunity in terms of flexibility is the redeployment of sensor and actuator nodes. The EU project DISIRE aims to deploy in-situ sensors sensors in the process which move with the material flow and integrate the local measurements in the control systems. Undoubtedly, these wireless sensors enable more flexible maneuvers and control actions as a consequence of more efficient monitoring and diagnosis. An open question is how to reconfigure the system to make an opportunistic use of the measurements from a swarm of sensors. Several difficulties on the CCS arise from this scenario which presents: i) the availability of a set of measurements larger than the set of available actuators, ii) sensors enter and leave the system together with the material flow, iii) the sensors are subject of harsh conditions which are likely to derive in sensor failures, since they might not even survive the complete process.

The methods for CCS have to therefore be extended to deal with potential of having a much larger number of sensors than actuators. A usual limitation is that the current CCS methods assume the availability of the same number of sensors and actuators.

Large challenges are derived from the fact that sensors are entering the process with the material flow and disconnecting when either leaving the process or due to their possible destruction. This means that CCS need not only to be able to produce re configurations of the system. Additionally the CCS methods have to either be applicable on time-varying models which describe the movement of the sensors through the process or become data-driven. In this context, the integrity of the configurations have to be studied to guarantee stability when new loops are brought in and out of service.

Additionally, the increased flexibility to close loops through a wireless network implies new opportunities in addressing processes control in a holistic perspective, increasing the topological complexity and the need of process decomposition prior to the use of CCS methods.

Wireless communications on the control loops not only create new opportunities, but also add additional problems which may affect closed-loop control performance. WSANs impose uncertainty, disturbances and constrains on the control system. Some of these negative effects are i) delay and jitter, ii) bandwidth limitations, iii) data loss, iv) interference v) outages and disconnection, vi) security. These communication imperfections can be addressed through two complementary approaches by using control-aware networking and communication and/or modifying the control algorithms. We discuss in the sequel of this section how the enumerated problems arising from WSAN can influence CCS.

Most of the current CCS methods are either insensitive to time delays like the RGA and $Sigma_2$, fail to give adequate indications in the presence of time delays like PM and HIIA, or their sensitivity to time delays has not been adequately explored like the DRGA or RHC. There is therefore a need of investigate CCS which can address time-delayed systems with special relevance on the WSAN scenario. A relevant theoretical study by Kao and Lincoln (2004) investigates on how large is the possible time delay that can happen in an TLI system with linear controller until we loose stability.

The bandwidth limitations in WSAN can influence the decision making during CCS, since it was indicated by Salgado and Rojas (2005) that the gramian-based IMs depend on the sampling.

The interference, outrages and disconnection motivates the study of the robustness of the CCS which will be discussed in the next section, as well as additional studies on integrity.

We finally discuss the security of WSAN, since wireless technology is vulnerable to attacks. It is natural to think that security should be tackled at the networking and communication level. However, it is of interest to explore of control configurations can be design which are more robust to network attacks. We have previously discussed that decentralized configurations are more robust to plant failures, and therefore they are more robust to attack which might brings down individual control loops.

10. SOME OPEN QUESTIONS AND CHALLENGES IN CONTROL CONFIGURATION SELECTION

Clearly, research in control configuration selection has been ongoing for a long time with varying interest in the community. One could say that the area is mature for a linear system approach. Nevertheless, the is no single systematic approach presented for practitioners which has been adopted by industry. Moreover, certain important issues are still not sufficiently well addressed. We will now shortly summarize these open questions and challenges in a number of categories.

10.1 Robustness

A process model with a description of the model uncertainty can be understood as a set of models which includes the nominal model. Therefore, the indications from the CCS methods may differ for different models in the uncertainty set.

The computation of the worst-case bounds on the IMs is an approach to robust control structure selection which has recently received increasing attentions, including the following publications. Results on the RGA for norm-bounded uncertain systems have been reported by Kariwala et al. (2006) and extended by Kadhim et al. (2015a), and results for 2×2 systems affected by multiplicative uncertainty have been reported by Castaño and Birk (2008). Results on the Gershgorin bands have been introduced by (Chen and Seborg, 2002). An approximation of the uncertainty bounds of PM for models under multiplicative uncertainty has been introduced by Halvarsson et al. (2010) and the results were later extended by Castaño and Birk (2011). Bounds on the HIIA for uncertain systems have been introduced by (Moaveni and Khaki Sedigh, 2008). Exact bounds on Σ_2 for models under multiplicative uncertainty have been introduced by Castaño and Birk (2016).

However the results in the computation of these bounds are often presented without a clear procedure for the selection of a robust control configuration. Recent results reported by Kadhim et al. (2017) introduce an integer programming method for considering model uncertainty in the decision making during the pairing selection for decentralized control with the use of RIA.

10.2 Estimation

By estimating IMs, the most important input-output interconnections for process performance can be obtained from an experiment. This has two clear advantages. First the control configuration can be determined without the need of parametric models. Additionally, the structure of a simplified model can be determined and modeling efforts can be focused on the significant input-output channels. This avoids the unnecessary work which is done when a model for an input-output channel is first created and discarded when the reduced model is selected.

Despite the clear advantages of estimating IMs, the published results are very limited, for example the work on the estimation of the RGA in Xu and Shin (2007) and an extension to weakly nonlinear systems by Kadhim et al. (2015b), which was later revised by Kadhim et al. (2016).

For the gramian-based interaction measures, a method for the estimation of PM using time-domain data has been introduced by Salgado and Yuz (2007) and later extended to obtain estimation bounds by Castaño et al. (2011). Methods for the estimation in the frequency domain of PM and Σ_2 have been described by Castaño and Birk (2016), and can be applied to weakly non-linear systems as described by Castaño and Birk (2015).

All these methods suffer from a large experimental burden which raises question on the practical usefulness of these approaches. Generally, the complete multivariable system need to be properly excited in order to achieve a sufficiently good performance of these methods.

An interesting idea in this context is related to the digitalization of industry and the trend of collecting uncorrupted data. One could easily think that there is sufficient excitation in the data from normal operation, we only need to identify the informative data sets which enable us to estimate an interaction measure for the selection. An open question now is what are the indicators and how can these data set efficiently extracted from the large amount of time series that are stored in SCADA systems.

Recent developments in this direction have been introduced by Carvalho Bittencourt (2016), where a unified framework for the estimation of gramian-based IMs from process data under closed loop in presented. Recursive solutions are presented which make the estimation practical for large datasets.

10.3 Visualization and tools

As indicated by Rohrer (2000), visualization techniques such as diagrams and flow sheets are important both from a collaborative perspective as well as to provide a comprehensive understanding of processes. Many authors have created and evolved visualization techniques for the analysis and visualization of complex processes, which include the use of interactive learning environments to aid users in learning to understand and control complex systems (Viste and Skartveit, 2004), the use of Self-Organizing Maps (Kohonen, 2001) for visualizing and exploring process dynamics (Díaz et al., 2008; Ylstalo and Hytyniemi, 1998), or the use of graph theory concepts for the structural analysis and visualization of complex processes Morari and Stephanopoulos (1980).

For the sub-problem of control configuration selection, the IMs provide the designer with process knowledge on how the process variables are interconnected. Control configurations are designed with the goal of minimizing the presence of loop interaction which is often unavoidable with the use of sparse configurations for the control of complex processes. This is often done in a heuristic approach, where interpretation is needed to select the process interconnections on which control will be based. The traditional IMs present information as an array of real numbers which is disjoint from the process layout. A goal of the results by Castaño and Birk (2009) later extended by Castaño and Birk (2012) is to create new methods for the interaction analysis of complex processes using weighted graphs, allowing integrating the analysis with process visualization for an increased process understanding.

10.4 Automated tools for CCS

Previously, a number of guidelines for the selection of control configurations have been published, like e.g. Lee et al. (1995), Samyudia et al. (1995), and Mc Avoy et al. (2003). Such guidelines can be very valuable for practitioners and also be seen as a starting point for an automated configuration selection procedure.

Two automatic pairing procedure based on RGA have been proposed. An early publication was the procedure by Kookos and Lygeros (1998) and then later by Fatehi (2011). Generally, linear programming strategies have been used to solve the pairing problem, although integer programming strategies can be made practical with the use of branch and bound methods Kariwala and Cao (2010). The integration of uncertainty bounds in the automatic pairing has been performed by Kadhim et al. (2017).

When optimization techniques are used to determine a selection, then the issue of trust arises, which means that the control engineer is not part of the optimization process and is only presented with the result. It requires trust of the engineer to actually belief in the result. From that perspective, guidelines have an advantage. Therefore, it is important to make use of known and established benchmark processes to enable the validation of these procedures. Although there are several processes, like the Tennessee Eastman, some additional processes are needed.

Moreover, the tools are only intended for decentralized control and there is a need to develop methods which enable more complex control structures.

10.5 Nonlinear systems

Most interaction measures have been derived for linear systems and in many ways, analyzing a system for a specific operating condition seems reasonable. In that way, a linear analysis might be sufficient. But for larger systems, operating conditions are rarely persistent unless the system is rather well decoupled. In these cases nonlinear analysis of interactions is necessary to conduct.

The attempts reported by Glad (2001) and Lee et al. (2000) do show a new direction, by directly analyzing the nonlinear system. These approaches have not yet led to methods that are applied in practice. Commonly, the approach is to make use of uncertainties and robustness concept to deal with the nonlinear dynamics.

From a control configuration selection perspective it is also an open question if one configuration for a large operating range of the nonlinear system should be selected or if a switching approach is employed. In the switching approach a number of operating conditions can be defined and for each of them a selection is performed.

In the later case the complexity of the controller logic becomes large, while in the first case the achievable performance for a linear control approach might be limited. No matter which approach is selected, the definition of the operating conditions becomes a crucial part of the selection process. Methods which would integrate this into the selection are still to be developed.

10.6 Consideration of closed-loop performance

Clearly, the CCS should ideally consider the achievable performance of the resulting closed-loop system. However, the evaluation of performance requires the design of controller parameters, which is a posterior step in the design of toe control system (as stated in Section 1).

The RGA considers the closed loop in the design of the configuration, since it is assuming that the system is closed under perfect control.

The calculation of the gramian-based IMs is not including the closed-loop, and has no explicit relationship to closed-loop performance. Their relationship to the closed-loop system is implicit in the fact that to achieve a diagonal closed-loop sensitivity function, the structure of the controller has to be equal to the structure of the inverse of the plant. With the use of the gramian-based IMs we target structural simplifications in expectation to achieve a closed to diagonal closed-loop sensitivity function.

There is therefore an interest in creating CCS tools which consider closed-loop performance. A possibility is to choose a standard control synthesis technique to benchmark the loop closing for the selection of configurations, like the use of LQG control by Halvarsson et al. (2009).

11. CONCLUSIONS

The origin of Control Configuration Selection (CCS) is in the use of Interaction Measures (IMs) based on relative gains, with the first publications dating from the 60's. The number of publications on Control Configuration Selection have significantly increased since the introduction of the gramian-based IMs in 2000. Since then, the CCS problem has branched in different classes of methods, including the use of convex optimization.

Additionally, there is a trending interest in extending the applicability of existing methods by addressing topics like robustness to uncertainty or data-driven applications.

The emerging use of Wireless Sensor and Actuator Networks (WSAN) opens opportunities and problems related to CCS. One of the discussed challenges is the increased flexibility when redeploying sensors and actuators, which may lead to the reconfiguration of the control system.

WSANs not only lead to new opportunities, but also present additional communication imperfections with significant effect on the control system. These imperfections imperfections can be considered in the CCS problem and include communication delays, security risks or limited communication bandwidth. A major unresolved problem is the consideration of time delays in the CCS.

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