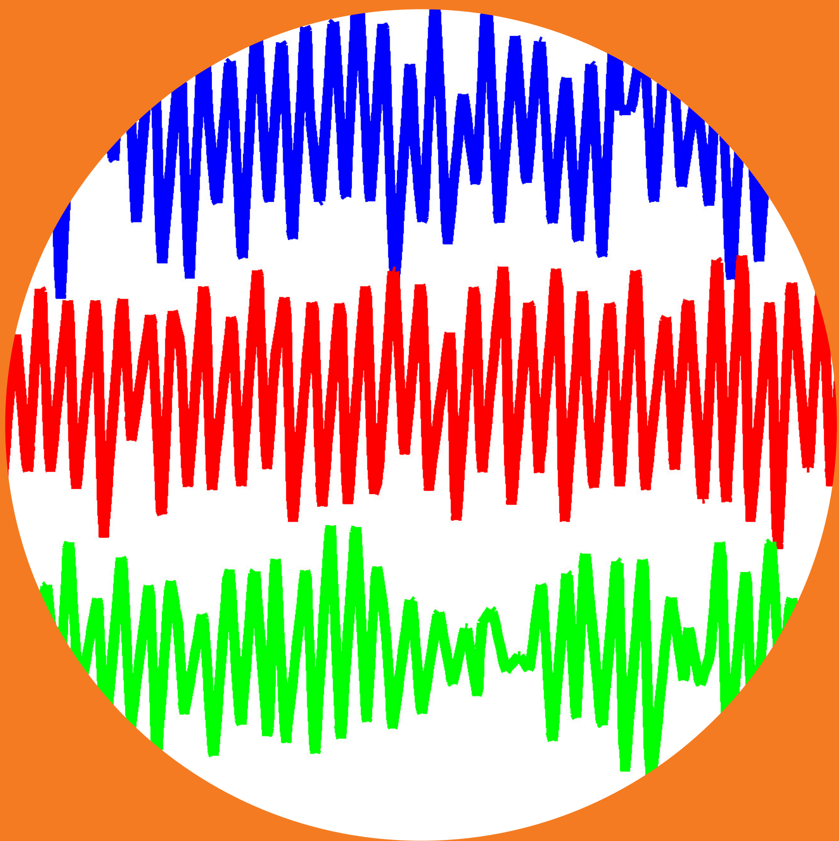
Department of Biotechnology and Chemical Technology

Integrated Fault Detection System for a Board Machine

Vesa-Matti Tikkala



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Integrated Fault Detection System for a Board Machine

Vesa-Matti Tikkala

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Abstract

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Abstract

The current process industry faces remarkable challenges due to global competition, tightening environmental regulations, and the increasing complexity and integration of process plants. Especially, the pulp and paper industry has been under pressure in recent years to improve the efficiency of operations and to optimize production.

Managing abnormal events, such as disturbances, faults and failures is an essential part of improving the operation of process plants. Traditional plant automation systems are able to handle the typical faults and disturbances and to restore the process into a normal state. However, in order to address more complex faults, the automation systems must be accompanied by fault detection methods which provide the plant operators and maintenance with additional information about the faults.

This thesis presents the development of an integrated fault detection system for a board machine. The system was developed according to a created methodology which exploited the decomposition and control strategy of the process as well as fault analysis. The presented fault detection system consisted of four fault detection algorithms that addressed the faults having the most significant effect on the economic performance and operability of the process. The fault detection system comprised of a valve stiction detection system employing a parallel configuration of four different stiction detection algorithms, a robust detection method for non-stationary oscillations, a dynamic causal digraph -based method for detecting consistency sensor faults, a detection method for leakages and blockages in the drying section using non-linear parity equations, and a self-organising map -based process monitoring method for detecting caliper sensor fouling.

The individual fault detection algorithms were tested and validated in case studies using simulations and industrial data. In addition, industrial experiments were carried out at the board machine.

The obtained results were very promising and showed that the presented methodology provided a systematic approach to the development of a fault detection system. The testing results indicated that the fault detection algorithms provide useful information for improving the operation and maintenance of the board machine.

Keywords Fault detection, Paper machine, Valve stiction, Oscillations, Causal digraph, Parity equation, Self-organising map, Industrial application

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Tiivistelmä

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Tiivistelmä

Globaali kilpailu, kiristyvät ympäristövaatimukset sekä entistä monimutkaisemmat ja suljetummat prosessit asettavat merkittäviä haasteita nykypäivän prosessiteollisuudelle. Erityisesti paperi- ja selluteollisuus on ollut murroksessa viime vuosina, mikä vaatii toiminnan tehostamista ja tuotannon optimoimista.

Olennainen tapa parantaa prosessien toimintaa on poikkeavien prosessiolosuhteiden ja vikojen hallinta. Normaalit prosessiautomaatiojärjestelmät pystyvät selvittämään tavallisimmat viat ja häiriöt sekä palauttamaan prosessin normaaliin tilaan. Kuitenkin kriittisimpien vikatilanteiden tapauksessa täytyy automaatiojärjestelmän rinnalle kehittää vianhavaintamenetelmiä, jotka tuottavat tietoa prosessin vioista operaattoreille ja kunnossapidolle.

Tässä työssä on kehitetty integroitu vianhavaintajärjestelmä kartonkikoneelle. Järjestelmän kehittämistä varten on luotu metodologia, jossa hyödynnetään prosessin rakenteen ja säätöjärjestelmän tuntemusta sekä vika-analyysiä. Vianhavaintajärjestelmä koostui useista eri algoritmeista, jotka olivat kehitetty havaitsemaan vikoja, joilla on merkittävin vaikutus prosessin taloudellisuuteen ja toimintaan. Järjestelmä kattoi venttiilien jumiutumisen havainnointijärjestelmän, epästationaarisille signaaleille soveltuvan oskillointien havainnointimenetelmän, dynaamisiin digraafeihin perustuvan menetelmän sakeusmittausten vikojen tunnistamiseen, menetelmän vuotojen ja tukosten havaitsemiseksi kuivatusosassa sekä itseohjautuviin karttoihin perustuvan paksuussensorin likaantumisen monitoroinnin.

Yksittäiset vianhavaintamenetelmät testattiin ja validoitiin tapaustutkimuksissa käyttäen apuna simulointeja ja teollista mittausdataa. Lisäksi kartonkikoneella suoritettiin koeajoja.

Testitulokset olivat erittäin lupaavia ja todistivat että esitetty metodologia tarjoaa systemaattisen lähestymistavan vianhavaintajärjestelmän kehittämiseen. Vianhavaintamenetelmien testeistä saadut tulokset puolestaan osoittivat että menetelmät tuottavat hyödyllistä tietoa prosessin toiminnan ja kunnossapidon parantamiseksi.

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Preface

The research work presented in this dissertation has been carried out in the research group of process control at the Aalto University School of Chemical Technology during the period 2009-2014. The work has been a part EU FP7 -funded project "Plug and Play monitoring and control architecture for optimization of large scale production processes, PAPYRUS" (EU-IST-2010-257580). Financial support for my research and post-graduate studies has been also received from the Finnish Foundation for Technology Promotion, Jenny and Antti Wihuri Foundation, the Research Foundation of Helsinki University of Technology, and the Finnish Automation Foundation.

First I wish to express my gratitude to professor Sirkka-Liisa Jämsä-Jounela for supervising my thesis and guiding me through my doctoral studies. It has been a great experience to work in her group and to learn the secrets and practices of scientific research. Next, I would like to thank PhD Alexey Zakharov for his role as an instructor and for all the inspiring discussions, on and off the topic, we have had along the way. He has been an invaluable colleague and I have always been able to turn to him in case of challenges in research. The pre-examiners and opponents, professors Tore Hägglund, Ping Zhang and Risto Ritala are acknowledged for reviewing the thesis manuscript.

I am pleased that I have collaborated with many inspirational professionals during my time at the university. Special thanks go to the co-authors of the publications included in this thesis, Octavio Pozo Garcia and Hui Cheng. The industrial partners, Tommi Myller and others at Stora Enso, Veikko Hämäläinen at Efora, Simo Säynevirta, Jan Christoph Schlake, Moncef Chioua and others at ABB as well as Jean-Baptiste Leger and Maxime Monnin at Predict, are acknowledged for the fruitful co-operation in the Papyrus project. Thanks also to the rest of the Papyrus consortium: Dominique Sauter and Christophe Aubrun *et al.* at the Université de Lorraine, and Steven Ding and the team at Universität Duisburg-Essen.

The people of the research group of process control, or the lab, also deserve acknowledgments for creating a creative atmosphere to work as well as for nice time outside the working hours. Thanks to Jerri, Jukka, Sasha, Michela, Nikolai, Markus, Mikko, Mats, Lari, Esa, Tushar, Miao, Rinat, Aleksi and to all others who were not mentioned, but not at all forgotten.

Finally, I wish to thank my family and ”heimo”, especially my dear wife Meeri for love, support and encouragement during this process as well as my kids, Joona and Enni, for keeping me busy also at home, when not working or writing.

Kirkkonummi, November 11, 2014,

Vesa-Matti Tikkala

Contents

List of Publications

This thesis consists of an overview and of the following publications which are referred to in the text by their Roman numerals.

I Pozo Garcia, O., Tikkala, V.-M., Zakharov, A. and Jämsä-Jounela, S.-L.. Integrated FDD system for valve stiction in a paperboard machine. *Control Engineering Practice*, **21**(6), pp. 818–828, 2013.

II Tikkala, V.-M., Zakharov, A. and Jämsä-Jounela, S.-L.. A method for detecting non-stationary oscillations in process plants. *Control Engineering Practice*, **32**, pp. 1–8, 2014.

III Cheng, H., Tikkala, V.-M., Zakharov, A., Myller, T. and Jämsä-Jounela, S.-L.. Application of the Enhanced Dynamic Causal Digraph Method on a Three-Layer Board Machine. *IEEE Transactions on Control Systems Technology*, **19**(3), pp. 644–655, 2011.

IV Zakharov, A., Tikkala, V.-M. and Jämsä-Jounela, S.-L.. Fault detection and diagnosis approach based on nonlinear parity equations and its application to leakages and blockages in the drying section of a board machine. *Journal of Process Control*, **23**(9), pp. 1380–1393, 2013.

V Tikkala, V.-M. and Jämsä-Jounela, S.-L.. Monitoring of Caliper Sensor Fouling on a Board Machine Using Self-Organizing Maps. *Expert Systems with Applications*, **39**(12), pp. 11228–11233, 2012.

Author's Contribution

Publication I: "Integrated FDD system for valve stiction in a paperboard machine"

V.-M. Tikkala developed the concept of the reliability indexes in co-operation with O. Pozo Garcia, and introduced the reliability index for the bicoherence method. The industrial tests were run by V.-M. Tikkala and O. Pozo Garcia. The results were analysed in co-operation by him, O. Pozo Garcia and A. Zakharov. He also co-wrote the manuscript with O. Pozo Garcia.

Publication II: "A method for detecting non-stationary oscillations in process plants"

The proposed oscillation detection method was developed by V.-M. Tikkala. He also performed all simulation and industrial tests, analysed the results and wrote the manuscript.

Publication III: "Application of the Enhanced Dynamic Causal Digraph Method on a Three-Layer Board Machine"

H. Cheng developed the enhanced dynamic causal digraph method which was applied to the board machine in co-operation with V.-M. Tikkala. In addition, V.-M. Tikkala assisted in the process analysis and the modelling of the process, defined and simulated the fault scenarios together with H. Cheng. He also ran a part of the simulation tests presented in the paper. In addition, he co-wrote the manuscript with H. Cheng.

Publication IV: "Fault detection and diagnosis approach based on nonlinear parity equations and its application to leakages and blockages in the drying section of a board machine"

A. Zakharov developed the non-linear parity equation method based on grey-box modelling that utilizes structural knowledge of the process for estimating mass balances. The method was applied to the drying section of the board machine in co-operation with V.-M. Tikkala. Furthermore, V.-M. Tikkala participated to the process analysis leading to defining the mass balance equations. He also analysed the fault diagnosis results in co-operation with A. Zakharov and participated to the writing of the manuscript.

Publication V: "Monitoring of Caliper Sensor Fouling on a Board Machine Using Self-Organizing Maps"

V.-M. Tikkala developed the monitoring scheme, analysed the data, created the calculated variables, performed the industrial tests, analysed the results, and wrote the manuscript under supervision of S.-L. Jämsä-Jounela.

List of Abbreviations

ACF	Auto-Correlation Function
AEM	Abnormal Event Management
BM	Board Machine
BMU	Best-Matching Unit
CDG	Causal Directed Graph
CTMP	Chemi-ThermoMechanical Pulp
CUSUM	CUMulative SUM
DCDG	Dynamic Causal Directed Graph
DCS	Distributed Control System
DPLS	Dynamic Partial Least Squares
FCDG	Fuzzy Causal Directed Graph
FDD	Fault Detection and Diagnosis
GR	Global Residual
IAE	Integral Absolute Error
ILR	Individual Local Residual
LR	Local Residual
MAD	Median Absolute Deviation
MIMO	Multi-Input Multi-Output
MLR	Multiple Local Residual
MPC	Model-Predictive Control(ler)
NGI	Non-Gaussianity Index
NLI	Non-Linearity Index
PCA	Principal Component Analysis
PLS	Partial Least Squares
QCS	Quality Control System
QTF	Qualitative Transfer Function
RZC	Robust Zero-Crossing method
SDG	Signed Directed Graph
SISO	Single-Input Single-Output
SOM	Self-Organizing Map
TLR	Total Local Residual
WDG	Weighted Directed Graph

1. Introduction

1.1 Background

The increasing complexity of modern production processes, intensifying global competition, and environmental regulations pose remarkable challenges to the operation of production plants. The plants must run safely and efficiently, with minimal disturbances to their operation or in the quality of their products. There is also a constant demand to decrease costs, reduce downtime, and to optimize production.

Improving operations is of particular importance in the papermaking industry which has seen a remarkable transformation of the operating environment in recent years. While some mills are being shut down due to decreasing consumption of paper, the remaining ones are facing challenges to enhance efficiency. Competitiveness in the current markets requires high quality products and high productivity of the paper mills.

An important aspect in improving process operation is the management of abnormal events, such as disturbances, faults, and failures. All of these events can have severe consequences to the production, process equipment and to the environment (Venkatasubramanian, 2010). Moreover, their economic impact can be remarkable; for example Nimmo (1995) has reported that the U.S. petrochemical industry suffers from 10 billion dollar losses annually due to improper abnormal event management (AEM).

In a wider context, AEM is a part of process supervision (Venkatasubramanian *et al.*, 2003c) that aims at showing the present state, indicating undesired or unpermitted states, and taking appropriate actions to avoid damage or accidents, as defined by Isermann (2006). Fault detection and diagnosis (FDD) is an integral part of process supervision, since its objective is the timely detection and determination of the size and location of faults (Isermann & Ballè, 1997). Therefore, FDD provides crucial information for taking corrective actions to adjust the process operation to the fault effects utilizing fault-tolerant control (e.g. Blanke *et al.*, 2003) or maintenance, for instance. In particular, the role of FDD in process supervision has been stressed by Venkatasubramanian *et al.* (2003c), who stated that the next grand challenge of control engineering is to automate these tasks to support process operators.

Automatic fault detection and diagnosis faces, however, significant challenges in modern production plants. Large scale, complexity, and the increased integration of processes impedes the reliable and timely detection of faults. In particular, in the pulp and paper industry, where raw material and water re-circulation is typical, fault effects propagate easily and large parts of a process can be influenced by a fault. Therefore, it is crucial to be able to detect faults at an early stage.

The development of fault detection and diagnosis theory and methods has already been active since the early 1970's (Ding, 2008). As a result, a plethora of detection and diagnosis methods have been developed. Several authors have been reviewed and classified these methods: early reviews of FDD methods have been published for example by Willsky (1976), Himmelblau (1978), Gertler (1988), and Frank (1990) and more recently e.g. by Venkatasubramanian *et al.* (2003c), and Ding (2008).

A comprehensive review by Isermann (2006) considers the fault detection and diagnosis as separate tasks and classifies the corresponding methods according to their characteristics. The methods used for fault detection include limit or trend checking, signal model -based methods, process model -based methods (e.g. Ding, 2008), and multi-variate statistical techniques (e.g. Chiang *et al.*, 2001). The fault diagnosis methods are categorized into classification techniques using, for example, pattern recognition or statistical classifiers, and inference methods based on logic rules or fuzzy and neural reasoning.

Each FDD method has its strengths and weaknesses, and it has been stated that no single method meets the requirements for a good diagnostic system (Dash & Venkatasubramanian, 2000). To overcome the disadvantages, hybrid approaches have been proposed that either combine the results of different methods or combine incomplete process information available from different types of methods (e.g. Chung *et al.*, 1994; Vedam & Venkatasubramanian, 1999; Lee & Yoon, 2001).

Furthermore, the role of process knowledge in the development of successful FDD systems has been stressed. An appropriate FDD method has also to be developed based on the process characteristics and the fault features (Jämsä-Jounela, 2011), as especially in large and complex processes understanding of process characteristics becomes increasingly important. Prasad *et al.* (1998) have classified the types of process knowledge involved in the FDD system development into structural, functional, malfunction, and behavioural knowledge. Structural and functional knowledge are typically formalized as process models to create analytical redundancy, whereas malfunction and behavioural knowledge are used to identify the needs and requirements of an FDD system.

1.2 Research problem and the asserted hypothesis

The main motivation for this thesis is to improve the operation of paperboard making processes by means of automatic fault detection. By developing a fault detection system, the abnormal situations caused by faults can be discovered earlier, which provides a possibility to tackle their effects more effectively and to increase the availability of the process. Generally the plant control system can handle typical disturbances, but in the case of more complex and critical faults, advanced fault detection methods are required.

The main benefits of fault detection and diagnosis are more stable production, improved product quality, the reduction of operation costs, and more efficient and appropriate maintenance. The diagnostic information can be further utilized to make predictions on the future operation of the process and/or to take corrective actions in terms of predictive maintenance or fault-tolerant control, for instance.

The research on FDD methods has been very active already for several decades, but still the literature on applications in process industry is in the minority. Especially, studies on approaching industrial problems in practice and on the utilization of process knowledge in the development phase have been scarce. Typically, the research emphasizes theoretical aspects and the fault detection applications are demonstrated on simulated benchmark problems, instead of industrial processes.

This thesis addresses these issues by creating a methodology for fault detection system development that can be applied to industrial processes. The work focuses particularly on boardmaking processes, which are large and complex systems. The aim is to cover the fault detection of a large-scale process by focusing on the faults that have the most significant effect on the economic performance or operability of the process.

The hypothesis asserted in this thesis is:

> An integrated fault detection system provides an opportunity to improve the operation and performance of a papermaking process through timely detection of faults. The fault detection methods for the system are selected based on fault types obtained from a fault analysis, and integrated to different process control hierarchy levels.

To prove the claims of the hypothesis presented above, the following tasks are carried out during the research:

Task 1. A methodology for the development of a fault detection system for an industrial process is created. The use of the methodology is illustrated on a boardmaking process.

Task 2. A fault analysis is performed on the case process in order to discover the main causes for production losses, to identify the faults having the most significant economic impact, their types and locations as well as to determine the main focus areas for the fault detection system development.

Task 3. The fault detection algorithms are developed for each focus area according to the fault types and their characteristics. In addition, the structure of the process and its control strategy are considered in the development.

Task 4. The developed fault detection system is tested with simulation studies and industrial tests and its performance is evaluated. In addition, the impact of the detection results on process operation is analysed.

1.3 Scope and significance of the thesis work

This thesis addresses the fault detection of an industrial boardmaking process by utilizing both model and data based methods. The main focus is on the methodology development and on the fault detection algorithms for the faults causing production losses and decreasing the performance of the process. The methodology for fault detection system development covers the process decomposition based on knowledge about the structure and control strategy of the process, the fault analysis as well as the development of the fault detection algorithms. Finally, the algorithms are tested and validated using simulations and industrial data.

The main contribution of this thesis is the integrated fault detection system for a boardmaking process which utilizes available process knowledge about the process characteristics and its control strategy. The fault detection system covers the basic control, stabilizing and supervisory control levels of the process control hierarchy by incorporating several fault detection algorithms to address the faults affecting each level. It is developed using the proposed systematic methodology that involves process decomposition and fault analysis to identify the focus areas of fault detection.

The contribution and novelty of this thesis are also demonstrated in the publications presenting the applications of the individual fault detection modules included in the overall fault detection system development. Publication I proposes a system for valve stiction detection that employs several different stiction detection algorithms in parallel, and a decision fusion technique to combine their results. Publication II presents a new method for detecting non-stationary oscillations. The method uses robust statistics to address noise and uncertainties related to industrial processes and a procedure to stationarize the analysed signals before oscillation detection is performed. Publication III proposes an enhanced dynamic causal digraph method and presents its application on the board machine to detect consistency sensor malfunctions. Publication IV deals with a non-linear parity equation method based on grey-box modelling which utilizes structural process knowledge to reduce the dimensionality of the process non-linearities. The method is applied to detection of leakage and blockage faults in the drying section of the process. Publication V presents a process monitoring application based on self-organizing maps to detect caliper sensor fouling. The self-organizing map method is adapted to the case by creating calculated variables to describe the chemical phenomena involved in fouling and by taking into account the time-variant nature of the process.

Outside of the thesis scope are root cause analysis, fault accommodation using fault-tolerant control or corrective actions as well as the software engineering aspects of the system implementation at a plant.

1.4 Outline of the thesis

This thesis is organized as follows. First, Chapter 2 presents the state-of-the-art of the fault detection methods addressed in this thesis in addition to a brief introduction to the field of fault detection and diagnosis in general. Next, the methodology for developing fault detection systems is outlined in Chapter 3. The paperboard making process and its control strategy are described in Chapter 4. Then, Chapter 5 presents the development of an integrated fault detection system for the case process. Chapter 6 summarizes the detection results obtained in the application of each developed fault detection algorithm, followed by concluding remarks and possible future research directions in Chapter 7.

2. Fault Detection in Process Systems; State-of-the-art

This chapter presents the state-of-the-art of fault detection in process systems. First, the general concepts, definitions, and the classification of fault detection and diagnosis methods are briefly described. Next, a survey of the relevant literature on the detection methods addressed in this thesis is presented.

2.1 Introduction to fault detection and diagnosis

Fault diagnosis is a part of the supervision of technical systems which aims at showing the present state, indicating undesired or unpermitted states, and taking appropriate actions to avoid damage or accidents (Isermann, 2006). In the general scheme of supervision, fault diagnosis aims at determining the presence of a fault as well as its type, location, size, and cause, see Figure 2.1. This information is crucial in order to deliver a corrective action to the process in terms of maintenance or fault-tolerant control (e.g. Blanke *et al.*, 2003), for instance.

According to the definitions by Isermann & Ballè (1997), the fault detection task consists of the determination of presence and time of detection, whereas the fault diagnosis task consists of the determination of type, position, size and cause of the fault. In literature, fault diagnosis has sometimes been further divided into two subtasks: fault isolation and fault identification, where fault isolation involves the determination of kind and location of the fault and fault identification means the determination of the size and time-variant behaviour of the fault. The scheme presented in Figure 2.1 describes the steps of FDD and the refinement of information in each step of the procedure (Isermann, 2006).

The first step, preceding fault detection, in the procedure is the feature generation in which the available signals from a plant, namely input, out-

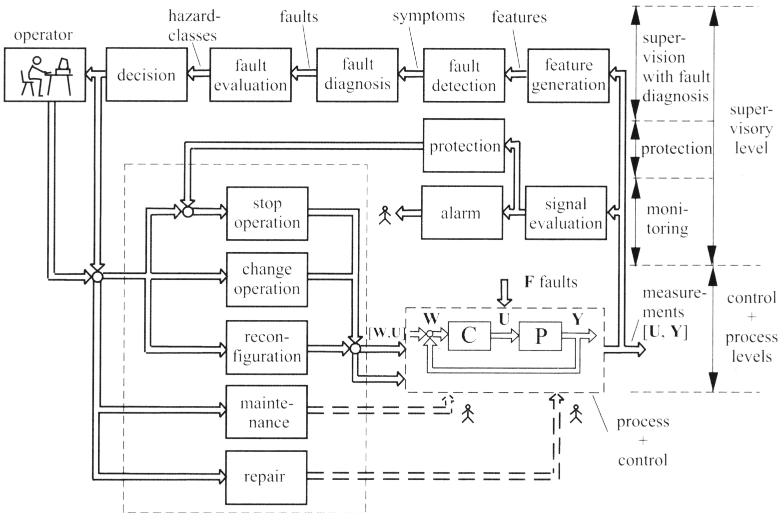

Figure 2.1. General scheme of supervision of technical systems (Isermann, 2006)

put, and state variables, are analyzed and the information is consolidated by means of various signal- or model-based methods. The features can be process parameters (e.g. friction coefficient, inductance), process states (e.g. pressure, a flow rate) or residuals.

Fault detection uses the features to decide whether a fault is present in the system or not. In this step, the features are compared with their nominal values and a fault is detected if the deviations exceed the specific thresholds. Fault detection results in symptoms for fault diagnosis purposes.

Finally, in the fault diagnosis step the symptoms are evaluated and a decision of the fault type and location can be made. The fault is diagnosed using the classification of symptoms or the inference techniques.

Fault detection can be achieved by utilizing either hardware redundancy or analytical redundancy (Gertler, 1998). The hardware redundancy refers to the parallel operation of identical hardware elements (Muenchhof *et al.*, 2009). For instance, three sensors are used for the same measurement and the values are statistically compared. The application of hardware redundancy is limited to very critical units due to its high cost. Analytical redundancy, on which this thesis solely focuses, refers to the comparison of plant behaviour with analytically computed behaviour using, for example, mathematical models .

Fault detection and diagnosis methods have been comprehensively surveyed and classified by Venkatasubramanian *et al.* (2003c,a,b) and Iser-

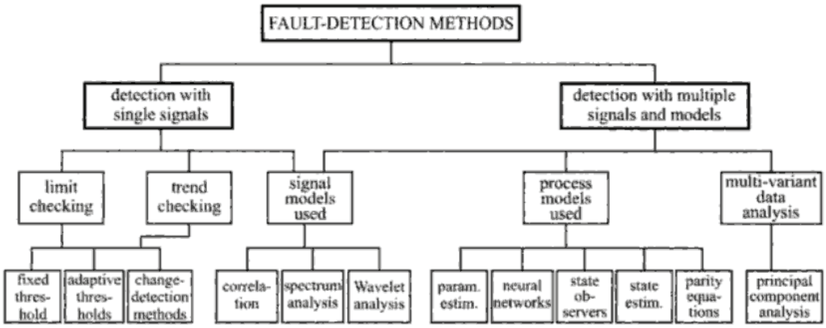

Figure 2.2. Classification of fault detection methods by Isermann (2006)

mann (2006, 2011). Here, the discussion follows the Isermann's classification in which the fault detection and diagnosis are addressed separately, as illustrated by Figures 2.2 and 2.3.

The fault detection methods are classified into limit or trend checking, signal model -based methods, process model -based methods, and multivariate statistical techniques. The limit and trend checking methods analyse individual measurement signals using fixed or adaptive thresholds, and change detection methods. The signal model-based methods can be applied to individual or multiple signals and comprise correlation, spectrum or wavelet analyses (see Isermann, 2011). The process model -based methods represent the largest category of fault detection methods and it includes the classical observer methods, state and parameter estimation techniques, parity equations, and neural networks. Finally, the category of multi-variate data-based methods includes, for example, principal component analysis (PCA) and partial least squares (PLS) and their extensions.

Isermann categorizes the fault diagnosis methods into classification and inference methods. The classification methods include pattern recognition techniques, statistical, polynomial and geometrical classifiers, and artificial intelligence methods, such as fuzzy and neural net classifiers. Classification methods are typically used when no structural knowledge between the faults and symptoms is available. In such cases, the reference symptoms for the faults are determined by training and learning (Isermann, 2006). By contrast, if structural knowledge is available, the symptoms can be related to the faults by using inference methods. The common inference methods include binary and approximate reasoning techniques.

However, none of the aforementioned fault detection and diagnosis methods are however sufficient alone to achieve effective diagnosis since all

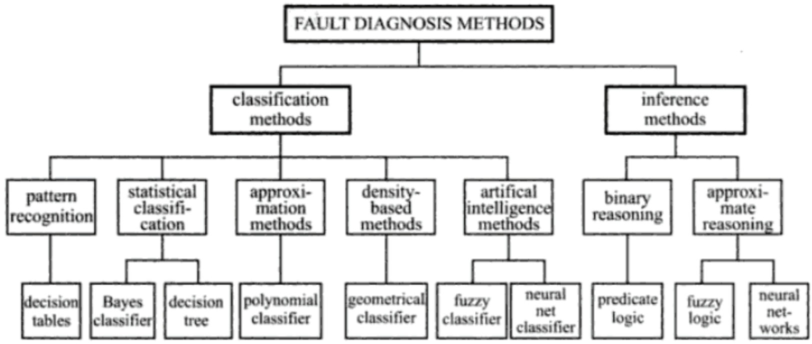

Figure 2.3. Classification of fault diagnosis methods by Isermann (2006)

methods have their characteristic strengths and weaknesses (Dinkar & Venkatasubramanian, 1997; Dash & Venkatasubramanian, 2000). As a solution, hybrid approaches that combine different methods have been developed. Thus, the weaknesses of individual methods can be compensated and more accurate diagnosis results obtained.

A hybrid FDD method can be developed in two ways. The first way is to operate several methods in parallel and then fuse the results of the individual methods in order to conclude a final decision. The second way is to combine the features generated by different methods and thereby combine different types of process knowledge such as model-based and data-based knowledge. (Dinkar, 1996).

The applications of hybrid FDD approaches to chemical processes have been published increasingly in the recent years, with especially the use of qualitative process models, such as signed digraphs (see Section 2.2.2) together with data-based methods, being particularly prominent. Lee *et al.* (2003) have presented an application of SDGs and dynamic PLS to diagnose multiple faults in a stirred tank reactor. The SDG has been also combined with dynamic kernel PLS and support vector regression (Lü & Wang, 2008) as well as qualitative trend analysis (Maurya *et al.*, 2007). Also, the neural networks have been utilized extensively in hybrid FDD systems. Applications to chemical plants have been presented, for example, by Becraft & Lee (1993), who combined the neural networks with an expert system, and Ruiz *et al.* (2001), who proposed a combination of them and fuzzy logic.

Although the hybrid approaches are more appropriate than the typical diagnosis methods, they do not address the size-related issues of large-scale process systems. Therefore, process decomposition based strategies have been introduced to address these issues, thus enabling adaptability and enhancing online detection and diagnosis. Such a strategy is referred to as a bottom-up strategy which consists of the analysis of each subsystem using lower level abstraction and combining their results via high level supervision to achieve a final diagnostic decision Lee & Yoon (2001).

The following sections present fault detection methods from the categories shown in Figure 2.2 and surveys the related literature. First, the model-based methods are addressed by describing the parity equation and the causal digraph methods. Next, the self-organizing map is discussed, which represents the data-based fault detection methods. Finally, the signal-based methods are dealt with by introducing detection methods for oscillations and valve stiction. The presented methods are selected due to their importance and relevance to the integrated fault detection system which will be described later in this thesis.

2.2 Model-based fault detection methods

2.2.1 Parity equation method

The parity equation method is one of the earliest approaches for fault detection in technical systems. It is a model-based technique which exploits the analytical redundancy principle; Figure 2.4 illustrates the method in which a redundant process model is utilized to generate residuals by comparing its output with the actual process measurement. The residuals are then evaluated for discrepancies caused by faults in the system.

According to Gertler (1998), the parity equation method was developed in the field of aerospace research in the mid-1970's. The first major contribution is considered to be the theoretical formulation by Chow & Willsky (1984), who presented the parity equation method for state-space models, called the parity space method. Other parallel developments were presented by Ben-Haim (1980), who utilized redundant balance equations for fault detection in nuclear systems. Later, the parity equation method has also been formulated for input-output models (Gertler & Singer, 1985). The parity space method for continuous time systems has also been presented by Medvedev (1995).

According to Isermann (2006), for a single-input single-output (SISO) process the parity equation can be written in its computational form using

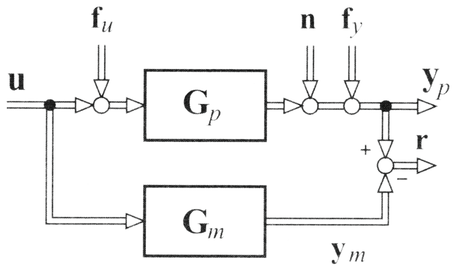

Figure 2.4. Fault detection with parity equations using transfer functions (Isermann, 2006)

transfer function notation as:

$$r(s) = y_p(s) - y_m(s) = y_p(s) - G_m(s)u(s), \tag{2.1}$$

where $y_p(s) = G_p(s)u(s)$ is the process output, $G_p(s)$ being the transfer function of the process, and $y_m(s) = G_m(s)u(s)$ is the model output, $G_m(s)$ being the process model. The process model is assumed to be known and has known, fixed parameters, such that:

$$G_p(s) = G_m(s) + \Delta G_m(s), \tag{2.2}$$

where $\Delta G_m(s)$ describes the model errors. By following the scheme presented in Figure 2.4, the parity equation $r(s)$ can also be written as:

$$r(s) = G_p(s)[u(s) + f_u(s)] + n(s) + f_y(s) - G_m(s)u(s), \tag{2.3}$$

where $f_u(s)$ and $f_y(s)$ are the input and output faults, respectively and $n(s)$ is noise. Substitution of (2.2) to the above yields:

$$r(s) = \Delta G_m(s)u(s) + G_p(s)f_u(s) + n(s) + f_y(s), \tag{2.4}$$

which indicates the dependability of the parity equation of additive input and output faults, the noise and model errors. Unfortunately, in the SISO case, these effects cannot be separated.

The parity equation can also be written for a multi-input multi-output (MIMO) process:

$$\mathbf{r}(s) = \Delta\mathbf{G}_m(s)\mathbf{u}(s) + \mathbf{G}_p(s)\mathbf{f}_u(s) + \mathbf{n}(s) + \mathbf{f}_y(s). \tag{2.5}$$

In the MIMO case, assuming only single input or single output faults, some elements of $\mathbf{r}(s)$ deviate differently and some do not, which makes the separation or isolation of the faults possible. These residual patterns are known as fault signatures and the approach is called structured residuals (Gertler, 1998). Gertler and co-workers have studied comprehensively the isolation ability and the optimality of the residuals (Gertler & Luo, 1989; Gertler & Kunwer, 1995; Gertler & Singer, 1990).

The parity equation method has been also developed to detect faults in non-linear systems. Guernez *et al.* (1997) presented an extension to non-linear polynomial dynamic systems and later Yu & Shields (2001) extended the method also to bilinear systems. By utilizing fuzzy parity equations, Ballé (1999) addressed the fault detection of a non-linear thermal plant. Gertler & Staroswiecki (2002) showed the connections between the parity space and input-output formulations and presented a design technique for parity equation-based residual generation involving mild non-linearities in inputs, outputs, and faults. Fully decoupled parity equations, i.e. the residuals are decoupled from the system states and unknown non-linearity, were developed by Chan *et al.* (2006). Recently, the parity equation method has been extended by Blesa *et al.* (2012) to linear parameter-varying systems to address non-linear behaviour. Furthermore, it is stated by Isermann (2006) that the computational form of a parity equation (2.1) can be extended to any non-linear process model.

Other important developments involve robust parity equations for uncertain systems in which model uncertainty is addressed by interval Ploix & Adrot (2006); Puig & Blesa (2013) or fuzzy techniques (Puig & Quevedo, 2002). Furthermore, adaptive parity equations have been presented by Höfling & Isermann (1996), who utilized single-parameter tracking by recursive system identification to adapt to changing process conditions.

2.2.2 Causal digraph methods

Causal digraph (CDG) based fault detection and diagnosis methods are based on process models formalized as directed graphs, or digraphs for short (Harary *et al.*, 1965). In these methods, the causal relationships, i.e. the arcs between nodes, are described by mathematical models and the consistency between the models with respect to the process is utilized for fault detection. The CDG based methods belong to model-based fault detection methods and can be divided into three main categories based on the mathematical techniques they utilize to describe the process variables and the causal relationships: signed digraphs (SDG), fuzzy causal digraphs (FCDG) and dynamic causal digraphs (DCDG).

The first reported application of a causal digraph method for FDD was by Iri *et al.* (1979) who introduced the signed digraph (SDG) method. In the SDG the causal effects are described with positive (+) and negative (−) effects and the states of the variables as ”+”, ”0” or ”-” for high, normal and low value, respectively. The diagnosis in (Iri *et al.*, 1979) was carried out by using the depth-first graph search algorithm proposed by Tarjan (1972).

In order to increase the diagnosis resolution of the SDG, Shiozaki *et al.* (1984) introduced a five-range pattern (+, +?, 0 , -?, -) of abnormality instead of the original three-range one. By this improvement, the number of false diagnosis results could be decreased. A further improvement to fault diagnosis resolution of SDG was presented by Palowitch & Kramer (1985), who introduced numerical deviation indices to measure the deviation of variable values from a steady-state. Also Chang & Yu (1990) proposed a solution to improve the fault diagnosis resolution by considering the steady-state gains within the process to find the dominant fault propagation path among multiple paths. Moreover, the resolution of the SDG method has been improved by introducing composite arcs (Kramer & Palowitch, 1987), by describing inverse and compensatory responses using the extended SDG (Oyeleye & Kramer, 1988), and by the Path-SDG method (Mohindra & Clark, 1993).

Umeda *et al.* (1980) were the first researchers to consider temporal information within the signed digraph methods. They considered the nodes of a SDG as variables in different time increments and as a result faults could also be detected during transient periods. Later, Chang & Yu (1990) proposed to discretize the process behavior into transient and steady state behavior and to use different detection rules for both states in order to determine the consistency of the arcs. Vianna & McGreavy (1995) introduced a weighted digraph (WDG) which contained information on the dynamic phenomena of the process in terms of differential nodes connected by temporal arcs (arcs representing the dynamics of the system) and of algebraic nodes to represent the state of the process.

Fault diagnosis using SDGs in the early applications was based on an assumption that a single fault is present at a time. This assumption led to incomplete diagnosis in the case of multiple faults. This problem was addressed by Finch *et al.* (1990), who introduced an additional arc called an induced failure link, which allowed the diagnosis of one fault and the expected induced faults. A more complete analysis of multiple faults was given later by Lee *et al.* (1999). Another approach to multiple fault diagnosis utilizing distributed diagnosis was proposed in (Lee *et al.*, 2003), where SDGs and dynamic PLS (DPLS) were combined. Locally constructed DPLS models were used to detect the fault and then the SDG was used to locate the fault origin. Wan *et al.* (2013) proposed a combined method in which SDG was used to derive a set of fault candidates and dynamic PCA to refine the set in order to diagnose the fault.

The causal digraph based FDD methods are naturally suitable for large-scale systems, since they contain information on the structure of the system. Distributed fault diagnosis approaches utilizing SDGs have been proposed e.g. by Mohindra & Clark (1993) and Lee *et al.* (1997). A two-tier strategy for the fault diagnosis of large-scale systems was presented by Tarifa & Scenna (1998a,b) who used SDGs along with fuzzy logic to detect faults in a multi-stage flash desalination process. Lee & Yoon (2001) proposed a decomposition strategy for a SDG-based fault diagnosis of large-scale systems and applied it to a boiler plant. Also, Maurya *et al.* (2004) addressed FDD in large-scale systems. They proposed to use redundant equations based on for example mass or energy balances in conjunction with an SDG in order to reduce the number of spurious diagnosis results.

The first step towards fuzzy causal digraph (FCDG) methods was taken in (Yu & Lee, 1991), where a membership function approach was adopted to combine the quantitative and qualitative representations for the cause-effect models (arcs of the digraph). They introduced steady-state gains to the arcs in terms of fuzzy sets. As a result, the fault diagnosis resolution was improved by eliminating spurious solutions and the method was extended to cover multiple fault situations. Han *et al.* (1994) expanded the idea by introducing fuzzy sets to describe also the variable states. However, the actual fuzzy causal digraph method was proposed later by Shih & Lee (1995a,b). They expressed the states of the variables with fuzzy sets and additionally used dynamic constraints called confluences to express the dynamic gain between variables.

The amount of quantitative information used in the causal digraph models has increased constantly along the development of these methods. The first step towards dynamic CDG methods was presented by Leyval *et al.* (1994), who introduced a concept of a qualitative transfer function (QTF) to describe the cause-effect relationships between variables. Montmain & Gentil (2000) extended this approach to use quantitative dynamic models, namely difference equations, to model the cause-effect relationships and provided a detailed discussion on the generation of residuals with the causal structure.

The dynamic causal digraph produced two kinds of residual to be used for fault detection and isolation: global (GR) and local residuals (LR). The global residual was produced from the difference between the measurement and the global propagation value:

$$GR(Y) = Y(k) - \hat{Y}(k), \tag{2.6}$$

where $Y(k)$ is the measurement and $\hat{Y}(k)$ is the global propagation value obtained by:

$$\hat{Y}(k) = f_Y\left(\hat{U}(k-1), \hat{U}(k-2), \ldots\right), \tag{2.7}$$

where f_Y is a discrete-time model describing the cause-effect relationship from n predecessor nodes U_i to node Y. $\hat{U}(k-\tau) = \{\hat{u}_1(k-\tau), \ldots, \hat{u}_n(k-\tau)\}$ are the lagged global propagation values from the predecessors with time lags $\tau = 1, 2, \ldots$ depending on the system order.

The local residuals were subcategorized into three types: individual local residuals (ILR), multiple local residuals (MLR) and total local residuals (TLR) (Montmain & Gentil, 2000). The individual local residual was produced by taking the difference between the measurement and the local propagation value using only one measured input, while all the others are propagation values from the parent nodes:

$$\begin{aligned} ILR_Y^m &= Y - \bar{Y}, \\ \bar{Y}(k) &= f_Y\left(\bar{U}(m, k-1), \bar{U}(m, k-2), \ldots\right), \end{aligned} \tag{2.8}$$

where

$$\bar{U}(m, k-\tau) = \left\{ \bar{u}_i(k-\tau) \middle| \bar{u}_i(k-\tau) = \begin{cases} \hat{u}_i(k-\tau), i \neq m \\ u_i(k-\tau), i = m \end{cases}, 1 \leq i \leq n \right\}, \tag{2.9}$$

$\hat{u}_i(k)$ is the lagged global propagated value from the predecessors, and $u_i(k-\tau)$ is the measurement for the i-th parent node. Similarly, the $MLR_Y^{P_Y^l}$ was produced as:

$$\begin{aligned} MLR_Y^{P_Y^l} &= Y - \bar{Y}, \\ \bar{Y}(k) &= f_Y\left(\bar{U}(P_Y^l, k-1), \bar{U}(P_Y^l, k-2), \ldots\right), \end{aligned} \tag{2.10}$$

where

$$\bar{U}(P_Y^l, k-\tau) = \left\{ \bar{u}_i(k-\tau) \middle| \bar{u}_i(k-\tau) = \begin{cases} \hat{u}_i(k-\tau), i \notin P_Y^l \\ u_i(k-\tau), i \in P_Y^l \end{cases}, 1 \leq i \leq n \right\}, \tag{2.11}$$

P_Y^l is the set of indices of the predecessors which used the measurement as an input. The $TLR(Y)$ is produced with $P_Y^l = P_Y$, where P_Y is the set of indices of all the predecessors of Y.

The cumulative sum (CUSUM) method (Hinkley, 1971) was used to evaluate the residual signals in order to detect a change in the signal, which would indicate a fault in the process. Later, other applications have been presented, where the use of e.g. state-space models (Cheng *et al.*, 2008) and non-linear differential equations (Vadam *et al.*, 1997) have been demonstrated.

The use of dynamic models to describe the cause-effect models has advanced the development of new inference mechanisms for fault diagnosis purposes. In the SDG and FCDG methods, the fault origin nodes have been located mainly by applying graph search methods, while using the DCDGs inference methods based on different types of quantitative residuals can be used. The concept of this approach was first introduced by Kramer (1987), who called this the general diagnostic framework. He, however, did not differentiate between the model types to be used to describe the causal relationships. Later, Montmain & Gentil (2000) provided an analysis of using this approach with dynamic causal digraph models. Cheng *et al.* (2008) presented an additional step to the diagnosis, where additional process knowledge was used to refine the results of causal inference.

The fault isolation using the DCDG method is based on the residuals represented by the equations above. Tables 2.1 and 2.2 describe the inference rules which are used to evaluate the CUSUM calculation results of different types of residuals, denoted by $CU(r)$, where r is a residual signal. By applying the rules to each detected residual, the fault can be isolated and its propagation path extracted.

Table 2.1. Fault isolation rules of the dynamic causal digraph

$CU(GR(Y))$	$CU(TLR(Y))$	$CU(ILR_Y(m))$	$CU(ILR_Y(i))$	$CU(MLR_Y(P_1))$	$CU(MLR_Y(P_2))$	Decision
0	0	0	0	0	0	No fault
1/-1	0	0*	1/-1*	0*	1/-1*	Fault propagates from the parent node m
1/-1	0	1/-1**	1/-1**	1/-1**	0**	Fault propagates from the nodes with subscript P_2
1/-1	1/-1	1/-1	1/-1	1/-1	1/-1	Local fault on variable Y

* $\forall i \neq m, i \in P_Y, m \in P_1, m \notin P_2$, P_Y is the set of subscripts of parent nodes of the node Y.
** $\forall i, m, i \in P_Y, m \in P_Y, \forall P_1, P_2 \subseteq P_Y$.

Table 2.2. Fault type rules of the dynamic causal digraph

$CU(GR(X))^*$	$CU(TLR(X))$	Fault nature
1/-1	1/-1	Local fault for that child node
1/-1	0	Process fault for the faulty node
0	1/-1	Measurement fault for the faulty node

* X is the subscript of any child node of the node Y.

2.3 Data-based fault detection using self-organizing maps

A self-organizing map, proposed by Kohonen (1982, 1998), is a type of artificial neural network that is trained using unsupervised learning to produce a low-dimensional representation of the input space of the training samples. The SOM produces a similarity graph of the input data, called a map, by converting the nonlinear statistical relationships between high-dimensional data into simple geometric relationships on a low-dimensional display, usually a two-dimensional grid of nodes. Therefore, the SOM compresses the data, but preserves their topological properties (Kohonen, 2001). The SOM is essentially a classification method and it belongs to the category of artificial intelligence methods in Figure 2.3.

A SOM consists of a number of nodes described with a d-dimensional weight vector $\mathbf{w}_i = [w_1\, w_2\, \ldots w_d]$. The SOM is trained by adapting the weights of the nodes to match the input data. Training consists of the search of the closest map units, called the best-matching units (BMU), of the data samples and then the update of the weight vector of the BMU and its neighbouring nodes. A BMU c is determined for a data sample $\mathbf{x} \in R^d$ as follows:

$$||\mathbf{x} - \mathbf{w}_c|| = \min_i ||\mathbf{x} - \mathbf{w}_i||, \quad i = 1, 2, \ldots, m \tag{2.12}$$

where $||\cdot||$ is Euclidean distance and m is the number of map nodes. The weight vector of the BMU and the neighbouring nodes are updated according to an update rule:

$$\mathbf{w}_i(t+1) = \mathbf{w}_i(t) + \alpha(t) h_{ci}(t)[\mathbf{x}(t) - \mathbf{w}_i(t)], \tag{2.13}$$

where t denotes time, $h_{ci}(t)$ is the neighbourhood kernel around the BMU and $\alpha(t)$ is the learning rate. In the batch training procedure the BMUs are calculated first for the whole data set, and then the weights are updated at once as follows:

$$\mathbf{w}_i(t+1) = \frac{\sum_{j=1}^{m} h_{ij}(t)\mathbf{s}_j(t)}{\sum_{j=1}^{m} n_{V_j}(t) h_{ij}(t)}, \quad \mathbf{s}_i(t) = \sum_{j=1}^{n_{V_i}} \mathbf{x}_j, \tag{2.14}$$

where n_{V_i} is the number of samples in the Voronoi set of the node i.

The SOM theory has been extensively studied and a large number of modifications and extensions have been proposed (Kangas & Kaski, 1998). One of these modifications is the adaptive subspace SOM, which can recognize changing patterns based on their invariant features described for example by linear subspaces (Kohonen, 2001). Another improvement, which addresses changing input information, is the feedback-SOM developed by Horio & Yamakawa (2001). Shah-Hosseini & Safabakhsh (2003) introduced the time-adaptive SOM, which adapts the learning rates and neighbourhood function radii during the training phase. Another branch of SOM evolution deals with hierarchical SOMs that consist of network of SOMs instead of individual nodes. The concept was first proposed by Simula *et al.* (1996) and later studied and formalized in detail by Furukawa (2009).

The self-organizing map has a vast number of applications in the field of computer science, such as visualization or pattern recognition. However, this survey concentrates on process industry applications, which typically include data analysis and process monitoring approaches. The SOMs have been applied to process analysis and the development of new control strategies (Corona *et al.*, 2010), product quality estimation and process optimization (Abonyi *et al.*, 2003), and to the modelling of a fluidized bed combustion process and its emissions, for instance (Liukkonen *et al.*, 2011). Next, some process monitoring case studies are introduced.

The SOM has been applied to monitoring of pulp quality in a continuous digester (Ahola *et al.*, 1999), the conditions of a steelmaking process, process states (Cuadrado *et al.*, 2002) and progress of a nuclear power plant (Hakala *et al.*, 2006), and of paper quality (Lampinen & Taipale, 1994). In all of these applications, the basic SOM was trained with process data and the regions of different process states were identified. Then, the state of the process was visualized on the map and its progress was followed.

In order to improve the separation of different process conditions, López Garciá & Machón González (2004) utilized k-means clustering. Following a regular SOM training phase, they divided the map nodes into clusters representing different process states using the k-means method. As a result, the classification of the process states of a wastewater treatment process was improved. A similar approach has been utilized by Liukkonen *et al.* (2009) to the analysis of a wave soldering process and by Heikkinen *et al.* (2011) to also study wastewaster treatment.

The SOM has been also combined with several other methods for process monitoring purposes. Kämpjärvi *et al.* (2008) proposed a monitoring system for an ethylene cracking process, combining PCA, a radial basis function network, and a SOM. The system incorporated a SOM for which the input data was transformed with PCA to capture only the most significant process variation. The radial basis function network was used in parallel to SOM to allow more accurate fault detection. The PCA pretreatment for SOM has been also used by Bouhouche *et al.* (2011) for monitoring of a metal production process. Fuertes *et al.* (2010) proposed a supervision and fault detection scheme based on observing the process state transitions using a SOM in conjunction with Petri nets and Markov chains to analysis the state transition probabilities. Aldrich *et al.* (1995) addressed the monitoring and control of a flotation process using the SOM and an adaptive neural net system, while Jämsä-Jounela *et al.* (2003) monitored a copper smelter using the SOM and heuristic rules for fault diagnosis purposes. Chen & Yan (2012) have applied SOM accompanied by correlative component analysis and later in Chen & Yan (2013) by Fisher discriminant analysis to Tennessee-Eastman process.

2.4 Signal-based fault detection methods

The signal-based fault detection methods presented in this section cover the methods for oscillation and valve stiction detection. Persistent oscillations and valve stiction are common problems in process plants and they cause inefficient operation and production losses; oscillatory disturbances readily propagate in processes and cause excessive variation in process variables as well as in product quality.

The oscillations in process plants are typically originated under feedback control (Desborough & Miller, 2001; Ender, 1993) and they may have various causes, which have been categorized by Thornhill & Horch (2007) into non-linear and linear causes. The non-linear causes include for example extensive static friction in the control valves, on-off or split-range control, sensor faults, process non-linearities, and hydrodynamic instabilities. The most common linear causes are poor controller tuning, controller interactions, and structural problems involving process recycles (Thornhill & Horch, 2007). Nevertheless, according to Choudhury *et al.* (2008b), excessive static friction (stiction) in valves is the most common cause of oscillatory control loops.

2.4.1 Oscillation detection methods

The research on oscillation detection originates from control loop performance analysis (see e.g. Qin (1998); Shardt *et al.* (2012)). Excessive oscillations are a significant problem in control loops, and therefore a number of methods have been developed to detect them, see e.g. Choudhury *et al.* (2008b) and (Horch, 2006a). The methods for oscillation detection can be classified into four categories: time-domain methods, auto-covariance function methods, spectral methods, and multivariate methods.

The earliest oscillation detection approaches were based on the time-domain properties of signals. One of the first methods developed by Hägglund (1995) utilized the integral absolute error (IAE) of a control error signal detect the oscillation:

$$IAE = \int_{t_{i-1}}^{t_i} |e(t)|dt, \tag{2.15}$$

where t_{i-1} and t_i are two consecutive instances of zero-crossings. If the IAE of a control error signal exceeds a certain limit IAE_{lim} frequently over a supervision period, an oscillation is detected. Further discussion on the industrial implementation of the IAE method has been presented by Hägglund (2005).

Thornhill & Hägglund (1997) proposed another IAE-based method with a similar approach as both methods studied the IAE between consecutive zero-crossings. If the IAE was found to exceed a pre-set limit, they studied the regularity of the periods using a regularity factor:

$$q = \frac{\text{mean}(R_{i+1})}{\text{std}(R_i)}, \tag{2.16}$$

where $R_i = \Delta t_{i+1}/\Delta t_i$ is the ratio between adjacent zero-crossing intervals Δt. If $q < 1.3$, an oscillation was detected. The Hägglund's original IAE method was improved by Forsman & Stattin (1999) who proposed consideration of the upper and lower IAEs separately in order to address the detection of asymmetric oscillations.

Another type of time-domain method was published by Salsbury & Singhal (2005) whose approach utilized the estimation of ARMA-models based on zero-crossings of a signal. The presence of oscillations could then be determined from the roots of characteristic equations. Time-domain analysis of signals was also exploited by Srinivasan *et al.* (2007) who extracted the dominant oscillation modes of a signal using empirical mode decomposition in order to detect oscillations. Xia & Howell (2003) proposed an overall control loop performance index which incorporated oscillation detection based on the signal-to-noise ratios of controller signals and process noise.

The time-domain methods also comprise the auto-covariance function (ACF) based methods. Miao & Seborg (1999) proposed a method based on the decay ratio of an ACF, which measures the attenuation of an oscillation, for the detection task. The decay ratio is defined as $R = a/b$, where a is the distance from the first maximum to the straight line connecting the first two minima of the ACF, and b is the distance from the first minimum and to the straight line that connects the the zero-lag auto-correlation coefficient and the first maximum. In case the decay ratio exceeds 0.5, the presence of an oscillation is determined.

The ACF method by Thornhill *et al.* (2003b) detects the oscillations by means of the regularity of zero-crossings in a filtered ACF and is capable of detecting multiple oscillations with different frequencies. The oscillation regularity is measured using the following statistic:

$$r = \frac{1}{3} \times \frac{\bar{T_p}}{\sigma_{T_p}}, \tag{2.17}$$

where $\bar{T_p}$ and σ_{T_p} are the mean and standard deviation of time between zero-crossings, respectively. Values of $r > 1$ indicate the presence of an oscillation.

Due to their periodic nature, oscillatory signals have been widely detected by utilizing spectral analysis. Thornhill *et al.* (2003a) proposed to seek significant peaks in a signal's power spectrum to detect oscillations. The spectral content of a signal is also exploited in a method by Jiang *et al.* (2007) who utilized the spectral envelope and statistical hypothesis tests. Li *et al.* (2010) proposed a method which decomposes signals into components using discrete cosine transform and detects the oscillation by studying the regularity of zero-crossings of the different frequency components. Improvements to their method were published in (Wang *et al.*, 2013). Signal decomposition has also been utilized by Srinivasan & Rengaswamy (2012), who proposed a empirical mode decomposition method which was capable to detect multiple oscillations.

The multivariate oscillation detection methods have proven to be particularly efficient in the analysis of plant-wide disturbances (Thornhill & Horch, 2007) and they also include time domain and frequency domain techniques. A time domain approach using multivariate autoregressive analysis was proposed by Saarela (2002) in which the prediction errors of linear autoregressive models were used to analyse oscillatory signals. This approach has been implemented into process analysis software presented in (Ritala, 1993). The frequency domain methods typically utilize different decompositions of the power spectral matrix of process measurements. Thornhill *et al.* (2002) presented an application of principal component analysis on the spectral matrix. Other matrix decomposition techniques, such as non-negative matrix factorization Xia *et al.* (2007); Tangirala *et al.* (2007) and independent component analysis (Xia *et al.*, 2005; Xia & Howell, 2005) have been applied to detect plant-wide oscillations. In addition, the spectral envelope method (Jiang *et al.*, 2007) has been applied to solve the oscillation detection task involving multiple signals.

In addition, wavelet analysis has been used for oscillation detection. Matsuo *et al.* (2003) developed a method which allows detecting multiple oscillations with different frequencies, also in non-stationary signals.

2.4.2 Valve stiction detection methods

Valve stiction detection methods are typically applied in conjunction with oscillation detection to verify whether the oscillation is caused by a faulty valve in the loop or by an external disturbance. Stiction, as defined by Choudhury *et al.* (2008a), refers to excessive static friction in valves that generates a stick-slip motion of the valve stem. This behaviour results typically in oscillations that propagate in the process and disturb the operation.

Fault detection and diagnosis in valves is typically based on supervision of the available measured variables (Isermann, 2011). Therefore, most methods can only detect the presence of a specific fault type. To avoid this limitation, special sensors can be installed in valves.

Kano *et al.* (2004) utilized special sensors installed on valves to detect valve stiction using the measurement information about the valve position and controller output. However, due to economic or operational issues these sensors are rarely used in industrial plants and the research interest has focused on methods that exploit the standard control-related signals and their characteristics. These methods have been extensively reviewed for example by Jelali & Huang (2010) and Choudhury *et al.* (2008b). Comparative studies have been given by Rossi & Scali (2005), Horch (2006a), and Jelali & Scali (2010).

The stiction diagnosis methods can be categorised into two basic types based on the information they utilize: signal-based methods and model-based methods. The signal based methods consider the controller output and process measurement signals and their key characteristics, whereas the model based methods use first-principle models or system identification techniques to diagnose sticky valves.

The signal-based methods can be further classified into shape-based methods and nonlinearity methods, from which the shape-based methods have been the most popular. There are however some methods outside of these groups, such as the cross-correlation method by Horch (1999).

The shape-based methods study the distinctive characteristics of oscillations induced by stiction. He *et al.* (2007) proposed a stiction index I_C based on a curve fitting approach that compares the fitting errors of sinusoidal and triangular signal shapes:

$$I_C = \frac{MSE_{sin}}{MSE_{sin} + MSE_{tri}}, \tag{2.18}$$

where MSE refers to mean squared error of fitting. When I_C with values close to 0 this indicate non-stiction while I_C values close to 1 indicate strong stiction. When $I_C = 0.5$ the method is unable to determine or rule out the presence of stiction. Triangular function fitting was also used by Scali & Ghelardoni (2008), who compared the shapes generated by stiction and relay control.

Another similar approach was adopted by Hägglund (2011) who used the fitting of a rectangular function to the control error signal to determine stiction. The stiction index I_R is defined as:

$$I_R = \frac{V_{sine} - V_{square}}{V_{sine} + V_{square}}, \tag{2.19}$$

where the loss functions V_{sine} and V_{square} (for a positive half-period) are defined as follows:

$$V_{sine} = \sum_{i=1}^{n} \left(e(t_i) - a_{sine} \sin\left(\frac{2\pi}{T_p} ih\right)\right)^2 \tag{2.20}$$

and

$$V_{square} = \sum_{i=1}^{n} \left(e(t_i) - a_{sine}\right)^2, \tag{2.21}$$

where h is the sampling period $e(t_i)$ is the control error signal, T_p is the oscillation period calculated based on zero-crossings, and n is the number of samples in the interval between zero crossings. The index I_R can have values between -1 and 1, with positive values indicating stiction.

Instead of the shape of a signal itself, Horch (2006b) analysed stiction by studying the shape of its histogram. To calculate the stiction index, a

Gaussian distribution defined as:

$$f_G(x) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left(\frac{-(x-\mu)^2}{2\sigma^2}\right) \tag{2.22}$$

and a camel distribution defined as:

$$f_C(z) = \frac{1}{\sigma\sqrt{2\pi\sigma}} \int_{-A}^{A} \frac{e^{\frac{-(z-x-\mu)^2}{2\sigma^2}}}{\sqrt{A^2-x^2}} dx \tag{2.23}$$

were fitted to the sample histogram of the twice differentiated and filtered signal $y_{df}(t)$, given by:

$$y_{df}(t) = \left(\frac{(1-\alpha)(1-q^{-1})}{1-\alpha q^{-1}}\right)^2 y(t) \tag{2.24}$$

where $y(t)$ is the process output, and α is a filter design parameter. Once the fittings have been performed for both distributions, the mean squared errors are calculated. If the fit for the Gaussian distribution is better, stiction is determined to be present in the loop.

The shape of oscillating signals has been studied also using qualitative analysis techniques. Yamasita (2006) utilized the shapes of the pv-op (process variable-controller output) plots during oscillations to identify parameters related to stiction. Rengaswamy *et al.* (2001) introduced qualitative shape analysis accompanied with neural networks to identify the shapes of stiction-induced signals. Furthermore, stiction can be recognized by analysing the symmetry of oscillations as presented by Singhal & Salsbury (2005).

The signal-based methods attempt also to detect stiction by measuring the non-linearity of the signals. These methods are based on an assumption that in linear systems the observed non-linear behaviour is caused by valve stiction. Choudhury *et al.* (2004, 2006) introduced a procedure in which higher-order statistics, namely the bicoherence of a signal, is used to measure non-linearity and stiction is then verified from pv-op plots using an ellipse fitting technique. The method is based on the squared bicoherence defined as follows:

$$bic^2(f_1, f_2) := \frac{|B(f_1, f_2)|^2}{E\{|X(f_1)X(f_2)|^2\}E\{|X(f_1+f_2)|^2\}+\epsilon} \tag{2.25}$$

where $B(f_1, f_2)$ is the bispectrum of the tested signal, ϵ is a small constant, see (Choudhury *et al.*, 2006), and $X(f)$ is the Fourier transform of the signal. To test the nonlinearity of a signal, two tests are required. The first evaluates whether the squared bicoherence $bic^2(f_1, f_2)$ is zero for all frequencies f_1 and f_2, indicating a Gaussian signal. If the signal is non-Gaussian, i.e. $bic^2(f_1, f_2)$ is non-zero, it is further tested for non-zero constant squared bicohence, to find out if the signal is nonlinear. Two indices representing these tests have been defined by Choudhury *et al.* (2006). The non-Gaussianity index (NGI) is defined as:

$$NGI := \frac{\Sigma bic^2_{significant}}{L} - \frac{c_\alpha^{\chi^2}}{2K} \tag{2.26}$$

where $bic^2_{significant}$ represents the bicoherence values that exceed the limit value $c_\alpha^{\chi^2}$, L is the number of $bic^2_{significant}$, and K is the number of data segments used in the bicoherence estimation, see e.g. Choudhury *et al.* (2006). The non-linearity index NLI is defined as:

$$NLI := bic^2_{max} - \left(\bar{bic^2}_{robust} + 2\sigma_{bic^2,robust}\right) \tag{2.27}$$

where $\bar{bic^2}_{robust}$ and $\sigma_{bic^2,robust}$ are the robust mean and the robust standard deviation of the estimated squared bicoherence, respectively. These parameters are calculated by neglecting the smallest and largest 10% of the bicoherence values. Both indices, NGI and NLI, are bounded between -1 and 1 and positive values of NGI and NLI indicate non-Gaussianity and non-linearity, respectively.

Another method measuring signal nonlinearity was introduced by Thornhill (2005). Her method employs surrogate data analysis to measure signal nonlinearity.

The model-based stiction detection methods rely mainly on system identification procedures to estimate stiction parameters. Srinivasan *et al.* (2005) and Lee *et al.* (2008) proposed similar approaches, where the main idea is the parameter identification of the non-linear part of a Hammerstein model. The difference between the methods is in the identification algorithm and the structure of the linear part of the model. Hammerstein models were utilized also by Karra & Karim (2009) as a part of a more comprehensive valve stiction diagnosis methodology. Nallasivam *et al.* (2010) presented a technique based on the identification of Volterra model parameters which allowed extending the stiction diagnosis to non-linear control loops. Another model-based approach was proposed by Stenman *et al.* (2003) who presented a method which utilizes a segmentation model to identify a jump sequences in the valve position to diagnose sticion.

Recently, the research focus has shifted from the development of individual stiction diagnosis algorithms to combine them to create comprehensive control loop monitoring systems. Scali & Farnesi (2010) have proposed such a system, in which stiction diagnosis is achieved by selecting between stiction detection algorithms according to control loop characteristics.

3. Methodology for Fault Detection System Development

This chapter presents the methodology for developing a fault detection system for process industry applications. The methodology consists of five major steps. The first step consists of process decomposition that is described in Section 3.1. Second, a fault analysis is conducted for finding out the main reasons for production losses by identifying the underlying faults, their locations, causes, and the faulty devices as explained in Section 3.2. As the third step, Section 3.3 describes the confirmation of the focus areas for the fault detection system development and the determination of user requirements and system specifications. Next, development of fault detection algorithms is presented in Section 3.4, and the testing, implementation and validation of the developed algorithms are described in Section 3.5.

This methodology provides a generic approach to fault detection system development using the steps presented in Figure 3.1.

3.1 Process decomposition

A centralized approach to fault detection and diagnosis is seldom sufficient for the investigation of large processes due to their complexity and the diversity of features, such as process dynamics, non-linearity, in different parts of the process (Roychoudhury *et al.*, 2009; Mjaavatten & Foss, 1997). Therefore, process decomposition, aimed at analysing the structure of the process, is the first step of developing a fault detection system for large-scale processes.

From a fault diagnosis point of view, an efficient decomposition scheme should have two desired properties. The first property involves the minimizing the strength of interactions among subsystems and maximizing that within each subsystem (Joe *et al.*, 2006). The former aspect enhances

Step 1	**Process decomposition** Decomposing the plant based on its topology and structure into process units, sub units, equipment, and components
Step 2	**Fault analysis** Acquiring and analysing plant and maintenance data Finding the main reasons for production losses Identifying the faults having most significant impact on the losses; Studying the fault locations and causes Selecting fault candidates for focus areas
Step 3	**Confirmation of fault detection focus areas, user requirements and system specifications** Interviewing experienced plant personnel Confirming focus areas for the system development from the fault candidates Specifying user requirements and system specifications
Step 4	**Development of fault detection methods** Developing fault detection methods according to the chosen faults, user requirements, process knowledge, and plant data Developing methods for combining diagnostic results (if applicable)
Step 5	**Testing, implementation and validation of fault detection algorithms** Modelling, training and parameter selection for the algorithms Off-line testing of the algorithms Implementing the algorithms On-line validation of the algorithms at the plant Evaluating the performance of the fault detection system Final implementation of the system

Figure 3.1. Main steps of the methodology for fault detection system development

fault localization among the subsystems, whereas the latter one improves the resolution within each subsystem. The second property involves a sufficient compromise between the number and sizes of subsystems.

Process decomposition relies on process knowledge that can be classified according to Prasad *et al.* (1998) into structural, functional, malfunction, and behavioural knowledge. Particularly, structural and functional knowledge about the process are exploited in the decomposition step. Therefore, most fault detection methods for large scale processes apply structural or functional decomposition. However, it is stated that neither the structural decomposition nor the functional decomposition alone is sufficient for fulfilling the above-mentioned desired properties of process decomposition (Prasad *et al.*, 1998). The functional decomposition can cause overlapping process units among subsystems. Moreover, it can result in a decomposition scheme, which has no analogy with the process structure. The structural decomposition, on the other hand, can cause issues about compromising the number and sizes of subsystems. In other words, decomposition can result in too complex subsystems in the case of complicated process units.

Consequently, in this thesis, the decomposition methodology proposed by Prasad *et al.* (1998) is suggested in order to obtain a hierarchical organization of a large-scale process. This decomposition methodology is based on the general structure of process plants and involves a combination of structural and functional decompositions.

The process decomposition methodology includes the following hierarchical levels:

1. Unit level: primary process systems
   The plant is decomposed into process units that represent the primary operations of a process. As a general structure, a chemical plant involves three main sections in order: feed, reactions and separation. In the case of a paper mill, the general structure includes raw material preparation, paper manufacturing and post-processing.
2. Sub unit level: process subsystems
   Each process unit is decomposed into subsystems by considering the interactions. Control loops are not split into different subsystems and strongly interacting control loops can be grouped together as well. Furthermore, closely related process systems can be coupled together, e.g., the reactor and the cooling jacket around it as well as recycle streams must be also considered.
3. Equipment level: process equipment and devices in each sub unit
   The sub units are decomposed into individual devices or instruments as they are determined as nodes under each subsystem.
4. Component level
   Each piece of process equipment can be further decomposed into equipment components for fault analysis purposes. In some cases, it may not be necessary to decompose the process at this level, but it allows precise analysis of fault locations.

The above methodology provides a hierarchical presentation of a large scale process which is easy to understand, considering that the hierarchy is based on the general structure of chemical processes. The process is decomposed first into primary process units, then into sub units, process equipment, and components.

3.2 Fault analysis

Fault analysis aims at obtaining the malfunction and behavioural knowledge about the process, see (Jämsä-Jounela, 2011). Specifically, its objective is to identify the sources of production losses and the most significant faults that are causing the losses in a large-scale process. These faults are then studied in accordance with the process decomposition to analyse their locations and effect on the process. Consequently, the development of fault detection methods is focused appropriately by concentrating on the key areas, i.e. the faults and subsystems, which have the most significant impact on plant performance. The emphasis is on the faults that cannot be handled by the standard process automation system.

Fault analysis is carried out mainly as a data analysis, but it is recommended to support it by interviewing plant personnel. The data sources for analysis are long-term maintenance and production data as well as a process measurement database. In addition, the alarm history is useful for the analysis. The interviews of the plant personnel provide valuable background information for the analysis and clarify the data findings.

When investigating the shut-downs and breaks in production, it is recommended first to categorize the types of production losses in planned and unplanned shut-downs and short-term breaks. Next, the causes of these events are divided into maintenance and operational. The benefits of the developed fault detection methods particularly arise from studying the faults that contribute the most to the shut-downs due to operational reasons and cutting down the production losses due to them.

Finally, the faults causing the production losses are analysed. The objective is to discover the locations and causes of the faults, and to identify the corresponding faulty devices. To this end, the faults shall be categorized into basic fault types and causes. Lastly, each fault is associated with the specific devices and components based on the maintenance data or root cause analysis.

The process decomposition is utilized in fault analysis by dividing the faults based on their location to the subsystems of the process. In each subsystem there can be fault types specific for that subsystem, and therefore it is not sufficient to analyse the faults at the process level. Within each subsystem, the faults can be further classified based on the process equipment and components.

3.3 Confirmation of fault detection focus areas, user requirements and system specifications

The development of a fault detection system for an industrial process requires background information concerning the aims of the system, expectations of plant personnel and the restrictions of technical platforms, for instance (Vermasvuori, 2008). The required background information can be obtained from the plant operators and maintenance personnel by interviews that support the fault analysis. The plant personnel shall describe their expectations and they shall prioritize and accept the fault analysis results and the development objectives for the fault detection system.

In addition, information related to the user requirements and specifications of the detection system are obtained. The information to be acquired includes the specifications for the required functionality of the system, description of the process conditions under which the system will be used, specifications of the technical environment in which the system will be implemented as well as the specifications of the user interfaces. All this data is crucial for the development and operation of the system and it should be acquired at an early stage of the development.

3.4 Development of fault detection methods

This step comprises the development of fault detection methods for the confirmed focus areas as well as the design of methods in order to combine diagnostic knowledge if applicable. The development of a suitable method for a specific fault detection problem depends on the process and its dynamics, available process knowledge and data, and especially the faults and their characteristics. The fault effects must be analysed and the detection methods are designed based on the features the faults generate.

Different fault detection methods possess different attributes that must be considered when developing a method for a fault. Table 3.1 lists the main fault detection approaches from the categories presented in Section 2.1 and their applicability to the most common process and fault features.

Generally, the signal-based methods have a very wide application domain. They do not require particular process knowledge and therefore are easily applied for processes with various dynamic properties. However,

Table 3.1. Suitability of the main fault detection approaches for different process and fault features. Sign '+' indicates the approach is suitable, '−' not suitable and '±' suitable to some extent or suitability very case-specific.

Feature of process and/or fault	Signal-based	Model-based: Parity eqs, State est.	Model-based: Parameter est.	Model-based: CDGs, Parity eqs[a]	Data-based: Statistical, NN[b]	Data-based: Classifiers
Linear and static	+	+	+	+	+	+
Linear and dynamic	+	+	+	+	+	+
Non-linear and static	+	±	−	+	+	+
Non-linear and dynamic	±	±	+	+	±	+
Complex/difficult to model	+	−	−	−	+	+
Causal dependencies not known	+	±	±	−	+	+
No faulty data available	−	+	+	+	+[c]	−
Distinctive signal behaviour	+	−	−	−	+	+
Fault effects compensated by SISO control	−	+	+	+	+	+
Number of faults is large	−	+	−	+	+	−

[a] Parity eqn's with structured residuals
[b] Neural network regression
[c] Applies only for fault detection

they are only suitable when there exist clear signal patterns or features and the fault effects are not compensated by process control (Choudhury *et al.*, 2008b; Thornhill & Horch, 2007).

The model-based approaches can cover linear dynamic and to some extent non-linear dynamic processes, but are typically inappropriate for processes with complex physical phenomena due to the required modelling effort (Venkatasubramanian *et al.*, 2003c). Detection of a large number of different faults is generally possible, except for the parameter estimation techniques. The causal digraphs and parity equation methods using structured residuals require detailed information about the causal dependencies of the process, but are very effective methods if such information is available (Montmain & Gentil, 2000).

Statistical data-based methods are also widely applicable, in particular for large-scale processes, but their suitability is restricted in case of dynamic and non-linear processes. Classification methods always require faulty data to be applied successfully and are rarely able to detect multiple faults simultaneously (Venkatasubramanian *et al.*, 2003b).

The suitability of fault detection approaches can also be studied with respect to the process decomposition hierarchy. The signal-based methods are typically suitable for individual components, devices, or equipment at the basic control level. The model-based methods require substantial efforts to develop and implement as well as in-depth knowledge about the process. Therefore, they are typically feasible only to medium-scale applications, namely equipment, sub units, or small process units. In contrast, the data-driven methods have a large applicability area, which can cover all levels of the decomposition. Since they do not require extensive process knowledge, the development effort is moderate even at the unit and plant levels.

In fault detection systems that incorporate several methods, the interactions and co-operation of the methods must be considered. Through the analysis of the process, its decomposition and the faults to be focused on, the requirements for combining diagnostic information can be derived. Typically, the results of several parallel methods monitoring the same fault or subsystem are combined using e.g. decision fusion (Sinha *et al.* (2008)). In the case of complex large-scale systems distributed or decentralized techniques presented for example by Mjaavatten & Foss (1997), Singh *et al.* (1983), or Vadigepalli & Doyle III (2003) can be adopted.

3.5 Testing, implementation and validation of fault detection algorithms

The implementation of fault detection algorithms based on the developed methods is a task in which the characteristics of each method have to be considered in the context of practical implementation. This step addresses the operational requirements, data preprocessing, the presentation of diagnostic information and user interfaces for the algorithms.

Prior to the testing, appropriate data are collected and the experiments are designed. The testing of the algorithms is typically performed offline using collected measurement data and simulation experiments. The outputs of the algorithms are evaluated with respect to available fault data, such as maintenance reports or expert analysis.

Next, the algorithms are implemented with respect to the requirements set by for example technical platforms and interfaces discussed in Section 3.3. In addition, the data preprocessing procedures are specified and implemented. Then, the validation of the algorithms is conducted on-line at the plant in a realistic operation environment or under similar conditions. The overall performance and applicability of the algorithms are assessed and finally the fault detection can be implemented at the plant.

4. Description of the Board Machine Process and Its Control Strategy

4.1 Overview of the case process

The case process is a paperboard machine (later board machine or BM) located in the Stora Enso's Kaukopää mills in Imatra, Finland. The BM produces three-layer uncoated liquid packaging boards and cup boards with basis weights ranging from 190 to 420 g/m^2. The raw materials used are hardwood and softwood kraft pulps, chemi-thermomechanical pulp (CTMP) and broke. The BM was originally built in 1961 and has undergone several improvements during its history; most recently its calender section and former has been upgraded along with the automation system. The basic features of the BM are summarized in Table 4.1.

The boardmaking process consists of the following primary sections: stock preparation, an approach flow system (or short circulation), a wire section, a press section, a drying section, and a calendar followed by reeling, see Figure 4.1. In addition, there are several secondary sections, such as broke processing, white water circulation, and reject handling.

Table 4.1. Basic features of the case board machine

Start-up	1961
Capacity	350000 t/a
Machine speed	200–600 m/min
Wire width	6.95 m
Max. trim width	6.36 m
Grammage	190-420 g/m2
Crew	8 + 1
Products	Liquid packaging boards, cup board

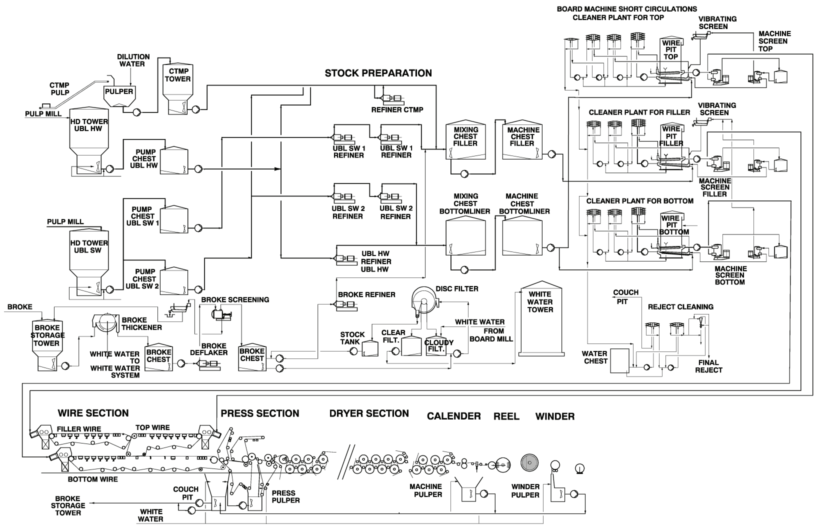

Figure 4.1. Overview of the boardmaking process (modified from (Sundholm, 2000))

4.2 Brief description of the boardmaking process

The boardmaking process begins with the preparation of raw materials in the stock preparation section. Different types of pulp are refined and blended according to a specific recipe in order to achieve the desired composition and properties for the board grade to be produced. In addition, several additives such as starch and various size chemicals are added to improve the quality of the final product. The consistency of the stock is controlled by the addition of dilution water. Since the BM produces three-layered board, there are two separate stock preparation sections: one to blend the stock for the middle layer and one for the top and bottom layers.

The blended stock passes from the stock preparation to the approach flow system. First, the stock is diluted in the wire pit to the correct consistency for web formation. Next, the diluted stock is cleaned in the hydrocyclone cleaning plant in order to remove impurities and screened in the machine screen. Then, the stock passes to the head box, from where it is sprayed onto the wire as evenly as possible in order to form a solid board web (Norman, 2000). For the production of three-layered board there are three different approach flow systems and wires.

Next, the board web is dried in several stages. The first stage is the wire section in which the water is drained through the wire. Furthermore, three webs are combined in the wire section to form the final structure of the product. The second stage is the press section in which the water is removed by mechanically pressing the web between the rollers. The press section of the case process consists of three press nips. Finally, the remaining water is evaporated in the drying section using the latent heat of steam inside the drying cylinders (Kuhasalo *et al.*, 2000). The drying section consists of five drying groups, each of which comprise 4–18 drying cylinders. For more details refer to Publication IV.

After the drying, the board is calendered in two phases in order to achieve the desired surface properties. The purpose of calendering is to manage the gloss, smoothness, density, and thickness of the board (Ehrola *et al.*, 1999). Finally, the board is reeled and transferred to post-processing.

4.3 Control of the boardmaking process

The process automation of a board machine consists of two main systems: a distributed control system (DCS) and a quality control system (QCS). The QCS represents the highest level in the control hierarchy by controlling the main quality variables, whereas the DCS system handles the basic controls at a lower level. The overall control strategy of the board machine is illustrated in Figure 4.2.

The QCS utilizes Honeywell's Robust Model-Predictive Control Technology (RMPCT) to control the main quality variables: basis weight moisture, and thickness (see e.g. Qin & Badgwell (2003) and Backström & Baker (2008)). The quality variables are measured after the calender section with a measurement scanner that traverses constantly across the web. The calculated control actions are delivered as setpoints to lower level controllers handled by the DCS.

Since the control of board web quality is a two-dimensional control problem, the QCS operates in a machine direction and in a cross direction. In the machine direction, the quality variables are controlled by providing setpoints for lower level controllers; the basis weight control is achieved by adjusting the stock flow controller setpoints, whereas the moisture control governs the steam pressure setpoints in the drying section. In the cross direction, the QCS system controls special actuators that adjust the profiles of the quality variables. The basis weight profile is controlled by the dilution water in the middle layer headbox, while the moisture profile is controlled with a steam box located before the press section and with a moisturizing device located in the drying section. The thickness profile is

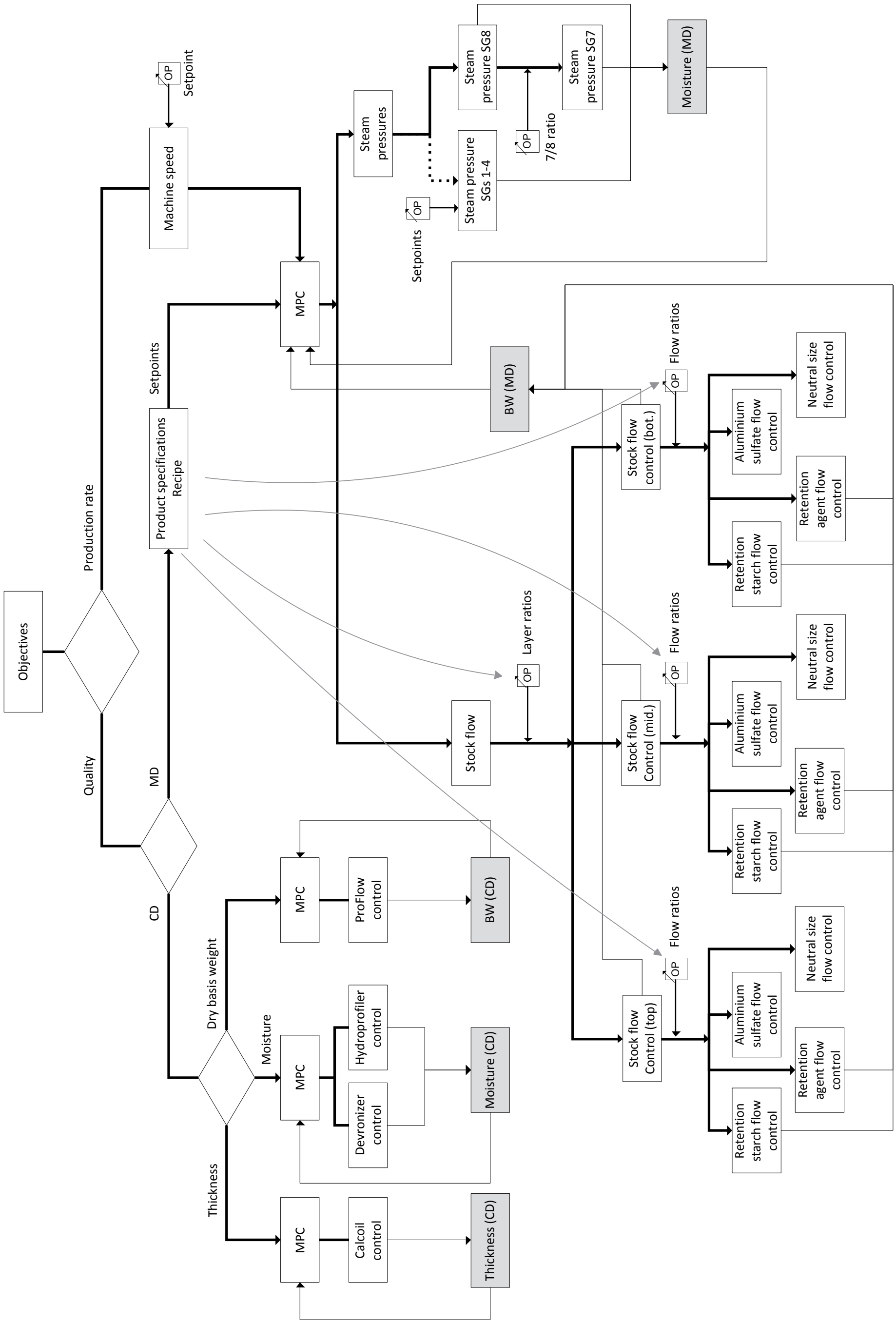

Figure 4.2. Overview of the board machine control

controlled at the second calender.

The control at the DCS level consists of approximately 500 control loops that adjust pressures, flows, level, etc. around the board machine. The main control loops handled by the DCS are the stabilizing controls, i.e. the control loops that receive their setpoints from the QCS: the stock flow controllers and the steam pressure controllers. The stock flow controllers are located in the approach flow system. There are three separate controllers for which the total required stock flow is divided according to the desired layer ratios. The stock flow is controlled by adjusting the rotation speeds of the pumps located in each approach flow system. The steam pressure controllers are located in the drying section and each drying group

5. Development of the Integrated Fault Detection System for a Board Machine

This chapter addresses the development of an integrated fault detection system for the case process. The methodology presented in Chapter 3 is followed stepwise to demonstrate its application. First, the decomposition of the board machine is given in Section 5.1. Then, the faults of the board machine are analysed in Section 5.2. The overall structure of the fault detection system is described in Section 5.3 and finally the development of fault detection algorithms is outlined in Section 5.4.

5.1 Process decomposition

The board machine process was decomposed into subsystems using a topology-based decomposition strategy presented in Section 3.1 in order to provide a framework for fault analysis and to facilitate the development of the fault detection system. First, the process was divided into primary process units. In the board machine case, there are seven main process units: the stock preparation, the short circulation, the wire section, the press section, the drying section, the calender section, the reeling section, and the quality control system, and several secondary units that were combined under 'Other functions', see Figure 5.1. Next, at the sub unit level, each primary unit was decomposed into smaller subsystems. For example, the drying section was divided into the cylinder groups, the hood, the steam and condensate system, and the pocket ventilation system. Then, each subsystem was divided on the equipment level and the corresponding components were listed.

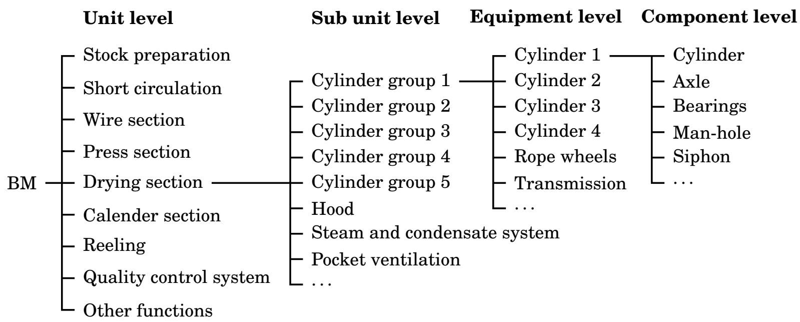

Figure 5.1. Process decomposition of the case board machine focusing on the drying section

5.2 Fault analysis

The fault analysis carried out at the case process aimed at finding the main focus areas for the development of the fault detection system. The work was concentrated on the faults that affected the most process operation or product quality and could not be handled by the standard algorithms in the automation systems. The main results of the analysis are presented in this section according to Jämsä-Jounela *et al.* (2013).

The fault analysis was based on long-term production and maintenance data that were collected from the board machine. Maintenance records, production logs, and process measurement data for the year 2010 were analysed. In addition, interviews of operating personnel were conducted.

5.2.1 Analysis of the production losses

The production losses, i.e. web breaks and shut-downs, were studied in the first phase of the fault analysis. The results showed that the board machine was operating 64% of time during the analysed time period, as reported in Table 5.1. Over thirty percent of production time was lost due to unplanned and planned shut-downs, whereas web breaks accounted for approximately 5%.

On closer inspection, the statistics showed that the web breaks were mainly due to operational reasons whereas the unplanned shutdowns were equally caused by operational and maintenance reasons. The operational causes consisted mainly of process disturbances whereas maintenance reasons included, among others, mechanical failures.

The results indicate that the most significant benefits could be achieved by reducing the unplanned shut-downs caused by operational causes.

Table 5.1. Distribution of production time, web breaks, and shut-downs, and the cause distribution of the web breaks and unplanned shut-downs

Event	Duration d	%	Cause	d	%
Web break	13.2	4.5	Maintenance	0.6	4.5
			Operational	12.4	93.9
			Unspecified	0.2	1.5
Unplanned shut-down	42.7	14.6	Maintenance	21.3	49.9
			Operational	20.4	47.8
			Unspecified	1.0	2.3
Planned shut-down	49.9	17.1			
Normal production	186.1	63.8			
Total	291.9	100			

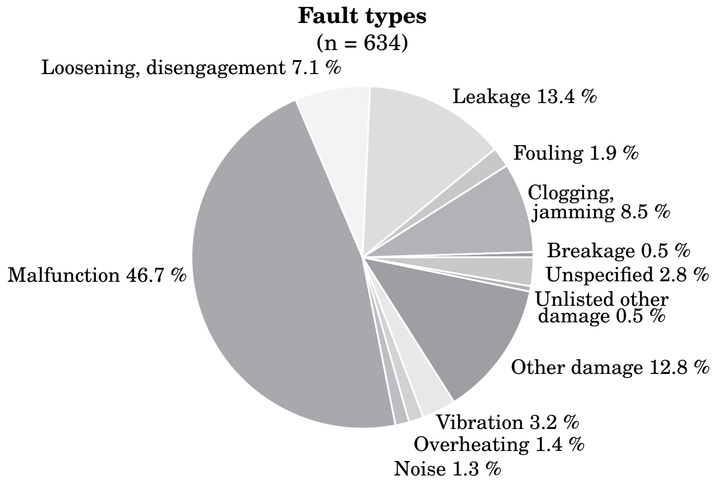

Figure 5.2. Distribution of faults by the fault type

5.2.2 Distribution of the fault types, locations, and devices

The next phase of the fault analysis focused on studying the fault types, the faultiest unit processes, and the devices associated with the faults. According to the results, among the 634 analysed faults, the most common fault type was malfunction, see Figure 5.2. Other significant fault types were leakage and loosening or disengagement, and clogging or jamming. The collected data were influenced by the major commissions of new process equipment in 2009, when the automation system, the calender section and a part of the wire section of the board machine were renewed. As a result, the number of faults in 2010 was noticeably higher than in a regular operating year. The number of faults is, however, at a typical level after such upgrades as reported by the plant experts.

The analysed faults were assigned to the corresponding process units

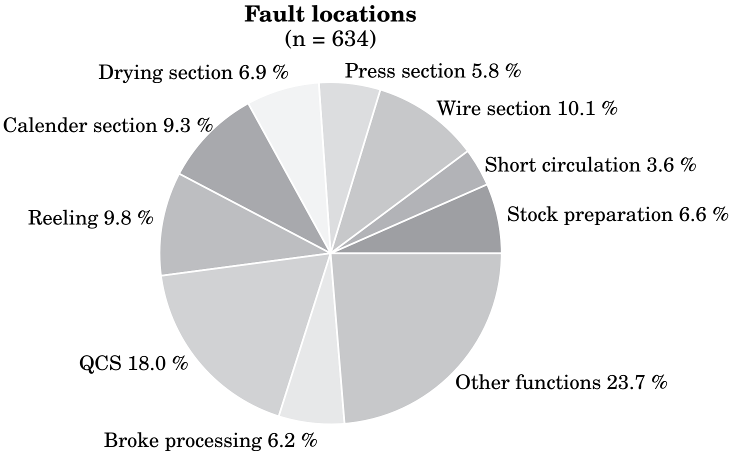

Figure 5.3. Distribution of the faults by the process sections

based on the process decomposition. Among the main process units, the faults were distributed quite evenly, but the QCS emerged as the most problematic section, see Figure 5.3. The faults related to ’Other functions’ were not considered further in the analysis, since they concerned the faults in the supporting facilities of the plant, such as the ventilation of the machine hall or electrical systems.

Within each process section, the main fault types and devices were identified. For the sake of brevity only the drying section, short circulation and QCS faults are presented here in Tables 5.2, 5.3 and 5.4, respectively. A more detailed examination of the fault types is given in (Jämsä-Jounela *et al.*, 2013) and in Publication I, which presents further analysis of the fault in basic control devices and actuators.

The faults located in the drying section are presented in Table 5.2 which indicates that leakages are the most common fault type in this process unit. Leakages were mainly focused on pumps, pipes and rolls. In addition, the share of malfunctions was considered significant, especially in valves and positioners.

Table 5.3 presents the faults in the short circulation sections of the BM. The most significant fault types are malfunction and vibration, which are mainly associated with valves and pumps, respectively. Another remarkable faulty device are the measurements, which in this case refer to a consistency sensor. They are very important in terms of controlling the basis weight of the board and therefore their importance was particularly stressed by the plant personnel.

The most common fault type associated with the QCS was malfunction which accounted for 82.5% of all QCS faults. These faults were mainly related to the measurement devices. The reasons for the malfunctions are presented in Table 5.4 which reports the causes of all faults, malfunctions and specifically of sensor malfunctions. It is immediately noted that impurities and moisture are the main causes of all QCS related faults and particularly the sensor malfunctions. A further analysis of the maintenance records revealed that fouling of the caliper sensor was the main problem in this part of the process.

5.2.3 Focus areas of the fault detection system development

The fault analysis results were validated by expert interviews at the case site. The process and maintenance experts reviewed the results and confirmed their validity as well as provided background information for determining the focus areas for fault detection system development. As a result, the following faults were identified as the main focus areas for the development of the fault detection system:

1. valve malfunctions
2. consistency sensor malfunctions
3. clogging, jamming, and leakages in valves and pipes in the drying section
4. board caliper measurement faults

Table 5.2. The fault types by device in the drying section of the board machine.

Device	Leakage (%)	Loosening, disengagement (%)	Malfunction (%)	Noise (%)	Other damage (%)	Overheating (%)	Total (%)
Drive	–	–	–	–	–	2.3	2.3
Drying cylinder	–	6.8	4.5	–	2.3	–	13.6
Gear and transmission	4.5	–	–	–	2.3	–	6.8
Heat exchanger	2.3	–	–	–	–	–	2.3
Mechanical	–	–	2.3	–	4.5	–	6.8
Other mech. device	–	–	4.5	2.3	–	–	6.8
Pipe	9.1	–	–	–	–	–	9.1
Positioner	–	–	9.1	–	–	–	9.1
Pressure device	2.3	–	–	–	–	–	2.3
Pump	11.4	–	–	–	6.8	2.3	20.5
Roll	6.8	2.3	–	–	2.3	–	11.4
Valve	2.3	–	6.8	–	–	–	9.1
Total	38.6	9.1	27.3	2.3	18.2	4.5	100.0

Table 5.3. The fault types by device in the short circulation of the board machine.

Device	Breakage (%)	Clogging (%)	Leakage (%)	Loosening, disengagement (%)	Malfunction (%)	Other damage (%)	Overheating (%)	Vibration (%)	Total (%)
Automation hw	–	–	4.3	–	8.7	4.3	0	0	17.3
Valves	–	–	4.3	–	21.7	–	–	–	26.0
Pipes	–	4.3	4.3	–	–	–	–	–	8.6
Pumps	–	–	–	–	4.3	–	4.3	17.4	26.0
Measurements	4.3	–	–	–	8.7	–	–	–	13.0
Electrical	–	–	–	–	4.3	–	–	–	4.3
Mechanical	–	–	–	4.3	–	–	–	–	4.3
Total	4.3	4.3	13.0	4.3	47.8	4.3	4.3	17.4	100.0

Table 5.4. Causes of all QCS faults, sorted by malfunctions in general and sensor malfunctions.

Cause	All faults (%)	Malfunctions (%)	Sensor malfunctions (%)
Component failure	1.8	1.1	1.6
Corrosion/ oxidation	0.9	1.1	–
Exceptional conditions	1.8	2.1	1.6
Impurities, moisture	38.6	46.8	69.4
Misoperation	6.1	7.4	–
Normal wear	7.9	8.5	8.1
Other failure	3.5	3.2	1.6
Program fault	5.3	6.4	–
Safety switch	2.6	3.2	–
Unknown/unspecified	31.6	20.2	17.7
Total	100.0	100.0	100.0

Focus areas 1, 2 and 3 were direct conclusions from the fault analysis results as they were clearly indicated by the fault statistics. The focus area 2 appeared also in the statistics, but its importance was emphasized by the process experts during the interviews. Further details of each focus area are presented in the corresponding publications.

5.3 Structure of the integrated fault detection system

The integrated fault detection system consisted of four detection modules, each representing an algorithm for addressing the valve, consistency sensor, leakage and blockage, and caliper sensor faults in the corresponding

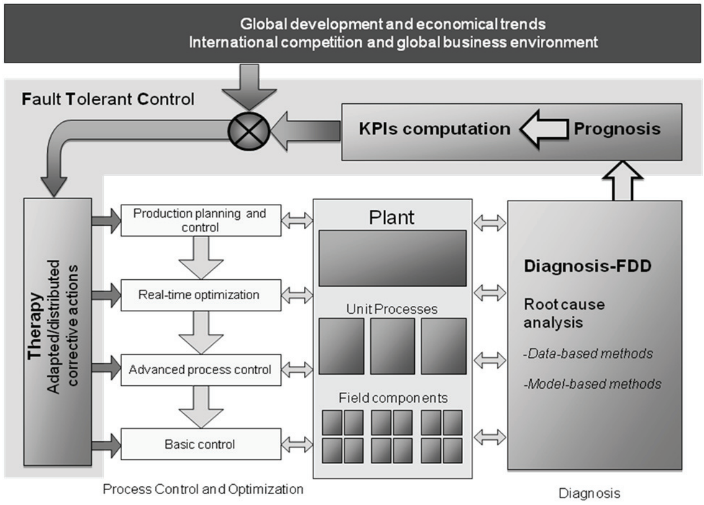

Figure 5.4. Overview of the PAPYRUS project concept for plant asset management. (Schlake *et al.*, 2011)

process units or equipment. The developed system was a part of the plant asset management framework which was created as a result of the research conducted within the project ”Plug and Play monitoring and control architecture for optimization of large scale production processes, PAPYRUS” (EU-IST-2010-257580). The aim of the project was addressing a complete process asset management loop from fault detection and diagnosis via prognosis to corrective actions in order to restore plant operation. The overall scheme of the PAPYRUS project and the role of the fault detection system as a part its diagnosis block is illustrated in Figure 5.4.

The system structure followed the decomposition and control strategy of the process and it aimed at detecting the faults at the lowest possible level of the process hierarchy, in order to prevent the fault effects from propagating to the higher levels and finally adversely affecting the plant performance and product quality. The fault detection modules were associated with the levels of the process decomposition and control strategy according to Figure 5.5.

The first and second fault detection modules concerned the basic control level and were related to the faults in the process equipment. For detecting valve stiction faults and the related oscillations, an approach utilizing four parallel methods was developed. The consistency sensor faults were addressed with an algorithm based on the dynamic causal digraph method.

The third module covered one unit of the process and was related to the

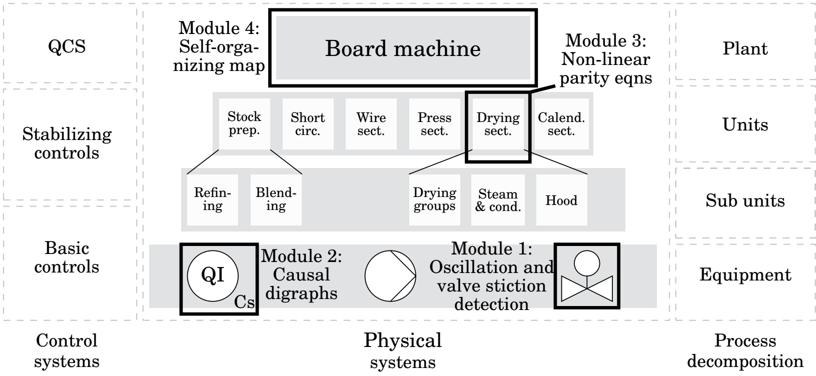

Figure 5.5. Overall structure of the fault detection system; the fault detection modules with respect to the process decomposition and the control strategy.

process unit level control, i.e. the stabilizing controls. A non-linear parity equation method based on grey-box modelling was developed, which addressed the fault detection and diagnosis in the steam and condensate system of the drying section by focusing on leaks and blocks in pipe lines as well as jamming and clogging of valves.

The fourth module focused on the highest process decomposition level and on the top of the process control hierarchy, as the QCS system covers the whole process from the stock preparation to the reeling, see Figure 5.5. The main problem related to the QCS was the fouling of the board caliper sensor, for which a self-organizing map based process monitoring application was developed.

The combination of results from the fault detection modules was not required with the current configuration, since the modules did not overlap with respect to the process topology and the faults to be detected. Although, the valve stiction detection module was applied to valves in the stock preparation and the drying section, for which the DCDG and the parity equation methods were developed respectively, the fault types were however different. Therefore, the detection results of each module could be handled independently.

The development and detailed descriptions of the algorithms for each fault detection module are presented in the following subsection.

5.4 Development of the fault detection algorithms

5.4.1 Detection of oscillations and valve stiction

Valve stiction is a special type of fault for which dedicated detection algorithms have been developed. Valve stiction generates a wide range of features due to the large diversity of controller dynamics and valve types. Valve stiction detection algorithms are typically able to detect a subset of the features and therefore each algorithm has its own advantages and drawbacks, i.e. it performs well in some cases but sometimes may fail completely to detect stiction. As a consequence, successful industrial applications typically require combinations of algorithms in order to comprehensively detect sticky valves. Therefore, the valve stiction diagnosis system developed for the board machine consisted of well-established algorithms running in a parallel configuration. In order to provide an overall detection result by combining the results of the individual algorithms, a decision fusion approach was created. The decision fusion was based on novel indices, which estimated the reliability of the detection decisions obtained by the individual algorithms in each case and were used as weights for the corresponding stiction indices. In this manner, all algorithms contributed to the final decision, improving the reliability of the results and avoiding ambiguous or contradictory detections.

Detection of oscillations is typically a prior step in valve stiction detection and therefore an algorithm for detecting oscillations was developed. The algorithm features a procedure which computes and removes the non-stationary baseline of the analysed signal before an oscillation detection index is calculated. The baseline computation procedure was introduced since the aim was to create an autonomous method that requires no tuning parameters and therefore filtering approaches were considered unsuitable. The method also utilizes robust statistics in order to increase its resistance against noise and outliers, which are common in industrial processes.

The detection system for oscillations and valve stiction consisted of the following phases: (1) data preprocessing during which tasks such as verifying sampling time and removing outliers, large disturbances, and gaps in the data were performed; (2) detection of oscillations; (3) calculation of stiction indices; (4) calculation of the reliability indices; (5) the final phase in which the integrated detection decision was achieved. The entire pro-

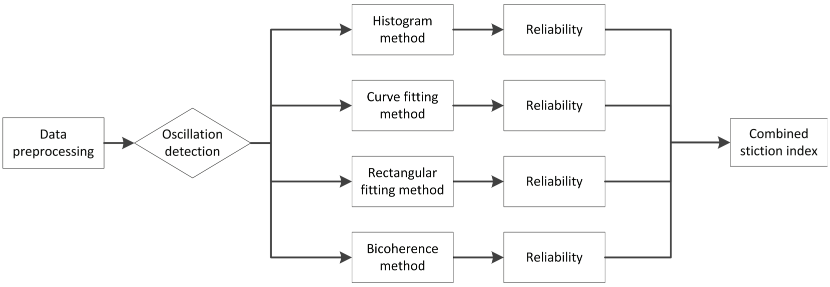

Figure 5.6. The oscillation and valve stiction detection system using parallel configuration of four stiction detection algorithms.

cedure is illustrated in Figure 5.6.

For detecting oscillations a new detection method was developed. In Publication I, the oscillation detection was carried out using the method presented by the author in (Tikkala *et al.*, 2010). However, an improved method called the Robust Zero-Crossing (RZC) method was later developed and reported in Publication II.

The RZC method computed the moving trend, or the "baseline" of a non-stationary signal by finding the consecutive ZC intervals and the local minimum and maximum values of the signal between them. Next, a statistical test was used to determine the presence of an oscillation. The RZC method is described in the following.

For a discrete-time signal $x(t)$, $t = 1, \ldots, n$, the time instants of zero-crossings $t_{z,i}$ were defined as:

$$\begin{aligned} t_{z,i} =& \{t \mid \mathrm{sign}\{x(t-1) - b(t-1)\} \neq \mathrm{sign}\{x(t) - b(t)\}\}, \\ & i = 1, \ldots, m \end{aligned} \tag{5.1}$$

where $b(t)$ is the baseline of the signal at time t and m is the number of zero-crossings in $x(t)$. The local maxima and minima, a_i^+ and a_i^-, are used to calculate the shift in the signal's baseline for each interval:

$$b(t) = \begin{cases} a_i^- + \frac{a_i^+ - a_i^-}{2}, & t = t_{z,i},\ i = 1, \ldots, m \\ b(t-1), & \text{otherwise,} \end{cases} \tag{5.2}$$

where

$$\begin{aligned} a_i^+ =& \max\{x(t_1) - b(t_1),\, x(t_2) - b(t_2)\}, \\ & t_{z,i-1} \leq t_1 \leq t_{z,i}, \quad t_{z,i-2} \leq t_2 \leq t_{z,i-1}, \end{aligned} \tag{5.3}$$

and

$$\begin{aligned} a_i^- =& \min\{x(t_1) - b(t_1),\, x(t_2) - b(t_2)\}, \\ & t_{z,i-1} \leq t_1 \leq t_{z,i}, \quad t_{z,i-2} \leq t_2 \leq t_{z,i-1}, \end{aligned} \tag{5.4}$$

In order to stationarize $x(t)$, the baseline was corrected by backward shifting and interpolation. The backward shifting was done because $b(t)$ is computed based on the last two half periods and therefore it lags behind the true baseline, the estimate of which is denoted as $b_c(t)$ hereinafter. The backward shifting was defined as $b_c(t_{z,i}) = b(t_{z,i+1})$, and the interpolation as follows:

$$b_c(t) = b_c(t_{z,i}) + (t - t_{z,i})\frac{b_c(t_{z,i}) - b_c(t_{z,i-1})}{t_{z,i} - t_{z,i-1}}, \; t_{z,i-1} < t \leq t_{z,i} \tag{5.5}$$

Finally, the signal was stationarized by subtracting the computed baseline $x_s(t) = x(t) - b_c(t)$.

The determination of the presence of an oscillation was based on an index r_{RZC} representing the regularity of zero-crossings:

$$r_{RZC} = \frac{1}{3}\frac{\tilde{\Delta t}_z}{\mathrm{MAD}(\Delta t_z)}, \tag{5.6}$$

where $\tilde{\Delta t}_z$ is the median of time between consecutive zero-crossings and

$$\mathrm{MAD}(\Delta t_z) = \frac{1}{m-1}\sum_{i=1}^{m}(|t_{z,i} - \tilde{\Delta t}_z|). \tag{5.7}$$

When an oscillation was detected, valve stiction detection was carried out using the histogram method (Horch, 2006b), the curve fitting method (He *et al.*, 2007), the rectangular fitting method (Hägglund, 2011), and the bicoherence method (Choudhury *et al.*, 2006). The first three methods based their diagnosis on the shape of a signal, or in case of Horch's method, its histogram and the fourth method was based on evaluating the non-linearity of a process signal (see Section 2.4). The methods were applied to the oscillating signal and the reliability indices were computed to obtain the final result. The overall detection result was computed as a weighted average of the stiction indices provided by the methods:

$$S = \frac{1}{n}\sum_{i=1}^{n} r_i s_i, \tag{5.8}$$

where n is the number of methods used in parallel, r_i are the reliability indices and s_i are the individual stiction indices. Specifically, the number n defines the number of reliable methods in the calculation period; a method i is considered as reliable if the reliability exceeds a certain threshold $w_i > \theta$. The threshold can be set to $\theta = 0.5$, for instance. In other words, if the reliability of a method is low, it is excluded from the overall index calculation.

The histogram method by Horch (2006b) is based on studying the shape of the histogram of the analysed signal. The reliability index for the histogram method r_{ih} was constructed using the Gaussian and camel fitting errors as follows:

$$r_{ih} = 1 - 2\frac{\min(d_g^2, d_c^2)}{d_g^2 + d_c^2}, \tag{5.9}$$

where d_g^2 is the squared 2-norm of the error fitting of the Gaussian distribution and d_c^2 is the squared 2-norm of the error fitting of the camel distribution. The values of r_{ih} range from 0 to 1; the closer the value is to 1, the more reliable the stiction index can be considered.

In the curve fitting method, the stiction index may provide inaccurate results when the MSE of both sinusoidal and triangular signals is unable to match the original signal. Thus, the reliability index was constructed using the fitting residuals of both signals:

$$r_{ic} = 1 - 2\frac{\min(d_{sin}, d_{tri})}{d_{sin} + d_{tri}}, \tag{5.10}$$

where d_{sin} and d_{tri} are the fitting errors of the sinusoidal and triangular signal respectively.

The rectangular fitting method presented by Hägglund (2011) evaluates the best match between a sine wave or a square wave and the oscillating control error signal. Thus, the reliability index of the rectangular fitting method r_{ir} employed the values of the sine and square loss functions, since functionally they are similar to the fitting errors used in the histogram and curve fitting methods:

$$r_{ir} = 1 - 2\frac{\min(V_{sine}, V_{square})}{V_{sine} + V_{square}}, \tag{5.11}$$

In terms of reliability, the most important feature of the data for the bicoherence based non-linearity indices is the stationarity of the data. This requirement is however seldom achieved when using real industrial data, even after it has been pre-processed. To this end, a reliability index was defined for the NGI and NLI computation. Standard statistical tests, Student's t-test and χ^2-test are used to calculate the mean and the standard deviation, respectively. To compute of the reliability index, the data was divided into l segments for which the mean $\bar{x}_i$ and standard deviation σ_i were calculated and tested against the null hypothesis $x_i = 0$ and $\sigma_i = 1$. The reliability index r_{ib} was defined as follows:

$$r_{ib} = r_{\bar{x}} \cdot r_{\sigma}, \tag{5.12}$$

where

$$r_{\bar{x}} = 1 - \frac{\#\{\bar{x}_i \,|\, |T_i| > T_{lim}\}}{l} \tag{5.13}$$

and

$$r_{\sigma} = 1 - \frac{\#\{\sigma_i \,|\, \chi_i^2 < \chi_{lim,l}^2 \text{ or } \chi_i^2 > \chi_{lim,u}^2\}}{l}. \tag{5.14}$$

In the above, $T_i = \bar{x}_i/(\sigma_i/\sqrt{n})$ is the t-statistic for testing the mean of the data segment i, T_{lim} is the limit for the confidence level of 0.05. The variable $\chi_i^2 = ((n-1)\sigma_i^2)/(\sigma^2)$ denotes the test statistic for testing the standard deviation for the data segment i, while $\chi_{lim,l}^2$ and $\chi_{lim,u}^2$ are the lower and upper limits for the confidence level of 0.05. The operator $\#\{\}$ takes the number of elements in the set.

5.4.2 Dynamic causal digraph for consistency sensor malfunctions

A dynamic causal digraph based fault detection algorithm was developed to address the detection of consistency sensor malfunctions in the stock preparation section. The consistency sensor faults cannot be detected directly from the measurement signal, since the consistency is tightly controlled and the faults are often compensated by the controller. Therefore, signal-based methods were not an option and model-based approaches were required. The selection of the DCDG method was justifiable, since the causal dependencies in the stock preparation and short circulation are straightforward, but dynamic models are however needed to describe the tank dynamics. Another contributing factor was the need for fault isolation properties.

The CDG model developed for the board machine covered the stock preparation and short circulation. The digraph model consisted a mixture of static and dynamic models for different parts of the process depending on the process dynamics in each part. The stock mixing part was represented with static equations describing the ideal mixing of stock and dilution water and the tanks were modelled with first-order dynamics, for instance. These models were used to create analytical redundancy for the consistency sensors for fault detection purposes. The resulted residuals were analysed using the causal inference mechanisms to confirm the faults.

The application of the DCDG method comprised an off-line modelling phase and an on-line phase. In the modelling phase, a causal digraph model of the process was derived. The overall structure of the CDG model containing two stock preparation sections and three short circulation sections is presented in Figure 5.7. In the following, the cause-effect models for the stock preparation 2 and short circulation 2 sections are briefly discussed to illustrate the modelling phase. The variables for the presented equations are listed in Table 5.5.

The equation for the consistency of pine pulp $pcon2$ was derived based on an ideal mixing model:

$$pcon2 = \frac{pdflow2 \cdot conlong + (pflow2 - pdflow2) \cdot spcon)}{pflow2}, \tag{5.15}$$

where $spcon = 4.5$ % and $conlong = 0.02$ % are the consistencies of dilution water and pine pulp, respectively. The flows $pdflow2$ and $pflow2$ were estimated from the corresponding valve openings using a neural network model.

The consistency of machine chest $conm2$ was modelled as follows:

$$conm2 = \frac{dflow2 \cdot conlong + bleflow2 \cdot blecon2}{bleflow2 + dflow2}, \tag{5.16}$$

where the intermediate flow variables $dflow2$ and $bleflow2$ were again estimated based on valve positions using neural networks and $blecon2$ was computed from equation:

$$\begin{aligned} \frac{d(M_b \cdot blecon2)}{dt} &= pflow2 \cdot pcon2 + cflow2 \cdot ccon2 + broflow2 \cdot brocon2 \\ &+ f_o \cdot sccon2 - bleflow2 \cdot blecon2. \end{aligned} \tag{5.17}$$

In (5.17), $f_o = bleflow2 - pflow2 - cflow2 - broflow2$ is the overflow from the machine chest to blend chest and M_b is the mass of pulp in the blend chest, which is assumed to be constant. The consistency in the machine chest $sccon2$ was modelled using the mass balance:

$$\frac{d(M_m \cdot sccon2)}{dt} = conm2 \cdot mcflow2 - f_o \cdot sccon2 - scflow2 \cdot sccon2, \tag{5.18}$$

where M_m is the mass of pulp in the machine chest and $mcflow2 = f_o + scflow2$.

The cause-effect models for the short circulation section consisted of static regression models for variables $headflow2$, $scflow2$, $acceptcon2$, and $headcon2$ and a first-order transfer function model for $wpcon2$. In addition, the white water consistency was calculated as follows:

$$wwcon2 = \frac{\alpha}{100 \cdot \beta} \cdot headcon2, \tag{5.19}$$

where $\alpha = 0.1$ and $\beta = 0.95$ are the ratios of solid content and water that pass through the wire, respectively.

Table 5.5. Description of the variables of the causal digraph model

Variable	Description	Type	Unit
Stock preparation 2			
broval2	valve opening for the broke line	A	%
broflow2	mass flow of the broke	M	kg/s
brodval2	dilution water valve opening for the broke line	A	%
brodflow2	dilution water flow for the broke line	E	kg/s
brocon2	broke consistency	M	%
pspeed2	pine pump rotation speed	A	%
pflow2	mass flow of the pine stock	M	kg/s
pdval2	dilution water valve opening for the pine line	A	%
pdflow2	dilution water flow for the pine line	E	kg/s
pcon2	pine consistency	M	%
cspeed2	CTMP pump rotation speed	A	%
cflow2	mass flow of the CTMP	M	kg/s
cdval2	dilution water valve opening for the CTMP line	A	%
cdflow2	dilution water flow for the CTMP line	E	kg/s
ccon2	CTMP consistency	M	%
mcval2	dilution water valve opening for the machine chest	A	%
dflow2	dilution water flow for the machine chest	E	kg/s
conm2	consistency before the machine chest	M	%
ppress2	pressure before the pine valve	M	kg/s
cpress2	pressure before the CTMP valve	M	kg/s
sccon2	consistency of the machine chest	M	%
Short circulation 2			
Variable	Description	Type	Unit
bwspeed2	basis weight pump rotation speed	A	%
scflow2	flow from the machine chest (thick stock flow)	M	kg/s
wpcon2	wire pit consistency	M	%
acceptcon2	consistency of accept flow from the hydrocyclone	M	%
headspeed2	headbox feed pump rotation speed	A	%
headflow2	mass flow through the headbox	M	kg/s
headcon2	headbox consistency	M	%
sliceopen2	slice opening of the headbox	A	mm
drybw2	dry basis weight of the layer 2	M	g/m2

The on-line phase was divided into three main tasks: residual generation, fault detection using the CUSUM method, and fault isolation. The four different types of residuals were generated using the digraph model and the process measurements, see Section 2.2.2. Then, the CUSUM method was used to detect significant changes in the residuals and to trigger fault isolation reasoning and fault type identification. Fault isolation aimed at finding the propagation path of the detected fault by utilizing the inference mechanism based on the global and local residuals (see Table 2.1) and finally the fault type was identified using the rules in Table 2.2.

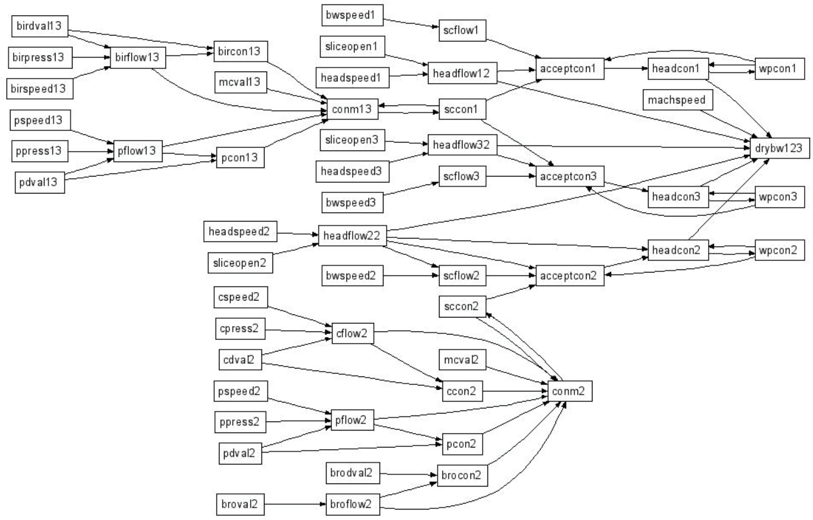

Figure 5.7. Causal digraph structure of the three-layer board machine.

5.4.3 Non-linear parity equation method based on grey-box models for the drying section faults

The leakage and blockage faults in the steam and condensate system of the drying section were addressed by a parity equation algorithm based on grey-box models utilizing structural knowledge of the process. Static equations were considered sufficient for the drying section, since there are no large volumes for the mass to accumulate. However, non-linear equations were required due to the strong non-linear behaviour of mass flow through a valve. The equations were derived according to the structure of the flow network and they described the mass balances of the drying groups. The steam and condensate system does not however feature sufficient flow measurements and therefore a special approach was adopted. Mass flows were estimated by a novel, patented technique that utilized the available pressure measurements and valve positions and iteratively solved the mass balance equations (Zakharov, 2011). By incorporating the structure of the process into the equations, the non-linearity of the process could be described with low-dimensional valve models instead of a high-dimensional black-box model for the whole process. The parameters of these functions were estimated board machine data.

The application of this method consisted of two phases. The off-line phase covered modelling of the mass balances, estimation of model parameters using measurement data, and determination of fault detection thresholds. The on-line phase consisted of residual generation, change detection using the cumulative sum (CUSUM) method (Hinkley, 1971), and fault isolation using a structured residuals technique.

The model equations were defined to be of the following form:

$$\sum_{i=1}^{k} a_i x_i + \sum_{i=1}^{l} F_i^1(x_i^1) + \sum_{i=1}^{m} F_i^2(x_i^2, y_i^2) + \sum_{i=1}^{n} F_i^3(x_i^3, y_i^3, z_i^3) = 0, \qquad (5.20)$$

where variables x, y and z are process or computed variables, k is the number of linear terms involved in the equation with coefficients a_i, and l, m and n are the numbers of nonlinear functions with one, two and three arguments, respectively. F^1, F^2 and F^3 were defined using the following parameterization:

$$F^1(x) = \sum_{i=1,\dots,p} b_i g_i^x(x), \qquad (5.21)$$

$$F^2(x, y) = \sum_{i=1,\dots,p} \sum_{j=1,\dots,q} b_{i,j} g_i^x(x) g_j^y(y) \qquad (5.22)$$

$$F^3(x, y, z) = \sum_{i=1,\dots,p} \sum_{j=1,\dots,q} \sum_{j=1,\dots,r} b_{i,j,k} g_i^x(x) g_j^y(y) g_k^z(z), \qquad (5.23)$$

where b_i, $b_{i,j}$ and $b_{i,j,k}$ are the coefficients of the non-linear functions, and p, q, and r are the number of the basis functions g_i^x, g_j^y and g_k^z related to process variables x, y and z, respectively. Piece-wise linear basis functions were selected for this case study.

A mass balance model was created to describe the steam feed and the steam balances of the steam groups (SG) 3, 4, 7, and 8 as illustrated by Figure 5.8. Since steam flow measurements were only available for the feed steam headers, the steam flow to each SG was estimated using a novel technique that is based on empirical valve models (Zakharov, 2011). The models for the valves were estimated using measurement data of the pressure difference across the valves and the valve openings. The complete model consisted of the following equations created based on the structure of the drying section:

$$f_{3,in10}(V_3, \Delta P_3) + f_{4,in}(V_4, \Delta P_4) + f_{7,in}(V_7, \Delta P_7) + f_{8,in}(V_8, \Delta P_8) = F_{in,10} \qquad (5.24)$$

$$f_{1,in}(V_1, \Delta P_1) + f_{2,in}(V_2, \Delta P_2) + f_{3,in5}(V_3, \Delta P_3) + F_{Cal} = F_{in,5} \qquad (5.25)$$

$$f_{8,c}(V_{8,c}, \Delta P_{8,c}) + f_{8,pd}(V_{8,pd}, \Delta P_{8,pd}) = F_{8,in} \qquad (5.26)$$

$$f_{7,c}(V_{7,c}, \Delta P_{7,c}) + f_{7,pd}(V_{7,pd}, \Delta P_{7,pd}) = F_{7,in} \qquad (5.27)$$

$$f_{3,c}(V_{3,c}, \Delta P_{3,c}) + f_{3,pd}(V_{3,pd}, \Delta P_{3,pd}) = F_{3,in5} + F_{3,in10} + F_{4,c} \qquad (5.28)$$

$$f_{4,c}(V_{4,c}, \Delta P_{4,c}) + f_{4,pd}(V_{4,pd}, \Delta P_{4,pd}) = F_{4,in} \qquad (5.29)$$

In the above equations, $f_i(V_i, \Delta P_i)$ refer to the identified valve model, where V_i is the valve opening and ΔP_i is the pressure difference across the valve for the drying group i. F_i are the mass flows. Subscripts c refer to the condensate flow and pd to pressure difference control valve located in the condensate line. The input and output variables of the Equations (5.19-25) are also summarized in Table 5.6.

Next, the detection thresholds for each residual were defined for the CUSUM method using the standard deviations of modelling errors. Finally, the residual-fault incidence matrix was determined for fault isolation purposes.

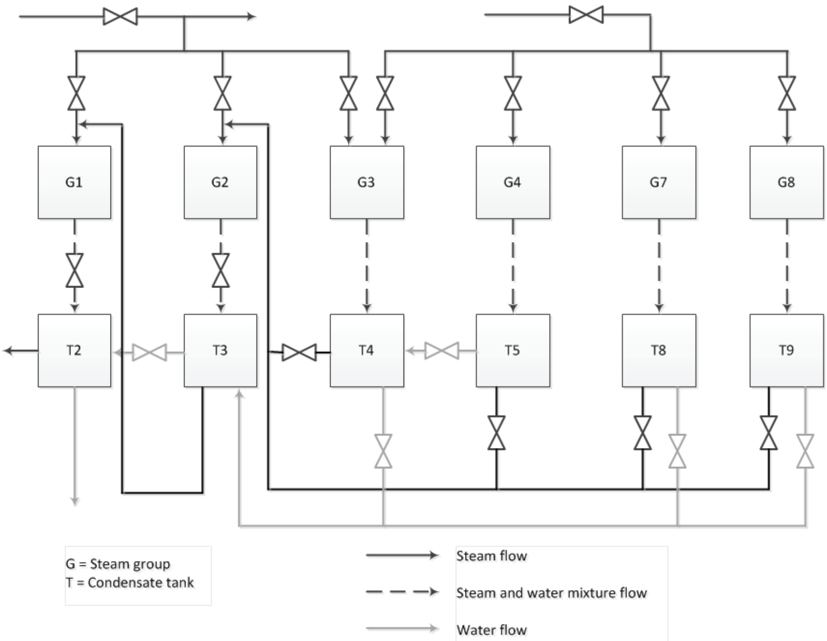

Figure 5.8. Simplified flowsheet of the drying section

5.4.4 Self-organizing map for caliper sensor fouling

A process monitoring method based on the SOM algorithm was developed in order to detect caliper sensor fouling. The mechanisms and chemistry behind the fouling phenomenon are very complex and therefore the problem was addressed with a non-linear data-based method. The SOM was selected due to its ability to handle a large number of variables having non-linear relationships and to identify the process condition in which fouling is occurring by classifying the process data. The use of a classifier method was motivated by the availability of faulty and healthy data.

Table 5.6. Summary of the developed parity equations

Equation	Inputs	Outputs
10 bar steam feed	10 bar feed steam flow	Steam flows to SGs 3, 4, 7, 8
5 bar steam feed	5 bar feed steam flow	Steam flows to SGs 1, 2, 3 Steam flow to calender
Steam group 8	10 bar steam flow to SG8	Steam flow from SG8 Condensate flow from SG8
Steam group 7	10 bar steam flow to SG7	Steam flow from SG7 Condensate flow from SG7
Steam group 4	10 bar steam flow to SG4	Steam flow from SG4 Condensate flow from SG4
Steam group 3	10 bar steam flow to SG3 5 bar steam flow to SG3 Condensate flow from SG4	Steam flow from SG3 Condensate flow from SG3

In addition, the known chemical phenomena related to fouling could be incorporated as calculated variables and appended to the training data. The SOM also possesses strong visualization properties, and it has successful applications in various process monitoring tasks (Jämsä-Jounela *et al.*, 2003; Hakala *et al.*, 2006).

The monitoring method consisted of two main phases: a training phase and an online phase. The training phase comprised the selection of input variables, data preprocessing, determining the training parameters, and training of the SOM using industrial data. The online phase consisted of the calculation of the best-matching units (BMUs), the visualization and analysis of the results.

The input variables for the SOM were selected based on process data analysis using correlation analysis, the SOM and process knowledge. The data analysis results are presented in (Tikkala *et al.*, 2011). Apart from the specific temperatures and chemical flows, the input variables for the SOM included calculated variables (see e.g. Komulainen *et al.*, 2004) describing the important process phenomena related to fouling. In (Tikkala *et al.*, 2011), it was discovered that the neutral size is the main chemical affecting fouling, and therefore the following variables were introduced.

The first calculated variable R described the chemical reaction between size molecules and wood fibers with an exponential function resembling the Arrhenius equation for the reaction rate constant. According to Neimo (1999), the reaction of size molecules with wood fibres is favoured by high pH. Therefore, the exponential term was multiplied by the pH of the stock as follows:

$$R = e^{-1/T_W} \cdot \text{pH}, \tag{5.30}$$

Table 5.7. List of variables for the SOM monitoring application

#	Variable	Description
1	F	Caliper control error (cv-sp)
2	dF	Filtered derivative of F
3	R	Reaction of the size molecules and fibres
4	C	Curing of the size molecules
5	S	Adsorption of size particles
6	T_{cal}	1st calender thermo roll temperature
7	P_0	Zero-pressure level of the secondary hood
8	T_{H}	Hood ventilation air temperature
9	F_{WS}	Wet strength size flow
10	F_S	Starch flow
11	F_{NS}	Neutral size flow
12	F_{RS}	Retention starch flow
13	F_{RA}	Retention agent flow
14	T_W	Temperature of the web

where T_W is the temperature of the web. The second calculated variable, C, provided insight into curing, i.e. orientation phase, of the size molecules. Curing is favoured by high temperature and impeded by the moisture of the web (Neimo, 1999), leading to the following expression for C:

$$C = \frac{T_W}{M}, \tag{5.31}$$

where M is the moisture of the web. The last calculated variable S describes the starch ratio of the stock. Since the amount of starch has a positive effect on the adsorption of the size particles (Neimo, 1999), S was defined as:

$$S = \frac{F_S}{F_{\text{top}}}, \tag{5.32}$$

where F_S is the starch flow and F_{top} is the stock flow for the top layer.

The final list of variables for the SOM monitoring is presented in Table 5.7. For the details on data preparation and preprocessing, please refer to Publication V.

The training was performed using the batch training algorithm and the relevant training parameters have been presented in Table 3 of Publication V. The SOM algorithm and defining the training parameters are further discussed by Vesanto *et al.* (2000). The training phase resulted in a map that described the process conditions and the regions of faulty operation could be identified.

In the online phase, the SOM was used to classify the current process state based on the different operation regions on the map. The best-matching units, i.e. the closest map nodes, were computed for each new data sample and the results were analysed and visualized on the SOM. In order for the SOM to adapt to the varying conditions of the board machine process, the SOM was re-trained during the online phase. The re-training phase consisted of a short training step, in which the weights of the map were updated using recent data and the previous weights as initial values.

6. Summary of the Fault Detection Results

The summary of the testing results of each fault detection algorithm is presented in this chapter. First, Section 6.1 discusses the results of oscillation and valve stiction detection. Then, the results of the consistency sensor malfunction detection are presented in Section 6.2, followed by the results of detecting the leakages and blockages in the drying section using the non-linear parity equation algorithm (Section 6.3). The monitoring results of the SOM-based caliper sensor fouling detection are addressed in Section 6.4. Section 6.5 deals with the industrial validation results of the developed fault detection algorithms and finally the fault detection results are evaluated and discussed in Section 6.6.

6.1 Detection of oscillations and valve stiction

The oscillation and valve stiction detection algorithms were tested with two different tests. The first test concentrated on oscillation detection, whereas the second test focused on the valve stiction detection and the reliability indices. The results are presented in Publication II and Publication I respectively, and summarized in the following.

The robust zero-crossing method was tested with ten control loops from the board machine; two flow control loops from the stock preparation (FC1 and FC2), one level control loop (LC1) and seven pressure control loops (PC1 to PC7) from the drying section. The selected control loops exhibited oscillatory behaviour with different and sometimes irregular shapes of oscillation and some of the signals were corrupted by noise, as illustrated in Figure 6.1.

The oscillations were detected successfully in each loop and the estimated periods were close to the actual observed periods. The oscillation indices r_{RZC} reported in Table 6.1 are all above the threshold $r_{lim} = 1$

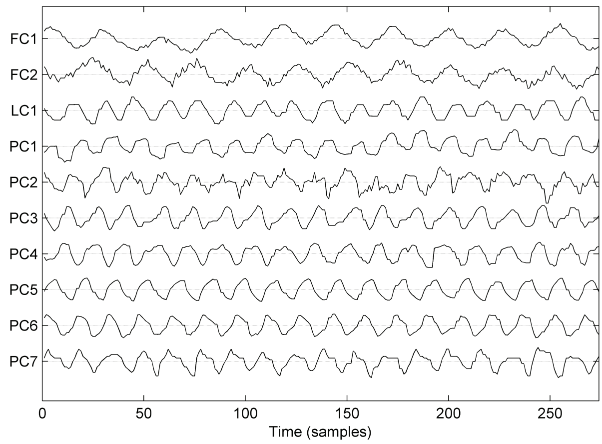

Figure 6.1. Board machine data for oscillation detection tests.

Table 6.1. Oscillation detection results on the board machine data.

Loop	Period samples	minutes	p_{RZC}	r_{RZC}
FC1	27–30	4.5–5.0	26	1.73
FC2	20–23	3.3–3.8	20	1.31
LC1	16–17	2.7–2.8	16	3.79
PC1	13–17	2.2–2.8	16	1.74
PC2	12–15	2.0–2.5	10	1.06
PC3	15–18	2.5–3.0	15	3.49
PC4	15–19	2.5–3.2	16	3.06
PC5	14–17	2.3–2.8	16	6.93
PC6	17–18	2.8–3.0	16	4.90
PC7	15–18	2.5–3.0	14	2.60

which indicate a correct detection result in each case. The oscillation periods p_{RZC} were correctly estimated in most of the cases. However, some variation in the results occurred in the case of loops FC2, PC2, PC6 and PC7 for which the estimated period is slightly less than the observed period. This was a consequence of measurement noise that skewed the distribution of zero-crossings and biased the estimation of the oscillation period. In particular, in the loop PC2, the measurement noise in the signal disturbed the oscillation detection. The oscillation index was just over the detection limit and the noise caused the period to be estimated significantly smaller than the actual value. However, a correct detection decision was still made by the RZC algorithm.

The second test employed data from four critical control loops of the case process: a pressure control loop in the steam group 2, a flow control loop in the birch dosing, a pressure difference loop in the steam group 8 and a flow loop in the stock mixing. The implemented valve stiction algorithms

Table 6.2. Valve stiction detection results. Stiction indices for the curve fitting method (s_C), the histogram method (s_H), the rectangular fitting method (s_R), the bicoherence method, and the integrated index.

Test cases and maintenance description	Month	s_C	s_H	s_R	Bicoherence NGI	Bicoherence NLI	Integrated index
Case 1:	Jan	0.59	0	-0.04	0.21	0.46	0.54
Sticky valve	Feb	0.71	1	0.17	0.21	0.87	0.65
	Mar	0.67	1	0.21	0.20	0.67	0.64
Case 2:	Jan	0.56	0.5	0.49	0.22	0.45	0.64
Malfunction	Feb	0.6	1	0.44	0.22	0.41	0.44
	Mar	0.55	1	0.43	0.21	0.50	0.58
Case 3:	Jan	0.59	1	0.60	0.19	0.56	0.50
Sticky valve	Feb	0.58	1	0.51	0.19	0.47	0.49
	Mar	0.58	1	0.41	0.19	0.69	0.44
Case 4:	Jan	0.50	1	0.13	0.29	0.22	0.61
Malfunction	Feb	0.57	1	0.43	0.21	0.41	0.55
	Mar	0.54	1	0.40	0.27	0.43	0.84

were first tested separately and then in parallel by weighting the results according to their reliability indices.

The individial stiction indices showed that the algorithms provided similar results in the cases in which the oscillation of a signal was strong, however, there were some time periods where the results did not agree. Table 6.2 summarizes the stiction indices produced by the individual methods and the integrated stiction detection for all cases in the first test. The obtained results showed that the use of the reliability indices was effective in combining and weighting the decisions. The parallel configuration provided more robust and stable results than the individual stiction detection algorithms.

6.2 Detection of consistency sensor malfunctions

The fault detection method for consistency sensor faults was tested in simulation studies using an advanced board machine simulator (Lappalainen, 2004) implemented in the APROS simulation environment (Silvennoinen *et al.*, 1989). This section briefly presents the results from Publication III, while further studies on consistency sensor faults have been carried out by the author in (Tikkala, 2008).

A consistency sensor fault in the stock preparation section was studied. The fault was simulated by introducing a negative bias to the sensor of the pine pulp line in the simulation model. The residuals were generated using collected data from the simulator, and the CUSUM method was used

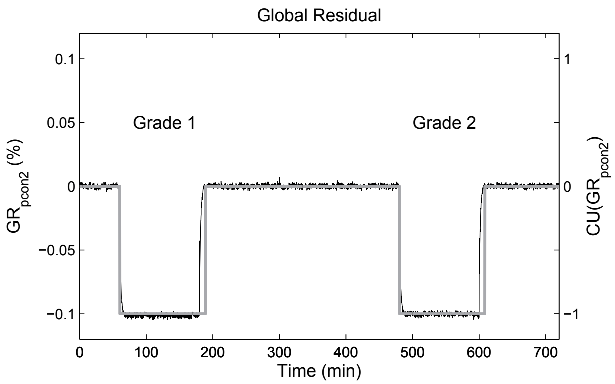

Figure 6.2. Global residual of pine pulp consistency $pcon2$ (left y-axis) and its detection results (right y-axis).

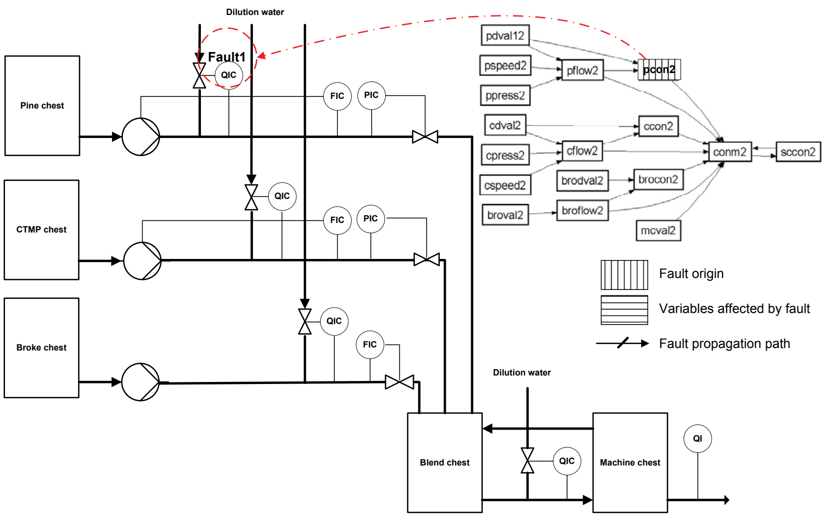

Figure 6.3. Fault diagnosis results for the fault scenario 1.

for fault detection. The fault was detected in variable $pcon2$, whose global simulation value, global residual and the detection results are illustrated in Figure 6.2. By applying the rules in Tables 2.1 and 2.2 in Section 2.2.2, it was inferred that the fault is a local sensor fault related to the consistency of pine pulp line, see Figure 6.3. Due to the nature of the fault, neither the fault separation nor the inference between the arcs needed to be performed.

6.3 Detection of leakages and blockages in the drying section

The operation of the non-linear parity equation algorithm was tested in two case studies. The first case considered a valve blockage, whereas the

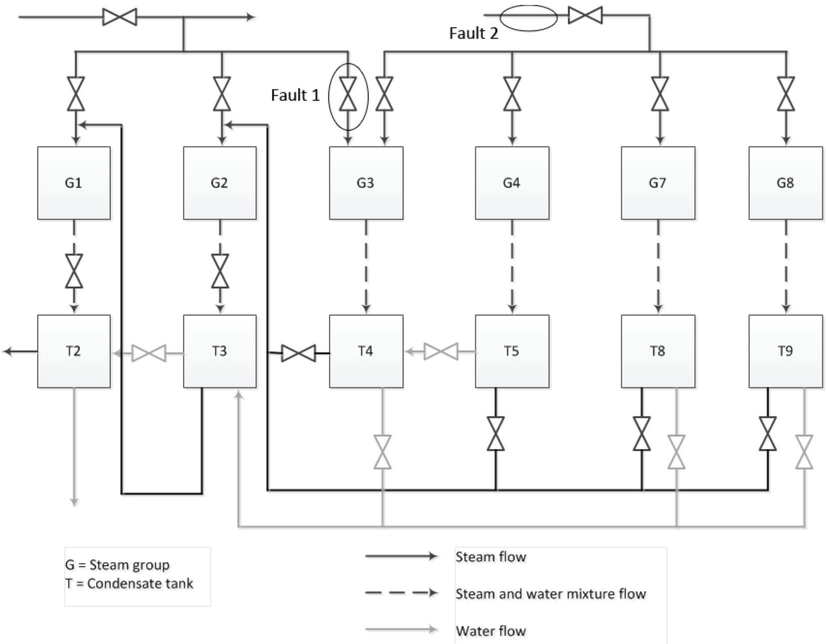

Figure 6.4. Schematic of the steam and condensate system of the drying section. Locations of fault case 1: valve blockage in steam group 3, and case 2: measurement fault in the 10 bar steam feed.

second case studied a measurement fault, both cases being confirmed by the maintenance records of the mill. The results are briefly presented in the following while a more detailed presentation of them is given in Publication IV.

The first fault considered a blockage of the valve located between the 5 bar steam header and the steam group 3, as shown in Figure 6.4. The comparison of the estimated flow rate to the steam groups and the 5 bar feed steam flow presented in Figure 6.5 (top) clearly indicates the discrepancy caused by the fault. During the periods between 2200–2400 and 2460–2630 samples, the flow should have been significantly higher than was actually measured. To isolate the fault correctly, the other residuals were inspected. The fault was also detected from Figure 6.5 (bottom) which shows the comparison of the estimated inflow and outflow of the SG3. All other residuals remained undisturbed which resulted in an unambiguous detection of the inflow to the SG3 being partly blocked. A confirmation was received from the maintenance records which reported a blockage in that valve.

The second case study considered a fault in the flow rate measurement of the 10 bar feed steam, the process location of which is shown in Fig-

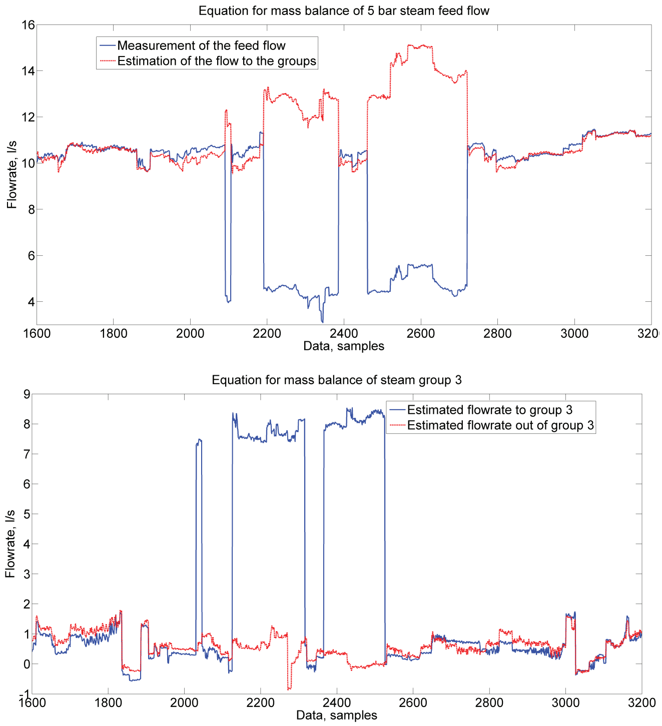

Figure 6.5. Estimations of the mass balances of the 5 bar feed steam flow (top) and the steam group 3 (bottom)

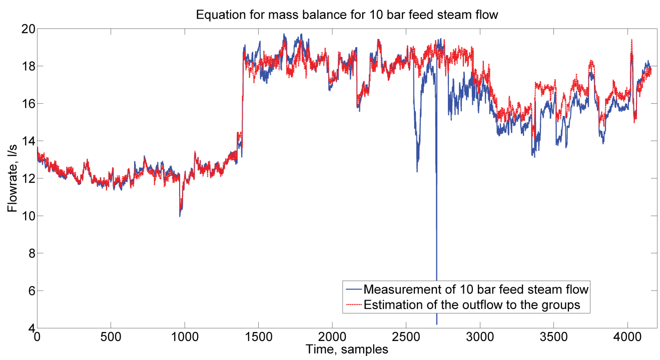

Figure 6.6. Estimation of the 10 bar feed steam flow

ure 6.4. A disturbed residual was detected in the estimation of the 10 bar feed steam flow as illustrated by Figure 6.6. The fault effect is visible since approximately $t = 2500$. Since all other residuals remained undisturbed, the fault was unambiguously isolated and it was concluded to be related to the flow measurement. The maintenance records verified the result as they reported that the flow meter had been replaced shortly afterwards.

6.4 Monitoring of the caliper sensor fouling

The process monitoring scheme for caliper sensor fouling was tested with industrial data collected from the board machine. The results presented in Publication V are summarized in the following.

Training and testing of the SOM was carried out using six data sets, each data set representing one month of operational data. Training was first carried out using data sets 1 and 2, and its results are illustrated in Figure 6.7. First, the top left panel of the figure, the unified distance matrix (U-matrix), displays the clustering of the training data. Next, the single variable maps describe the distribution of high and low values of each variable on the map and finally, the bottom right panel shows the distribution of faulty and normal data samples on the map. A major cluster of faulty samples is located in the middle of the left hand side of the map. Furthermore, a minor faulty data cluster is located in the bottom left corner of the map. These were identified as the faulty regions for the on-line test phase. In addition to the identification of the faulty regions, the effects of the individual variables on fouling were studied. Especially, the effect of temperature conditions and neutral size chemistry on dirt build-up was confirmed from Figure 6.7.

The monitoring test results using the SOM are presented in Figure 6.8, where the panels from top to bottom show the process state estimation results for the data sets D_3, D_4, D_5 ,and D_6, respectively. To reduce noise and the rate of false alarms, the estimated state was filtered using a moving average filter with a window length of 5 samples. By comparing the estimated state and the fault indicator presented in Figure 6.8, it was confirmed that the SOM gave a rather good estimate of the actual process conditions. Caliper sensor fouling was detected in most of the cases. Especially when fouling had been occurring for a longer time period, as demonstrated with the data sets D_3 and D_6, the SOM was able to detect the conditions correctly. Difficulties with the detection however arose in shorter faulty periods.

The performance of the SOM was summarized by computing the rates of correctly estimated states, falsely estimated states and uncertain states, see Table 6.3. The SOM was on average able to estimate the state of the process correctly in over 70% of the time. The rate of falsely estimated states was rather low, on average below 20%.

The perceived errors may have resulted from the fault indicator, which

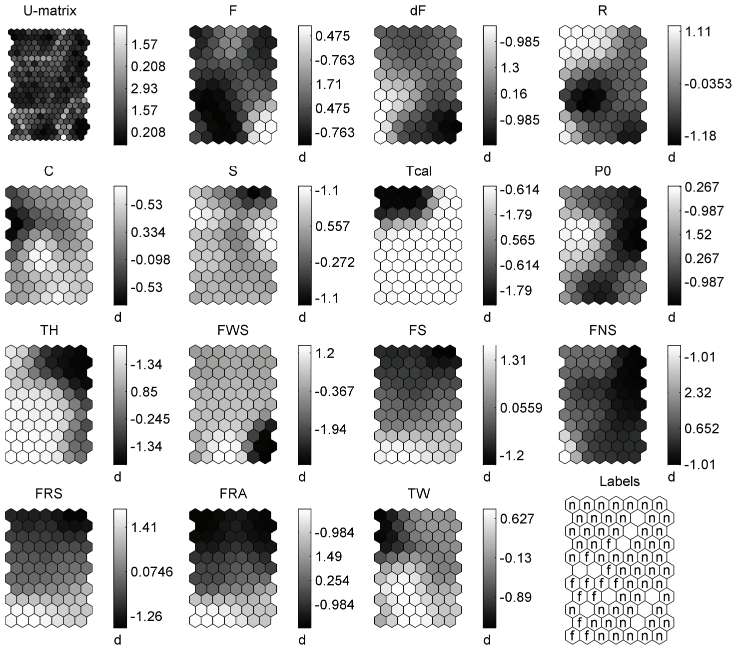

Figure 6.7. Overview of the SOM analysis for the training data: U-matrix, single variables maps and distribution of the faulty and normal operation samples.

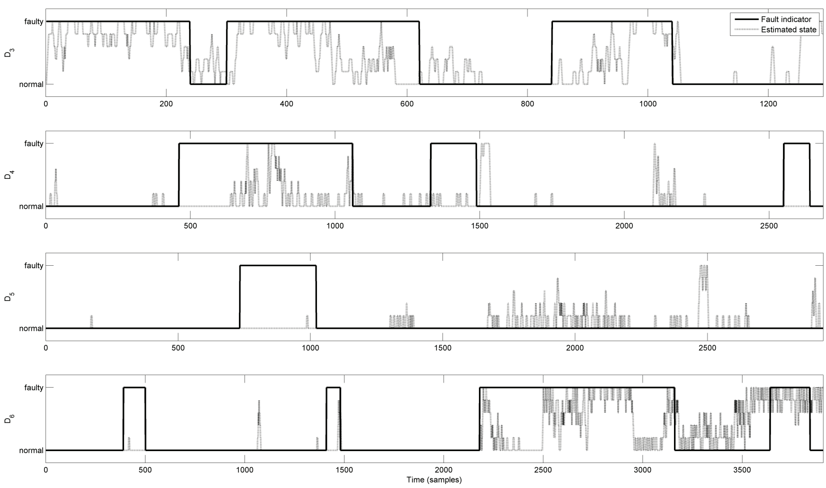

Figure 6.8. The monitoring results using the SOM. From top to bottom: D_3, D_4, D_5, and D_6

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had been created based on the dates of the maintenance reports and then confirmed by visual inspection of the data. As a result, the fault indicator might not have been exactly aligned with actual fouling and all fouling instances might not have been reported properly in the database.

Table 6.3. Results of the monitoring tests using the SOM

	D_3 (%)	D_4 (%)	D_5 (%)	D_6 (%)
Correct process states	61.7	67.0	86.2	69.9
False process states	19.0	29.0	10.8	19.8
Uncertain process states	19.3	4.0	3.0	10.3

6.5 Industrial validation results

The fault detection algorithms developed for the board machine were also tested with industrial experiments in order to validate their operation. The objective of the experiments was to artificially generate faults in the process and to collect data for testing the detection algorithms. Two experiments were conducted to study the performance of the non-linear parity equation algorithm and the valve stiction detection system, since they were considered as the algorithms with most commercial potential by the industrial partners. Experiments were not carried out to further validate the SOM or the DCDG method, because such experiments could not be done during the normal operation of the board machine.

6.5.1 Industrial validation experiments

The experiments were conducted during normal production on December 13, 2012 by the industrial partner and they consisted of two separate cases related to the board machine drying section. Due to production and quality limitations, the experiments were short, lasting in total about two hours, and the magnitude of the created faults was relatively low.

The first experiment case was an emulated measurement fault in the pressure measurement of Steam Group 3. According to the plant personnel, the measurement signal was frozen for three times during one hour (12:00–13:00) causing disturbance to the pressure control and thus excessive variation in board moisture. Figure 6.9 shows the behaviour of board moisture, pressure in the Steam Group 3 and the pressure control valve opening during the experiment case 1 (highlighted area). The measurement signal was frozen for the first time at 12:05, released and frozen again at 12:26. After releasing the measurement at 12:37, the control loop was allowed to stabilize, until the pressure measurement was frozen again at 12:40 and finally released at 12:48. A small portion of data was lost from the beginning of the experiment due to communication problems in the information systems.

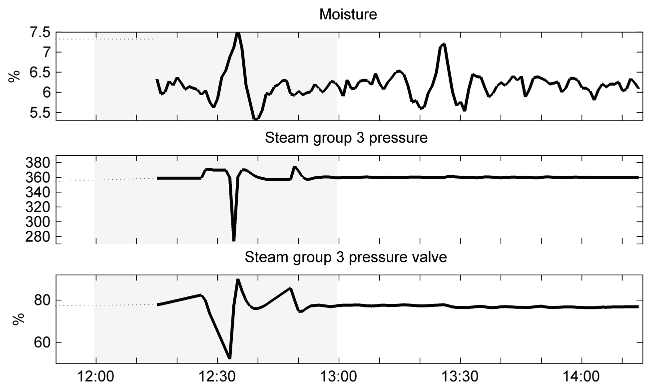

Figure 6.9. Industrial validation experiment case 1 (highlighted area): Moisture of the board (top), Pressure measurement of steam group 3 (middle), and the corresponding pressure valve opening (bottom). Missing data (11:50–12:15) indicated with dots

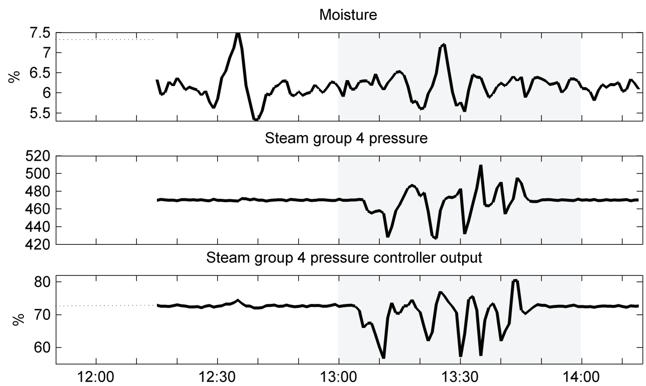

Figure 6.10. Industrial validation experiment case 2 (highlighted area): Moisture of the board (top), Pressure measurement of steam group 4 (middle), and the corresponding pressure valve opening (bottom). Missing data (11:50–12:15) indicated with dots

As the second validation case, an artificial valve stiction fault was created in the Steam Group 4. The pressure control valve of that group was disturbed by disconnecting the pressurized air supply to its actuator in order to replicate stiction. The actuator was obstructed five times during the experiment, which lasted for one hour (13:00–14:00), again causing disturbance to the pressure control and board moisture. The setpoint of the pressure controller was changed several times in order to evoke oscillations for stiction detection algorithms. Figure 6.10 presents the variables related to this case, from top to bottom: board moisture, pressure measurement in the Steam Group 4, and the pressure controller output.

Table 6.4. Stiction and reliability indices for the validation experiment 2

Method	s_i	w_i	S
Curve fitting	0.58	0.17	0.82
Histogram	1	0.59	
Rectangular fitting	0.62	0.54	
Bicoherence	0.65	0.5	

6.5.2 Validation of the non-linear parity equation algorithm

The non-linear parity equation algorithm for detecting leakages and blockages was evaluated using both validation cases. The experimental data were used to compute the residuals according to the Equations (5.19-25). The residual signals during the validation cases are presented in Figure 6.11 together with the detection thresholds. Due to the missing data segment at the beginning of the experiments, the residuals were not computed reliably before 12:40.

However, the measurement fault was successfully detected by the parity equation method. The residual for the Steam Group 3 was exceeding the detection threshold, as illustrated by Figure 6.11. The other residuals remained undisturbed, which suggested that the fault was isolated correctly to the Steam Group 3.

For the second validation case there were two residual exceeding the detection threshold, which was set to 0.5 based on the standard deviation of model errors from the training phase. The detected residuals were related to the 10 bar steam supply and the Steam Group 4 which indicated a fault in the steam feed to Group 4. This result also coincides with the experiment description and the fault was detected and isolated successfully. Despite the fact that the objective of this experiment was to emulate valve stiction, it also disturbed the mass balance calculation and the fault was detected by this algorithm.

6.5.3 Validation of the valve stiction detection system

The valve stiction detection algorithms were used to analyse the validation experiment in which stiction was created artificially. The pressure measurement and controller output signals were analysed using all four stiction detection algorithms and the corresponding reliability indices were calculated. Table 6.4 presents the results, which clearly demonstrated stiction in that loop; the combined stiction index was 0.82. All stiction algorithms indicated stiction also individually, however the reli-

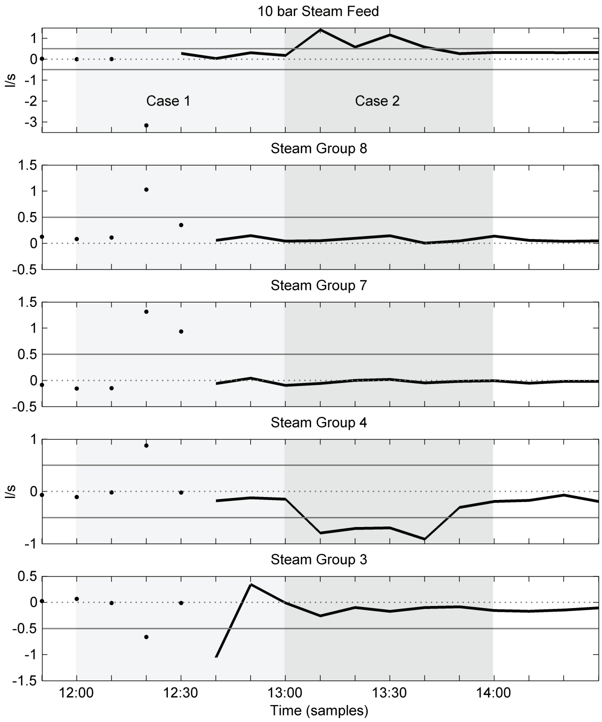

Figure 6.11. Residuals of the non-linear parity equation algorithm for the industrial validation experiments. The solid black line indicates the residual and the horizontal grey lines denote the detection thresholds.

ability of the curve fitting method was low and therefore that result was disregarded.

6.6 Discussion

The testing of the fault detection algorithms delivered promising results regarding industrial implementation. Each algorithm proved to be able to detect the respective faults, and the most of the results could be verified by the plant personnel or maintenance data. Systematic fault propagation analysis was not carried out since it was outside of the scope of this thesis. The benefits of timely fault detection were, however, estimated based on expert opinions.

The valve malfunction case studies proved that the oscillation detection and valve stiction diagnosis algorithms performed well in the industrial environment. The oscillation detection method seemed to be robust against noise and uncertainties in data and to handle non-stationary signals well. The method can be applied to automatically analyse large amounts of signals, since it does not require any tuning parameters set by the user.

The integrated valve stiction diagnosis system also provided promising results. The use of reliability indices facilitated the interpretation of stiction indices and allowed the fusion of the individual indices into an overall diagnosis decision. The results of the individual algorithms were not consistent in all cases, but by evaluating the respective reliability indices the false or uncertain results could be successfully neglected. This kind of approach possesses major potential for industrial implementation on already existing automation system platforms, therefore, it could be easily commissioned at the plant.

The oscillations induced by stiction in control valves are detrimental to the process. By detecting oscillations and stiction, the process variability, which typically propagates to large parts of the process, can be reduced. Lower variability will result in lower product quality variation and less wear in the control valves.

The CDG algorithm was successful in detecting the consistency sensor malfunctions. The method is very general and thus it can be utilized for various other fault types as demonstrated in Publication III. The extent of the CDG model can be adjusted based on the requirements of the application. In this case, the model covered two process units, namely the stock preparation and the short circulation, for which the consistency sensors are the most crucial. More significant benefits could be obtained by applying the CDG method to difficult process faults.

The benefits of detecting consistency sensor malfunctions are more accurate control of pulp quality and tracking of used raw materials. The improved control of stock consistency decreases fluctuations in the pulp quality and therefore it contributes to reducing production losses due to basis weight variations. Another important economic aspect is the tracking of raw material consumption. False consistency measurements may lead to the wrong proportions of raw materials. As a result, excessive amounts of expensive pulp grades can be consumed instead of more inexpensive mechanical pulps.

Faults in the drying section were detected and diagnosed successfully by the non-linear parity equation method. As shown by the cases presented in Section 6.3, the non-linear parity equation method was capable of detecting typical faults in the steam and condensate system. These results were also validated by the maintenance records of the plant. The novel algorithm, which estimated the flows indirectly using the available pressure measurements and valve positions, provided means to compute the mass balances for a system that lacks of sufficient measurements information for traditional methods.

Detection of drying section faults, such as blockages and leakages has direct consequences on the economy of the process. The early detection of leakages is important in order to trigger maintenance actions to prevent energy losses due to wasted steam. Energy savings are also obtained by detecting blockages which increase pumping costs and might reduce drying capacity. By reducing the capacity of the drying section, these faults can also affect the moisture of the board which is not desirable since moisture is one of the key quality variables and has strict limits set by customers.

The SOM algorithm was shown to be a useful tool for monitoring and visualizing the process conditions related to caliper sensor fouling. The main contributing factors were the integration of process knowledge in terms of calculated variables and the adaptation to changing process conditions by the re-training steps. The calculated variables improved the classification ability of the SOM by taking into account the main chemical phenomena related to fouling. Furthermore, the regular re-training steps of the SOM addressed the time-invariant nature of the process. The obtained results were fairly good, however for industrial implementation and use their reliability must be improved. For this reason, more detailed data about the rate of fouling in different conditions should be acquired.

The analysis of fouling and related chemical phenomena have benefited the plant operations. According to the plant experts, the results have contributed to the operation of the plant and as a consequence more attention has been paid to the cleaning of the sensor. The sensor fouling does not cause direct production losses, but with close monitoring of the sensor state the maintenance actions can be planned better and the quality of the product can be followed more accurately.

The above discussion points out that the developed fault detection algorithms have potential to decrease the operational costs of the case board machine. Timely fault detection allows the planning of the maintenance actions in a more appropriate way and the minimization of the fault effects on the process operation and economy. These results therefore support confirming the hypothesis outlined at the start of this thesis.

7. Conclusions

This thesis presented a methodology for developing fault detection systems for industrial processes and illustrated its application to a board-making process. The fault detection system development was based on a process decomposition and fault analysis of the case process. First, the process was decomposed into process units, subsystems, and process equipment and its control strategy was analysed to examine the structure of the process and to facilitate the fault analysis. The fault analysis in turn aimed at identifying the faults causing production losses as well as the sections of the process which are affected by them. Then, the fault detection algorithms were developed to address the faults and finally they were tested and validated in industrial test cases.

The methodology provided a systematic approach for fault detection system development. Since modern production processes are large-scale and complex, the number of possible faults that can occur is too large to be covered by any single fault detection method or system. As a consequence, the developed system comprised multiple algorithms that concentrated on the most significant faults of the board machine.

The developed fault detection algorithms were successfully tested and validated with industrial case studies. The tests were mainly carried out using industrial data provided by the plant. Simulations were used only for the testing of the dynamic causal digraph method, since the experiments related to cause-effect model identification could not be carried out at the plant. The detection results obtained using real measurement data demonstrated the actual industrial potential of the algorithms.

The results indicated that the algorithms provide essential information for planning maintenance actions and to improve the operation of the machine. There is a need to integrate the production and maintenance information systems at the plant in order to facilitate such system development in the future.

The hypothesis of this thesis was that an integrated fault detection system, for which the development of fault detection algorithms is based on fault types obtained from fault analysis, provides an opportunity to improve the operation and performance of the process through the timely detection of faults. By referring to the fault detection results presented in Section 6 and to their practical implications as well as to the discussion above, the hypothesis was verified.

The results of and the experience on industrial testing of these fault detection algorithms provide several possible directions for further development and future research.

The valve stiction and oscillation detection algorithms have significant potential for future research. The system combining different stiction detection algorithms could be improved by a more comprehensive analysis of the applicability of each algorithm and by developing an automatic selection procedure to choose the best algorithms for each case. Such an approach could then be implemented directly to a process automation system to assess the performance of control loops.

Further research could also be focused on applying the reliability estimation and decision fusion approach to the monitoring of caliper sensor fouling. The SOM could be accompanied with other monitoring methods in order to improve the resolution and accuracy of the results. In addition, the adaptivity of the SOM could be studied in more detail to investigate the conditions and optimal points for re-training.

However, the most interesting and theoretically challenging topic will be the combination of diagnostic knowledge from different fault detection modules via systematic analysis of the interactions between them and the faults. Merging detection and isolation results from several modules would allow more comprehensive diagnosis of faults on a large-scale basis and provide an opportunity to develop new control strategies that are able accommodate the faults. After the diagnosis step, plant behaviour could be predicted using the knowledge about fault propagation and the controllers reconfigured to mitigate the fault effects in order prevent propagation to a higher level of control hierarchy and to maintain acceptable product quality. Such an approach would facilitate closing the plant asset management loop discussed in Section 3.

References

Abonyi, J., Nemeth, S., Vincze, C. & Arva, P., 2003. Process analysis and product quality estimation by self-organizing maps with an application to polyethylene production. *Computers in Industry*, vol. 52, pp. 221–234.

Ahola, J., Alhoniemi, E. & Simula, O., 1999. Monitoring industrial processes using the self-organizing map. In: *1999 IEEE Midnight-sun Workshop on soft Computing Methods in Industry Applications*, Martikainen, J., ed., pp. 22–27, Kuusamo, Finland, Jun 16–18, 1999.

Aldrich, C., Moolman, D. W. & van Deventer, J. S. J., 1995. Monitoring and control of hydrometallurgical processes with self-organizing and adaptive neural net systems. *Computers & Chemical Engineering*, vol. 19, pp. S803–S808.

Backström, J. & Baker, P., 2008. A benefit analysis of model predictive machine directional control or paper machines. In: *Proceedings of Control Systems 2008*, Vancouver, Canada, July 16–18, 2008.

Ballé, P., 1999. Fuzzy-model-based parity equations for fault isolation. *Control Engineering Practice*, vol. 7, pp. 261–270.

Becraft, W. R. & Lee, P. L., 1993. An integrated neural network/expert system approach for fault diagnosis. *Computers & Chemical Engineering*, vol. 17(10), pp. 1001–1014.

Ben-Haim, Y., 1980. An algorithm for failure location in a complex network. *Nuclear Science and Engineering*, vol. 75, pp. 191–199.

Blanke, M., Kinnaert, M., Lunze, J. & Staroswiecki, M., 2003. *Diagnosis and Fault-Tolerant Control*. 1st ed., Springer-Verlag, Berlin, Germany, 571 pp.

Blesa, J., Puig, V. & Saludes, J., 2012. Robust identification and fault diagnosis based on uncertain multiple input-multiple output linear parameter varying parity equations and zonotopes. *Journal of Process Control*, vol. 22, pp. 1890–1912.

Bouhouche, S., Yahi, M. & Bast, J., 2011. Combined use of principal component analysis and self organisation map for condition monitoring in pickling process. *Applied Soft Computing*, vol. 2011, pp. 3075–3082.

Chan, C. W., Hua, S. & Hong-Yue, Z., 2006. Application of fully decoupled parity equation in fault detection and identification of DC motors. *IEEE Transactions on Industrial Electronics*, vol. 53(4), pp. 1277–1284.

Chang, C.-C. & Yu, C.-C., 1990. On-line fault diagnosis using the signed directed graph. *Industrial and Engineering Chemistry Research*, vol. 29, pp. 1290–1299.

Chen, X. & Yan, X., 2012. Using improved self-organizing map for fault diagnosis in chemical process industry. *Chemical Engineering Research and Design*, vol. 90, pp. 2262–2277.

Chen, X. & Yan, X., 2013. Fault diagnosis in chemical process based on self-organizing map integrated with fisher discriminant analysis. *Process Systems Engineering and Process Safety*, vol. 21(4), pp. 382–387.

Cheng, H., Nikus, M. & Jämsä-Jounela, S.-L., 2008. Fault diagnosis of the paper machine short circulation process using novel dynamic causal digraph reasoning. *Journal of Process Control*, vol. 18(7–8), pp. 676–691.

Chiang, L. H., Russell, E. L. & Braatz, R., 2001. *Fault detection and diagnosis in industrial systems*. 1st ed., Springer-Verlag, London, 273 pp.

Choudhury, M. A. A. S., Jain, M. & Shah, S. L., 2008a. Stiction — definition, modelling, detection and quantification. *Journal of Process Control*, vol. 18, pp. 232–243.

Choudhury, M. A. A. S., Shah, S. L. & Thornhill, N. F., 2004. Diagnosis of poor control loop performance using higher order statistics. *Automatica*, vol. 40, pp. 1719–1728.

Choudhury, M. A. A. S., Shah, S. L. & Thornhill, N. F., 2008b. *Diagnosis of Process Nonlinearities and Valve Stiction*. 1st ed., Springer.

Choudhury, M. A. A. S., Shook, D. S. & Shah, S. L., 2006. Linear or nonlinear? a bicoherence based metric of nonlinearity measure. In: *Proceedings of IFAC-Safeprocess 2006 Symposium*, Chang, H.-Y., ed., Beijing, China, Aug 30 – Sep 1, 2006.

Chow, E. Y. & Willsky, A. S., 1984. Analytical redundancy and the design of robust failure detection systems. *IEEE Transactions on Automatic Control*, vol. 29, pp. 603–614.

Chung, H., Bien, Z., Park, J. & Seong, P., 1994. Incipient multiple fault diagnosis in real time with application to large-scale systems. *IEEE Transactions on Nuclear Science*, vol. 33(8), pp. 1943–1954.

Corona, F., Mulas, M., Baratti, R. & Romagnoli, J. A., 2010. On the topological modeling and analysis of industrial process data using the SOM. *Computers & Chemical Engineering*, vol. 34, pp. 2022–2032.

Cuadrado, A. A., Díaz, I., Diez, A. B., Obeso, F. & González, J. A., 2002. Visual data mining and monitoring in steel processes. In: *Conference Record of the 37th Annual IAS Meeting*, pp. 493–500 vol. 1, Pittsburgh (PA), USA, Oct 13–18, 2002.

Dash, S. & Venkatasubramanian, V., 2000. Challenges in the industrial applications of fault diagnosis systems. *Computers & Chemical Engineering*, vol. 24, pp. 785–791.

Desborough, L. & Miller, R., 2001. Increasing customer value of industrial contol performance monitoring — Honeywell's experience. In: *Proceedings of CPC VI*, Rawlings, J. B., Ogunnaike, B. A. & Eaton, J. W., eds., pp. 172–192, Tucson (AZ), USA, Jan 7–12, 2001.

Ding, S. X., 2008. *Model-Based Fault Diagnosis Techniques*. 1st ed., Springer-Verlag, Berlin, Germany, 493 pp.

Dinkar, M., 1996. *DKit: A Blackboard-Based, Distributed, Multiexpert Environment for Abnormal Management System*. Ph.D. thesis, Purdue University.

Dinkar, M. & Venkatasubramanian, V., 1997. A hybrid framework for large scale process fault diagnosis. *Computers & Chemical Engineering*, vol. 21, pp. 935–940.

Ehrola, J., Hernesniemi, A., Kuosa, H., Kyytsönen, M., Linnonmaa, P., Mäenpää, T., Pietikäinen, R., Stapels, R., Tani, M. & Vuorikari, H., 1999. Calendering. In: *Papermaking Part III, Finishing*, Jokio, M., ed., pp. 10–140, FAPET Oy.

Ender, D., 1993. Process control performance: not as good as you think. *Control Engineering*, vol. 40(10), pp. 180–190.

Finch, F. E., Oyeleye, O. O. & Kramer, M. A., 1990. A robust event-oriented methodology for diagnosis of dynamic process systems. *Computers & Chemical Engineering*, vol. 14(12), pp. 1379–1396.

Forsman, K. & Stattin, A., 1999. A new criterion for detecting oscillations in control loops. In: *European Control Conferenre ECC'99*, p. 878, Karlsruhe, Germany, August 31 - September 3, 1999.

Frank, P. M., 1990. Fault diagnosis in dynamic systems using analytical and knowledge-based redundancy: A survey and some new results. *Automatica*, vol. 26(3), pp. 459–474.

Fuertes, J. J., Domínguez, M., Reguera, P., Prada, M. A., Díaz, I. & Cuadrado, A. A., 2010. Visual dynamic model based on self-organizing maps for supervision and fault detection in industrial processes. *Engineering Applications of Artificial Intelligence*, vol. 2010, pp. 8–17.

Furukawa, T., 2009. SOM of SOMs. *Neural Networks*, vol. 22, pp. 463–478.

Gertler, J. & Kunwer, M., 1995. Optimal residual decoupling for robust fault diagnosis. *International Journal of Control*, vol. 61(2), pp. 395–421.

Gertler, J. & Luo, Q., 1989. Robust isolable models for failure diagnosis. *AIChE Journal*, vol. 35(11), pp. 1856–1868.

Gertler, J. & Singer, D., 1985. Augmented models for statistical fault isolation in complex dynamic systems. In: *Proceedings of American Control Conference*, pp. 317–322, Boston (MA), USA, Jun 19–21, 1985.

Gertler, J. & Singer, D., 1990. A new structural framework for parity equation-based failure detection and isolation. *Automatica*, vol. 26(2), pp. 381–388.

Gertler, J. & Staroswiecki, M., 2002. Structured fault diagnosis in mildly nonlinear systems: Parity space and input-output formulations. In: *Proceedings of the 15th IFAC World Congress*, Basanez, L. & de la Puente, J. A., eds., pp. 341–346, Barcelona, Spain, Jul 21–26.

Gertler, J. J., 1988. Survey of model-based failure detection and isolation in complex plants. *IEEE Control Systems Magazine*, vol. 8(6), pp. 3–11.

Gertler, J. J., 1998. *Fault Detection and Diagnosis in Engineering Systems*. Marcel Dekker Inc.

Guernez, C., Cassar, J. & Staroswiecki, M., 1997. Extension of parity space to non-linear polynomial dynamic systems. In: *Preprints of IFAC – SAFEPROCESS 1997 Symposium*, Patton, R. J. & Chen, J., eds., pp. 861–866, Hull, UK, Aug 26–28, 1997.

Hägglund, T., 1995. A control loop performance monitor. *Control Engineering Practice*, vol. 3(11), pp. 1543–1551.

Hägglund, T., 2005. Industrial implementation of on-line performance monitoring tools. *Control Engineering Practice*, vol. 13, pp. 1383–1390.

Hägglund, T., 2011. A shape-analysis approach for diagnosis of stiction in control valves. *Control Engineering Practice*, vol. 19, pp. 782–789.

Hakala, R., Similä, T., Sirola, M. & Parviainen, J., 2006. Process state and progress visualization using self-organizing map. *Lecture Notes on Computer Science*, vol. 4224, pp. 73–80.

Han, C., Shih, R. & Lee, L., 1994. Quantifying signed directed graphs with the suzzy set for fault diagnosis resolution improvement. *Industrial and Engineering Chemistry Research*, vol. 33, pp. 1943–1954.

Harary, F., Norman, R. Z. & Cartwright, D., 1965. *Structural Models: An Introduction to the Theory of Directed Graphs*. 1st ed., John Wiley & Sons, New York, 415 pp.

He, P., Wang, J., Pottmann, M. & Qin, J., 2007. A curve fitting method for detecting valve stiction in oscillating control loops. *Industrial & Engineering Chemistry Research*, vol. 46, pp. 4549–4560.

Heikkinen, M., Poutiainen, H., Liukkonen, M., Heikkinen, T. & Hiltunen, Y., 2011. Subtraction analysis based on self-organizing maps for an industrial wastewater treatment process. *Mathematics and Computers in Simulation*, vol. 2011, pp. 450–459.

Himmelblau, D. M., 1978. *Fault detection and diagnosis in chemical and petrochemical processes*. 1st ed., Elsevier, Amsterdam, 414 pp.

Hinkley, D. V., 1971. Inference about the change-point from cumulative sum tests. *Biometrika*, vol. 58, pp. 509–623.

Höfling, T. & Isermann, R., 1996. Fault detection based on adaptive parity equations and single-parameter tracking. *Control Engineering Practice*, vol. 4(10), pp. 1361–1369.

Horch, A., 1999. A simple method for the detection of stiction in control valves. *Control Engineering Practice*, vol. 7, pp. 1221–1231.

Horch, A., 2006a. Benchmarking control loops with oscillations and stiction. In: *Process Control Performance Assessment – From Theory to Implementation*, Ordys, A., Uduehi, D. & Johnson, M. A., eds., pp. 227–257, Springer-Verlag, New York.

Horch, A., 2006b. Method and a system for evaluation of static friction. United States patent US 7047152.

Horio, K. & Yamakawa, T., 2001. Feedback self-organizing map and its application to spatio-temporal pattern classification. *International Journal of Computational Intelligence and Applications*, vol. 1(1), pp. 1–18.

Iri, M., Aoki, K., O'Shima, E. & Matsuyama, H., 1979. An algorithm for diagnosis of system failures in the chemical process. *Computers and Chemical Engineering*, vol. 3, pp. 489–493.

Isermann, R., 2006. *Fault-Diagnosis Systems: An Introduction from Fault Detection to Fault Tolerance*. Springer, 475 pp.

Isermann, R., 2011. *Fault-Diagnosis Applications*. 1st ed., Springer-Verlag, Berlin, Germany, 354 pp.

Isermann, R. & Ballè, P., 1997. Trends in the application of model-based fault detection and diagnosis of technical processes. *Control Engineering Practice*, vol. 5(5), pp. 709–719.

Jämsä-Jounela, S.-L., 2011. Fault diagnosis methods and their applications in the process industry. In: *COSY 2011, Special International Conference on Complex Systems: Synergy of Control, Computing & Communications*, ohrid, Macedonia, Sep 16–20, 2011.

Jämsä-Jounela, S.-L., Tikkala, V.-M., Zakharov, A., Pozo Garcia, O., Laavi, H., Myller, T., Kulomaa, T. & Hämäläinen, V., 2013. Outline of a fault diagnosis system for a large-scale board machine. *International Journal of Advanced Manufacturing Technology*, vol. 65(9–12), pp. 1741–1755.

Jämsä-Jounela, S.-L., Vermasvuori, M., Endén, P. & Haavisto, S., 2003. A process monitoring system based on the Kohonen self-organizing maps. *Control Engineering Practice*, vol. 11(1), pp. 83–92.

Jelali, M. & Huang, B., 2010. *Detection and diagnosis of stiction in control loops — state of the art and advanced method*. 2nd ed., Springer-Verlag, London, 180–190 pp.

Jelali, M. & Scali, C., 2010. Comparative study of valve-stiction-detection methods. In: *Detection and Diagnosis of Stiction in Control Loops*, Jelali, M. & Huang, B., eds., pp. 295–358, Springer, London.

Jiang, H., Choudhury, M. A. A. S. & Shah, S., 2007. Detection and diagnosis of plant-wide oscillations from industrial data using the spectral envelope method. *Journal of Process Control*, vol. 17, pp. 143–155.

Joe, Y. Y., Ho, W. K., Lim, K. W., Ding, Z. Q., Zhang, J. B., Ling, K. V. & Romagnoli, J. A., 2006. Clustering intelligent sensor nodes for distributed fault detection and diagnosis. In: *IEEE International Conference on Industrial Informatics*.

Kämpjärvi, P., Sourander, M., Komulainen, T., Vatanski, N., Nikus, M. & Jämsä-Jounela, S.-L., 2008. Fault detection and isolation of an on-line analyzer for an ethylene cracking process. *Control Engineering Practice*, vol. 16, pp. 1–13.

Kangas, J. & Kaski, S., 1998. 3043 works that have been based on the self-organizing map (SOM) method developed by Kohonen. Tech. Rep. A49.

Kano, M., Maruta, M., Shimizu, K. & Kugemoto, H., 2004. Practical model and detection algorithm for valve stiction. In: *7th International Conference on Dynamics and Control of Process Systems*, Shah, S., ed., Cambridge, Massachusetts, USA, Jul 5–7, 2004.

Karra, S. & Karim, N., 2009. Comprehensive methodology for detection and diagnosis of oscillatory control loops. *Control Engineering Practice*, vol. 17, pp. 939–956.

Kohonen, T., 1982. Self-organized formation of topologically correct feature maps. *Biological Cybernetics*, vol. 43, pp. 59–69.

Kohonen, T., 1998. The self-organizing map. *Neurocomputing*, vol. 21, pp. 1–6.

Kohonen, T., 2001. *Self-Organizing Maps*. 3rd ed., Springer-Verlag, Berlin, Germany, 501 pp.

Komulainen, T., Sourander, M. & Jämsä-Jounela, S.-L., 2004. An online application of dynamic PLS to a dearomatization process. *Computers & Chemical Engineering*, vol. 28, pp. 2611–2619.

Kramer, M. A., 1987. Expert systems for process fault diagnosis: General framework. In: *Foundations of computer-aided process operations*, Reklaitis & Springs, eds., pp. 557–587, Elsevier, New York.

Kramer, M. A. & Palowitch, B. L., 1987. A rule-based approach to fault diagnosis using the signed directed graph. *AIChE Journal*, vol. 33(7), pp. 1067–1078.

Kuhasalo, A., Niskanen, J., Paltakari, J. & Karlsson, M., 2000. Introduction to paper drying and principles and structure of a dryer section. In: *Papermaking Part 2: Drying*, Karlsson, M., ed., pp. 16–53, FAPET Oy.

Lampinen, J. & Taipale, O., 1994. Optimization and simulation of quality properties in paper machine with neural networks. In: *IEEE World Congress on Computational Intelligence*, pp. 3812–3815 vol. 6, Orlando (FL), USA, Jun 27 – Jul 2, 1994.

Lappalainen, J., 2004. *Paperin- ja kartonginvalmistusprosessien mallinnus ja dynaaminen reaaliaikainen simulointi*. No. 518 in VTT Publications, 144 pp.

Lee, G., Lee, B., Yoon, E. S. & Han, C., 1999. Multiple-fault diagnosis under uncertain conditions by the quantification of qualitative relations. *Industrial and Engineering Chemistry Research*, vol. 38, pp. 988–998.

Lee, G., Mo, K. J. & Yoon, E. S., 1997. The methodology for knowledge base compression and robust diagnosis: Application to a steam boiler plant. *Expert Systems with Applications*, vol. 12(2), pp. 263–274.

Lee, G., Song, S.-O. & Yoon, E., 2003. Multiple-fault diagnosis based on system decomposition and dynamic PLS. *Industrial & Engineering Chemistry Research*, vol. 42(24), pp. 6145–6154.

Lee, G. & Yoon, E., 2001. A process decomposition strategy for qualitative fault diagnosis of large-scale processes. *Industrial & Engineering Chemistry Research*, vol. 40, pp. 2474–2484.

Lee, K. H., Ren, Z. & Huang, B., 2008. Novel closed-loop stiction detection and quantification method via system identification. In: *International Symposium on Advanced Control of Industrial Processes (ADCONIP)*, Jasper, Canada, May 4–6, 2008.

Leyval, L., Gentil, S. & Feray-Beaumont, S., 1994. Model-based causal reasoning for process supervision. *Automatica*, vol. 30(8), pp. 1295–1306.

Li, X., Wang, J., Huang, B. & Lu, S., 2010. The DCT-based oscillation detection method for a single time series. *Journal of Process Control*, vol. 20, pp. 609–617.

Liukkonen, M., Havia, E., Leinonen, H. & Hiltunen, Y., 2009. Application of self-organizing maps in analysis of wave soldering process. *Expert Systems with Applications*, vol. 36, pp. 4604–4609.

Liukkonen, M., Hiltunen, T., Hälikkä, E. & Hiltunen, Y., 2011. Modeling of fluidized bed combustion process and NO_x emissions using self-organizing maps: An application to the diagnosis of process states. *Environmental Modelling and Software*, vol. 26, pp. 605–614.

López Garciá, H. & Machón González, I., 2004. Self-organizing map and clustering for wastewater treatment monitoring. *Engineering Applications of Artificial Intelligence*, vol. 2004, pp. 215–225.

Lü, N. & Wang, X., 2008. Fault diagnosis based on signed digraph combined with dynamic kernel PLS and SVR. *Industrial and Engineering Chemistry Research*, vol. 47, pp. 9447–9456.

Matsuo, T., Sasaoka, H. & Yamashita, Y., 2003. Detection and diagnosis of oscillations in process plants. In: *Proceedings of the 7th International Conference on Knowledge-based Intelligent Information and Engineering Systems (KES2003)*, Palade, V., Howlett, R. J. & Jain, L. C., eds., pp. 1258–1264, Oxford, UK, September 3–5, 2003.

Maurya, M. R., Rengaswamy, R. & Venkatasubramanian, V., 2004. Application of signed digraphs-based analysis for fault diagnosis of chemical process flowsheets. *Engineering Applications of Artificial Intelligence*, vol. 17, pp. 501–518.

Maurya, M. R., Rengaswamy, R. & Venkatasubramanian, V., 2007. A signed directed graph and qualitative trend analysis-based framework for incipient fault diagnosis. *Chemical Engineering Research and Design*, vol. 85(10), pp. 1407–1422.

Medvedev, A., 1995. Fault detection and isolation by a continuous parity space method. *Automatica*, vol. 31(7), pp. 1039–1044.

Miao, T. & Seborg, D. E., 1999. Automatic detection of excessively oscillatory feedback control loops. In: *Proceedings of the 1999 IEEE International Conference on Control Applications*, pp. 359–364, Kohala Coast — Island of Hawai'i, Hawai'i, USA, August 22–27, 1999.

Mjaavatten, A. & Foss, B. A., 1997. A modular system for estimation and diagnosis. *Computers & Chemical Engineering*, vol. 21(11), pp. 1203–1218.

Mohindra, S. & Clark, P. A., 1993. A distributed fault diagnosis method based on digraph models: Steady-state analysis. *Computers & Chemical Engineering*, vol. 17(2), pp. 193–209.

Montmain, J. & Gentil, S., 2000. Dynamic causal model diagnostic reasoning for online technical process supervision. *Automatica*, vol. 36, pp. 1137–1152.

Muenchhof, M., Beck, M. & Isermann, R., 2009. Fault-tolerant actuators and drives-structures, fault detection principles and applications. *Annual Reviews in Control*, vol. 33(2), pp. 136–148.

Nallasivam, U., Babji, S. & Rengaswamy, R., 2010. Stiction identification in nonlinear process control loops. *Computers & Chemical Engineering*, vol. 34, pp. 1890–1898.

Neimo, L., 1999. Internal sizing of paper. In: *Papermaking Chemistry*, Neimo, L., ed., pp. 151–203, FAPET Oy.

Nimmo, I., 1995. Adequately address abnormal operations. *Chemical Engineering Progress*, vol. 9, pp. 36–45.

Norman, B., 2000. Web forming. In: *Papermaking Part 1, Stock Preparation and Wet End*, Paulapuro, H., ed., pp. 192–250, FAPET Oy.

Oyeleye, O. O. & Kramer, M. A., 1988. Qualitative simulation of chemical process systems: Steady-state analysis. *AIChE Journal*, vol. 34(9), pp. 1441–1454.

Palowitch, B. J. & Kramer, M. A., 1985. The application of a knowledge-based expert system to chemical plant fault diagnosis. In: *Proceedings of American Control Conference*, Boston (MA), USA, Jun 19–21, 1985.

Ploix, S. & Adrot, O., 2006. Parity relations for linear uncertain systems. *Automatica*, vol. 42, pp. 1553–1562.

Prasad, P., Davis, J., Jiranpinyo, Y., Josephson, J. & Bhalodia, M., 1998. Structuring diagnostic knowledge for large-scale process systems. *Computers & Chemical Engineering*, vol. 22(12), pp. 1897–1905.

Puig, V. & Blesa, J., 2013. Limnimeter and rain gauge FDI in sewer networks using an interval parity equations vased detection approach and an enhanced isolation scheme. *Control Engineering Practice*, vol. 21, pp. 146–170.

Puig, V. & Quevedo, J., 2002. Passive robust fault detection using fuzzy parity equations. *Mathematics and Computers in Simulation*, vol. 60, pp. 193–207.

Qin, S. J., 1998. Control performance monitoring — a review and assessment. *Computers & Chemical Engineering*, vol. 23, pp. 173–186.

Qin, S. J. & Badgwell, T. A., 2003. A survey of industrial model predictive control technology. *Control Engineering Practice*, vol. 11(7), pp. 733–764.

Rengaswamy, R., Hägglund, T. & Venkatasubramanian, V., 2001. A qualitative shape analysis formalism for monitoring control loop performance. *Engineering Applications of Artificial Intelligence*, vol. 14, pp. 23–33.

Ritala, R., 1993. A new tool for powerful process analysis. *Paperi ja Puu*, vol. 75, pp. 488–490.

Rossi, M. & Scali, C., 2005. A comparison of techniques for automatic detection of sticion: simulation and appplication to industrial data. *Journal of Process Control*, vol. 15, pp. 505–514.

Roychoudhury, I., Biswas, G. & Koutsoukos, X., 2009. Designing distributed diagnosers for complex continuous systems. *IEEE Transactions on Automation Science and Engineering*, vol. 6(2), pp. 277–290.

Ruiz, D., Nougues, J. M. & Puigjaner, L., 2001. Fault diagnosis support system for complex chemical plant. *Computers & Chemical Engineering*, vol. 25, pp. 151–160.

Saarela, O., 2002. *Multivariate Autoregressive Analysis in Locating the Origin of Fluctuation in Continuous Industrial Processes*. Ph.D. thesis, Tampere University of Technology, Tampere, Finland.

Salsbury, I. & Singhal, A., 2005. A new approach for ARMA pole estimation using higher-order crossings. In: *2005 American Control Conference*, pp. 4458–4463, Portland (OR), USA, June 8–10, 2005.

Scali, C. & Farnesi, M., 2010. Implementation, parameters calibration and field validation of a closed loop performance monitoring system. *Annual Reviews in Control*, vol. 34, pp. 263–276.

Scali, C. & Ghelardoni, C., 2008. An improved qualitative shape analysis technique for automatic detection of valve stiction in flow control loops. *Control Engineering Practice*, vol. 16, pp. 1501–1508.

Schlake, J. C., Chioua, M., Xu, C., Schimdt, W., Sand, G. & Horch, A., 2011. A concept for plant asset management for large-scale systems. In: *1st Papyrus Workshop on fault diagnosis and fault-tolerant control*, Sauter, D., ed., Porticcio, France, October 6–7, 2011.

Shah-Hosseini, H. & Safabakhsh, R., 2003. TASOM: A new time adaptive self-organizing map. *IEEE Transactions on systems, man, and cybernetics — Part B: Cybernetics*, vol. 33(2), pp. 271–282.

Shardt, Y., Zhao, Y., Qi, F., Lee, K., Yu, X., Huang, B. & Shah, S., 2012. Determining the state of a process control system: Current trends and future challenges. *The Canadian Journal of Chemical Engineering*, vol. 90, pp. 217–245.

Shih, R.-F. & Lee, L.-S., 1995a. Use of fuzzy cause-effect digraph for resolution fault diagnosis for process plants. 1. fuzzy cause-effect digraph. *Industrial and Engineering Chemistry Research*, vol. 34, pp. 1688–1702.

Shih, R.-F. & Lee, L.-S., 1995b. Use of fuzzy cause-effect digraph for resolution fault diagnosis for process plants. 2. diagnostic algorithm and applications. *Industrial and Engineering Chemistry Research*, vol. 34, pp. 1703–1717.

Shiozaki, J., Matsuyama, H., Tano, K. & O'Shima, E., 1984. Fault diagnosis of chemical processes by the signed, directed graphs. extension to five-range patterns of abnormality. *Kagaku Kogaku Ronbunshu*, vol. 10(2), pp. 233–239.

Silvennoinen, E., Juslin, K., Hänninen, M., Tiihonen, O., Kurki, J. & Porkholm, K., 1989. *The APROS software for process simulation and model development*. No. 618 in Valtion teknillisen tutkimuskeskuksen tutkimuksia, 106 pp.

Simula, O., Alhoniemi, E., Hollmén, J. & Vesanto, J., 1996. Monitoring and modeling of complex processes using hierarchical self-organizing maps. In: *In Proceedings of the IEEE International Symposium on Circuits and Systems (ISCAS'96), volume Supplement*, pp. 737–741.

Singh, M. G., Hassan, M. F., Chen, Y. L., Li, D. S. & Pan, Q. R., 1983. New approach to failure detection in large-scale systems. *IEE Proceedings*, vol. 130(5), pp. 243–249.

Singhal, A. & Salsbury, T. I., 2005. A simple method for detecting valve stiction in oscillating control loops. *Journal of Process Control*, vol. 15, pp. 371–382.

Sinha, A., Chen, H., Danu, D. G., Kirubarajan, T. & Farooq, M., 2008. Estimation and decision fusion: A survey. *Neurocomputing*, vol. 71, pp. 2650–2656.

Srinivasan, B. & Rengaswamy, R., 2012. Automatic oscillation detection and characterization in closed-loop systems. *Control Engineering Practice*, vol. 20, pp. 733–746.

Srinivasan, R., Rengaswamy, R. & Miller, R., 2005. Control performance assessment. *Industrial and Engineering Chemistry Research*, vol. 44, pp. 6708–6718.

Srinivasan, R., Rengaswamy, R. & Miller, R., 2007. A modified empirical mode decomposition (EMD) process for oscillation characterization in control loops. *Control Engineering Practice*, vol. 15, pp. 1135–1148.

Stenman, A., Gustafsson, F. & Forsman, K., 2003. A segementation-based method for detection of stiction in control valves. *International Journal of Adaptive Control and Signal Processing*, vol. 17(7–9), pp. 625–634.

Sundholm, P., 2000. Mill operations in production of main paper and board grades. In: *Papermaking Part 1, Stock Preparation and Wet End*, Paulapuro, H., ed., pp. 12–55, FAPET Oy.

Tangirala, A., Kanoda, J. & Shah, S. L., 2007. Non-negative matrix factorization for detection and diagnosis of plantwide oscillations. *Industrial and Engineering Chemistry Research*, vol. 46, pp. 801–817.

Tarifa, E. & Scenna, N., 1998a. A methodology for fault diagnosis in large chemical processes and an application to a multistage flash desalination process: Part I. *Reliability Engineering and System Safety*, vol. 60, pp. 29–40.

Tarifa, E. & Scenna, N., 1998b. A methodology for fault diagnosis in large chemical processes and an application to a multistage flash desalination process: Part II. *Reliability Engineering and System Safety*, vol. 60, pp. 41–51.

Tarjan, R., 1972. Depth-first search and linear graph algorithms. *SIAM Journal of Computing*, vol. 1, pp. 146–160.

Thornhill, N. F., 2005. Finding the source of nonlinearity in a process with plant-wide oscillation. *IEEE Transactions on Control Systems Technology*, vol. 13(3), pp. 434–443.

Thornhill, N. F., Cox, J. W. & Paulonis, M. A., 2003a. Diagnosis of plant-wide oscillation through data-driven analysis and process understanding. *Control Engineering Practice*, vol. 11, pp. 1481–1490.

Thornhill, N. F. & Hägglund, T., 1997. Detection and diagnosis of oscillations in control loops. *Control Engineering Practice*, vol. 5(10), pp. 1343–1354.

Thornhill, N. F. & Horch, A., 2007. Advances and new directions in plant-wide disturbance detection and diagnosis. *Control Engineering Practice*, vol. 15, pp. 1196–1206.

Thornhill, N. F., Huang, B. & Zhang, H., 2003b. Detection of multiple oscillations in control loops. *Journal of Process Control*, vol. 13, pp. 91–100.

Thornhill, N. F., Shah, S. L., Huang, B. & Vishnubhotla, A., 2002. Spectral principal component analysis of dynamic process data. *Control Engineering Practice*, vol. 10.

Tikkala, V.-M., 2008. *Fault Diagnosis of a Board Machine Based on Causal Digraph Method*. Master's thesis, Helsinki University of Technology, Helsinki, Finland.

Tikkala, V.-M., Myller, T., Kulomaa, T., Hämäläinen, V. & Jämsä-Jounela, S.-L., 2011. Data analysis and monitoring of thickness sensor fouling using self-organized maps. In: *1st Papyrus Workshop on fault diagnosis and fault-tolerant control*, Sauter, D., ed., Porticcio, France, October 6-7, 2011.

Tikkala, V.-M., Zakharov, A. & Jämsä-Jounela, S.-L., 2010. Detection and diagnosis of oscillations using dynamic causal digraph method. In: *Conference on Control and Fault Tolerant Systems*, nice, France, Oct 6–8, 2010.

Umeda, T., Kuriyama, T., O'Shima, E. & Matsuyama, H., 1980. A graphical approach to cause and effect analysis of chemical processing systems. *Chemical Engineering Science*, vol. 35(12), pp. 2379–2388.

Vadam, O., Montmain, J. & Cassar, J. C., 1997. Fault detection using parallel simulations. In: *Preprints of IFAC – SAFEPROCESS 1997 Symposium*, Patton, R. J. & Chen, J., eds., pp. 121–126, Hull, UK, Aug 26–28, 1997.

Vadigepalli, R. & Doyle III, F. J., 2003. Structural analysis of large-scale systems for distributed state estimation and control applications. *Control Engineering Practice*, vol. 11, pp. 895–905.

Vedam, H. & Venkatasubramanian, V., 1999. Pca-sdg based process monitoring and fault diagnosis. *Control Engineering Practice*, vol. 7, pp. 903–917.

Venkatasubramanian, V., 2010. Systemic risks management in complex process plants: Challenges, opportunities and emerging trends. In: *Conference on Control and Fault Tolerant Systems*, Maquin, D., ed., Nice, France, Oct 6–8, 2010.

Venkatasubramanian, V., Rengaswamy, R. & Kavuri, S. N., 2003a. A review of process fault detection and diagnosis, part ii: Qualitative models and search strategies. *Computers and Chemical Engineering*, vol. 27, pp. 313–326.

Venkatasubramanian, V., Rengaswamy, R., Kavuri, S. N. & Yin, K., 2003b. A review of process fault detection and diagnosis, part iii: Process history based methods. *Computers and Chemical Engineering*, vol. 27, pp. 327–346.

Venkatasubramanian, V., Rengaswamy, R., Yin, K. & Kavuri, S. N., 2003c. A review of process fault detection and diagnosis, part i: Quantitative model-based methods. *Computers and Chemical Engineering*, vol. 27, pp. 293–311.

Vermasvuori, M., 2008. *Methodology for Utilizing Prior Knowledge in Constructing Data-Based Process Monitoring Systems With an application to a Dearomatisation Process*. Ph.D. thesis, Helsinki University of Technology.

Vesanto, J., Himberg, J., Alhoniemi, E. & Parhankangas, J., 2000. Som Toolbox for Matlab 5. Tech. Rep. A57.

Vianna, R. F. & McGreavy, C., 1995. Qualitative modelling of chemical processes — A weighted digraph (WDG) approach. *Computers & Chemical Engineering*, vol. 19, pp. S375–S380.

Wan, Y., Yang, F., Lu, N., Xu, H., Ye, H., Li, W., Xu, P., Song, L. & Usadi, A. K., 2013. Statistical root cause analysis of novel faults based on digraph models. *Chemical Engineering Research and Design*, vol. 91, pp. 87–99.

Wang, J., Huang, B. & Lu, S., 2013. Improved DCT-based method for online detection of oscillations in univariate time series. *Control Engineering Practice*, vol. 21, pp. 622–630.

Willsky, A. S., 1976. A survey of design methods for failure detection in dynamic systems. *Automatica*, vol. 12, pp. 601–611.

Xia, C. & Howell, J., 2003. Loop status monitoring and fault localisation. *Journal of Process Control*, vol. 13, pp. 679–691.

Xia, C. & Howell, J., 2005. Isolating multiple sources of plant-wide oscillations via independent component analysis. *Control Engineering Practice*, vol. 13, pp. 1027–1035.

Xia, C., Howell, J. & Thornhill, N. F., 2005. Detecting and isolating multiple plant-wide oscillations via spectral independent component analysis. *Automatica*, vol. 41, pp. 2067–2075.

Xia, C., Zheng, J. & Howell, J., 2007. Isolation of whole-plant multiple oscillations via non-negative spectral decomposition. *Chinese Journal of Chemical Engineering*, vol. 13(3), pp. 353–360.

Yamasita, Y., 2006. An automatic method for detection of valve stiction in process control loops. *Control Engineering Practice*, vol. 14, pp. 503–510.

Yu, C.-C. & Lee, C., 1991. Fault diagnosis based on qualitative/quantitative process knowledge. *AIChE Journal*, vol. 37(4), pp. 617–628.

Yu, D. L. & Shields, D. N., 2001. Extension of the parity-space method to fault diagnosis of bilinear systems. *International Journal of Systems Science*, vol. 32(8), pp. 953–962.

Zakharov, A., 2011. A method for detecting faults or controlling and /or optimizing of an industrial process or a part of it. Finnish Patent Application 20116321 (submitted).

Errata

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Figure 14: Caption should read ”. . . for fault scenario 2”.

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