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Abstract

The emerging environmental and energy system related requirements urge renewed combustion systems, with a focus on extended flexibility and decreased emissions. At the same time, monitoring and measurement reliability requirements are increasing. All these requirements also increasingly affect existing combustion plants.

To tackle the increasing needs and requirements of existing combustion processes, this thesis' objective is to integrate process and domain knowledge, models, and online estimation to provide cost effective and practically feasible solutions for online emission monitoring and control in existing combustion processes. These solutions are domain specific, comprising power level, main fuel, boiler technology, process environment, and market. This thesis presents a framework to provide practically justified, online monitoring and control solutions that is applied to selected combustion applications.

The first application is combustion control of small-scale (<0.5 MW) wood chip combustion systems, to tackle fuel feed disturbances and provide stabilized combustion conditions with improved process performance. The second application area is medium-scale (15 MW – 50 MW) natural gas fired boilers. Indirect, data based, NO_x monitoring methods were developed for such boilers, to cost effectively fulfil emerging monitoring requirements. The third application area is large-scale power plants (>100 MW). A novel, first principle combustion model was developed for these. The generic combustion model interlinks the combustion related measurements distributed within any boilers regardless of boiler type or fuels. The interlinking enables combustion processes to be considered as an entity that reveals if a measurement provide realistic readings compared with others. The static, computationally light model enables simultaneous data reconciliation and gross error detection and hence several attractive online applications, such as reliable estimation of unmeasured variables, and separation of process disturbances from sensor malfunctions.

The results verify that the process performance improved in all studied practical applications, providing feasible solutions for increasing requirements.

Preface

The work in this thesis was carried out at Laboratory of Automation and Hydraulics (AUT), and its predecessor Department of Automation Science and Engineering (ASE), from 2005–2017. During that time, I had the opportunity to participate in many interesting projects. The most relevant ones for this thesis were “Control of Wood Chip Combustion (HakeHall 1 & 2)” and “Measurement, Monitoring and Environmental Assessment (MMEA)”. The HakeHall 1 & 2 –projects were carried out from 2005–2008 in cooperation with HT Enerco Ltd, Säätötuli Ltd, and Jatloc Ltd. The MMEA SHOK-project from 2012–2015 comprised of several subprojects, of which the most relevant for the thesis were carried out with Helen Ltd and IndMeas Ltd. These projects were primarily financed by Tekes – the Finnish Funding Agency for Technology and Innovation. Other projects also contributed to this work, especially the latest “Flexible Energy Systems (FLEXe)” and “Transition to a resource efficient and climate neutral electricity system (EL-TRAN)” projects, which Tekes and the Academy of Finland funded. I would like to acknowledge all the project partners and financers for fruitful cooperation over the years. Additionally, I express my gratitude to the support from Finnish Foundation for Technology Promotion, Fortum Foundation, Industrial Research Fund (Wärtsilä) at Tampere University of Technology, and the Finnish Foundation for Automation. Moreover, I am grateful to Faculty of Engineering Sciences at Tampere University of Technology for the support to finish the thesis.

I want to express my gratitude to my instructors, Professor Pentti Lautala and Professor Matti Vilkko, for their guidance and support over the years, especially while preparing the dissertation. Indeed, the work would never have been finished without the kind push and supervision of Professor Lautala, for which I am even increasingly grateful. Moreover, I want to express my gratitude to my instructors, colleagues, and friends, Tomas Björkqvist and Yrjö Majanne, for the best cooperation along the years. Additionally, I am grateful to my co-authors Pekka Kumpulainen and Olli Suominen. I also acknowledge the current and former colleagues and staff at the institute, especially Timo Yli-Fossi, Mikko Huovinen, Terho Jussila, Pekka Pietilä, and Antti Jaatinen. ASE has always been a great place to work!

I am grateful to the pre-examiners of the thesis, Professor Sirkka-Liisa Jämsä-Jounela and Dr. Hans Aalto, for their valuable comments and suggestions. Moreover, I want to thank Professor Sirkka-Liisa Jämsä-Jounela and Professor Esa Vakkilainen for being my opponents at the public examination of the thesis.

I have had the pleasure to work with so great many people, so it is impossible to mention you all here. I am especially grateful to Anna Häyrinen, Anton Laari, Olli Salminen, Tero Salotuomi, Raimo Paajanen, Antti Komulainen, Jorma Kytömäki, Jutta Fränti, and Virve Vaahtera from Helen Ltd; Ville Laukkanen, Aki Juutistenaho, and Anders Brunström from IndMeas Ltd; Marko Pihlajamäki and Petri Piipari from Säätötuli Ltd; Hannu Teiskonen and Veli-Matti Järvelä from HT Enerco Ltd; Mika Ruusunen, Esko Juuso, and Riku-Pekka Nikula from University of Oulu; Sirkka Koskela and Jáchym Judl from Finnish Environment Institute; Jyri Kaivosoja, Leo Laakkonen, Maria Nurmoranta, Ville Ylä-Outinen from Valmet; Juha Vilhunen from Kuopio Innovation; Teija Laitinen and Tero Eklin from CLIC Innovation; Jan Hrdlička and colleagues from Czech Technical University in Prague, and Professor Harald Weber and Christian Ziems from University of Rostock.

Beside the research projects and typical university activities, I worked as the coordinator of *Energy and Eco-Efficiency* –profile area of Tampere University of Technology during 2014–2016. During the time, I took part in many instructive activities and discussions that I could not have been otherwise able to do. Most of all, I had the pleasure to get to know many professionals from different energy research areas. Thank you all, especially Professor Pertti Järventausta, Anna Pääkkönen, Fanni Mylläri, and Mirva Seppänen, and the representatives of the steering group. In fact, I drew the Figure 8 of this thesis for an advertisement wall that was present in an exhibition. The content of the picture was designed in cooperation with Professor Risto Raiko and many others.

Moreover, I want to thank all my relatives and friends. Especially, I am grateful to my parents Raija and Markku Korpela, and my parents-in-law Maija and Jorma Syvälä for their help and support along the way.

Above all, I want to warmly thank my dear wife Soile and daughters Tuuli and Saana for their love and support, also during this long process. It is my greatest pleasure and privilege to share my life with you!

Tampere, August 2017

Timo Korpela

Contents

List of Symbols, Subscripts, and Abbreviations

Symbols and subscripts

λ	Excess air ratio
d.b	Dry basis
el	Electric
fu	Fuel
prim	Primary
sec	Secondary
th	Thermal
tot	Total
w.b.	Wet basis

Substances

$CaCl_2$	Calcium chloride
$CaCO_3$	Calcium carbonate
$Ca(OH)_2$	Calcium hydroxide
$CaSO_3$	Calcium sulphite
$CaSO_4$	Calcium sulphate
CO	Carbon monoxide
CO_2	Carbon dioxide
C_xH_y	Hydrocarbon
GHG	Greenhouse gas
HCl	Hydrogen chloride
H_2O	Water
N_2	Element nitrogen
NG	Natural gas
NO	Nitrogen monoxide
NO_2	Nitrogen dioxide
NO_x	Nitrogen oxide
O_2	Oxygen
OGC	Organic gaseous compound
PAH	Polycyclic aromatic hydrocarbons
PM	Particle matter
SO_2	Sulphur dioxide

Models and Modelling

CFD	Computational fluid dynamics
FIS	Fuzzy inference system
LSSVM	Least squares support vector machine
MLP	Multilayer perceptron
PLS	Partial least squares
SOM	Kohonen's self-organising maps
SVR	Support vector regression
RMSE	Root mean square error

Institutions, Standards, and Technologies

AST	Annual surveillance test
BAT	Best-available techniques
BFB	Bubbling fluidized bed
CEMS	Continuous emission monitoring system
CEN	European Committee for Standardization
CFB	Circulating fluidized bed
CHP	Combined heat and power
DH	District heating
ESP	Electrostatic precipitator
ETS	Emission Trading System
EU	European Union
FG	Flue gas
FGD	Flue gas desulfurization
IED	Industrial Emission Directive (201075/EU)
IFAC	International Federation of Automatic Control
MCP	Medium combustion plant directive (2015/2193/EU)
MPC	Model predictive control
PEMS	Predictive emission monitoring system
PID	Proportional, integral, derivate
RES	Renewable energy source
SCR	Selective catalytic reduction
SNCR	Selective non-catalytic reduction
QAL	Quality-assurance level

List of Publications

I. Korpela, T., Björkqvist, T., Lautala, P. 2008. Durable feedback control system for small-scale wood chip combustion. *Proceedings of World Bioenergy 2008 Conference*, May 27–29, 2008, Jönköping, Sweden. 224–230.

II. Korpela, T., Björkqvist, T., Lautala, P. 2009. Control strategy for small-scale wood chip combustion. 7th IFAC Symposium on Power Plants and Power Systems Control, July 5–8, 2009, Tampere, Finland. *IFAC Proceedings Volumes (IFAC-PapersOnline)*, 119–124.

III. Korpela, T., Kumpulainen, P., Majanne, Y., Häyrinen, A., Lautala, P. 2017. Indirect NO_x emission monitoring in natural gas fired boilers. *Control Engineering Practice*. 65, 11–25.

IV. Korpela, T., Björkqvist, T., Majanne, Y., Lautala, P. 2014. Online monitoring of flue gas emissions in power plants having multiple fuels. 19th IFAC World Congress, August 24–29, 2014, Cape Town, South Africa. *IFAC Proceedings Volumes (IFAC-PapersOnline)*. 19, 1355–1360.

V. Korpela, T., Suominen, O., Majanne, Y., Laukkanen, V., Lautala, P. 2016. Robust data reconciliation of combustion variables in multi-fuel fired industrial boilers. *Control Engineering Practice*. 55, 101–115.

VI. Korpela, T., Majanne, Y., Salminen, O., Laari, A., Björkqvist, T. 2015. Monitoring of spraying in semi-dry desulfurization processes in coal fired power plants. 9th IFAC Symposium on Control of Power and Energy Systems, December 9–11, 2015. New Delhi, India. *IFAC-PapersOnLine*, 48(30), 403–408.

1 Introduction

Due to increasing environmental awareness and climate change, the impact of energy production on the environment has become a global concern. Renewable, carbon-free, and intermittent energy sources – mainly wind and solar energy – have permanently changed energy markets, especially in Germany and Nordic countries (NER, 2016). Despite the continuous increase of these energy sources, energy production will still significantly rely on combustion of fuels, particularly non-fossil fuels for the foreseeable future (Child & Breyer, 2016); (Mikkola & Lund, 2016); (Rinne & Syri, 2015); (Tafarte *et al.*, 2017). In combustion, solar energy stored as chemical energy is converted into heat by oxidizing organic compounds at high temperatures. The energy storage capacity of fuels emphasises the role of combustion in future energy systems, which are increasingly dominated by these intermittent renewable energy sources (RES).

The emerging environmental and energy system related requirements urge for renewed combustion systems. The new requirements comprise extended dynamical flexibility, diversified fuel exploitation, and extended efficient power ranges with lower minimum power levels (Henderson, 2014); (Weber *et al.*, 2011); (Ziems *et al.*, 2011). At the same time, emissions, such as CO_2, NO_x, CO, SO_2, particles and PAH, should be reduced. The most suitable power plants are those that were originally designed for contemporary requirements and operational environments. However, it is difficult to make rapid changes in energy systems. In many cases, it is not cost or resource efficient to replace existing boilers, whose technical lifetime is usually several decades, with modern ones. Instead, it makes more sense to improve the performance of existing boilers and their monitoring capabilities. The most efficient way to improve their process performance is to run the processes at their full potential in all prevailing conditions. If the performance is still not enough to meet the prevailing requirements, further investments in processes and their instrumentations will be required. If these actions are still not enough, or otherwise feasible, other means should be considered.

To tackle the increasing needs and requirements of existing combustion processes, the objective of this thesis is to integrate process and domain knowledge, models, and online estimation to provide optimal solutions for online emission monitoring and control in existing commercial combustion processes. In this context, *optimal* stands for the most technically and economically feasible solution. The problems are approached from the process perspective, and the applied methods are chosen on demand. The focus is on gaseous emissions (CO, CO_2, SO_2, NO_x), but other emissions are also indirectly considered. The solutions are technically feasible, because the seven boilers considered in this work were commercial at the time, and all operated in their normal environments without special arrangements. Moreover, the solutions are also economically feasible, because their application do not require unrealistic extra instrumentation or computational power. Therefore, the solutions provide practically justified options to tackle emerging issues in continuously operated boilers.

The combustion in boilers is challenging, as it is a multivariable nonlinear process with changing dynamics and time-variant behaviour, and is affected by deterministic and stochastic disturbances (Ikonen & Kovács, 2006). Moreover, each boiler type has its own characteristics and requirements that need unique solutions (Ruusunen, 2013). Developing new solution to existing processes increases the challenge, because existing environments and system structures set additional constraints that may be cumbersome or expensive to circumvent. Moreover, needs and requirements change over time, and between domains. This is illustrated in Figure 1, which presents the framework of the thesis. It means that the optimal solutions in existing combustion plants are also somewhat domain specific. The domains in this context comprise the power level, main fuel, boiler technology, process environment, and market. Due to the different domain properties, the research questions and the solutions are also domain specific. The best solutions are those that are the most generic, so the solutions are generalized as much as possible.

To limit the scope of the thesis, solutions to extend the dynamical flexibility of boilers (Majanne *et al.*, 2017) and their operation in heat and power grids (Korpela *et al.*, 2017a) are not the focus of this

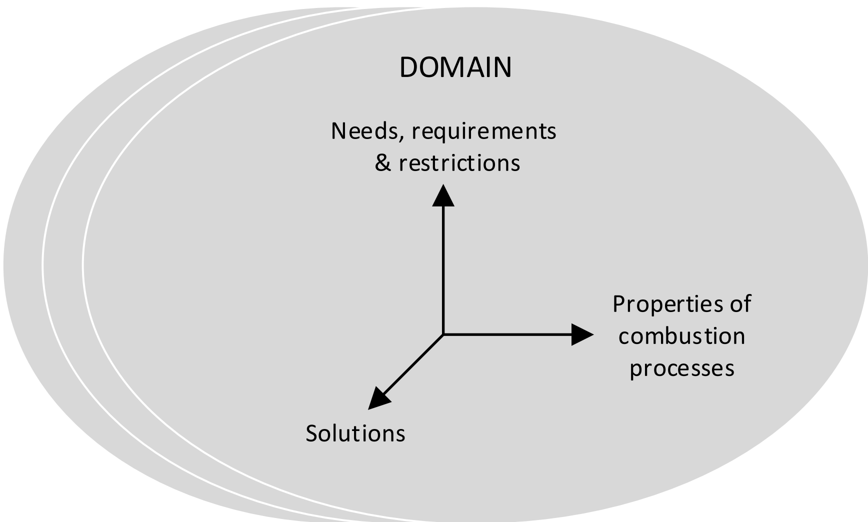

Figure 1. Framework to provide optimal solutions.

thesis. However, their emerging role is recognized and considered when appropriate. Similarly, the significant role of research of combustion phenomena and process and component development (Korpela & Björkqvist, 2008a) are recognized but are not in focus.

1.1 Background and Scope of the Thesis

Combustion is a high-temperature chemical reaction between a fuel and an oxidant, which is typically oxygen in air. The main fuels are coal, peat, natural gas, waste, oil, and biomass, the latter of which include several woody and agro fuels with varying properties. The combustion technologies used for these fuels differ considerably. However, it is possible to detect similar phases during the combustion. The main stages of combustion are drying, pyrolysis (devolatilization), gasification, char combustion, and gas-phase oxidation. The duration and overlapping of the stages within a fuel particle depends on, for example, fuel particle size and properties, and both on combustion temperature and conditions. (Turns, 2000); (Van Loo & Koppejan, 2008) Combustion is an exothermic process that releases thermal energy, which can be exploited in boilers to generate heat, steam, and electrical power by the water-steam cycle. The size, structure, complexity, and level of instrumentation vary between fuels and domestic-scale boilers to power plants. Nevertheless, the basic phenomena in combustion and the main operation principles are similar, and this feature enables the knowledge from one combustion process to be utilized in another.

To mitigate environmental effects, new combustion processes are developed and the existing ones are improved. Still, a major contributor to actual process performance and emissions is how the combustion processes are actually operated at each moment in time and in relation to their full potential (Bignal *et al.*, 2008); (Hrdlička *et al.*, 2016), subject to prevailing operating conditions and restrictions. The significance of this aspect has substantially increased within a decade due to new flexibility requirements of energy systems that have a significant share of intermittent renewable energy sources. The fundamental requirement to assess process performance is to have an indication of current process behaviours (Ruusunen, 2013). This indication is obtained by direct or indirect measurements. In many cases, such as in small-scale systems or harsh conditions, it is not possible to directly measure the features of interest due to lack of cost effective or technically feasible measurements. In these cases, it might be possible to utilize indirect measurements, based on information that is extracted from other measurements, and a model that interlinks the direct measurement information to the information of interest. In these cases, measured information can be utilized in numerous ways, such as for decision-making, estimation, control, reporting, and analysis. Despite the end use, measurement quality must be such that the information is reliable. Measurement reliability can be improved by regular maintenance and calibrations, hardware and analytical redundancy, advanced data quality control, and restricted measurement time in harsh environments. Suitable tool and method selection significantly depends on the application.

To fully understand the process performance and improve it, the main features and dynamical interlinks must be known. This process knowledge can be formulated to verbal or mathematic models. Particularly in the case of technical systems, mathematical models can be further classified into data-based models or physical models, i.e. first principles models. The former are derived from observations of the studied systems, and the latter are derived based on laws of nature. The models are used in several ways, including improving process performance.

This thesis focuses on model utilization for online estimation in combustion applications. According to Ljung & Glad (1994), there are two kinds of knowledge necessary for constructing models. *Domain expertise* is about understanding the application and mastering all relevant factors for the model. *Knowledge engineering* is about understanding how these facts can be transferred into a useful, explicit model. The most significant contribution of this thesis focuses on *domain expertise* (Figure 1) to provide feasible and cost-effective solutions to emerging issues of existing boilers by utilizing *knowledge engineering* and exploiting models to improve the performance or monitoring of the processes in online operation. The foundation of the work is a solid understanding of combustion processes and their operation environments. This foundation is shown in three practical cases, including seven combustion applications in three heat power ranges: <0.5 MW, 15 MW–50 MW, and >100 MW. These power ranges are linked to main European Union (EU) standards of the field, but are still informative, rather than conclusive. The cases are summarized in Figure 2.

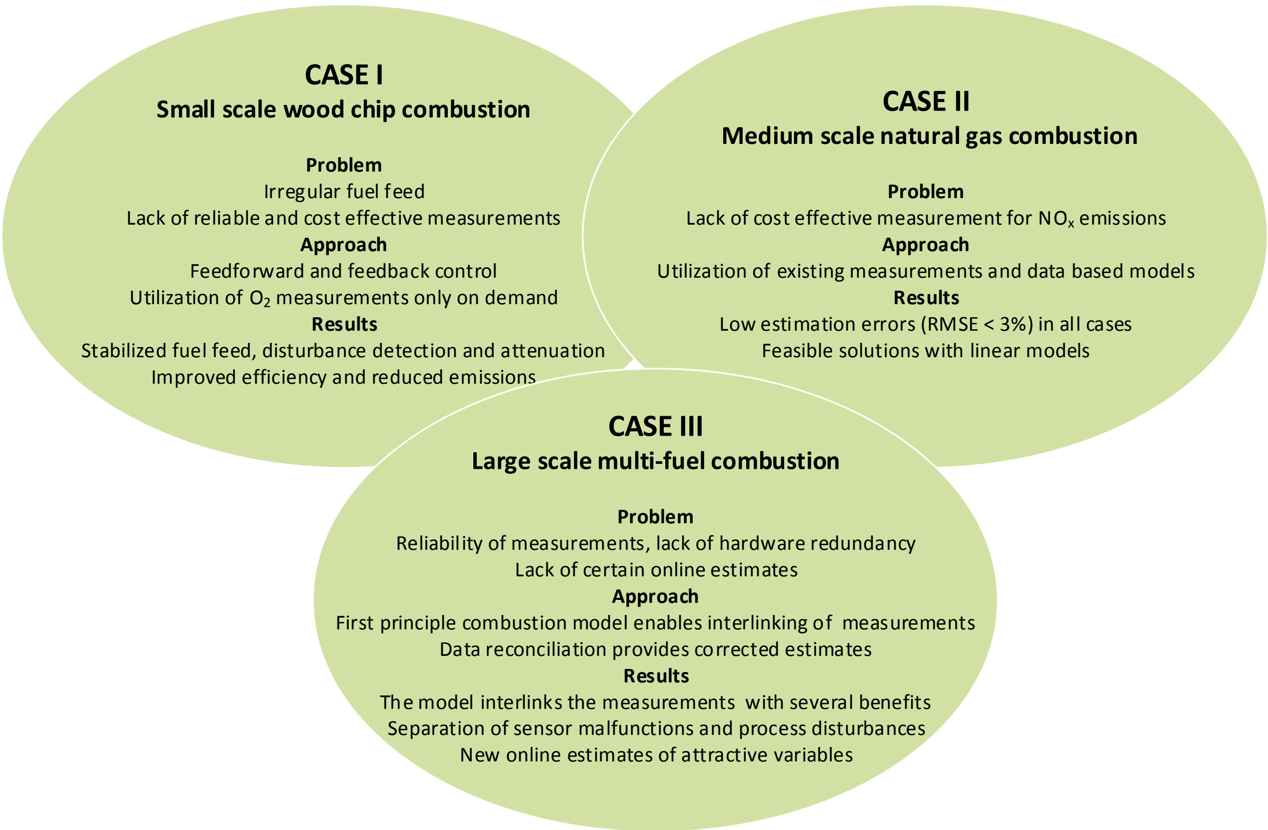

Figure 2. The summary of the cases of this thesis.

The process environment in Case I is small-scale (<0.5 MW) wood chip combustion systems. Unclean small-scale combustion is the major source of fine particles and local air quality issues in Europe (Saarikoski *et al.*, 2008). Even if these issues are dominant in domestic combustion applications, it is important to pursue high quality combustion in all small-scale systems. As the ECOdesign requirements set by the European Commission will not come into effect until 2020–2022, there are currently no EU-level emission standards for small-scale combustion systems. However, there is a variety of regulations and suggestions. Hence, there is significant variation in boiler structures, instrumentation levels, and boilers performances. In particular, wood chip combustion in small-scale systems is disturbed by irregular fuel energy feed that originates from fuel quality variations (Ryu *et al.*, 2006); (Thunman & Leckner, 2005) and difficulty with implementing a stable solid fuel feed (Dai & Grace, 2011); (Dai *et al.*, 2012); (Rackl & Günthner, 2016). This induces significant variations in combustion, contributing to momentary emission level increases and efficiency losses. The effect of variations in the fuel feed can be reduced by selecting favourable operating conditions for combustion and then compensated by feedback control. However, since small-scale production cannot bear high costs, measurement instrumentation should be minimal. Moreover, sensors must function long term in challenging combustion environments without defects or drifting. For this background, Publications I and II present preventive actions that alleviate the effects of fuel feed variations and grate sweeping in two commercial wood chip fired boilers (80 kW_{th} and 200 kW_{th}). Moreover, the papers present a verbal process model utilized in developing a fuzzy controller. All solutions significantly improved process performance in terms of process operability, efficiency, and emissions.

Case II's process environment comprises of medium-scale (15 MW – 50 MW) natural gas fired boilers, whose online NO_x emission monitoring is the focus. The demand for reliable, cost effective NO_x monitoring solutions emerged from the extended requirements of the Industrial Emission Directive (IED) to certain medium-scale boilers interlinked with shared flue-gas (FG) chimneys. Typically, such medium-scale heat only boilers serve as peak load and back-up boilers in district heating (DH) networks with low annual operation hours. For this purpose, Publication III presents a novel approach for such boilers, by indirectly estimating NO_x emissions online by a data based mathematical model and existing process measurements. The tested models include linear, multivariate regressions and three nonlinear models: Multilayer Perceptron (MLP), Fuzzy Inference System (FIS), and Support Vector Regression (SVR). The results with two similar 43 MW_{th} industrial boilers indicate that linear models with two input variables can estimate the NO_x emissions online with a root mean square error (RMSE) of <3 percent. The novel results suggest that this method can be generally applied in respective boilers, also providing extended monitoring prospects compared to the minimum standard requirements.

Case III is the most extensive and generic, presented in Publications IV, V, and VI. Contrary to the previous cases with limited measurement instrumentation, there are many combustion related measurements in large-scale power plants. However, their long-term reliability might be an issue, despite regular calibrations and maintenance procedures. In particular, with measurements with uncertainties, it is not always easy to separate abnormal process conditions and sensor malfunctions. Publication IV presents a novel, first principle combustion model that is founded on element balances of generic combustion reactions. The generic combustion model interlinks the combustion related measurements distributed within any (>100 MW)[1] boilers, regardless of boiler type or fuels. Interlinking enables the combustion process to be considered an entity that, for example, can reveal if a measurement provides realistic readings compared with the others. The static, computationally light first principle model enables several attractive online applications, such as estimation of unmeasured variables, and separation of process disturbances from sensor malfunctions, which cannot be practically implemented with data based solutions. Publication IV also presents estimation results of a 180 MW_{th} bubbling fluidized boiler with biomass, peat, bark, and slurry fuels. Publication V extends the combustion model to include the water-steam cycle of combined heat and power plants (CHP), to increase redundancy and improve estimation accuracy. Most significantly, Publication V applies simultaneous data reconciliation and gross error detection, which exploit the model by significantly improving estimation performance. As an alternative approach, Publication VI applies the generic combustion model in two coal fired boilers (506 MW_{fuel} and 185 MW_{fuel}), whose flue gases are mixed and cleaned in a semi-dry flue gas desulphurization process. The model enables the estimation of flue gas flows and their compositions in varying fuel and boiler conditions. In Publication VI, the model outputs are successfully utilized in monitoring spraying quality in SO_2 removal reactors, which is the most critical factor of the SO_2 removal in such processes.

To summarize, the objective of this thesis is to derive and apply a framework to provide practically justified online monitoring and control solutions for selected combustion applications. Figure 3 illustrates the main objectives of Cases I–III in a graph presenting number versus quality of measurements or estimates.

1.2 Hypothesis and Research Questions

The hypothesis of this thesis is:

> *Utilization of models enable significant improvements to process performance of existing combustion plants*

[1] The power level is only informative: In EU, boilers >100 MW have measurements considered in the approach. Smaller boilers with similar instrumentation are equally valid.

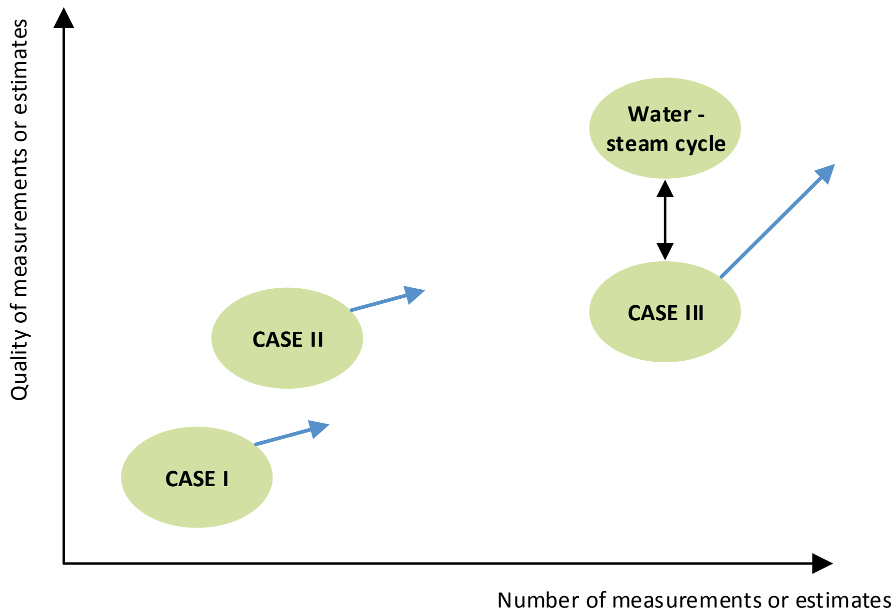

Figure 3. The number versus quality of measurements or estimates in Cases I–III. The objectives of Cases I–III are indicated with blue arrows. The black double-arrow describes the model extension in Publication V.

In this context, process performance improvements include decreased emissions, improved efficiency, and increased monitoring capabilities. To study the asserted hypothesis, the main research questions in this thesis are:

RQ1. How can the quality of combustion in small-scale wood chip combustion systems be monitored and maintained online, considering cost effectiveness and sensor reliability requirements?

RQ2. How can NO_x emissions be reliably and cost effectively online monitored in relatively simple, natural gas fired hot water boilers?

RQ3. How can distributed, combustion related measurements in power plants be interlinked to improve the reliability of individual measurements?

RQ4. How can process disturbances be separated from sensor disturbances in power plant online monitoring?

RQ5. How can the generic, element balance based combustion model be utilized in combustion applications?

RQ1 is answered in Chapter 4 (Publications I and II), RQ2 in Chapter 5 (Publication III), RQ3 in Chapter 6.1 (Publications IV and V), RQ4 in Chapters 6.2.1–6.2.2 (Publications IV and V), and RQ5 in Chapter 6.2 (Publications IV–VI).

1.3 Contribution

This thesis presents model-based estimation, monitoring and control solutions for three main applications: Small-scale wood chip combustion systems, medium-scale natural gas fired boilers and large-scale power plants. This thesis' main contributions are:

- Integrating process and domain knowledge, models, and online estimation, to provide optimal solutions for online emission monitoring and control in existing commercial combustion processes, including
    - Developing an approach to provide feedforward and feedback solutions for small-scale wood combustion systems, subject to prevailing requirements and limitations
    - Developing a modelling framework to provide cost effective and feasible, indirect monitoring solutions for flue gas NO_x emissions in medium-scale natural gas fired boilers
    - Developing a novel, generic combustion model to interlink distributed, combustion related measurements, to differentiate sensor malfunctions and process disturbances, and provide estimates of process variables.

The application of the thesis framework are presented in Publications I–VI. The author's contribution in the publications are:

Publication I Durable Feedback Control System for Small Scale Wood Chip Combustion: Timo Korpela wrote the article and was the corresponding author. He planned and performed the experimental work with guidance from Tomas Björkqvist and the assistance of cooperating companies, especially Marko Pihlajamäki from Säätötuli Ltd. and Veli-Matti Järvelä from HT Enerco Ltd. All co-authors helped finalize the paper.

Publication II Control Strategy for Small-Scale Wood Chip Combustion: Timo Korpela wrote the article and was the corresponding author. He planned and performed the experimental work with guidance from Tomas Björkqvist and the assistance of cooperating companies, especially Marko Pihlajamäki from Säätötuli Ltd. All co-authors helped finalize the paper.

Publication III Indirect NO_x Emission Monitoring in Natural Gas Fired Boilers: Timo Korpela wrote most of the article and was the corresponding author. He planned and performed the experimental work in cooperation with Anna Häyrinen and the plant personnel. He also designed the data analysis strategy. Pekka Kumpulainen realized the data analysis, calculated the results, plotted the figures, and wrote Section 4 and some of the text in Section 5. The other authors provided assistance along the way and took part in finalizing the paper.

Publication IV Online Monitoring of Flue Gas Emissions in Power Plants Having Multiple Fuels: Timo Korpela derived the model, wrote the article, and was the corresponding author. The cooperating company, IndMeas Ltd., provided the data. The other authors provided assistance along the way and took part in finalizing the paper.

Publication V Robust Data Reconciliation of Combustion Variables in Multi-Fuel Fired Industrial Boilers: Timo Korpela derived the process model, wrote most of the article, and was the corresponding author. Timo Korpela, Yrjö Majanne, and Olli Suominen wrote Section 1. Timo Korpela and Olli Suominen designed the data reconciliation approach. Olli Suominen wrote Section 2 and some parts of Section 4, derived the data reconciliation application, calculated most of the results, and finalized the text at the end. Ville Laukkanen from IndMeas Ltd. provided the data and gave valuable feedback about the approach. Pentti Lautala provided assistance along the way. All co-authors helped finalize the paper.

Publication VI Monitoring of Spraying in Semi-Dry Desulfurization Processes in Coal Fired Power Plants: Timo Korpela developed the monitoring approach, wrote the article, and was the corresponding author. Olli Salminen and Anton Laari from Helen Ltd. provided vital process information and data. The other authors provided assistance along the way and helped finalize the paper.

1.4 Outline of the Thesis

This thesis comprises of eight chapters. Chapter 2 presents the *domain expertise* of combustion systems, which is required in the following chapters. It focuses on three main topics. The first is combustion fundamentals, which include fuel properties, combustion in general, and emission formations and their primary reduction. The second topic involves boiler process technologies, concentrating on boiler technologies, measurements, control, and secondary flue gas cleaning. The third topic discusses boiler operation environments, including operation in energy systems. Prevailing and future energy policies, and emission legislation, are briefly discussed, to clarify the needs and requirements for the developed solutions.

Chapter 3 presents the *knowledge engineering* for the thesis. In particular, it presents the model types applied in Cases I–III, including verbal, data based, and first principles models. The discussion focuses on derivation, validation, and especially on domain of validity, which are all relevant when applying the results of this thesis. The data reconciliation approach is also presented, which is applied in Case III.

To conclude, Chapters 2 & 3 present the thesis framework that enables the development of the practically justified online monitoring and control solutions. The framework is then applied in Chapters 4–6, which present Cases I–III, respectively. They include, when relevant, case specific literature surveys, process descriptions, solutions, and case-specific discussions.

Chapter 7 generally discusses the thesis' main contributions. Chapter 8 presents the main conclusions from the thesis.

2 Combustion Processes – Domain Expertise

Existing combustion processes were designed and built to fulfil certain heat, power and steam production needs in certain locations. The main design parameters of the combustion processes included power range, main fuel properties, boiler technology, and boiler operation principles. These parameters were interlinked with certain prevailing requirements in terms of emissions, efficiency, and operability. All these aspects set certain features and limitations that must be considered when adapting plants to present and future requirements. Future requirements stem from needs to extend the fuel mix; tighten emission limits and monitoring requirements; extend power ranges; and change operation principles, including increasing dynamical operation flexibility. These new requirements, caused by tighter legislation and operation requirements, pose challenges to existing combustion plants. Their ability to adapt to these new environments determines their long-term feasibility and future viability.

This chapter describes the main features of combustion processes that define their properties and performance. It mainly focuses on general combustion principles that are independent of technology. Instead, this chapter focuses on boiler operation and particularly on emission formation and control, since these aspects are at the core of the thesis. More specifically, it emphasizes boiler processes presented in Cases I–III, including small-scale biomass combustion, medium-scale natural gas combustion and large-scale solid fuel combustion in power plants. However, the backgrounds are presented such that the emerging issues, prospects, and limitations can be understood in a wider context. In particular, Chapters 2.1 and 2.2 present the properties of combustion processes (Figure 1), including combustion fundamentals and technologies. Chapter 2.3 presents the needs, requirements, and restrictions (Figure 1) that set the objectives for solutions presented in Cases I–III.

2.1 Combustion Fundamentals

This subchapter presents the fundamentals of combustion, including descriptions of fuel properties, combustion, and emission formation.

2.1.1 Fuel Properties

Fuel chemical and physical properties have a significant impact on boiler structure, combustion properties, emissions, and boiler operation. The fuels constitute of several chemical elements, mainly carbon (C), hydrogen (H), oxygen (O), nitrogen (N), sulphur (S), and chloride (Cl). Additionally, the fuels contain water and ash, of which the latter constitute several inorganic elements and their compounds. Ash components are typically minor in proportion, but may significantly contribute to ash deposit and boiler corrosion (Nunes *et al.*, 2016), and particle emissions (Sippula *et al.*, 2007).

Fuels can be categorizes into liquid (such as heavy and light fuel oil, biofuel, etc.), gaseous (such as natural gas, shale gas, methane, etc.) and solid fuels (such as woody biomass, agro fuels, peat, coal, waste) that require their own combustion technologies. The main features of gaseous and liquid fuels are heating value, composition, sulphur content, and ignition and handling properties (Asikainen & Jalovaara, 2002). The compositions of these fuels from one fuel source are stable, and they are easy to burn with their own burner technologies (Asikainen & Jalovaara, 2002).

On the other hand, there are several aspects to consider when combusting solid fuels. The key parameters of solid fuels are fuel chemical composition, heating value, moisture contents, particle size distribution, ash contents and properties, and the amount of volatile matter (Moilanen *et al.*, 2002). The most significant parameter of solid fuels and especially wood chips is the fuel moisture content, which varies from 20 to 60 weight percent. Evaporation of fuel moisture during combustion consumes energy and hence reduces combustion temperatures (Maskuniitty, 2002), so high moisture content may disturb combustion and reduce efficiency.

Fuel physical property requirements differ, depending on the fuel, fuel feeding system, and combustion technology. In pulverized coal combustion, adequate grindability of coal is the main feature as it enables stable feeding and narrow particle size distributions. Similarly, narrow particle size distribution is an objective in biomass combustion and especially in small-scale systems. The fuel feed is based on volumetric feeding that is implemented by fuel feeding screws, such that combustion is sensitive to fuel quality variations. Solid fuel feeding is impeded by large particles, wide size distribution, large bulk densities and high moisture contents (Dai & Grace, 2011). Additionally, the fuel feed capacity of the screw might be temporally reduced due to uneven unloading of fuel from storage (Publication II). Therefore, implementing stable solid fuel feeding is challenging (Dai *et al.*, 2012); (Rackl & Günthner, 2016), which causes significant combustion disturbances. Several variables contribute to varying particle size distributions. The variations originate from chipper configurations (Abdallah *et al.*, 2011); (Krajnc & Dolšak, 2014), including cut length (Facello *et al.*, 2013a), blade wear (Facello *et al.*, 2013b); (Nati *et al.*, 2010), and potential screen usage (Nati *et al.*, 2010); (Spinelli *et al.*, 2011). Moreover, the size of the chipped piece and the section of the chipped tree affect (Assirelli *et al.*, 2013). Due to the significance of stable fuel feed, controlling fuel feed disturbance is of utmost importance. This issue is discussed in Chapter 4.

Standardisation is one method to ensure high fuel quality (Alakangas, 2011). However, wood chips for small-scale systems are primarily made in Finland by end-users, so no standards apply. Therefore, small-scale combustion systems should be designed to also operate with nonstandard fuels. However, the use of standardised wood pellets and chips is far more common in Central Europe, which can also be seen in their boiler technologies. Another approach is to blend different fuel batches to balance variations in fuel quality (Rackl & Günthner, 2016), which is already the case in practice with large power plants.

There are numerous other fuels, especially biomass fuels, globally available. Saidur *et al.* (2011) present the properties of such biomass fuels. Alakangas *et al.* (2016) respectively reviewed Finnish fuels. To conclude, fuel properties have a significant role in combustion, which is discussed next.

2.1.2 Combustion

In combustion, high-temperature chemical reactions take place between a fuel and an oxidant. The oxidant is typically oxygen in air. Dry air contains c. 21 volume percent oxygen (O_2) and 79 volume percent nitrogen (N_2), which means that 1 mole of O_2 in air carries 3.76 moles of N_2. The nitrogen is primarily an inert gas that cools the combustion and reduces boiler efficiency due to flue gas losses. Therefore, the main parameter in combustion is the excess air ratio (λ) that describes the ratio between locally available and the stoichiometric amount of combustion air (Nussbaumer, 2003).

The main chemical overall reactions in the combustion environment with oxygen excess (λ>1) are

$$C + O_2 + 3.76 \cdot N_2 \rightarrow CO_2 + 3.76 \cdot N_2 \tag{R1}$$

$$C + 0.5 \cdot (O_2 + 3.76 \cdot N_2) \rightarrow CO + 1.88 \cdot N_2 \tag{R2}$$

$$2 \cdot H + 0.5 \cdot (O_2 + 3.76 \cdot N_2) \rightarrow H_2O + 1.88 \cdot N_2 \tag{R3}$$

$$S + O_2 + 3.76 \cdot N_2 \rightarrow SO_2 + 3.76 \cdot N_2. \tag{R4}$$

$$N + 0.5 \cdot O_2 \rightarrow NO. \tag{R5}$$

$$N + O_2 \rightarrow NO_2. \tag{R6}$$

As the result of overall combustion reactions, the main flue gas components are carbon dioxide (CO_2), water (H_2O), nitrogen (N_2), and sulphur dioxide (SO_2). Additionally, flue gases contain carbon monoxide (CO), nitrogen monoxide (NO), and dioxide (NO_2). All these reactions require numerous elementary reactions to take place (Van Loo & Koppejan, 2008). Depending on prevailing operation conditions and particularly local oxygen availability, the dominating reaction paths may change from one to another, especially from undesirable to desirable. For that to happen, combustion should be made favourable, such that there exists distinct primary and secondary combustion zones implemented with their own air supplies. The objective of the primary air zone is to supply air so that there is oxygen deficit (λ_{prim}<1), contributing to incomplete combustion with reduced NO_x formation (Kilpinen, 2002); (Van Loo & Koppejan, 2008) and fine particle emissions (Khodaei *et al.*, 2017); (Lamberg *et al.*, 2011). The objective of the secondary air zone is to supply enough air (λ_{prim} + λ_{sec} >

1) to enable complete burnout of gaseous compounds that escape the primary zone. Figure 4 illustrates the main reactions during two-stage biomass combustion. Similarly, the principle of primary and secondary combustion zones is also common in oil and gas combustion, in which the zones are implemented within the flame.

The fundamental requirements for good quality combustion are turbulence, time, and temperature (TTT). The turbulence must be sufficient to enable efficient mixing of intermediate combustion products and oxygen, especially in the secondary air zone. At the same time, a long enough residence time at a high enough temperature is required for ignition and complete burnout of combustible compounds. The limiting factor in combustion is typically the turbulence at low oxygen excess levels and temperature at high oxygen excess levels, due to cooling of excess air. (Nussbaumer, 2003) Several parameters (presented in the next sections) affect these factors. Next, the main principles of emission formation and prevention are presented.

2.1.3 Emissions Formation and Prevention

Emission Categories

The emissions of combustion are categorized into three groups: Gaseous pollutants from complete combustion, gaseous pollutants from incomplete combustion; and ash, contaminants and particles that are mainly formed from fuel constituents (Nussbaumer, 2003). In the first category, the main

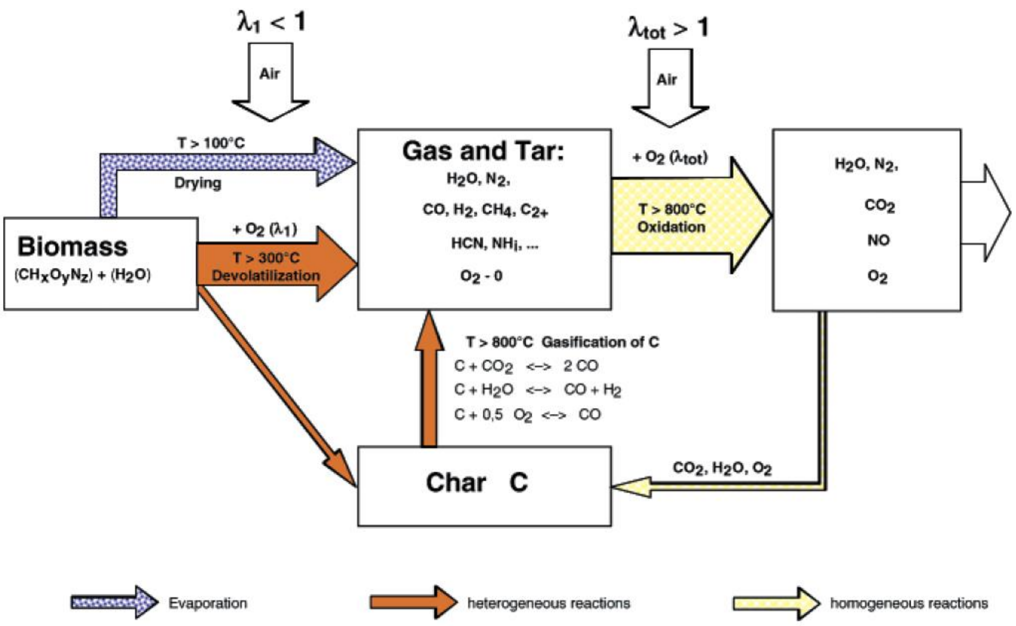

Figure 4. The main reactions during two-stage combustion of biomass, with primary and secondary air feeds. Reprinted with permission from (Nussbaumer, 2003). Copyright (2003) American Chemical Society.

emission from complete combustion is CO_2, which is the dominating greenhouse gas (GHG) contributing to climate change (IPCC, 2014). Second, almost all the sulphur in the fuel, especially in coal and heavy fuel oil, converts to SO_3 and dominantly to SO_2, which is denoted SO_x (Turns, 2000). SO_x emissions contribute to aerosol formation and acidification. Third, flue gases contain nitrogen oxides (NO_x), of which almost 95 percent are in the form of nitrogen monoxide (NO) and approximately 5 percent is in the form of nitrogen dioxide (NO_2) (Van Loo & Koppejan, 2008). NO_x emissions are responsible for health issues and environmental problems, such as photochemical smog, acid rain, tropospheric ozone and ozone layer depletion. (Skalska *et al.*, 2010) The nitrogen contributing to NO_x emissions originates from two sources: Bound nitrogen from fuel and elemental nitrogen (N_2) primarily from air. Based on these nitrogen sources, nitrogen oxides form in combustion by four mechanisms: Fuel NO_x; thermal NO_x; prompt NO_x; and via nitrous oxide (N_2O). The dominating NO_x formation mechanism depends on several factors, including fuel, boiler construction and process conditions. (Skalska *et al.*, 2010). Typically, the thermal NO_x mechanism dominates in oil and gas combustion, and the fuel NO_x mechanism dominates in biomass combustion (Kilpinen, 2002), which sets the guidelines for NO_x monitoring and control actions. NO_x formation and abatement are profoundly discussed e.g. by Kilpinen (2002), Turns (2000), and Skalska *et al.* (2010).

The second emission category constitutes gaseous pollutants from incomplete combustion. Some combustible gases do not fully oxidize, due to lack of combustion air, too low combustion temperature or residence time, or incomplete mixing of oxygen and fuel (Van Loo & Koppejan, 2008). The incomplete combustion produces carbon monoxide (CO), methane (CH_4), soot, and organic gaseous compounds (OGC). The excess air level of a process at certain combustion conditions determines the CO level, which is illustrated in Figure 5 in case of small-scale wood combustion. The behaviour of the lambda-CO curve also depends on boiler technology, air supply, draught conditions, fuel properties, and power levels. Despite that, all boilers behave similarly. Figure 15 shows respective curves in different power levels for medium-size natural gas boilers. Figure 5 also shows that CO and OGC emissions correlate with each other as a function of excess air, which can exploited in combustion control and emission monitoring solutions.

The third emission category include ash or extraneous material related contaminants, and particles. They constitute inorganic and organic liquid and solid particles, which are called *aerosols*. Incomplete combustion causes the organic constituents, such as black carbon, soot, and tar. The aerosols and larger fly ash particles nucleate, coagulate, condensate, and react with gaseous compounds (Figure 6). Some of them deposit to heat exchange and superheater surfaces, causing corrosion, fouling, and reduction of boiler efficiency (Nunes *et al.*, 2016). Moreover, they may foul sensors causing them to drift and malfunction, which is detrimental for control and monitoring applications.

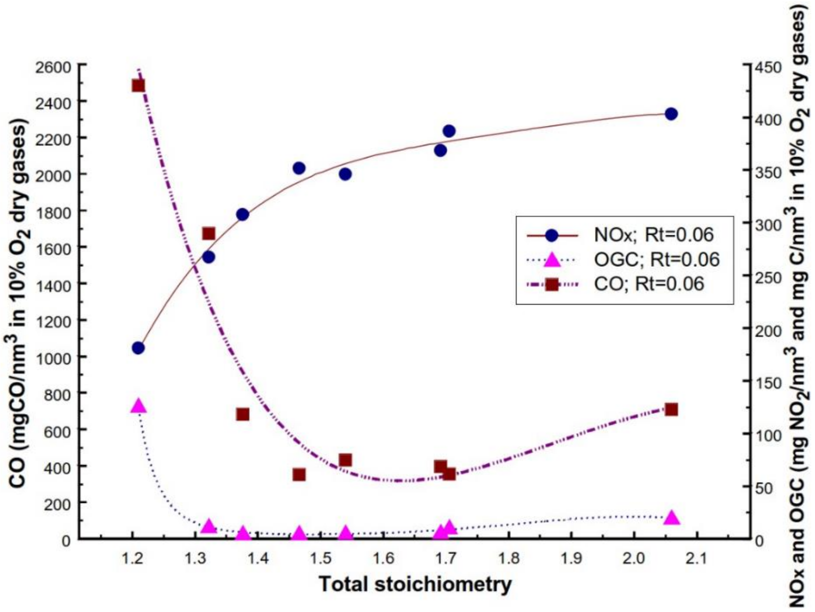

Figure 5. NO_x, OGC and CO emissions as a function of total stoichiometry in a modified, commercial wood pellet burner (residence time [Rt] of 0.06 seconds). The figure is modified from Eskilsson *et al.* (2004). Reprinted with permission from Elsevier.

Some fine particles, < 2.5 micrometres ($PM_{2.5}$), and fly ash emit to the atmosphere. The particle quantity, quality, and size distributions differ among the cases, depending on several factors.

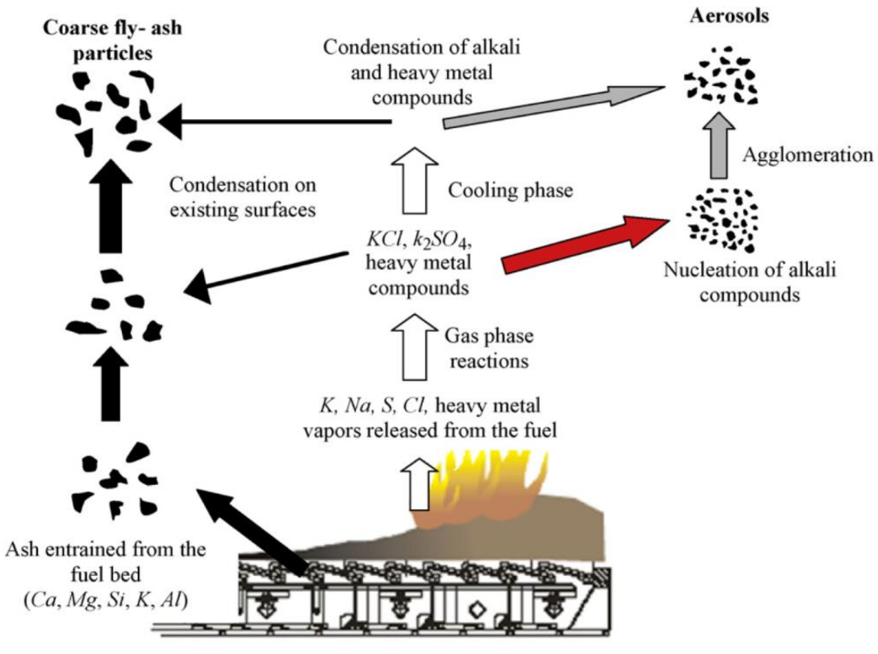

Figure 6. Aerosol formation during fixed bed combustion of biomass. Reprinted from (Ghafghazi *et al.*, 2011) with permission from Elsevier.

Fuel, boiler technology, and potential flue gas cleaning technologies primarily determine the fine particle and black carbon emissions of combustion plants (Frey *et al.*, 2014). The most significant source of fine particles is small-scale wood combustion, due to ash in biomass and the lack of feasible flue gas cleaning technology (Van Loo & Koppejan, 2008). Approximately half of total particle matter ($PM_{2.5}$) emissions in Europe are carbonaceous aerosols, of which residential wood combustion is the largest source (Denier Van Der Gon *et al.*, 2015). It is also the most significant source of both $PM_{2.5}$ and black carbon emissions in Finland, accounting for 37 percent and 55 percent of total respective emissions (Savolahti *et al.*, 2016). On the other hand, fine particle emission levels are much lower with oil (Frey *et al.*, 2014) and especially with coal fired power plants, due to efficient flue gas cleaning (Frey *et al.*, 2014); (Mylläri *et al.*, 2016); (Saarnio *et al.*, 2014). Furthermore, natural gas combustion emits much less particles than heavy fuel oil (Bond *et al.*, 2006).

Fine particle emissions have harmful effects on local air quality (Hellén *et al.*, 2008); (Yli-Tuomi *et al.*, 2015) and serious health effects (Bølling *et al.*, 2009); (Pope III & Dockery, 2006). Aerosols and particles escaping the chimneys may react in air producing secondary particles (Jimenez *et al.*, 2009), which may even increase the number of particle emissions in the atmosphere (Mylläri *et al.*, 2016). Indeed, there are many connections between air quality and climate change, with cooling and specially warming effects (Fiore *et al.*, 2015). Therefore, it is necessary to provide well performing, clean combustion technologies in all power ranges.

To conclude, high-quality combustion causes significantly less harmful fine particle emissions compared to low-quality combustion (Tissari *et al.*, 2008). In particular, good combustion from the CO and OGC points of view also reduces fine particle (Kelz *et al.*, 2012) and PAH (Bignal *et al.*, 2008) emissions compared to poor combustion. When the CO level remains low, the other emissions that are hazardous to health are also low (Flyktman *et al.*, 2012). Therefore, the CO emission level and ultimately oxygen level acts as good quality indicators of combustion. This can be utilized in control and monitoring applications, as an objective to minimize CO emissions.

Primary emission reduction

There are two ways to reduce combustion emissions, called primary and secondary reduction methods. The objective of primary emission reduction is to prevent emissions from forming. The objective of secondary emission reduction is to neutralize or remove the emissions that have formed (discussed in Chapter 2.3). Primary reduction methods must produce low emission levels, particularly when no secondary reductions methods are available.

Primary emission reduction methods depend on the emission and its formation principle. For example, thermal NO_x emissions can be reduced by limiting excess air levels and combustion temperature, e.g. by limited air preheating, flue gas recirculation, water spraying, and favouring long and radiative flames (Skalska *et al.*, 2010). Still, the main primary emission reduction method is staged combustion with primary and secondary air zones by air or fuel staging, and guaranteeing complete gas burnout in the secondary air zone. Together with sufficient temperature, residence time, and turbulence, these conditions enable CO, OGC, fuel NO_x, PAH, and particle emission reduction and hence good quality combustion.

Most emissions, particularly total emissions of complete combustion, form during normal boiler operation. However, boiler start-up and shutdown phases, idle operation, low power level operations, fast power transients, and process disturbances may substantially increase emissions (Bignal *et al.*, 2008); (Carlon *et al.*, 2015); (Venturini *et al.*, 2015); (Win *et al.*, 2012); (Win & Persson, 2014). Therefore, in addition to high quality fuels, properly designed combustion processes, functional sensors, and properly operating combustion control are required to enable low emissions in all operation conditions. These aspects are discussed next.

2.2 Boiler Process Technologies

Combustion is an exothermic process, releasing heat that boilers and furnaces use to generate heat, steam, and electrical power by a water-steam cycle. The objective of combustion systems is to produce the desired output with high efficiency and low emissions, subject to prevailing conditions and requirements. The main design parameters of the combustion processes include power range, main fuels and their main properties, boiler technology and boiler operation requirements. The requirements for combustion plants originate from national or EU regulations, and energy system requirements. These are discussed in Chapter 2.3.

Combustion processes can be classified according to fuel type, power level, and technology. First, the fuel type (liquid, gaseous, or solid fuels) differentiates the combustion technologies, due to their naturally distinct properties. Second, the nominal power level determines the requirements and prospects, such as instrumentation level, which also significantly contributes to control and monitoring systems. Classification based on technologies depends on the other two classifications variables, but not consistently. For example, grate firing can be reasonably applied in ranges from 0.01 MW – 100 MW. The main technologies relevant for Cases I–III are described next.

2.2.1 Combustion Technologies

Small-Scale Wood Chip Fired Boilers

The main features and structures of large-scale combustion technologies have long been established, due to extensive development, uniform legislation and requirements in several important markets, and a limited number of technology providers. However, the technologies are not similarly established in small-scale applications. This is due to dissimilar markets and their requirements, even within the EU, and a large number of boiler manufacturers (Míguez *et al.*, 2012). Austria and Germany have been particularly fast in developing small-scale combustion technologies, where strict emission limits, high energy prizes, quality labels, and governmental subsides steer customers towards high-end products (Büchner *et al.*, 2015); (Verma *et al.*, 2009). These system structures are very different from those manufactured in Nordic countries. Small-scale wood chip and pellet fired systems in Sweden and Finland typically constitute of a separate burner and boiler, which are often produced by different manufactures. Therefore, their overall system operation have not been optimized, so their system performances are somewhat limited compared to Central European integrated systems. Therefore, small-scale combustion processes vary significantly and have varying properties. Additionally, wood pellet and wood chip combustion systems in different sizes have different technologies (Míguez *et al.*, 2012), which extends the scope. Therefore, this thesis only presents the main features, and the boilers studied in Case I are described in more detail in Section 4.2. Surveys of different small-scale combustion technologies are provided, such as Míguez *et al.* (2012), Van Loo & Koppejan (2008), Büchner *et al.* (2015), and Fiedler (2004).

Nordic small-scale wood-chip fired burners are primarily implemented by grate combustion technology. The primary combustion zone is within the fuel pile, which is burned on the grate. The released combustible gases burn within a flame that typically comes out from the burner to the boiler's combustion chamber. The main burner inputs are typically the fuel flow and separate primary and secondary air feeds. However, there might be only one air fan in the smallest burners. In these cases, primary and secondary air division is mechanically fixed, which significantly limits boiler control and performance. The fuel bed is typically affected by grate sweepers, which are metal rods that move ash away from the grate and equalize the fuel pile. The grate dimensions are designed for a certain range of fuel moisture content and power.

Medium- and Large-Scale Power Plants

In medium- and large-scale combustion applications, oil and gas are burned with dedicated burner technologies, whose maximum power output is approximately 70 MW per unit (Asikainen & Jalovaara, 2002). Overall gas combustion emissions are low with sufficient excess air, but thermal NO_x formation is the main challenge. There are several burner structures available, of which Low-NO_x burner technology is the most common. In this technology, the fundamental goal is providing a flame that includes a primary air zone inside the flame, and a secondary air zone at the flame boundaries and at the end. These kinds of diffusion flames are achieved by air and fuel feeding with properly designed nozzles that cause the flame to swirl, improving the mixing and hence the burnout.

Medium- and large-scale solid-fuel boilers are implemented by several boiler technologies, which are only mentioned here with representative references. Grate combustion is applied for biomass and peat combustion in medium-scale applications and for waste combustion in large-scale ones (Yin *et al.*, 2008). Bubbling fluidized bed (BFB) combustion technology is applied in medium- and large-scale applications for biomass and peat combustion (Khan *et al.*, 2009), whereas circulating fluidized bed (CFB) technology is applied in large-scale power plants for biomass, peat and coal combustion (Miller, 2011). Still, pulverized coal combustion with burners dominates in large-scale coal combustion (Miller, 2011). A state-of-the-art review of the best available techniques for large-scale power plants is presented in (European Commission, 2016).

The aforementioned technologies determine combustion plant potential, but the actual process operation determines how well this potential is really achieved. Boiler operation is tied to boiler measurement and control, which are discussed next.

2.2.2 Measurements

Measurements play a vital role in all combustion processes, as they provide real-time indications about the behaviour of process phenomena. There are a few measurements in small-scale boiler processes, but power plants have hundreds of them. The measurements can be categorized based on their main application. Some measurements are used for financial purposes that are typically related to fuel or energy flows. Some others are used for feedforward or feedback control, directly affecting process behaviour. Some other measurements are used to fulfil the monitoring requirements of boiler emissions and performance, which originate from environmental legislation. Other measurements provide information and redundancy about the process behaviour, which can be utilized in various applications. The fundamental requirement is that the measurement information is reliable. The measurements' main purpose determines regular sensor maintenance procedures, so the most important measurements are under regular maintenance. However, reliability might not be obvious for other measurements, especially in a harsh process environment. This should be kept in mind when using measurements for purposes other than the ones for which they were originally designed, such as data based monitoring applications. The main measurements and their applications are described for large- and small-scale applications in the next section.

There are regulations for power plant emission monitoring, originating from the Industrial Emission Directive (IED) applied in the EU. For power plants >100 MW_{th}, there are general requirement to continuously monitor SO_x, NO_x and dust emissions. There are also supplementary measurements, including flue gas temperature, pressure, O_2, and H_2O measurements in the chimney. These auxiliary measurements are used to present the emission contents in standard conditions[2], such as mg/Nm[3]. For power plants in ranges of 50 MW – 100 MW, the monitoring requirement constitutes CO, SO_x, NO_x, and dust emission measurements every six months. On the other hand, the Emission Trading System (ETS) requires two independent methods to monitor CO_2 emissions of non-biomass fuels in power plants >20 $MW_{thermal}$ (European Commission, 2015). For that, there are CO_2 and flue-gas flow measurements in the chimney. Moreover, air and fuel flows are typically measured. There are also numerous measurements with varying properties, especially in power plants with a water-steam cycle and a turbine.

There are special requirements for measurements reporting on IED and ETS. These requirements are presented in standard EN 14181 (EN 14181), which define three Quality Assurance Levels (QAL 1–3) and Annual Surveillance Test (AST) procedures:

- QAL1: Quality check of measurement principle defined by EN 14956
- QAL2: Calibration and quality assurance of installation
- QAL3: Ongoing quality assurance during normal operation
- AST: Annual surveillance tests to evaluate correct measurement function, s.t. calibrations

To conclude, there might be numerous highly accurate measurements in power plants. This is very different from small-scale combustion systems, which have no requirements for online monitoring. The minimum measurement level in small-scale boilers are boiler water and flue-gas temperature, which monitor boiler operation and maintenance needs. Typically, there are also boiler inlet and outlet water temperate measurements. There might also be an energy meter and a pressure measurement in the flue gas duct to measure draught. These measurements enable simple boiler monitoring and control, but not combustion control.

Chapter 2.1 stated that combustion control has a significant potential to reduce emissions and improve boiler performance in small-scale applications. Oxygen measurement by lambda sensors is the most common combustion control measurement. Utilization of lambda sensors is far more common in Austria and Germany than in Scandinavia, and is more common in bigger boilers. (Míguez *et al.*, 2012) The lambda sensor has significantly improved within 40 years. The 5-wire, wideband, planar type lambda sensors (presented in Figure 7) currently provide temperature compensated and linearized responses in combustion applications with a wide oxygen range (De Souza Sobrinho & De Lima, 2012). However, the cost of temperature control system required for heating the measure-

[2] O_2=fuel specific constant that is 3 percent for gas and 6 percent for biomass, T = 0 °C, and p = 101,325 Pa.

ment probe is one downside of the modern lambda measurement system (Ruusunen, 2013). Therefore, older versions of the lambda sensors are also utilized, with significantly limited performance. CO-emission measurements are also available, but their application is still modest. However, gas sensor technologies are developing, so new cost-effective sensors are emerging in the near future. However, the need for inexpensive solutions still limits the scope of available measurements. For example, Flyktman *et al.* (2012) noted that online emission measurements are hardly a solution in small-scale systems due to economics. For further information, Liu *et al*. (2014), Kim *et al.* (2013), and Docquier & Candel (2002) reviewed gas sensor technologies for combustion applications.

In addition to requiring cost-effectiveness (Hrdlička & Šulc, 2011), the other significant limitation for gas sensors is long-term reliability in harsh combustion environments (Ruusunen, 2013). Such environments include normal process operations but also fast power transients, start-up and shutdown phases, and idle states with pilot flame. The contamination aspect is especially critical because most low-cost gas sensors, including lambda sensors, are developed for automotive applications (Liu *et al.*, 2014), which are significantly less harsh than biomass combustion environments. The more challenging the combustion environment, as related to fly ash and incomplete combustion products, the more likely the sensor will become contaminated, leading to drift and inaccuracy. In other words, when the sensors are most necessary, they are the least reliable. Although reduced accuracy might be acceptable for some applications (Good & Nussbaumer, 1998), this aspect sets significant requirements for fuel quality and clean combustion technologies, including boiler and fuel feed structures, sensors, and controls.

Figure 7. A Bosh LSU 4.0, wideband, planar type, lambda sensor after a challenging trial run with a 20 kW pellet boiler.

2.2.3 Combustion Control

Properties and requirements generally vary for different combustion units. Therefore, system structures, main disturbances, and prevailing requirements and limitations must be considered when designing control strategies for existing boilers. The available sensors and actuators specifically set limits to control design, whereas additional measurements provide new prospects. Combustion control has two objectives: Running the plant with low emissions and high efficiency in all operating conditions and circumstances; and fulfilling prevailing load requirements. These requirements are linked to heat-production requirements for heat boilers, power-production requirements in condensing boilers, and them both in CHP plants. These requirements originate from the energy system in which they operate, which is briefly discussed in Chapter 2.3.1.

In the most widely applied combustion control solution in combustion plants (Kovács & Mononen, 2007), the fuel flow and primary air feed are set based on the power requirement. Secondary air feed control is based on flue gas O_2 levels. The primary air feed rate determines the pyrolysis and gasification rate at the fuel pile, and the secondary air feed is controlled so that the released combustible gases burn while maintaining low excess O_2 levels. The benefit of this control structure is that the secondary air feed response is quite fast, and there is adequate secondary air for complete burnout. The secondary air feed must be independent of the combustion rate, meaning that the secondary air feed must not interfere with combustion in the fuel bed. Additionally, the O_2 level must be continuously measured. However, neither requirement is necessarily valid, as discussed in Chapter 4.

One of the boiler control's main features is related to where and how fast the fuel burns, which depend on fuel properties and combustion technology. The fuel burns almost instantly in gas, oil, and pulverized solid-fuel combustion. In those cases, there is no fuel storages to be considered in boiler control, which enables fast power level changes and large power ranges. On the other hand, the combustion in fluidized bed boilers (BFB or CFB) varies from seconds to some minutes depending on fuel characteristics. In fluidized bed combustion, fuel stored in the bed and the hot sand equalizes fuel feed variations and enables a momentary energy storage exploitation in fast power transitions (Majanne *et al.*, 2017). In grate combustion, the solid fuel particles burn in a fuel bed at longer burnout times. The stored fuel affects the dynamic boiler properties, which can be utilized by accelerating the combustion rate by increasing the primary air.

One important factor for clean, efficient combustion is a stable draught at the right level. Boiler draught variations disturb the air feed, which disturb the combustion on the grate and oxygen control operation. In domestic combustion applications, a mechanical draught regulator can control the draught. In larger boilers, an exhaust gas fan in the chimney, controlled by a pressure sensor in the combustion chamber, enables the stabilization of the draught.

It is also important to select suitable set points for all controllers in all operation conditions. As an example, the general objective of boilers is to produce power with high efficiency, which can be improved by lowering the excess air level. However, higher excess air levels are required at lower power levels, compared to nominal power levels, to guarantee proper gas mixing, which on the other hand increases NO_x emissions (Figure 5). Similarly, the combustion must be adapted to the fuel moisture content, as combustion of wood chips with high moisture content requires more total and especially primary air, compared to fuel with low moisture content (Yang *et al.*, 2004).

Despite the combustion control and primary emission reduction method, pollutant emission rates are too high to undercut current power plant emission limits. Therefore, secondary flue gas cleaning methods are required, which are discussed next.

2.2.4 Flue Gas Cleaning

The requirements for emission reduction originate from relative standards and regulations, of which the IED prevails in the EU. It sets emission limits for dust, NO_x, and SO_x emissions, so their reduction is vital to reach the IED goals. Additionally, CO_2 removal by carbon capture and storage (CCS) technology is being studied, but will not be applicable for a long time. Moreover, CO and other incomplete combustion products can be removed by catalysts (Ozil *et al.*, 2009), but their application is at low levels other than automotive applications.

There are two main strategies to reduce NO_x emissions: Selective catalytic reduction (SCR) and selective non-catalytic reduction (SNCR). In these technologies, the urea is dosed to the flue gas duct (SCR) and combustion zone (SNCR), in which NO_x emissions are converted back to N_2 and H_2O. (Skalska *et al.*, 2010) These abatement technologies are only applicable in large power plants, so smaller plants must rely on primary NO_x emission reduction methods.

In combustion processes, most of the sulphur of the fuel converts to SO_x, dominated by SO_2 and in a smaller amount to SO_3. Due to the dominating sulphur conversion, there are two options to reduce SO_x emissions: Remove the sulphur from the fuel or remove the SO_x from the combustion products. (Turns, 2000) The first method applies in oil fired heat stations, which changed from heavy fuel oil to sulphur free light fuel oil after the IED took effect. The second method primarily relies on wet limestone flue-gas desulphurization process. It is the leading post-combustion SO_2 removal technology, with a global 86 percent market share (Cristóbal *et al.*, 2012). There, slurry with calcium carbonite ($CaCO_3$) and calcium hydroxide ($Ca(OH)_2$) capture SO_2 to produce calcium sulphite ($CaSO_3$), which can be filtered from the flue gas. Still, the main technology for SO_2 removal in Finnish coal fired power plants is spray-dray absorption, which is the preceding technology to the wet limestone process. Nevertheless, it removes 85 – 90 percent of SO_2 emissions (Jamil *et al.*, 2013) and more than 97 percent of fine particle emissions from the flue gas flow (Saarnio *et al.*, 2014). The process is presented in more detail in Publication VI, which covers spray monitoring in such processes.

There are various dust removal technologies (Ghafghazi *et al.*, 2011); (Singh & Shukla, 2014); (Van Loo & Koppejan, 2008). Such technologies include cyclones, electrostatic precipitators (ESP), scrubbers, and baghouse filters. Flue gas condensation also removes particles. The flue gas cleaning has a major contribution on particle emission reduction. For example, ESP reduced the PM_1 emission values from a 10 MW wood chip fired grate boiler from 264 mg/MJ to 0.6 mg/MJ (T. Kaivosoja *et al.*, 2013). Another study stated that ESP availability was 90 percent in seven wood chip fired plants in the range of 0.45 MW – 3.5 MW (Nussbaumer & Lauber, 2016), which significantly reduce dust emissions. However, there are currently no feasible technologies for removing particles in small-scale biomass fired boilers (Lim *et al.*, 2015), despite several attempts. Therefore, proper boiler performance is required.

The presence of flue gas cleaning systems must be considered in boiler operation, including enabling and limiting aspects. For example, the utilization of NO_x removal enables a deviation from optimum primary reduction conditions, which is sometimes beneficial from combustion control viewpoint. The drawback is that flue gas cleaning systems must also properly operate during very fast power transients and low loads. The operation modes are especially challenging for removing NO_x and SO_x at low power levels, to maintain high enough temperatures in NO_x removal and even spraying of calcium slurry in SO_2 removal. These aspects might limit feasible boiler operation ranges, which is limiting in terms of the energy system. This aspect is discussed in the next section.

2.3 Boilers in Future Energy Systems

Several aspects define combustion plant operation, performance, and ultimately the emissions as they operate in their energy systems. Figure 8 presents a schema of the Finnish energy system. It illustrates combustion plant operations in a wider context, and some major linkages and aspects in the energy system. These aspects include domestic and foreign energy sources; various energy carriers and energy conversion technologies; several energy networks with storages; varying, flexible consumption; energy system balancing; numerous actors; markets (presented implicitly in the figure); EU and national regulations; and energy policies. These aspects directly or indirectly affect existing combustion plant viability and future investments. This chapter next discusses energy policies, emission regulations, and operation requirement related aspects, as these affect boiler operations in energy systems. The end briefly looks at current market trends.

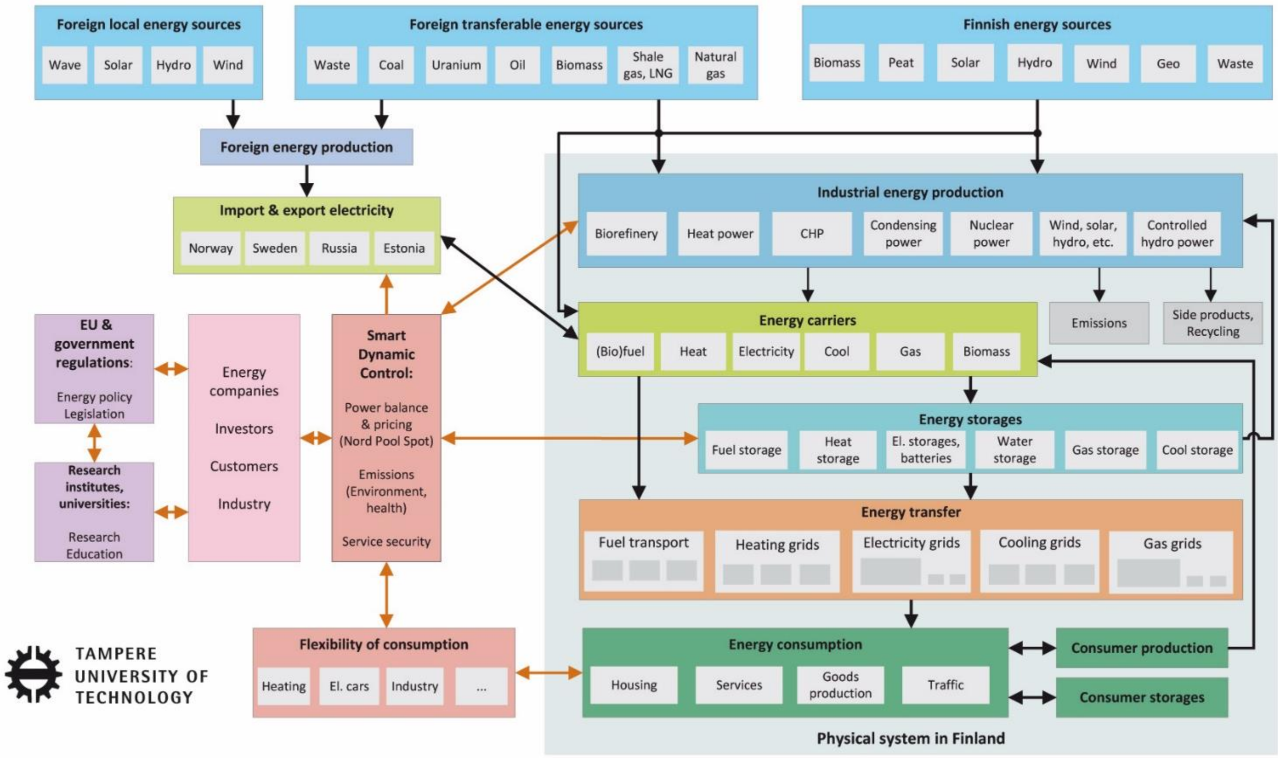

Figure 8. Finnish energy system schema.

2.3.1 Energy Policies

Main combustion plant legislation requirements and energy policies originate from EU and consequently from national legislation. As a significant upgrade to the former “20–20–20” policy, current EU policy requires a 40 percent reduction of GHG emissions by 2030 compared to 1990; and a 27 percent reduction of both energy intensity and RES in final energy consumption compared to 2005 (European Commission, 2014). The “40–27–27” policy is in line with the Paris Agreement (2015), which aims to limit the global warming to 1.5 °C compared to pre-industrial levels. A significant tool to reduce emissions in the EU is the Emission Trading System (ETS), which will be further extended in 2020, at the beginning of the fourth ETS period (European Commission, 2015). As a Finnish policy, the EU level targets are also to be met by phasing out coal combustion by 2030, favouring biomass combustion in CHP production and flexibility in power markets; increasing energy-system efficiency; providing incentives to RES technology neutrally; and reducing oil consumption by 50 percent by 2030 (Työ- ja elinkeinoministeriö, 2017). These policies directly or indirectly change the dynamics of energy systems and the operating environment of existing combustion plants.

2.3.2 Future Emission Regulations

In addition to reducing GHG emissions, other related objectives are subject to these energy policies. In the EU, various national laws regarding small-scale and medium-scale boilers in combustion plants will be unified by the following directives:[3]

- **Small solid fuel combustion systems** will be regulated by the ECODesign Directive:
    - Solid fuel fired local space heaters <50 kW are regulated by 2015/1185/EU directive that takes effect in January 2022.
    - Solid fuel boilers in ranges 50 kW – 500 kW are regulated by 2015/1189/EU directive that takes effect in January 2020. The extension of the directive to cover also ranges 500 kW – 1000 kW will be considered by 2022.
- **Medium combustion plants** in ranges 1 MW – 50 MW_{fuel} will be regulated by Medium Combustion Plant Directive (MCP; 2015/2193/EU) that takes effect in January 2025 (5 MW_{fuel} – 50 MW_{fuel}) and January 2030 (1 MW_{fuel} – 5 MW_{fuel})
- **Large combustion plants** >50 $MW_{thermal}$ are regulated by Industrial Emission Directive (IED; 2010/75/EU), which took almost full effect in 2016. However, the requirements will be reconsidered, based on Best Available Techniques (BAT) Reference Document (European Commission, 2016), whose final draft was released in June 2016. The draft proposes significant emission restrictions to existing emission limits, which may significantly affect existing large-scale power plants.

There is also a standard EN 303-5:2012 (<500 kW) for heating boilers for solid fuels. The standard is in effect in Finland, but is not binding. The ECODesign emission regulations for small-scale combustion systems will be effective in 2020–2022, but only apply to new installations, so it will take a long time before regulations begin to affect Finnish emissions (Savolahti *et al.*, 2014). On the other hand, the MCP and IED directives also apply for existing plants, whose impacts are lowered by transitional national plans (NTP).

If flue gases from several combustion plants, exceeding 15 $MW_{thermal}$, could be discharged through a common stack, the IED states that the combination formed by the individual plants is considered a single combustion plant, whose capacities are added together when calculating total thermal input. This aggregation rule extends the scope of the IED to combustion plants with a rated thermal power of 15 MW–50 MW, which also initiated Case II. A similar complement is also in the MCP directive.

[3] The directives include several exceptions that are not listed here.

2.3.3 Operation of Boilers in Energy Systems

The previous chapters and most of the solutions in this thesis only consider relative emissions (in mg/Nm^3) of boilers in different operational conditions. However, total emissions (in tons) released to the atmosphere depend on boiler efficiencies and, particularly, the operation of boilers in their energy systems. The latter topic is extensive and only briefly mentioned. Heat-only boilers operate in their local heat networks, condensing power plants in the northern European electricity network, and CHP plants in both networks. Therefore, the operation of a single boiler depends on other production units that may have competing technologies and boilers that may use different fuels. All these energy producers have individual features and, particularly, production costs. Momentary and forecasted energy consumption, available production units, and potential storages determine market prices, and operating units and their power levels for each hour. Therefore, the feasibility of boiler technologies depends not only on technical potential but also on competing technologies and prevailing operational environments, including fuel prices, ETS, and emission regulations. Specifically, investments to improve emission-reduction systems increase the production costs, which will have a negative impact on future feasibility of the boilers.

Numerous simulation studies have estimated viable future energy systems. They concluded, subject to significant uncertainties, that energy production still significantly relies on fuel combustion, especially on non-fossil fuels, despite the dominating role of carbon-free RES (Child & Breyer, 2016); (Mikkola & Lund, 2016); (Rinne & Syri, 2015); (Tafarte *et al.*, 2017). However, future energy-system operations, with significant shares of RES, sets new requirements for combustion plants, focusing on extended dynamic flexibility; diversified fuel exploitation; and extended efficient power ranges, including lower minimum power levels (Henderson, 2014); (Weber *et al.*, 2011); (Ziems *et al.*, 2011). Steps toward these new requirements have already been taken (Korpela *et al.*, 2017a); (Majanne *et al.*, 2017). Moreover, system level optimization in district heating networks become more important (J. Kaivosoja *et al.*, 2017); (Laakkonen *et al.*, 2017). In particular, heat accumulators in district heating networks enable smoother power level transients, which benefit boiler operation at all power levels (Lundgren *et al.*, 2004), (Korpela *et al.*, 2017a).

2.3.4 Current Market Trends of Combustion Plants

The popularity of small-scale biomass fired systems substantially increased in Europe within a decade, primarily due to increasing oil and electricity prices, gained public awareness of climate change and both national (Kivimaa & Mickwitz, 2011) and EU policies (Verma *et al.*, 2009). During that time, the role of small-scale wood pellet and chip fired systems significantly diverged in Europe. The increase was fastest in Sweden, Austria, and Germany, but was only modest in Finland. The increase stopped in 2010, especially with wood pellets in Finland, mainly due to lack of economic competitiveness compared to other heating technologies (Proskurina *et al.*, 2017). Instead, the number of heat entrepreneurs operating biomass fired systems in ranges 100 kW – 1000 kW has steadily increased (Alm, 2016).

The CHP and especially condensing power production in Finland has decreased steeply since 2010. The reduction is primarily due to lowered electricity prizes, which are largely caused by increased wind power production and imported power, and reduced domestic power use. As an example of the market change, the Finnish wind power sector will make investments of € 1.5 billion during 2016–2017, with a capacity increase of 750 MW in 2016. (Alm, 2016) As a result of market changes, some condensing coal fired boilers have been decommissioned, such as Inkoo. At the same time, CHP production investments have decreased, which are primarily replaced by heat-only boilers, such as in Helsinki and Lahti, and heat pumps in Helsinki. For further information, Alm (2016) presents an up-to-date survey of Finnish energy market conditions.

2.4 Discussion

To conclude, several aspects define combustion-plant operation, performance, and emissions (Figure 8). Current and future energy policies and legislation requirements set guidelines for energy markets, which affect available energy production units, flexible consumers, and energy storages. Long-term trends and volatility of marginal costs determine which technologies are the most feasible to prevailing conditions. Due to system complexity, any significant changes to energy policies must be diligently considered. It is especially important to avoid problem shifting, which was concerned e.g. by Judl *et al.* (2014).

Emission regulations determine the application of primary emission reduction technologies, including the measurement, control and monitoring solutions in combustion plants. If the performance of these methods is insufficient, secondary emission reduction methods are applied. If they have already been utilized, their technology must be upgraded or totally renewed, to guarantee the ability of existing combustion plants to meet new requirements. However, new investments increase production cost, which weaken the economic feasibility of existing boilers in energy systems. Therefore, feasible low-cost solutions that improve boiler operation and performance are important. Chapters 4–6 provide some solutions to these needs. Prior to that, estimation methods and their models are discussed.

3 Online Estimation of Combustion – Knowledge Engineering

Online estimation solutions are based on available process measurements and a model that interlinks measurements to desired estimates. The concept has several established names, including inferential or indirect measurements, virtual or soft sensors, and domain specifically Predictive Emission Monitoring System (PEMS). Measurement availability depends on boiler size and emission regulations, discussed in Chapter 2. This chapter concentrates on estimation methods, specifically models that are core for the estimates.

The models are classified in several ways. One obvious classification can be made according to the modelling object, especially process type, for example, coal fired power plant, gas turbine, or small-scale biomass fired boiler. Another classification can be made according to estimated variables, such as NO_x emissions, fuel moisture content, or boiler efficiency. Alternatively, the model types differ according to modelling principle, including verbal, data, and first principle, all of which cover a wide range of models with static or dynamic properties. Additionally, some models are derived from process perspective, while some others test the properties of certain method properties in some test processes. Moreover, classifications can be made according to the number and quality of measurements used as model inputs.

The predetermined aspect of dynamics is especially important in combustion applications. Combustion processes are dynamic and have a wide range of dynamics. The dynamics of fuel pile on the grate and boiler are significant compared to the dynamics of combustion in flames. Stiff models can handle both these dynamics simultaneously. However, their application is impractical in many cases, so they are not utilized in monitoring and control applications. Therefore, dynamics should be considered only to the extent that they are important for the modelling task. Even static or steady-state models can successfully be utilized, if the significant role of dynamics are understood when deriving the model and analysing the results. Still, dynamic models are able to depict the process better than steady-state models, but deriving precise dynamic models require by far more information on process conditions and parameter values, which may not be realistically available in practical installations. Moreover, deriving and operation of complex dynamic models require significantly more effort and computational power. The significance of dynamics in control design and system structure design are of utmost importance, but its role is not as straightforward in diagnostics and monitoring. There, the challenge is that when solving inconsistencies in process conditions or measurements with varying dynamics, each new variable increases the uncertainty over the time horizon, including the uncertainty related to initial values and process conditions. Therefore, steady-state or static models are typically more suitable for such monitoring objectives, and were therefore selected to be focused in the thesis.

This chapter introduces the relevant model principles for Cases I–III, which include verbal, data based, and first principles models. All these models have distinctive features and validity ranges, which are enabling on one hand but restrictive on the other hand. Considering these aspects, the models applied in this thesis were selected based on needs and requirements of the case processes. The main features and limitations of these models are presented next.

3.1 Models for Online Estimation

Online estimates in combustion environments can be categorized into two groups. In the first category applied in Cases II and III, the emission components (such as NO_x and CO_2) are the estimated variables utilized directly for monitoring or control purposes. In the second category, the estimate is calculated for a secondary process variable that is used for emission monitoring or control. The latter approach is applied in Case I, where temperature measurements from the upper part of the furnace estimate the fuel burning rate affected by the actually realized fuel feed and hence the size of the fuel pile on the grate. The temperature measurement can then control the fuel feed, to achieve stable heat production and low emissions. A similar indirect approach can also monitor the fuel burning rate (Hsi & Kuo, 2008), moisture content (Kortela & Jämsä-Jounela, 2013); (Odgaard & Mataji, 2008); (Ruusunen, 2008), and heat value (Hsi & Kuo, 2008); (Van Kessel *et al.*, 2004). However, this chapter focuses on direct estimation of emission components, as applied in Cases II and III.

Soft sensors can be either model or data driven. Model driven soft sensors are also called white-box models because they have full phenomenological knowledge about the process background. In contrast, purely data-driven models are called black-box models, because they do not know about the process behaviour, as they are only based on process measurements. However, there are many combinations of these two, which are grey-box models. (Kadlec *et al.*, 2009) Based on this grouping, the mental and verbal models are white- or grey-box models, which will be discussed next.

3.1.1 Mental and Verbal Models

Mental models of technical systems are based on intuition or experience. Mental models can be utilized as a basis for designing certain operational practice or control systems to implement a certain objective. (Ljung & Glad, 1994) In this context, the background for mental models of combustion and their related aspects were described in Chapter 2. The mental models can be utilized to generate verbal models that describe the system behaviour as rules, such as IF–THEN rules. These rules can be utilized in fuzzy models or expert systems (Karray & De Silva, 2004). Fuzzy models, based on fuzzy sets (Zadeh, 1965), formally determine the cause-effect reasoning of an action, such as IF oxygen level goes down THEN increase secondary air. The rules can be generated by an expert, such as in Case 1. However, the prevailing method is gathering the rule base from process data, for example with Adaptive-Network-Based Fuzzy Inference System (ANFIS) (Jang, 1993). The latter method, which was applied in Case II, is a grey-box method that preserves the intuitiveness of the rule bases. Additionally, there are numerous other fuzzy and neuro-fuzzy models and systems (Karray & De Silva, 2004).

Fuzzy models have also been utilized in fuzzy estimation and control of combustion processes. For example, Ruusunen & Leiviskä (2004) presented a Takagi & Sugeno (TS, 1985) fuzzy model-based approach for estimating CO_2 content in a wood-fired batch combustion process. Grosswindhager *et al.* (2014) developed Multiple Input Single Output (MISO) TS-type fuzzy models for heat power and both flue gas O_2 content and temperature in a 3.5 MW biomass fired grate boiler. Joronen (2005) presented a fuzzy control framework to process performance improvements in fluidized bed boilers. Šulc *et al.* (2009) estimated flue gas CO and CO_2 concentrations in a small-scale pellet boiler with a neuro-fuzzy model, utilizing an oxygen measurement. Norhayati & Rashid (2017) presented an ANFIS based CO soft sensor for a clinical waste incineration plant, which had two temperature measurements and an oxygen measurements as inputs. Ikonen & Najim (1996) and Ikonen *et al.* (2000) utilized neuro-fuzzy model for estimating NO_x emissions of a 25 MW BFB boiler with a distributed logic processor (DLP) rule base. Additionally, the paper applied several data based methods, which are discussed next.

3.1.2 Data Based Models

Data based models are mathematical descriptions that depict the estimated variables based on input variables. In the context of the thesis, the input variables are continuous process measurements. The estimated output variables can also be continuous process measurements, but they are usually periodic measurements, such as a portable flue gas analyser. In this work, the data based models are mainly related to estimating NO_x emissions in natural gas fired medium-scale boilers, discussed in Case II.

There are numerous linear and especially nonlinear data based model types. The most commonly applied model type is linear regression. Examples of nonlinear data based methods include: multilayer perceptron (MLP), radial basis function (RBF), partial least squares (PLS), least squares support vector machine (LSSVM), fuzzy inference systems (FIS), and Kohonen's self-organising maps (SOM). Each of these models can at best replicate the particular process conditions that existed at the time the identification data was collected (Kano & Fujiwara, 2013). Therefore, the main aspect in model identification is to collect an information rich set of process data. The data for model derivation can be generated by measuring the normal operation of the combustion plant, conducting separate trial runs to stimulate the process, or simulating the process with other models. The first approach typically requires input data collection for a long time, but, the process may not be stimulated to cover all the potential operation conditions. Separate trial runs may improve this situation significantly, but the amount of data collected with this approach is usually somewhat limited. In the third approach, input data can be derived by complex combustion models, such as computational fluid dynamic (CFD) models.

Several other aspects must be considered with data based soft sensor derivation in practical installation. These aspects include data pre-processing, input data selection, model selection, training and validation, and soft sensor maintenance (Kadlec *et al.*, 2009). Maintenance is required when the identification data no longer describes the process or sensor conditions, or if the operating range of the process is extended, as discussed in Publication III. Moreover, there are issues related to process data, including missing values, data outliers, sensor output drifting, and measurement delays, all of which should be considered (Kadlec *et al.*, 2009). For further information, Kano & Fujiwara (2013) and Kadlec *et al.* (2009) discuss reliability of data based soft sensors.

Despite several aspects to consider, data based models have been extensively used for industrial and combustion applications (Kadlec *et al.*, 2009); (Kalogirou, 2003); (Kano & Fujiwara, 2013); (Souza *et al.*, 2016). In particular, data based soft sensors can estimate emission components. For example, Ruusunen (2013) presented signal correlations between temperature measurement based features and typical flue-gas components (CO_2, O_2, NO_x), and both combustion and thermal efficiencies in several small-scale boilers and a large-scale biomass fired boiler. Of those gas components, data based NO_x emission estimation literature is extensive. Therefore, this work only focuses on estimating NO_x emissions in natural gas-fired boilers, by providing a comprehensive review for Case II. Shakil *et al.* (2009) developed a soft sensor for NO_x in a natural gas fired boiler by utilizing static and dynamic neural networks. Kumpulainen *et al.* (2015) and Korpela *et al.* (2015) presented a comparison of linear and non-linear models in natural gas fired 43 MW hot water boilers. Iliyas *et al.* (2013) presented NO_x and O_2 estimates produced with RBF and MLP models that were trained with data from a three-dimensional (3D) CFD model for a 160 MW gas boiler. Similarly, Ferretti & Piroddi (2001) utilized a 3D CFD model and developed a neural network-based strategy for estimating NO_x emissions in an oil and methane fired 320 MW thermal power plant, utilizing two different learning strategies. Li *et al.* (2005) derived Eng-genes and MLP neural networks for the same plant by utilizing Arrhenius-type equations in a semi-empirical model. Bebar *et al.* (2002) presented another semi-empirical model, in which simplified kinetic equations described the NO_x formation in a test facility.

All these data based models replicated the process conditions in which they were trained. Indeed, data based soft sensors can be used for interpolation in their validation range but should not be used to extrapolate out of it (Kano & Fujiwara, 2013). However, comparison between history values and prevailing states can extend the scope of process state monitoring (Nikula *et al.*, 2016). Still, the data based methods cannot estimate correct values out of their identification data range. First principles models do not have such a limitation, which are discussed next.

3.1.3 First Principles Models

First principles or physical models are based on phenomenological knowledge about the processes (Kadlec *et al.*, 2009). They originate in combustion applications from known physical and chemical interconnections described by mathematical models. The model derivation is typically based on mass and energy balances. Specifically, the mass balance can be further extended to chemical element balances, which are particularly useful in emission modelling in combustion applications. Element balances are also the foundation of the combustion model presented in Case III.

First principles models enable the utilization of experimental and theoretical process knowledge, process structure independently. The models consist of parameters that have physical or chemical backgrounds, linking models and real process parameters. Typically, these model parameters are selected depending upon process relevancy, but sometimes their values are unknown. Tuning these parameters might be laborious, especially in complex processes. However, this issue can be handled by multivariable optimization methods as Yli-Fossi (2014) showed. Additionally, there may be additional tuning parameters to compensate for inaccuracies in the model structure. Still, these models enable estimation of process behaviour before the process might even exist. This ability is extensively utilized in process and control design.

First principles models can be either dynamic or static. Combustion processes are dynamic, so various dynamic models are available, such as (Bauer *et al.*, 2010); (Boriouchkine *et al.*, 2012); (Boriouchkine & Jämsä-Jounela, 2016); (Yli-Fossi *et al.*, 2011). Alobaid *et al*. (2017) provided an in-depth review of dynamic modelling and thermal power-plant simulation. Dynamic models enable direct and indirect process and control development. An example for direct utilization is model predictive control (MPC), which is increasingly applied in boiler control applications (Gölles *et al.*, 2014); (Kortela & Jämsä-Jounela, 2014); (Kortela & Jämsä-Jounela, 2015); (Leskens *et al.*, 2005); (Paces *et al.*, 2011).

Static models can also be utilized, if the process dynamics are considered in deriving the model and interpreting the results. Case III presents such a model, which is an element balance-based first principle model for estimating flue gas emissions. Element balances have also been utilized to estimate some individual features, such as fuel heating values (Fellner *et al.*, 2007); (Hsi & Kuo, 2008); (Van Kessel *et al.*, 2004), fuel burning rates (Hsi & Kuo, 2008), flue gas composition (Sartor *et al.*, 2014a), and flue gas specific heat and exergy values (Coskun *et al.*, 2009). The balances have also been used for organic fraction separation of fossil and biogenic waste components (Fellner *et al.*, 2007). Moreover, it has been utilized, together with chemical equilibrium model, to estimate NO_x, CO and SO_x emissions in a medium-scale CHP plant (Sartor *et al.*, 2014b). For comprehensive process and sensor monitoring purposes it has not been applied prior to Publications IV & V.

The drawback of first principles models is that their development requires a lot of effort and process knowledge. However, the models are generic, whose domain of validity primarily depends on the validity of assumptions made in model derivation, such as assumption of gas compressibility. However, the domain of validity of soft sensors based on first principles models is also restricted by the measurement range of utilized sensors. Therefore, these boundaries might limit the domain of validity more than model validity. Still, both these aspects must be considered when interpreting estimation results. However, static first principles models enable data reconciliation calculation, which can also consider the model boundaries and measurement ranges. Therefore, data reconciliation is discussed next.

3.2 Data Reconciliation

Measurement reliability can be improved by data reconciliation when there are excess measurements providing redundancy. This requirement hinders such applications in small-scale systems, but is attractive for medium- and especially large-scale systems. Data reconciliation corrects corrupted process data, by using a process model and optimization methods that also consider process related constraints (Narasimhan & Jordache, 1999). For that, there must be a model that interlink the signals of the studied process measurements. The model is defined in the form of equality and inequality constraints derived from conservation laws, equilibrium constraints, and physical process constraints. Typically, the process model is defined by the mass and energy balances of the system, also taking into account the sensors' physical limitations. Therefore, first principles models are ideal for this purpose. However, the model must be computationally light to allow for the numerous iterations required by nonlinear optimization methods to successfully reconcile the data. The feature of computational lightness is particularly required for online monitoring and diagnostic applications, in which data reconciliation differentiates sensor malfunctions and process disturbances. The differentiation can be conducted by simultaneous data reconciliation and gross error detection (Tjoa & Biegler, 1991). Özyurt & Pike (2004) reviewed these estimators, which are also used in Case III.

Data reconciliation has been applied in power plant environments in several cases. Sarkar *et al.* (2017) integrated a data reconciliation algorithm in a model predictive control (MPC) loop of a medium-scale biomass power plant, to prevent faults in flue-gas oxygen measurement to disturb the control performance. Fellner *et al.* (2007) utilized data reconciliation to determine the fractions of biogenic and fossil matter in a waste to energy plant. Gulen & Smith (2009) derived a generic form of data reconciliation method and demonstrated it with simulated data of a single shaft combined cycle system. Szega (2011) utilized data reconciliation to improve the reliability of measurement data in calculating parameters of the thermal process in a waste-heat boiler. Touš *et al.* (2013) utilized nonlinear optimization and data reconciliation to improve the evaluation of lower heating value of waste and boiler efficiency. Huovinen *et al.* (2012) presented an on-line data reconciliation application that estimated the reliability of measurements in the water-steam cycle of power plants. Jiang

(2014a) and (2014b) demonstrated with simulated data the performance of simultaneous data reconciliation and gross error detection for monitoring sensor and equipment performance of a coal-fired power plant. Martini *et al.* (2013) presented a data reconciliation and gross error detection application for a microturbine-based test rig. Syed *et al.* (2013) demonstrated the efficiency of data reconciliation and gross error detection in gas turbine cogeneration systems. Most of these papers focused on limited sub-processes and mainly on the water-steam cycle of power plants. Instead, Publication V applies simultaneous data reconciliation and gross error detection to the main combustion variables in a multi-fuel fired BFB boiler.

3.3 Discussion

All models have a certain domain of validity that defines the range in which the model can be reliably applied (Ljung & Glad, 1994). The aspect of domain of validity is particularly important in process-monitoring applications, in which the model should provide reasonable estimates in a wide range of process conditions. As data based models can only replicate the process conditions that prevailed when data was collected for model identification, these models do not extrapolate to other process conditions. Instead, the domain of validity of first principles models is much larger, limiting to sensor measurement ranges, sensitivities of tuning parameters, and model assumptions. However, the uncertainty in soft sensor applications originate from both sensors and models, so their validity should be carefully considered when interpreting the results. Therefore, modellers should understand the process in a wider context than that required for the modelling task. In particular, understanding dynamics is important, especially when static models are applied.

To conclude, Chapters 2 and 3 presented the framework to provide practically justified, online monitoring and control solutions. The framework is applied in Cases I–III, which are presented in Chapter 4–6, respectively. Case I is presented next, which focuses on control of small-scale wood chip combustion.

4 Control of Small-Scale Wood Chip Combustion

This chapter presents Case I, which covers control of continuous small-scale wood chip fired systems and answers to Research Question 1. There is no well-established definition for small-scale combustion systems, but the limit of <500 kW is applied, according to Standard EN 303-5:2012 and directive 2015/1189/EU. There are numerous wood chip and especially wood pellet fired boilers in power ranges <50 kW that have their own features, enablers, and requirements. These systems are not the focus of this chapter but are considered when relevant. Instead, this chapter focuses on wood chip fired boilers in ranges 50 kW – 500 kW. Most of these boilers also combust wood pellets, and the solutions are also valid for them.

An extensive number of publications discuss factors affecting control of small-scale biomass fired systems, but only a limited number focus on control issues. This chapter focuses on the latter, as the former was discussed in Chapter 2. There it was stated that several aspects affect control structures of small-scale biomass fired boilers, including fuel type and properties, boiler technology and potential restrictions, available measurements and actuators, and potential emission limits or requirements. Additionally, the operating environment, particularly boiler size, significantly affect availability and reliability of sensors and actuators. Moreover, wood pellet and chip fired systems are in different positions, due to pellets' fairly stable fuel quality, even though the pellet systems have their challenges related to variations in pellet length and fines (Ståhl & Wikström, 2009). Indeed, many solutions work better in standardised conditions than normal operation. As an example, there is a substantial gap between small-scale biomass fired boiler performance with standard (EN 303-5:2012) runs and actual process performance (Carlon *et al.*, 2015); (Venturini *et al.*, 2015); (Win *et al.*, 2012); (Win & Persson, 2014). Considering these aspects, the literature review is presented next.

Placek *et al.* (2011) discussed grate sweeping compensation and compared continuous and on-off control of a domestic pellet boiler. Good & Nussbaumer (1998) presented a control method for a 1 MW stoker burner that minimized the set point of a secondary air controller by CO/lambda curve. Pitel & Mižák (2012) and Pitel *et al.* (2013) presented a control system for two biomass boilers, in which CO, lambda, and boiler temperature measurement signals optimized the secondary air feed. Tóthová & Dubják (2016) presented a control method for medium-scale boilers, which adjusted the set point for a secondary air controller by a CO/lambda –curve and neural network estimate. Additionally, they presented a nonlinear Varela controller, based on an artificial immune system, to stabilize the time delay of a boiler output-water temperature controller. Kang *et al.* (2013) presented a PID controller that controlled the air feed of a 24 kW domestic pellet burner by a lean lambda sensor (LSM 11). Haapa-aho *et al.* (2011) tested several PI and PID controller tunings and measurement signal filters for air and fuel feed control by lambda and temperature measurements in a 25 kW pellet boiler. Hrdlicka *et al.* (2011) also compared PI control solutions and identified potential lambda sensor malfunctions of the same process. As a state of the art solution, Gölles *et al.* (2014) presented an MPC control solution for a 30 kW commercial biomass boiler. Due to the lack of measurements other than lambda and feed water temperature measurements, a Kalman filter estimated the missing state variables. The MPC controller was designed from a linearized state model. The results were robust in both steady state and transient conditions. To conclude, there are several lambda and lambda/CO control structures, which are typically implemented by PI/PID controller.

As already pointed out, there is a significant difference between process performance in standard test conditions and normal operation. This also indicates that operating conditions for sensors are not always favourable, which is mentioned in several of the presented references. The consequent question is that which measurements are truly feasible for combustion control in real combustion environments and that set guidelines for control design? This chapter presents an application of the thesis framework by providing a realistic control solution for wood chip fired systems, focusing on preserving heat power output and low emissions, regardless of varying process conditions. As the process design has a significant role in solutions, the process descriptions are presented before the control solutions.

4.1 Process and Case Description

The studied processes were commercial 80 kW and 200 kW wood chip fired grate burners and biomass boilers. The starting point was boiler heat power control using a thermostat, but no combustion control. The company had tested lambda sensors for secondary air feed control, but the solution was not commercialized, due to cost and sensor reliability issues. However, the main concern was an unstable fuel feed, which caused unintentional combustion power drops that were deleterious to stable heat delivery for consumers, especially during cold seasons. Therefore, the main task was to stabilize the fuel feed, while reaching high efficiencies and low emissions, considering cost-effectiveness requirements and sensor reliability.

The processes and their contribution to the proposed control structures are presented next. Figure 9 (left) and Figure 10 shows the 80 kW wood chip fired system that was the test setup in Publication I. Respectively, Figure 9 (right) and Figure 11 present photos of the 200 kW system that was the test setup in Publication I & II. Figures 10 and 11 (middle) show grate sweepers, which are metal rods that move ash away from the grate and equalize the fuel pile. Primary air fed up, through the grate in both burners. Secondary air fed down from the roof and horizontally, from the back of the burner to the boiler, and from the walls to the fuel pile (80 kW) or the opposite wall (200 kW). Due to the compact size and air-outlet locations, the secondary air feed reached the fuel pile, especially at high powers. This unintentional back-mixing must be considered when designing the control structures.

Figure 9. Left: 80 kW wood chip burner and 120 kW biomass boiler. (Korpela, 2006). Right: 200 kW heat container. The left side of the container constitutes of boiler room and the right side constitutes fuel storage. (Korpela & Björkqvist, 2008b)

Figure 10. The 80 kW wood chip burner. Primary air feeds upward from the grate. Secondary air is fed from the walls and ceiling. The grate sweepers are at the innermost (left) and outermost (middle) positions. Typical fuel pile on the grate (right). (Korpela, 2006).

4.2 Control of Wood Chip Combustion

Combustion processes are affected by several disturbances, which should be compensated or removed. The best action to take is to neutralize the disturbances before they affect the process operation. In addition to stabilizing draught, such preventive actions include grate sweeping compensation and selecting suitable operating points, which are discussed in Publication I. Grate sweeping compensation, which Haapa-aho *et al.* (2011) and Placek *et al.* (2011) also discuss, changes air distribution during and immediately after sweeping. The idea is to reduce combustion intensity and guarantee complete burnout of the increasingly released combustible gases around the fuel-bed

Figure 11. The 200 kW wood chip fired boiler. Left: Boiler room. Middle: Burner without the fuel feeding screw: Primary air feeds upward from the grate. Secondary air feeds from the walls and ceiling. The grate sweepers are at their outermost position. Right: Fuel feeding screw (lower) and auxiliary screw (upper) at partially revealed state in the fuel storage. (Korpela & Björkqvist, 2008b).

mixing. This can be implemented by decreasing primary air and increasing secondary air. On the other hand, selecting suitable operating points involves enlarging the size of the fuel pile to decrease the significance of potential fuel-feed disturbance during normal operation. This can also be conducted by reducing primary air feed, which also reduces fine-particle emissions, as described in Chapter 2. However, care must be taken that the combustion intensity is high enough for complete char burnout before the particles fall off the grate. Both of these actions are easily implemented and provide improved process performance, easing the task of feedback control.

Since the main requirement of the control structure was to stabilize fuel-feed quality variation, a cascade control structure was developed (Figure 12). The main manipulated variable is fuel feed, and the dominating measurement is FG temperature at the upper part of furnace. The temperature measurement signal correlates with O_2 (Haapa-aho *et al.*, 2011); (Ruusunen, 2013) and OGC and CO emissions (Pettersson *et al.*, 2010). Moreover, it is inexpensive, reliable, fast, and less vulnerable to contamination than gas sensors. Therefore, it is an applicable sensor to provide controlled signal. However, several factors contribute to flue gas temperature, so stand-alone solutions should be carefully considered.

The temperature controller, which is also the secondary controller of the cascade control structure, comprises two parallel units. The first is a PD-type fuzzy controller, whose task is to compensate for significant temperature changes primarily caused by fuel feeding disturbances. The Mandeni-type fuzzy controller infers the compensation requirement based on temperature error signal (e) and its

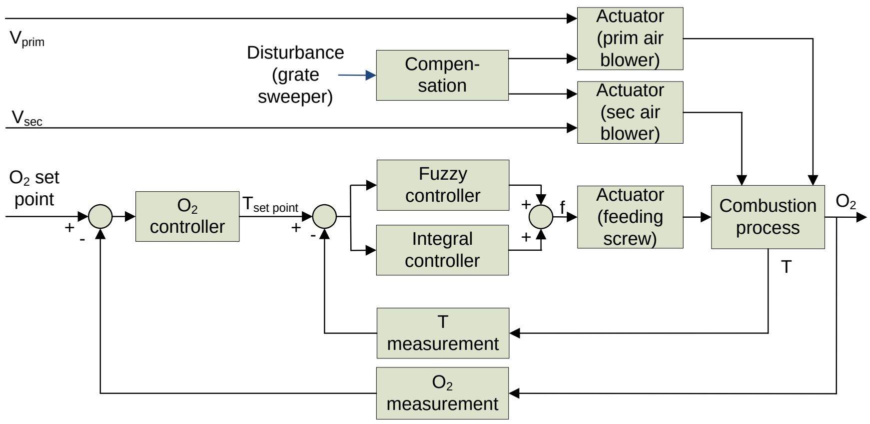

Figure 12. A cascade control system.

rate of change (Δ*e*). These both are divided into five regions that comprise a 25-rule base (Table 1). Based on the rules, inference is made between five compensation levels as to whether to keep the normal feeding level or change it. The fuzzy model is static as such, but dynamics are considered in the rule base. When a disturbance occurs, the temperature measuring signal rapidly decreases, bottoms out, and finally slowly increases after the disturbance. The idea of the fuzzy system is that the steeper the decline, the larger the compensation. Therefore, a forceful compensation occurs immediately after the fuzzy system concludes there was a severe temperature drop. When the temperature decline slows, the fuel increase was already subtracted. Finally, the bottom of the temperature is reached and from thereon, the fuel feed is kept at a constant normal level to avoid overcompensation. This kind of nonlinear control signal cannot be implemented with a standard PID control structure. However, similar output could be achieved with other nonlinear controllers, but the fuzzy control structure was selected, due to its simplicity and intuitiveness. However, as it only reacts to fast, intensive fuel-feed changes, an integral controller was set in parallel with the fuzzy controller to compensate for slow fluctuations.

Table 1. Fuzzy rule base. Vertical and horizontal headings stand for error signal (*e* = set point – measurement) and its rate of change ($\Delta e=e_2-e_1$). Headings: N=negative, P=positive, S=small, L=large, Z=zero. Content: S=-subtract, A=add, H=hold, S= small, L=large. For example, if *e* is Positive Large AND if Δ*e* is Positive Small THEN Add Large.

e/Δ*e*	NL	NS	Z	PS	PL
NL	SL	SL	H	H	H
NS	SL	SS	H	H	H
Z	H	H	H	H	H
PS	H	H	H	AS	AL
PL	H	H	AS	AL	AL

In the control structure (Figure 12), the primary controller defines the temperature set point for the secondary controller. It is an O_2 controller that exploits measurement signal from a lambda sensor. With this construction, the unintentional parameters affecting the temperature set point, such as sensor location, combustion conditions and system structure, are primarily eliminated. This is beneficial both from operability and generalizability perspectives.

The system is run by adjusting the primary and secondary air feeds to suitable levels, which sets the power level, as the cascade control loop settles the fuel feed to balance with the air feeds. The appropriate oxygen set point is a function of, for example, fuel moisture content, power level, and system structure. The oxygen controller finds the suitable temperature set point in prevailing conditions. The benefit is that when the primary controller stabilises the temperature set point and the operation conditions remain somewhat unchanged, the primary loop can be switched off. This means that the lambda sensor can be taken away from the flue gas channel, since the secondary controller can maintain the operation point. Moreover, temperature set points can be tabulated, which allows for different power levels. When there will be significant changes in the process, the lambda sensor is installed back into the process for a few hours, and a new temperature set point is obtained for the new operation point. Therefore, the worst conditions for the sensors, such as start-ups, shut downs and pilot flame situations, can be avoided. As a result, the lambda sensor's lifetime can be extended substantially, which fulfils the sensor's robustness requirements. Meanwhile, active feedback control can obtain proper efficiency levels and low emissions.

Figure 13 presents a trial run made with the 200 kW system at a power level of 140 kW. During the trial, the primary and secondary air feeds were constants, except around grate sweeping instances while the controllers were switched off. The first figure presents lambda measurement and its set point. The second figure illustrates the temperature measurement from the upper part of the furnace and its set point. The third figure introduces the fuel feeding frequency. The fourth figure illustrates primary and secondary air flows, and the fifth figure shows CO emissions. The run illustrates that the control system decreased the oxygen level to its set point after the start-up prior to the run. This was achieved by increasing the temperature set point, which the temperature measurement followed fairly well. Despite of the decreased oxygen level, the CO emissions also decreased. Therefore, efficiency was increased and emissions decreased. Since the temperature drops were also compensated, the controller reached the set goals.

The primary controller was sluggish during the run, which is a feasible solution when the heat load changes are slow or there is heat storage to stabilize heat load variations. These conditions are not met in every case. The power change rate can be increased by changing the primary controller from I to PI. However, the primary controller must have at least five times larger average residence time than the secondary controller (Åström & Hägglund, 2006). Preferably, the power rate can be quickly

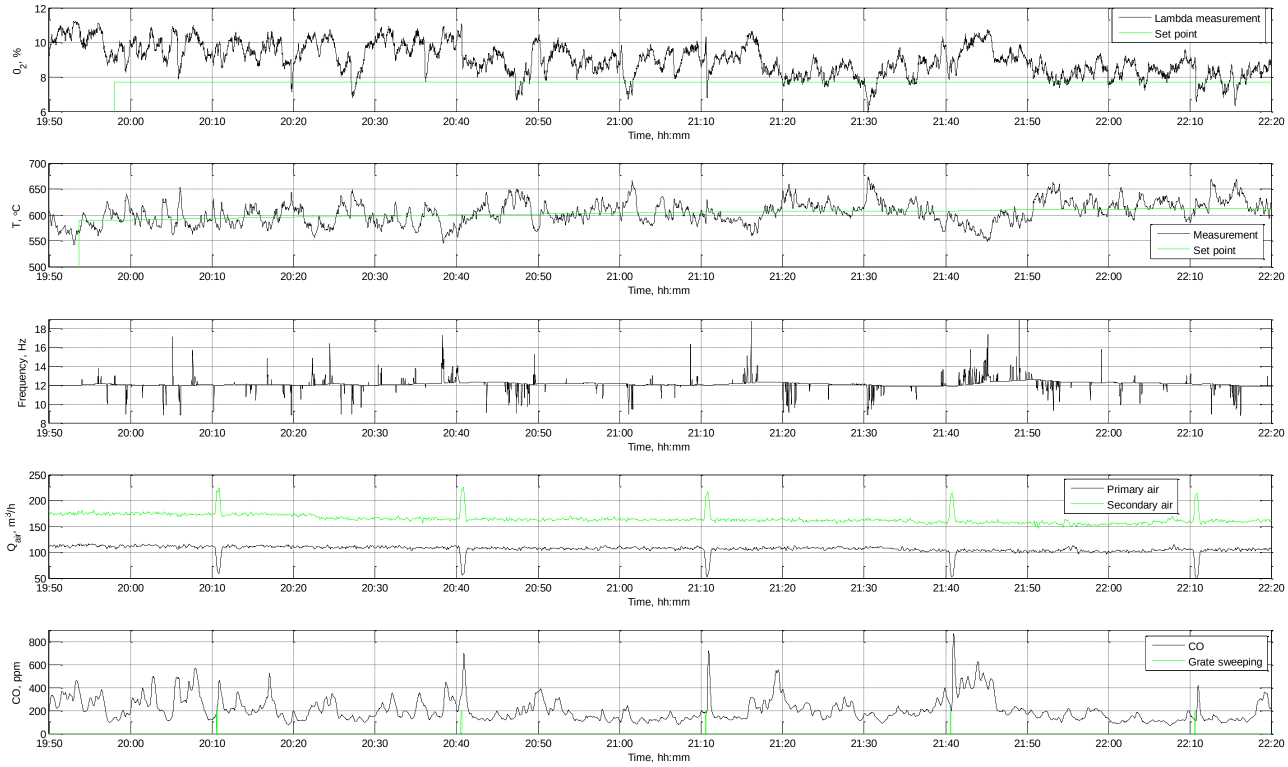

Figure 13. Test run with cascade controller with the 200 kW burner, using whole-tree chips with moisture content of 33.5 percent. First figure presents lambda O_2 measurement and its set point. Second figure illustrates the temperature measurement from the upper part of the furnace and its set point. Third figure presents the fuel feeding frequency. Fourth figure illustrates the measured primary and secondary air flows. Fifth figure shows CO (O_2 = 10 %) emissions and time instances of grate sweeping.

changed when conducting the change in a coordinated way. This also ensures that enough secondary air is present in all cases. This can be conducted by changing the primary air feed and fuel feeds at the same time. The secondary air is changed first in the power increase, and vice versa. This operation principle is the same for large boilers (Kovács & Mononen, 2007).

Additionally, Publication II presents an extended control structure that enables automatic setting of air distribution. The required fuel moisture can be user defined or obtained from a fuel moisture soft sensor, such as one presented by Ruusunen (2008).

An additional, untested method to reduce long-term fuel-feed fluctuations could be achieved by an additional feedforward signal from the fuel feeding frequency to the interval of rod dischargers in the fuel storage. When the secondary controller increases the fuel feeding frequency to a relatively high level, the rod-discharger intervals are significantly lowered. This additional compensation would automatically reveal the prevailing unloading challenges in the fuel storage and contribute to equalized fuel unloading from the storage, equalizing the fuel feed.

4.3 Discussion

The research in Publications I and II were conducted a decade ago. Despite several technical improvements in small-scale boilers, challenges remain for providing stable solid-fuel feed and sensor reliability in harsh combustion environments. Moreover, similar combustion systems are still for sale, primarily with similar set-ups. Therefore, the work described in Publications I and II is still valid and applies the thesis framework. Additionally, this chapter answers Research Question 1. However, the solutions must be upgraded accordingly if the processes or requirements change. An emerging step up for such boilers could be applying MPC, similar to one proposed by Gölles *et al.* (2014), which could also consider the restrictions related to boiler structure. However, the application of MPC would require substantial development and validation work related to the determination of long term operation reliability.

5 Indirect Estimation of NO_x Emission in Gas Fired Boilers

This chapter presents Case II and answers Research Question 2. It comprises of Publication III, which is a complement of Korpela *et al.* (2015) and Kumpulainen *et al.* (2015). The objective here is to provide easily maintainable, tangible, and cost-effective solutions to monitor NO_x emissions in existing medium-scale natural gas (NG) fired boilers, which also applies this thesis' framework. The objective favours the application of static models, which are presented next. The studied processes were two similar 43 MW NG fired hot water boilers serving as peak load and backup capacity plants in a DH network. Considering the comprehensive literature review on NO_x modelling of NG-fired boilers in Chapter 3.1.2, there are no more publications to provide solutions to this objective.

The motivation for indirect NO_x emission monitoring emerged from new IED emission monitoring requirements that came into effect in 2016. The 43 MW boilers are classified as medium-scale boilers, but they still fall under IED jurisdiction because of the joint-stack rule. Therefore, the NO_x emissions must be measured with a continuous emission monitoring system (CEMS) or semi-annually by an external expert. Both options are impractical or costly for plants that have low annual operating hours. However, the IED states: "As an alternative to the (direct) measurements of SO_2 and NO_x, …, other procedures, verified and approved by the competent authority, may be used to determine the SO_2 and NO_x emissions. Such procedures shall use relevant CEN standards or, if not available, ISO, national or other international standards which ensure the provision of data of an equivalent scientific quality." As there are no relevant standard available, this case presents a scientifically justified method to indirectly monitor NO_x emissions in NG-fired boilers. The novelty is not about the presented models as such, because each boiler behaves differently, as Publication III and Pulles & Heslinga (2004) shows. Instead, Case II presents an approach (Figure 14) for feasible, indirect monitoring for the two boilers and generalizes the results to similar boilers.

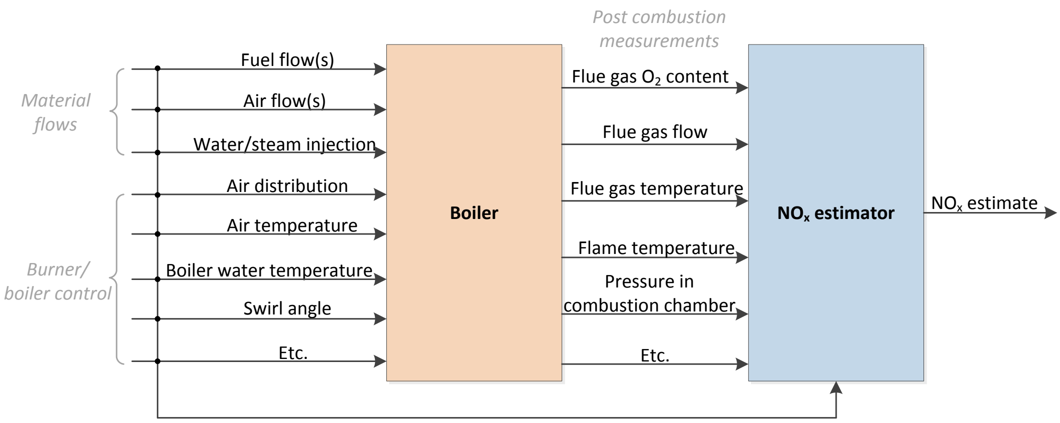

Figure 14. An approach for NO_x estimation. (Korpela *et al.*, 2017b)

5.1 Utilization of Data-Based Models for Estimating NO_x

When monitoring NO_x emissions indirectly, there are two main aspects to consider. The first is the available measurements that can be utilized as model inputs. The second is the combustion properties that determine NO_x formation. For the latter, the combustion system design, fuel type, process operation, and prospective NO_x abatement techniques significantly influence the NO_x emission formation (Skalska *et al.*, 2010); (Bělohradský & Kermes, 2012); (Habib *et al.*, 2008); (Ilbas *et al.*, 2016); (Skryja *et al.*, 2015). When analysing one specific boiler, the interest focuses on the dominating NO_x formation mechanism of the ones presented in Chapter 2.1.3. In NG fired boilers, the dominant NO_x formation mechanism is thermal (Turns, 2000), as the contribution of fuel NO_x is insignificant and the contributions of prompt and N_2O based NO_x mechanisms are typically less than 5 percent each (Kilpinen, 2002). In thermal NO_x formation, the primary variables on NO_x yields are time, temperature, and oxygen excess (Turns, 2000). Therefore, any variables or actions affecting flows and flame temperatures in particular (such as via fuel power, air distribution, active flame cooling, air preheating, and boiler water temperature) or flue gas oxygen contents must be considered.

Data based models, at best, can replicate operating conditions in identification data. Therefore, deriving input data should be carefully considered. Publication III presents comprehensive trial runs conducted to enable reliable model identification. The models were validated with data from normal process operations, with increased excitations. The frequent controller set point changes reveal the model performance in realistic conditions, which is a prerequisite for the study objectives.

Publication III presents the process description of the studied boilers, called Boiler A and B. Despite several variables in these boilers, the only controllable variables are air and fuel flows, the latter of which directly determines fuel power output and hence the boiler power output in steady state conditions. First, input signals were manually set in identification runs that were selected such that they included fuel feed levels close to minimum, maximum and one to two intermediate power levels. At every fixed power level, the air feed was changed in manual mode in exceeded values not normally used. The upper and lower air levels were selected to find potential nonlinearities and optimum operating points for the process. The power level changes were conducted in automatic mode to collect test data of the identification runs. All other parameters were at usual values that is valid for their purpose. Altogether, the identification trial runs extensively covered the boiler operating range. Second, validation runs were conducted in automatic mode that corresponded to normal plant operation. The runs represent the main boiler features since the identification and validation runs were separate and conducted in different, but representative, conditions. If there were more environmental conditions to consider, substantially more trial runs would be needed, which would seriously challenge the cost effectiveness of the proposed method.

Figure 15 presents the measured NO_x and CO emissions as a function of oxygen excess in identification data of Boiler A (left) and Boiler B (right). The figures illustrate that the power level significantly affects the NO_x response. Within the power levels, the NO_x responses are almost linear in Boiler A and two of the lowest power levels of Boiler B. However, two of the highest power levels of Boiler B are clearly nonlinear, especially at high oxygen levels, which are out of normal operating range. Despite the nonlinearity, linear NO_x emission estimates [mg NO_2/Nm^3, O_2=3 %, d.b.] were calculated for Boilers A and B, respectively:

$$NO_{x,est,\ Boiler\ A} = 13.8 \cdot O_2 + 29.6 \cdot \dot{V}_{gas} + 66.6 \tag{1}$$

$$NO_{x,est,\ Boiler\ B} = 9.1 \cdot O_2 + 10.4 \cdot \dot{V}_{gas} + 117.4, \tag{2}$$

in which O_2 stands for flue gas oxygen content (%) and $\dot{V}_{gas}$ stands for NG-flow (Nm^3/s). Additionally, nonlinear models (MLP, SRV, and FIS) were derived for both boilers. For Boiler A, the linear model was the most consistent, as it predicted the NO_x emissions the best in test sections of the identification run, with a relative root mean square error (RMSE) of 2.2 percent. In the validation run, the linear model showed equal performance with MLP and SVR, with a relative RMSE of 1.9 percent. Therefore, the linear model outperformed in Boiler A, which is consistent with the linearity presented in Figure 15.

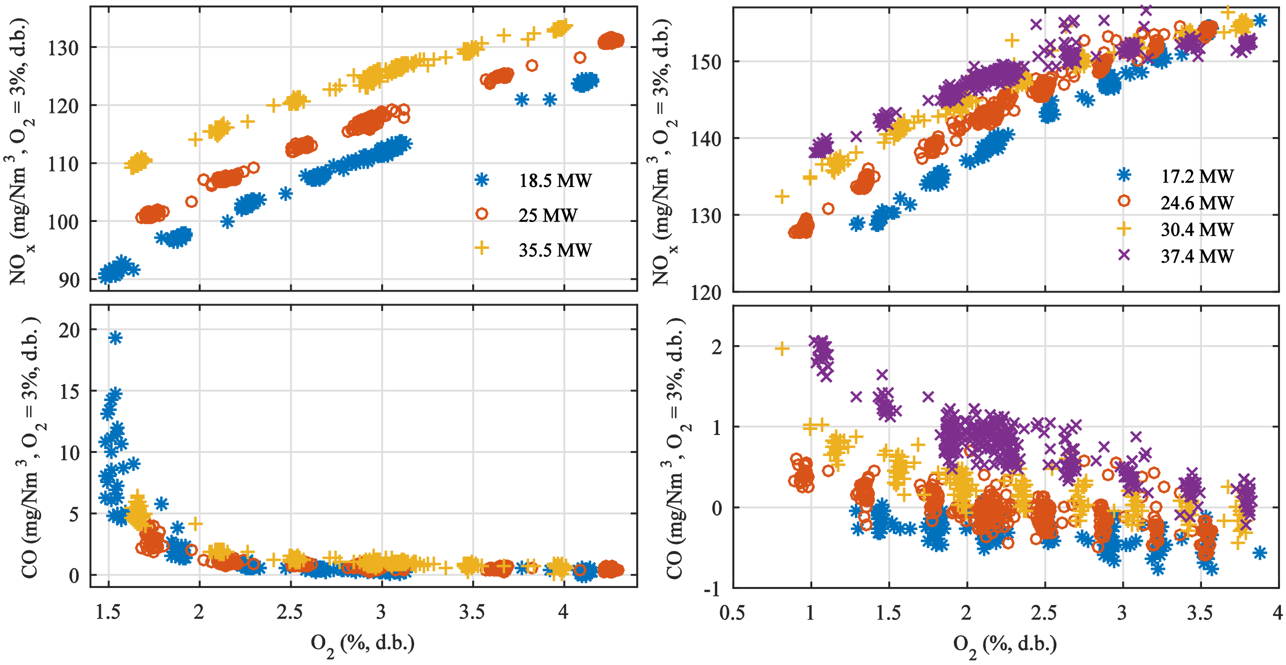

Figure 15. Measured NO_x (top) and CO (bottom) emission as functions of O_2 level at constant power levels at the identification run of Boiler A (left) and Boiler B (right). (Korpela et al., 2017b)

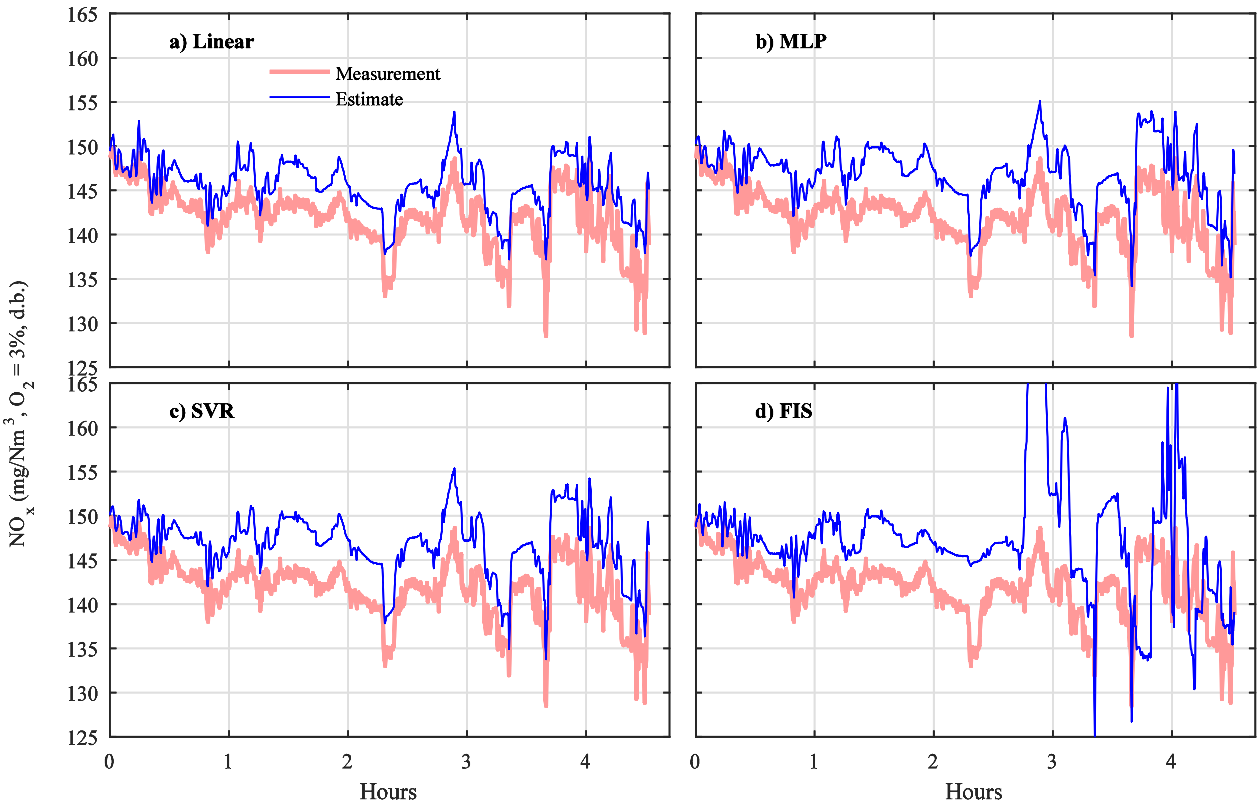

Figure 16. NO_x emission estimates in Boiler B's validation run. (Korpela et al., 2017b)

The linear model for Boiler B performed well in test sections of the identification run, except at high oxygen levels, contributing to a relative RMSE of 1.9 percent. Still, the MLP and SVR models performed even better, with relative RMSEs of 1.6 percent and 1.5 percent, respectively. All these results were expected, due to the nonlinearity in Figure 15. However, Boiler B's validation run is particularly interesting, as it presents the worst-case scenario of the presented approach. In addition to nonlinearity, Boiler B's validation run was conducted seven months after the identification run. The process did not change, but the measurements were calibrated between the runs. Figure 16 presents the NO_x estimates of the run, which indicates a clear bias of 2.5 percent in NO_x estimates. Despite the nonlinearity, the linear model was the best, with a relative RMSE of 2.7 percent, which is a solid result. Moreover, the estimate would have been even better without the bias.

Publication III studied the cause for this bias by analysing the results of models with additional input variables, but accuracy did not consistently improve. Therefore, the conclusion was that the outdoor, process, or sensor conditions slightly changed between the two trial runs. One explanation is that the identification run was conducted in mild winter conditions, and the test run was in warm fall conditions, with a seven-month time difference. Another plausible explanation for the bias was drifting of sensors used as model inputs. Both main input measurements of Boiler B were calibrated between the runs. Fuel flow measurement provided correct values, and the calibration curve was not changed. The O_2 sensor, on the other hand, indicated 1.1 percent, with the calibration gas containing 1.0 percent of O_2. According to Eq. 2, such an error of 0.1 percent-units corresponds to an error of 0.9 mg/Nm^3, which is almost a quarter of the bias. However, the process-measurement calibrations were not checked before the trial runs. Therefore, it was impossible to know when this measurement error occurred, or if it explains the difference. This type of error is unfortunate from a research perspective, but typically happens when working with practical installations. However, that is what the proposed methods would face if they were put into action in reality. Fortunately, the bias was very modest, because the total RMSE error was only 2.7 percent. However, the long-term effects, such as aging, must be carefully observed in practical applications of the approach.

Moreover, Publication III discusses the modelling approach from additional viewpoints, including studying limited oxygen ranges in Boiler B and extending modelling identification data. Neither study improved previously presented model estimates. Moreover, a sensitivity analysis of Eqs. 1 & 2 was presented.

5.2 Tackling the Uncertainties of Indirect NO_x Monitoring

The total uncertainty of the approach constitutes of several uncertainties, caused by the process condition changes, drifting of measurements used as model inputs, model inaccuracy, and the application of the approach by end users. These aspects are briefly discussed next.

The uncertainties of process conditions can be tackled by regular maintenance of process and its components that is standard in developed countries. That includes reporting changes, faults, and unexpected incidents. If the process permanently changes, model validity should be reconsidered. However, the non-modelled parameters might affect process performance and hence NO_x estimates, so model performance should be further verified in different process conditions before commissioning.

The effect of measurement uncertainty can be handled by regular sensor calibrations, hardware or software redundancy, and monitoring process measurements and NO_x estimates compared to history data. However, advanced sensor quality control procedures, such as those presented in Publication V, are not practical solutions considering the cost effective requirements of PEMS applications.

The uncertainty of data based models is typically handled by selecting representative input data, applying functional model types, and verifying the models with other representative data. In particular, the model type should be selected such that it estimates NO_x emissions well enough, but generalizes to all relevant process conditions. The model validity should be checked on a regular basis by reference measurements, and the model parameters should be updated if necessary. Any biases seen as constant prediction errors must be removed, which is easy in the case of linear models.

To reduce uncertainty about how to apply the method, plant personnel and service providers must be instructed about the operating principles and approach limitations. With this knowledge, they can estimate if the circumstances are favourable to apply the method. When using an estimation approach based on indirect measurement for regulatory purposes, the responsible authority is likely to set limits and requirements, which also set guidelines to the plant personnel.

5.3 Discussion

This chapter presented a novel data based monitoring method for NO_x emissions in relatively simple medium-scale natural gas fired boilers. It also answers to Research Question 2. Moreover, the presented solutions applies the thesis framework.

NG combustion is a stiff process, with a close to immediate response to combustion phenomena, while the boiler dynamics is substantially longer. As the dynamical variations in boiler conditions are stable, the dynamics have a minor effect on the presented approach. Therefore, the selection of static models was a feasible solution in this context.

The general conclusion is that the simple linear models are the best in terms of model accuracy (relative RMSE error <3 % in all cases) and reproducibility. These models can be adopted in existing boilers with a modest effort, as long as each boiler is considered separately. Therefore, the case presents feasible solutions to existing boilers, which is within the core of the thesis. The approach also enables improved monitoring prospects in flexible operation. The models enable estimating actual NO_x emissions in true process conditions, which is an upgrade from the intermittent measurements and the requirements of IED. This aspect is increasingly important in the future, when the heat only boilers next to CHP plants are increasingly interlinked to provide flexibility to power grids (Korpela *et al.*, 2017a).

6 Online Monitoring of Combustion Processes and Sensors

This chapter presents Case III and answers Research Questions 3–5. Moreover, it applies the thesis framework. The case is based on Publications IV–VI, of which Publication V is the most significant. This chapter's general objective is to derive a method to monitor the quality of combustion processes and measurements in large-scale power plants (>100 MW). This method should be valid in wide operating ranges. Additionally, it should be independent of fuel quality and quantity, as multi-fuel and co-combustion are overtaking single-fuel combustion, even in coal-fired power plants (Judl *et al.*, 2014). Therefore, the objective is to create a generic model that could interlink fuels and main combustion related measurements available at large-scale power plants. Since it is impossible to reach the objective by data based modelling approaches in practice, the first principle modelling approach is used instead. The developed model is static and novel for this purpose. The model is based on element balance equations that are derived from the main chemical reactions in combustion environments. The element balances can be analytically solved, which is a major benefit that enables their utilization in monitoring applications with only minor computational requirements. The model is valid in cases in which fuel properties are somewhat known and fuel flow and flue gas O_2 measurements are available. These requirements are met in practice in all large-scale power plants.

The model background is presented next, followed by case examples of a multi-fuel fired BFB boiler and two coal-fired boilers in a power plant.

6.1 Element Balance Calculation of Combustion Processes

The first principle model is based on element balance equations and a priori information. The main a priori information is fuel chemical compositions (fuel ultimate analysis) expressed in the form of $C_xH_yO_zN_vS_wCl_o$, in which *x*, *y*, *z*, *v*, *w*, and *o* represent the molecular ratio of the respective element compared to carbon. For example, C_2H_6 corresponds to C_1H_3. Additionally, the moisture, ash contents, and higher heating value must be known for all fuels (fuel proximate analysis). Similarly, potential inert material within the fuels, such as soil that comes along with biomass, can be taken into account when appropriate. The fuel specific compositions of dry fuels and ashes can be obtained from literature presented in Chapter 2.1.1. However, the fuel moisture contents of solid fuels may vary significantly, so history values provide reasonable initial values that can then be adjusted.

By gathering reactions R1–R6, presented in Chapter 2.1.2, the overall chemical reaction for over-stoichiometric (λ_{tot}>1) combustion of multiple fuels ($k \in \mathbb{N}$) can be expressed as

$$\sum_k \left(r_{F,k} \cdot C_{x_k} H_{y_k} O_{z_k} N_{v_k} S_{w_k} Cl_{o_k}\right) + r_{Air} \cdot (O_2 + 3.76 \cdot N_2 + \eta \cdot H_2O) + \gamma \cdot H_2O \rightarrow$$
$$b \cdot CO + c \cdot CO_2 + d \cdot H_2O + e \cdot O_2 + f \cdot N_2 + g \cdot NO + h \cdot SO_2 + i \cdot HCl, \tag{R7}$$

whose symbols are described in Table 2.

Table 2. Nomenclature

Symbol	Description	Unit
$r_{F,k}$	Ratio of molecular flow of fuel k over total molecular fuel flow	-
u	Fuel moisture content	-
x	Molecular ratio of C to C, i.e. x = 1	-
y	Molecular ratio of H to C	-
z	Molecular ratio of O to C	-
v	Molecular ratio of N to C	-
w	Molecular ratio of S to C	-
o	Molecular ratio of Cl to C	-
r_{Air}	Air-to-fuel mole ratio	-
γ	H_2O-to-fuel mole ratio	-

The parameters b, c, d, e, f, g, h, and i determine the molecular proportions of the flue gas. From the overall reaction R7, the element balance equations for C, H, O, N, S, and Cl can be described, respectively, as

$$\sum_k \left(r_{F,k} \cdot x_k\right) - (b + c) = 0 \tag{3}$$
$$\sum_k \left(r_{F,k} \cdot y_k\right) + 2 \cdot r_{Air} \cdot \eta + 2 \cdot \gamma - (2 \cdot d + i) = 0 \tag{4}$$
$$\sum_k \left(r_{F,k} \cdot z_k\right) + r_{Air} \cdot (2 + \eta) + \gamma - (b + 2 \cdot c + d + 2 \cdot e + 2 \cdot h) = 0 \tag{5}$$
$$\sum_k \left(r_{F,k} \cdot v_k\right) + 2 \cdot 3.76 \cdot r_{Air} - (2 \cdot f + g) = 0 \tag{6}$$
$$\sum_k \left(r_{F,k} \cdot w_k\right) - h = 0 \tag{7}$$
$$\sum_k \left(r_{F,k} \cdot o_k\right) - i = 0. \tag{8}$$

The balance 7 states that all the sulphur reacts to SO_2. Similarly, the balance 8 states that all the chloride reacts to HCl. The validity of these assumptions are process and process condition dependent, and can easily be adjusted to smaller levels or set to zero. From (R7), the concentrations of O_2, CO, and NO in the flue gas can be expressed by molecular ratios as

$$X_{O_2,est} = e/(b + c + d + e + f + g + h + i) \tag{9}$$
$$X_{CO,est} = b/(b + c + d + e + f + g + h + i) \tag{10}$$
$$X_{NO,est} = g/(b + c + d + e + f + g + h + i). \tag{11}$$

Equations (9–11) can be interlinked with the flue-gas measurements by balances

$$X_{O_{2,me}} - X_{O_2,est} = 0 \quad (12)$$

$$X_{CO,me} - X_{CO,est} = 0 \quad (13)$$

$$X_{NO,me} - X_{NO,est} = 0. \quad (14)$$

Equations (3–8) and (12–14) form a system of nine polynomial equations, which equal the unknown flue gas composition parameters, i.e. b, c, d, e, f, g, h and i, and the oxygen-to-fuel mole ratio r_{Air}. When the other parameters are known, the variables of interest can be solved analytically. The analytical solution can be formed in parametric form, for example, with MATLAB Symbolic Math Toolbox™. The analytical solution only needs to be conducted once, and then the parametric functions can be easily transferred to any automation system. However, it requires some effort to convert the fuel and measurement related variables to the forms that the model requires and then back to the corresponding estimates (described in detail in Publications IV and V). After the conversions, the static model equations are expressed as parametric functions that can easily be solved in any calculation environment with minor computational power. The computational lightness qualifies the model applicability in diagnostic applications, which are discussed in the next subchapters.

6.2 Online Applications of First Principles Combustion Models

The first two subchapters test the element balance model in an industrial 200 MW_{th} BFB boiler (Figure 17). One should note that the fuel flow measurements used as model inputs are located before the intermediate fuel silos. Therefore, silo dynamics might disturb the application of static models in this case, which should be considered when analysing the results of air and fuel flows. However, this does not affect gas compositions, if the fuel proportions of dissimilar fuels do not significantly change. The main fuels of the boiler were woody biomass, peat, bark, and slurry, whose chemical compositions and main properties are presented in Publications VI and V.

6.2.1 Online Estimation of Combustion Variables

This subchapter highlights the results of Publication IV, presented in Figure 18. The first two figures present the air and flue-gas flow measurements and estimates, which match well in normal conditions but miss some peaks. Most of the inconsistencies are at the same time in the air and the flue gas flows. This indicates that the actual fuel flows were different from the measurements. This behaviour is presumably mainly due to the intermediate fuel silos. On the other hand, the last three figures present CO_2, H_2O and SO_2 measurements and estimates, which are consistent in normal conditions. However, there are two instances, in which something exceptional happens. At the beginning of the test section, the oxygen level peaks (excluded here but is presented in Publication IV),

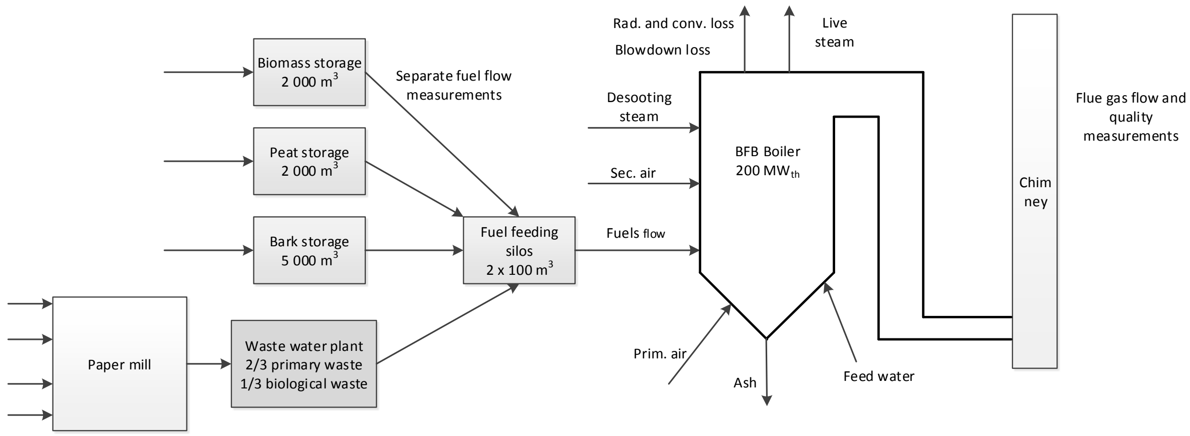

Figure 17. Outline of the case process. (Korpela *et al.*, 2016)

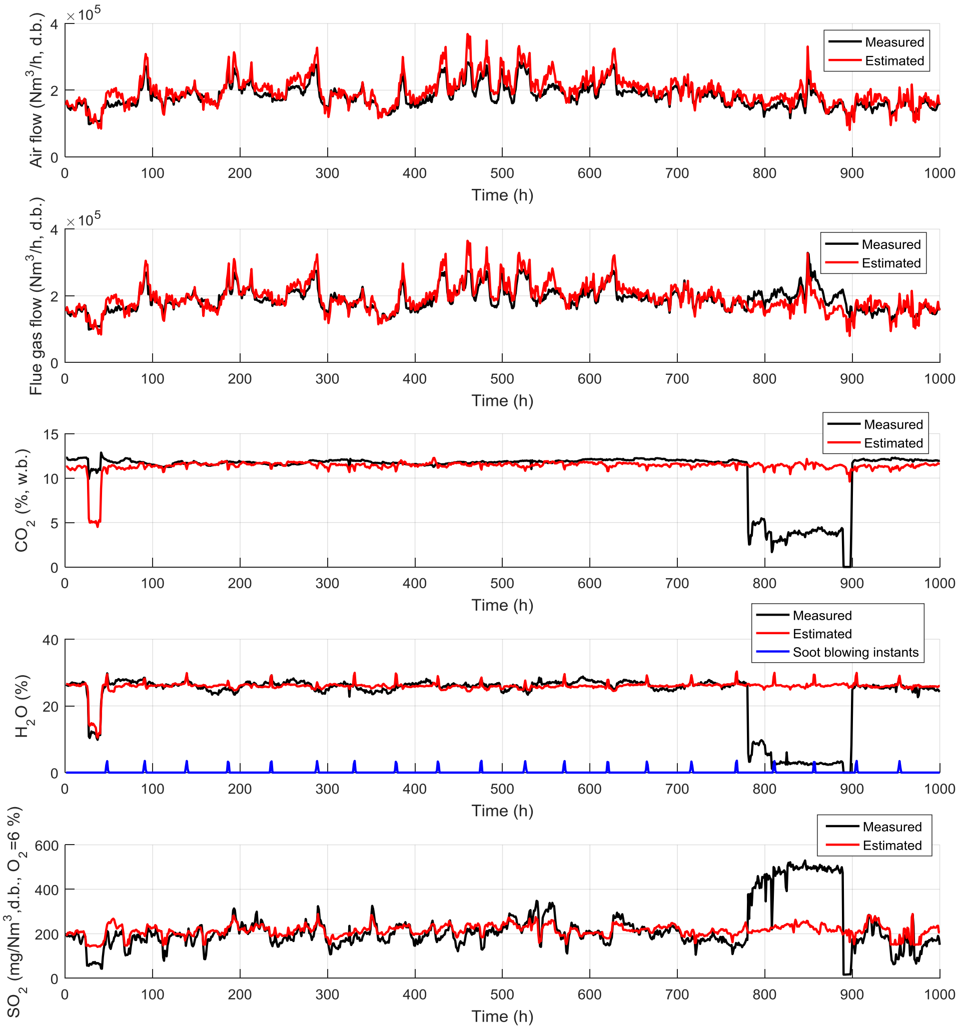

Figure 18. Measured and estimated air and flue gas flows, flue gas CO_2, H_2O, and SO_2 contents, respectively. The H_2O figure also indicates the time instances of steam-assisted soot blowing.

which can be seen in the last three measurements. As the air and fuel flows match at the same time, this indicates that fuel power reduces, while the air feeds remain. The method roughly predicts the change in gas components. Still, it can be concluded that there was a process disturbance to cause the response.

The second exception occurs close to the end of the run, in which estimation error substantially increases in all but airflow measurement. The CO_2 and H_2O measurements drop significantly while the SO_2 peaks. This was caused by a failure in the device measuring the CO_2 and H_2O contents. As a result, the disturbed measurement signal was also reflected in SO_2 and flue-gas flow measurements via the H_2O compensation described in Publication IV. However, the model is able to provide plausible estimates even during the failure, which is highly beneficial in terms of plant operations, diagnostics and emission reporting.

Although the model provided consistent estimates, it could not adapt to process condition and sensor uncertainties. Therefore, the model was upgraded to include additional sensor redundancy and adaptation features, which is discussed next.

6.2.2 Data Reconciliation of Combustion Variables

This subchapter is based on Publication V, which is a comprehensive extension of Publication IV. The most significant extension is related to the application of simultaneous data reconciliation and gross error detection, which was briefly introduced in Chapter 3.2. A computationally light model was required for their applications, which was fulfilled (Chapter 6.1). Data reconciliation adjusts the estimates, such that the mass and energy balances hold in all conditions. The most adjusted estimates have the lowest reliability, seen as the highest variances. These variances are primarily calculated from data collected during normal process conditions.

The model was also extended with the boiler energy balance, which also considers the main components of the water-steam cycle. The cycle has many reliable measurements, mainly due to the clean operating environment, reliable measurements types, and regular maintenance procedures. Therefore, combustion measurement estimates in harsh operation conditions can benefit from reliable measurements in significantly better environments, which are enabled by element and energy balance models. This extension was also illustrated in Figure 3. Based on these models, the origin of measurement errors can be determined by examining the data's statistical properties and analysing the data-reconciliation procedure's corrections.

Next, the extended calculation procedure is applied to the case process introduced in the previous subchapter. Similarly, the fuel element compositions and calorific values were kept constant during the estimation period, but the moisture contents were varied as a part of the data reconciliation procedure. As the calculation cannot differentiate from which fuel(s) the moisture content variations originate, all the moisture contents varied with the same portion.

The foundation of the data reconciliation approach are balance equations in the form '*measurement–estimate = 0*'. In this case, such balances were derived for dry flue gas flow, combustion airflow, and flue-gas H_2O and CO_2 contents. Additionally, a power balance was derived, but it was not based on one direct measurement but several indirect ones. Therefore, a power balance was derived in form '*power input to the boiler – power output from the boiler = 0'.* Additionally, the O_2, CO, and NO balances were automatically included in the analysis as a part of element balance calculus. Publication V illustrates the original misbalances of the first five balances before data reconciliation. Additionally, it presents a sensitivity analysis of contribution of random initial values. Moreover, the data reconciliation calculus was tested with simulated errors.

Figure 19 presents the reconciled estimates of the same data as in Figure 18, but the section 301–700 (h) is skipped for convenience. The five balances are separately set to zero at every time instance. The figure constitutes measured and reconciled values of selected variables: Fuel flow of wood, peat, bark and slurry; flue gas O_2, H_2O, and CO_2 contents; flue gas, primary and secondary airflows; total fuel moisture; and live steam flows. Moreover, measured and estimated flue gas SO_2 and HCl contents are presented, assuming full conversion.

Three different periods can be distinguished from the figures: Normal operating period (consists of several parts), minimum power period, and the sensor-failure period. In normal operating periods, the reconciled estimates are similar to the measurements, so significant adjustments are not typically needed. However, the largest alterations are with flue gas H_2O contents and total fuel H_2O flows, which indicate fuel moisture content variations. This is expected, as fuel moisture contents vary significantly. To conclude, the reconciled estimates behave well and consistently in normal process operation, which is a prerequisite for the application of the method.

The minimum load operation at time steps 20–40 (h) is not a process disturbance, as such, but has several features that are different from normal operation. The most significant alteration takes place in flue gas O_2 estimates. The reconciliation cuts the O_2 peak significantly, to which the other variables react to varying degrees. The reconciliation operates fairly reasonably, but more tuning should be done at this operating point to improve estimates. On the other hand, the sensor failure directly affecting the H_2O and CO_2 measurements occurs at time steps 380−500 (h). From the reconciliation point of view, two distinctive failures occur at once, because the calculation has no indication that these measurements are conducted with the same measurement unit. Duo to the malfunction, the H_2O sensor malfunction disturbed several other measurements, due to the H_2O compensation. However, the reconciliation calculates plausible estimates for all measurements during the sensor failure, which verifies the ability of the method to tackle gross errors.

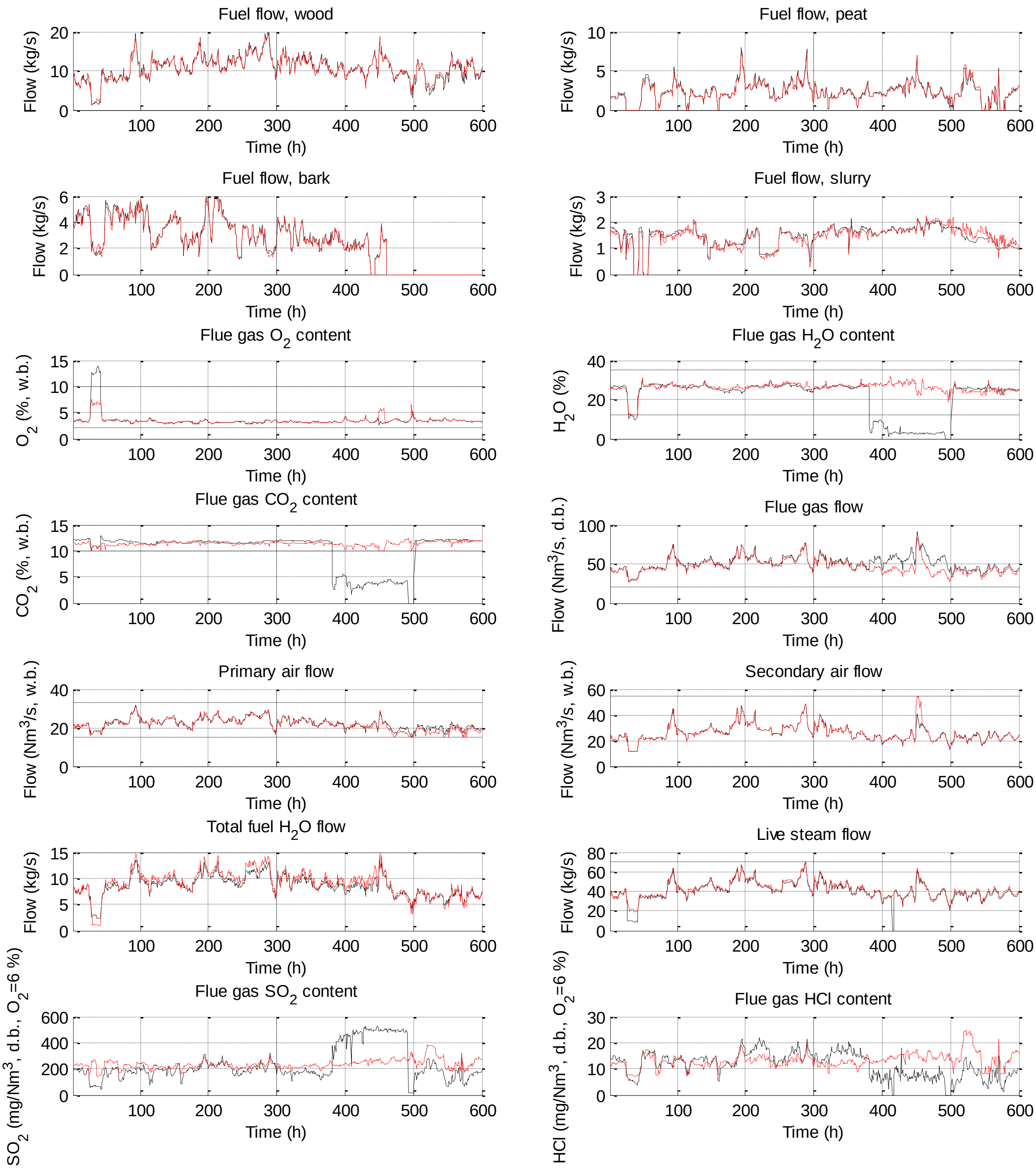

Figure 19. Measurements (black solid line), reconciled estimates (red solid line), and upper and lower limits (black dashed line, presented only if within range) of monitored variables. Data reconciliation only indirectly affects flue gas SO_2 and HCl estimates. (Korpela *et al.*, 2016)

This example points out the benefit of simultaneous data reconciliation and gross error detection in industrial power plant environments. These methods rely significantly on the computationally light combustion model, based on element balances. Calculus can also be utilized to provide first principles based estimates of variables that may not be measured at all. As an example, such an approach is applied in a coal-fired power plant that is described next.

6.2.3 Monitoring of Spraying in Desulphurization Processes

This subchapter presents an application that utilizes the element balance model to estimate flue gas composition in a coal fired power plant. The study objective, presented in Publication VI, was to improve the usability and efficiency of semi-dry flue-gas desulphurization (FGD) processes. This objective was approached by introducing an indirect method to monitor spray quality in FGD reactors. The monitoring method is based on an energy balance that estimates flue-gas exit temperatures of the reactors. The temperature is of particular interest, as it determines the continuation of SO_2 removal in subsequent bag filters and is hence one of the main controlled variables in the process. The temperature estimate indicates the exit temperature of the FG in case the spraying is functioning properly. By comparing the temperature measurement and the estimate, an indication of the success of the spraying can be obtained.

The semi-dry FGD process, illustrated in Figure 20, is based on reactions of SO_2 and calcium hydroxide $Ca(OH)_2$ that first take place in SO_2 removal reactors. The $Ca(OH)_2$ is fed into the reactor with other components of slurry, which are water and recycled reaction products. In the process, slurry suspension is injected through nozzles into two parallel reactors, in which acid components of the flue gas (SO_2 and HCl) are rapidly absorbed into the alkaline droplets to form calcium sulphite ($CaSO_3$), sulphate ($CaSO_4$) and calcium chloride ($CaCl_2$) while the slurry water vaporizes. However, the spray nozzles (illustrated in Publication VI) tend to clog and form obstructions that hinder smooth spraying that is a prerequisite for efficient SO_2 removal. Slurry droplets may remain large enough to directly fall to the bottom of the reactor, causing lowered SO_2 removal and some secondary issues. There is no direct way to determine if the spraying is functioning adequately in all the nozzles. Therefore, indirect monitoring methods are used.

The first principle modelling approach is also relevant in this case. This is due to varying process conditions, including co-combustion of coal, pellets, and auxiliary heavy fuel oil, varying coal qualities, power transitions, and changes in slurry composition. These are all challenging for data based approaches. Due to the first principle approach, the method is generic and can be applied in any spray dry absorption process.

The energy balance of the reactor can be calculated by knowing the flows, contents, and temperatures of injected flue gas, slurry, and distribution air. The challenge with this approach is that many variables affect flue gas and slurry flow compositions, but few of them are typically measured before

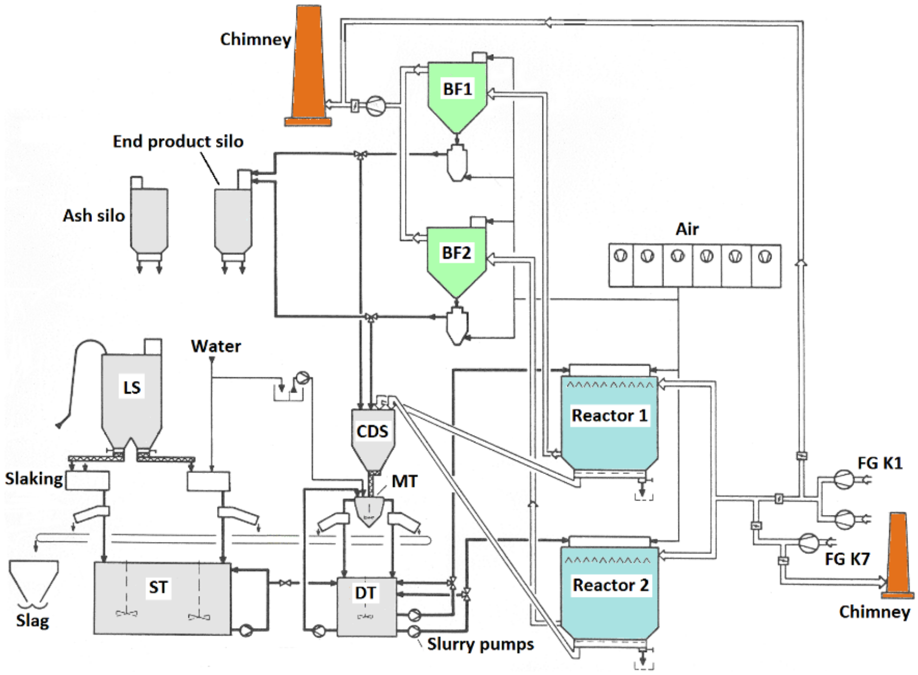

Figure 20. Description of FGD process. Abbreviations: FG ≡ flue gas, BF ≡ bag filter, CDS ≡ circulating dust silo, MT ≡ mixing tank, DT ≡ dosing tank, ST ≡ storage tank, LS ≡ lime storage.

the FGD. Therefore, the FG estimates are provided with the element balance model. The studied power plant consists of two boilers. K1 is a steam boiler with capacity of 506 MW_{fuel} and boiler K7 is a hot water boiler with capacity of 185 MW_{fuel}. In normal operating conditions, the flue gases from these boilers are mixed before fed evenly to two almost identical FGD lines (Figure 20).

Publication VI presents the details, assumptions, and estimates for all the energy flows, which derive the components of the energy balance

$$\dot{Q}_{in,r} - \dot{Q}_{out,r} = \dot{Q}_{FG,r} + \dot{Q}_{SL,r} + \dot{Q}_{air,r} - \dot{Q}_{out,r} = 0. \tag{15}$$

$$\dot{Q}_{in,r} = \sum_i c_i\, \dot{m}_{FG,r,i}\left(T_{FG} - T_{ref}\right) + \sum_k c_k\, \dot{m}_k\left(T_{SL} - T_{ref}\right) - \dot{m}_{SL,H2O}\Delta H_{vap} + c_{air}\dot{m}_{air,r}\left(T_{Air} - T_{ref}\right) \tag{16}$$

$$\dot{Q}_{out,r} = \sum_l c_l\, \dot{m}_l\left(T_{exit,l,rr} - T_{ref}\right), \tag{17}$$

in which i includes flue gas components CO, CO_2, H_2O, O_2, N_2, SO_2 and HCl; k includes the solid and liquid components of the slurry H_2O, $Ca(OH)_2$, $CaSO_3$, $CaSO_4$, $CaCO_3$, $CaCl_2$, and l them all. In this application, the balance is used to solve for the output temperatures of the reactors $T_{exit,r}$, which can then analytically be calculated, such as with Matlab Symbolic Math Toolbox™.

Figure 21 presents a simulated case with measured process data. The first two figures present the fuel powers of boilers K1 and K7. The third figure indicates a misbalance between FG flows to the two parallel reactors, R1 and R2. The misbalance originates from the pressure measurements (not presented here), which determine the realized division of FG to R1 and R2. The temperature estimate and measurement at reactor R1 (fourth figure) match well, except during a simulated error at period 25–35 (h), which illustrates a situation in which 4.4 percent of the water in the slurry does not vaporize. The error corresponds to a situation in which two of 45 nozzles do not spray the slurry in small droplets but output the slurry without any evaporation. Instead, the temperature estimate at R2 (fifth figure) differs from the measurement by an average 3 °C. The plausible cause is the misbalance in the third figure. Still, the estimates fit fairly well with the measurements in normal conditions. Therefore, the simulation results indicate that the method can predict the reactor exit temperature by an error of less than a few degrees Celsius, regardless of the process state with two, varying coal fired boilers. Despite the presented estimation errors, the simulated case illustrates that the method could alert if there is something unexpected in the process. Additionally, the estimates enable comparison of two parallel reactors, directly or by indexes, as described in Publication VI.

The reliability of estimates could be further improved by regular maintenance of the pressure measurements, which are not originally meant for such estimation purposes. Furthermore, case specific tuning parameters could be applied. Especially, this approach would benefit from data reconciliation presented in previous section, but it was not tested in this case.

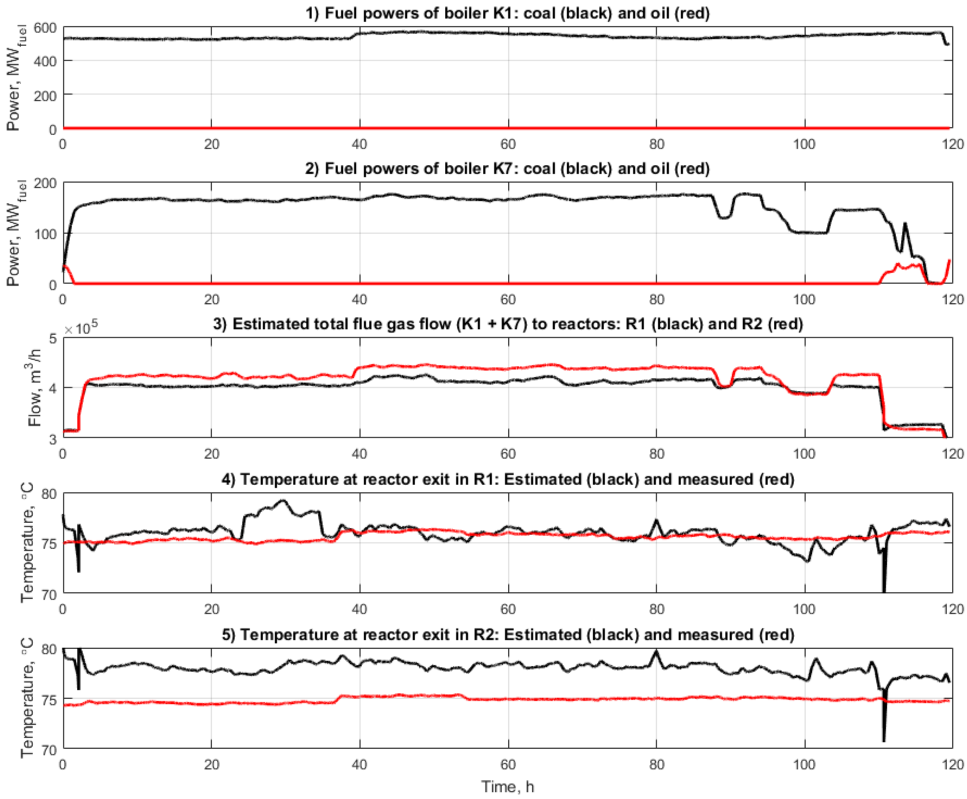

Figure 21. Simulation with process data. There is a simulated error in the fourth figure at period 25–35 (h) that presents a situation in which 4.4 percent of the water in the slurry to R1 does not vaporize.

6.3 Discussion

This chapter presented the first principle combustion model, based on element balances. The model interlinks combustion related measurements to form an entity that can be used in several applications. The model was presented in Chapter 6.1, which also answers Research Question 3. The computationally light model was then successfully applied in Chapter 6.2.1 in the case of a multi-fuel fired BFB boiler. The model predicted process behaviour in normal process conditions and indicated process disturbances and sensor malfunctions. The model was then extended with the energy balance in Chapter 6.2.2. The total model with simultaneous data reconciliation and gross error detection improved the reliability of estimates, which further improved the ability to separate process disturbances and sensor malfunctions. Therefore, Chapters 6.2.1 and 6.2.2 answer Research Question 4. Moreover, the model outputs were tested in a coal fired power plant, to provide estimates to a monitoring application. Therefore, Chapter 6.2 answers Research Question 5. This chapter also illustrates the thesis framework.

The chapter applied first principles models and process measurements to process monitoring. The benefit of this approach is that information from several sensors is interlinked to form an entity that can be analysed as one. However, several process details must be considered: Sensor locations, units of measurements, potential compensations, major dynamics, and main control principles. Therefore, the approach requires more initial effort compared to data based models. After the model and the configurations are finished, the approach provides relevant information regardless of process states. The estimates then enable extended monitoring prospects that provide insight to process behaviour, which can be used in several applications in process and sensor monitoring.

The element balance model fundamentally assumes that fuel compositions are known. Dry-fuel compositions vary to some extent, typically presented as ranges in literature. For example, the element carbon component of wood varies in ranges of 48 percent to 50 percent (Alakangas *et al.*, 2016), which is a narrow relative range, with a modest impact on estimation results. However, sulphur content of dry coal might vary in ranges of 0.3 percent to 1.5 percent. This is a relatively extensive range (five-fold in this example) that significantly affects SO_2 estimates. Therefore, additional information on actual fuel qualities may significantly improve the flue gas estimates. This is particularly true with coal, whose origin primarily determines fuel composition and properties. The coal is imported to Finland by ships from several origins. As fuel quality is a major aspect in coal trade, power plant owners are well aware of the coal properties before the fuel finally enters the boiler. Therefore, the estimates could be significantly improved by knowing the prevailing coal batch and its properties. The information on coal properties, especially sulphur and chloride contents, are vital for FGD process operation and fuel blending. Therefore, such information might be realistically available in power plants, which could also be utilized in estimation applications. In fact, such a system was on development in the coal-fired power plant discussed in Chapter 6.2.3, but was not yet available at the time of the test runs.

On the other hand, dry biomass compositions modestly vary and peat somewhat more, which are not typically measured beforehand. However, the variations are significantly flattened out in large fuel storages that mix different fuel batches. Therefore, the dry fuel compositions of such fuels can be reasonably handled by average values. However, fuel moisture content is another thing, despite the mixing of fuels in the storages. Therefore, emerging fuel moisture content measurements or estimates may significantly contribute to estimates. Alternatively, data reconciliation can tackle this aspect, as Chapter 6.2.2 shows.

Dynamics are another matter with the proposed modelling approach, as all combustion process are dynamic. The dynamics play a significant role in the proposed approach when there are dynamical components between measurements that are interlinked with the balance models. A dynamical component is the intermediate fuel silo before the BFB boiler, which disturbed static estimates calculated with one-hour means. Another dynamical component is the boiler itself, which affects when the energy balance of the boiler is included in the model. However, the static model can be utilized, as long as the dynamics are considered when interpreting the results. The dynamics can be considered by applying long enough time averages or data reconciliation. Still, better solutions could be achieved, by compensating for delays by cross correlation analysis or utilizing fuel-bed level measurements in the silo, which could provide information on loading or unloading the silo during the analysed period. Alternatively, the nonlinear combustion model could be applied with linear dynamic models similar to Hammerstein-Wiener models. Such models describe dynamic systems using one or two static nonlinear models and a linear dynamic model, as proposed by Leppäkoski (2006).

The ability to solve the element balance analytically and the resulting computational lightness enable several prospects, of which only a few are presented in this thesis. For example, the calculus can be easily modified to consider also oxygen-enriched combustion that replaces the constant oxygen-to-nitrogen ratio (3.76 in reactions R1–R4) by a parameter that is altered by the oxygen content measurement of the enriched airflow. Moreover, the amount of air leakage of the rotating air preheater can be easily considered, and was already implemented in the model of Publication VI. On the other hand, the element balance model can be solved in numerous ways considering different model input information and initial values, and the computational lightness enables their simulations almost instantly. Additionally, considering dynamics in the model or interpreting the results significantly increases the scope. All these aspects could provide feasible solutions in several applications in the future.

7 Discussion

The thesis objective was to derive and apply a framework to provide practically justified online monitoring and control solutions for existing combustion plants. The framework was presented in Figure 1. The practically justified solutions in existing combustion plants are domain specific, comprising several aspects for consideration. This thesis presents model-based estimation, monitoring, and control solutions for three main applications – small-scale wood chip combustion systems, medium-scale natural gas-fired boilers, and large-scale power plants. All cases verify that needs and requirements are case-specific and vary in time. Therefore, there is a genuine need for different kinds of models and methods.

The selection of suitable methods is case-specific, which primarily depends on the objectives set to the application but also on the process prospects and available instrumentation. Ideally, the most generic solutions are the best, which stand for first principles models in this context. However, their derivation is laborious and thus costly, requiring expertise and process specific information that may be difficult to reach in practice. The situation is somewhat opposite with the data based models, which can, at best, replicate the process conditions present in the identification data. However, such models are rather straightforward and fast to derive when suitable data is available. Still, their generalizability is modest, and long-term performance cannot be guaranteed without regular maintenance. Therefore, there is a trade-off between generalizability and modelling costs, including development and maintenance.

When designing combustion process solutions, the process, measurements, and operating environment should be understood for a fair evaluation of result validity, as the weakest link determines the performance of the total system. When something changes in the domain, the validity, generality, and hence feasibility of solutions must be carefully reconsidered. The feasibility of technologies presented in this thesis focuses on existing boiler systems. Many of the foregoing regulations also require major changes to combustion processes and their components. Therefore, the validity of proposed solutions must be reconsidered in these new environments. Fortunately, the process oriented perspective enables the methods to be modified to prevailing conditions, as long as the causes and effects of the changes are properly understood.

8 Conclusions

This thesis presents and applies a framework to provide practically justified monitoring and control solutions to existing combustion applications. It particularly focuses on utilization of models for online estimation in combustion applications. As Ljung & Glad (1994) described, model construction can be divided into *domain expertise*, which constitutes understanding the application and mastering all relevant factors for the model; and *knowledge engineering*, which is understanding how these facts can be transferred into useful models. The contribution of this thesis focuses on the former, to provide feasible, cost-effective solutions to emerging issues with existing boilers. This is achieved by utilizing *knowledge engineering* and further exploiting the models to improve performance or process monitoring in online operation. The foundation of the work was a solid understanding of combustion processes and their operating environments. This was utilized in three practical cases (Cases I –III) that included seven combustion applications in three heat power ranges.

Case I focused on small-scale (<0.5 MW) wood chip combustion systems. As an answer to Research Question 1 of the thesis, the case presented preventive actions to alleviate the effects of fuel feed variations and grate sweeping in two commercial wood chip fired boilers. The developed cascade-control structure enabled stable boiler operation and extended lifetime of critical lambda sensor. The derived solutions are feasible, enabling significantly improved process performance in varying process conditions in terms of operability, efficiency, and emissions. As a future research prospect, utilization of emerging low-cost gas sensors and MPC control seem attractive for further process performance improvements.

Case II focused on indirect NO_x emission monitoring of medium-scale (15 MW – 50 MW) natural gas fired boilers. As an answer to Research Question 2, the case presented novel, data modelling based monitoring solutions to provide NO_x estimates, of which the simple linear models were the best in terms of model accuracy (relative RMSE error <3 % in all cases) and reproducibility. The generalizability of these models in different operating environments was verified so that the method is feasible and attractive as a low-cost solution in practical installations. Still, future work should include long-term verification of the models in various operation conditions. Additionally, the effect of fuel quality changes due to changed gas types should be researched, especially if PEMS is to be widely applied.

Case III is the most generic and extensive of the cases, and answers Research Questions 3–5. The case presented first principles modelling solutions for large scale (>100 MW) power plants. The novel element-balance based combustion model interlinked distributed combustion related measurements, thus enabling attractive monitoring prospects. The most significant one is power plant level process monitoring including sensor malfunction and process disturbance differentiation. This is yet improved by applying simultaneous data reconciliation and gross error detection, enabled by the computationally light element balance model. The model also provides first principles estimates of potentially unmeasured variables, which was exploited in a developed FGD monitoring application of a coal-fired power plant. As a future research prospect, the element balance calculus can also be applied to solve research questions related to fuel element composition and moisture content, and oxy-fuel combustion. Moreover, addition of dynamic considerations to element balance calculus and plant-wide process monitoring emerge as an attractive future research prospect.

As all the Research Questions were answered, the hypothesis of the thesis can be verified.

The framework of the thesis is rather extensive, due to the naturally large scope of aspects that affect the domain in question. Therefore, the framework enables the solutions to be adapted to current and near future conditions.

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Original Publications

Publication I

Korpela, T., Björkqvist, T., Lautala, P. 2008. Durable feedback control system for small-scale wood chip combustion. *Proceedings of World Bioenergy 2008 Conference*, May 27–29, 2008, Jönköping, Sweden. 224–230.

DURABLE FEEDBACK CONTROL SYSTEM FOR SMALL SCALE WOOD CHIP COMBUSTION

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ABSTRACT: The purpose is to control wood chip combustion in an inexpensive and durable way. A control concept in order to reduce the effect of fluctuation of the fuel feed is introduced. The concept is based on temperature and lambda measurements. The main task of the control system is to set the fuel feed at a desired level after a change in the combustion conditions. Additionally, temporary fluctuations of the degree of filling of feeding screw are compensated. Test results of a 80 kW and a 200 kW commercial wood chip fired systems are introduced. The process experiments indicate that the high level control system is able to adapt to varying combustion conditions and to maintain low emission levels. Furthermore, passive means that can be exploited to stabilize the combustion are discussed. As the control concept is not dependent on the design of the combustion system, the concept is adaptable to present systems.
Keywords: Control systems, feedback, biomass, wood chip, sensor

1 INTRODUCTION

Popularity of small scale (10–1000 kW) biomass fired systems has increased substantially over the last few years in Europe. This is e.g. due to increased oil and electricity prices and gained public awareness of climate change. By combusting wood as pellets, chips and logs, inexpensive and CO_2 neutral energy can be exploited. However, wood chip combustion in small scale systems is challenging, because combustion is primarily disturbed by irregular fuel feed. This is mainly due to the variation in the degree of filling of the feeding screw. Additionally, the energy density of the wood chips varies even in the same batch. Moreover, the moisture content may vary substantially. Thus, the quality of the wood chips is usually not good enough to provide stable fuel energy feed. This induces significant variation to combustion. As a result, emission levels are high and optimal efficiency is not reached. Therefore, active control actions have to be made to compensate for the fluctuation in the fuel feed. However, to maintain the inexpensiveness of small scale wood chip systems with better controllability, physical instrumentation should be kept at minimum. Additionally, robustness of sensors used must be such that the sensors last in the challenging combustion environment [8] for a long time without defects or drifting. This work aims to provide a durable and inexpensive control solution for these challenges. The background of the work was to discover control solutions for existing combustion systems and to generalize solutions in wider scale. Still, the control development should be closely coupled to the process development in order to design sophisticated combustion systems.

Small scale wood combustion produces significant amount of fine particles and therefore causes serious health hazards [9]. It has been verified, that good combustion in CO and OGC point of view reduces fine particle emission compared to the poor combustion [9]. Fortunately, the CO and OGC emissions correlate well with the amount of excess air in the small scale combustion systems [1]. Therefore, the goal of the control system is to minimize the CO emissions. However, the optimum in the emission point of view is not exactly the same as in the efficiency point of view [8], because the efficiency optimum is got when the CO and OGC emissions are slightly increased due to lack of excess air. Hence, enough excess air must be provided to reduce emissions with price of the lower efficiency. Unfortunately, NOx emissions increase as the excess air increases [1]. Altogether, a suitable operation regime for the combustion system must be found and maintained in order to satisfy these conflicting requirements.

Lambda sensor is the main sensor used for feedback control in modern wood chip fired systems. However, experiences of durability and long term accuracy of the lambda measurement vary. Lifetime of the sensor might not be optimal, if the sensor is exposed to highly unclean gas. Especially this is the case with discontinuous combustion with iterative start-ups, shut downs and pilot flame [10]. Hence, the better the quality of combustion is, the longer lifetime is expected for the sensor.

Temperature measurements from the upper part of furnace are common in wood pellet fired systems. Temperature measurement is a reliable and inexpensive measurement. Its measurement signal has a good negative correlation with the oxygen content, if suitable amount of excess air is guaranteed [3]. Physical modelling results have also been published, in which temperature behaviour at the upper part of furnace of wood pellet fired system is modelled [4]. The temperature measurement signal does not, however, describe reliably the absolute value of the oxygen content. This is in particular the case if the fuel quality and especially the moisture content of the fuel vary. Therefore, the temperature measurement does not suit with the wood chip combustion as well as for the wood pellet combustion. In this paper, a soft sensor (e.g. [6], [7]) based control solution is introduced, in which the positive properties of temperature and lambda sensors are joined in order to get suitable efficiency, low emissions and extended lifetime for the sensors.

2 EXPERIMENTAL SET UP

2.1 Combustion systems

Combustion tests with two commercial wood combustion systems were made. Both burners, Säätötuli 80 kW and Säätötuli 200 kW, are stoker burners. They are designed primarily for wood chip combustion, but can also be used with other solid biomass fuels.

Therefore, both burners are equipped with grate sweepers. Grate sweepers are metal rods, which are used to move the ash away from the grate and to equalize the fuel pile. In both of the burners, primary and secondary air is fed to the burner by two separate blowers. Primary air is fed trough the grate upwards. Secondary air in both cases is fed from the roof downwards, from the back of the burner to boiler direction and from walls to the fuel pile (80 kW) or to the opposite wall (200 kW). The walls and the roof of combustion space of the 80 kW burner are made of metal and correspondingly of paste of the 200 kW burner. The fuel feed of the 80 kW burner was realized as on/off control and the fuel feed of the 200 kW burner was realized continuously with inverter control. Both burners are not normally equipped with feedback combustion control.

The 80 kW burner was installed in a commercial Tulimax 120 ST boiler with nominal capacity of 120 kW. A 0.92 m^3 fuel storage was integrated to the burner and it was equipped with two rotating plate dischargers to balance the fuel feed. The 200 kW burner was installed in a commercial Arimax Bio 250 SP boiler with nominal capacity of 250 kW. Correspondingly a 24 m^3 fuel storage was equipped with back and forth moving rod dischargers. The 200 kW system was pressure controlled by pressure measurement and exhaust fan.

2.2 Measurement systems

Control and measurement systems with both test systems were implemented in LabVIEW environment. In the 80 kW system, all the measurements were collected with a DT9806 data acquisition system. Additionally in the 200 kW system, hardware and instrumentation of the commercial installation was utilized via an OPC connection from an OMRON logic.

Flue gas analysis was made by Testo 330-2 flue gas analyzer, which was equipped with O_2, CO and NO measurements. K type and 1.5 mm thick sensors were used for temperature measurements. In the 200 kW system, a lambda measurement by Motec PLM and air flow measurements by Produal 10-105 were also used. A more detailed description of the 80 kW combustion system and the instrumentation is presented in [3].

3 PASSIVE CONTROL

All processes are disturbed by not fully manageable outer sources. The properly working processes are designed to a high level of passive self stabilisation. From a control point of view the processes, which can not be designed as self-stabilising processes, should be designed to enable a properly working active control. In small scale solid biomass fired systems, the most fatal disturbance is the fluctuation of energy content in the fuel feed. So far no cost effective feed forward solution for this disturbance has been presented, as there is no proper fuel flow and quality measurement available. The remaining solution is then to manage the combustion by active feedback control. The effect of feedback control, however, can be improved by passive control actions.

3.1 Passive stabilization

Passive stabilization stands for actions without feedback control. By setting primary air supply level the combustion rate [11] and therefore the size of the fuel pile at the grate [3] can be controlled in a passive way. This can have a positive influence on the dynamic behaviour of the combustion. In order to provide suitable overall excess air to prevailing combustion conditions, the control of primary air means actually controlling the amount of primary air portion of the overall air feed.

The disturbance in the fuel feed changes the energy feed of the screw. It can be assumed that the larger the fuel pile is the smaller the effect of change in fuel feed is to fuel pile and hence to the combustion. Therefore, in order to reduce the effect of fluctuation in the fuel feed, it is desirable that the fuel pile is as large as possible for prevailing conditions.

Figure 1 indicates normalized distributions calculated from process data generated with the 80 kW system. First figure indicates temperature distributions with small and large pile. Feedback control responses presented in the figure are discussed later in chapter 4.1. It can be seen, that with the large pile the temperature distribution is narrow and high compared to one with the small pile. This means that process fluctuations are smaller with the large pile compared with the small pile. In second figure it can be seen, that at the same time, the oxygen content is at lower level with the large pile, which indicates improved efficiency. In third figure, the CO distribution with the large pile is higher at low CO concentrations and smaller at high CO concentrations compared with the small fuel pile.

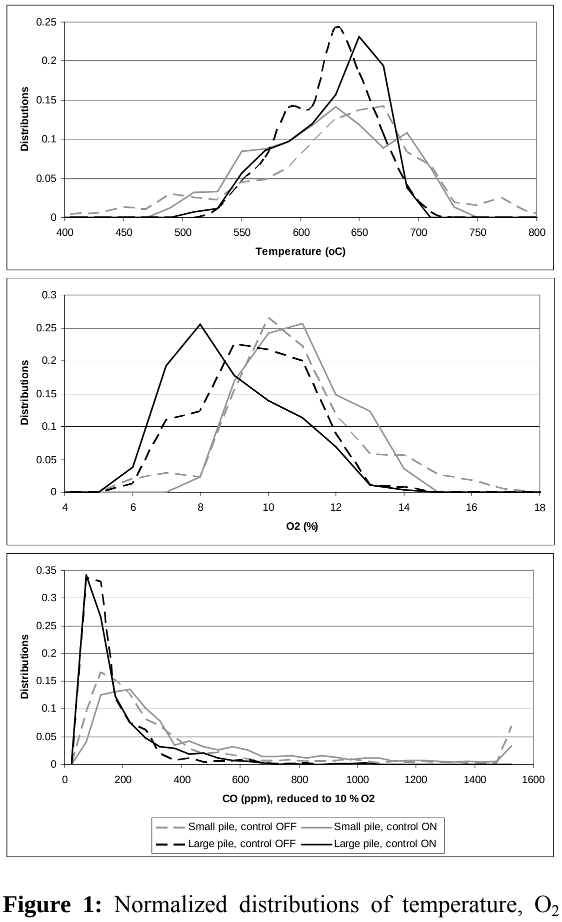

Figure 1: Normalized distributions of temperature, O_2 and CO (10% O_2) with small and large fuel pile both without and with fuzzy control. Tests have been implemented with the 80 kW wood chip burner and with stem chips with moisture content of 25 %.

It can be concluded form Figure 1, that combustion, which is emphasized by secondary air supply, can be seen to be more stable than the combustion which is emphasized by primary air supply. The reason is that by combustion with larger proportion of secondary air, gasification of fuel pile is calmer than with larger proportion of primary air. This is because small amount of primary air keeps the char combustion rate small [11]. Because of limited temperature and energy production at the pile, the pyrolysis rate is limited, so the amount of produced pyrolysis gases is restricted also at dynamically changing conditions. Therefore, with the smaller primary air feed it is more likely that there is always enough secondary air that all the produced pyrolysis gases can be burned. As a result, the overall behaviour of the process is calm and emission levels are low. One must be careful, however, that enough primary air is fed, that proper combustion takes place and that the surface of the grate is large enough for the fuel pile. Combustion with higher moisture content requires larger portion of primary air and total amount of air compared to lower moisture content [11]. A reasonable air staging ratio depends also on power level and structure and geometry of the system.

Information about the size of the fuel pile is very useful for control purposes. E.g. a manufacturer [5] uses mechanical sensors to measure the size of the fuel pile at their wood chip combustion systems.

3.2 Feedforward compensation of the grate sweeping

Grate sweepers are used to move the ash away from the grate and to equalize the fuel pile. Grate sweeping, however, causes significant disturbances to combustion [3]. This can be seen in Figure 2, in which test results implemented with the 200 kW wood chip burner are introduced. Upper figure indicates time of grate sweeping and lower figure CO emissions. It can be seen, that the CO emissions are momentarily after sweeping almost 10 times higher than average CO level before the sweeping. This is because fuel is swept away from some of the primary air holes. As a result, flow resistance of the primary air flow is reduced and the amount of primary air is increased. This accelerates locally char combustion, and more heat is released. Therefore, pyrolysis is accelerated as well [4]. Moreover, the layers of combustion zones in the pile are mixed, so fresh fuel is also revealed. If air feeds are normally set to suitable level in efficiency point of view, the amount of secondary air is not sufficient for good combustion as grate sweeping occurs. Therefore, soot, CO and OGC emissions are increased, efficiency is decreased [1] and heat surfaces and sensors get dirty in the long term. As the size of the fuel pile is decreased because of accelerated combustion, it is advantageous that the size of the fuel pile is large before the sweeping disturbance.

The harmful effect of grate sweeping increases as the fuel moisture is decreased. This is because dry fuel is more reactive than moist fuel.

The effect of grate sweeping can be compensated e.g. by reducing primary air around the sweeping. In this case, the idea is to momentarily slow down the combustion and to avoid increased effects of primary air. An example of this can be seen also in Figure 2. First figure illustrates the times, at which reductions of 63 % of primary air flow are done for compensation purposes. It can be seen in the second figure, that improvement to CO levels is achieved. The drawback with this control practise is, however, that the overall excess air is also reduced. The effect of compensation can then be improved by increasing the secondary air feed at the same time as the primary air is reduced. An illustration of this is shown in Figure 7 as part of a control test run.

In order to have a sufficient compensation effect, the changes in air flows must be moderate. Unfortunately, the grate sweeping and the compensation interferes the operation of a feedback control system. Hence, the feedback control system must be switched off during and straight after the compensation. Still, it is reasonable in emission and efficiency point of view to change the air feed proportions around grate sweeping so that the nominal excess air levels do not have to be dimensioned for the grate sweeping disturbances.

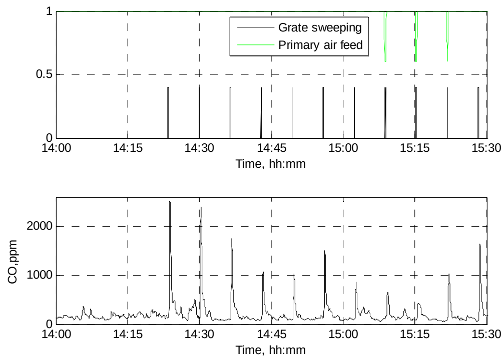

Figure 2: Time of grate sweeping and reduction of primary air are shown with pulses at the upper figure. Lower figure indicates CO emissions reduced to 10 % O_2. Reductions of 63 % of primary air flow are done to compensate for the disturbance caused by grate sweeping. Tests have been implemented with 200 kW burner with wood chips with moisture content of 32.5 %.

4 ACTIVE LOW LEVEL CONTROL

In the previous chapter, passive and feedforward actions that can be done to stabilize the combustion were introduced. They are, unfortunately, not anywhere near to be sufficient means to gain stable combustion conditions. Therefore, feedback control actions must be utilized. In this chapter, a feedback control system based on temperature measurement from the combustion chamber is presented. The system requires a desired temperature level which is tried to maintain by control actions. How the suitable temperature set point can be obtained is discussed in next chapter.

The goal of the low level control system is to stabilize the fuel feed in prevailing conditions. Therefore, the objective is to narrow the distributions presented in Figure 1 and to move them to more suitable locations despite of the fuel feeding disturbances. Typical fuel feed disturbance is when the degree of filling of the feeding screw decreases. This is mainly due to uneven exhaustion of the fuel in the storage. The size and the duration of the disturbance depend on the volume, dimensions and structure of the storage, potential equalizing equipment in the storage and properties of the screw. Also the amount, quality, density and moisture of fuel affect. As a result of the fuel feeding disturbance, less fuel is fed to the burner compared to the normal level. Therefore, the size of the pile decreases. If the disturbance is substantial, the combustion starts to fade. This can be observed e.g. with temperature measurements.

As the properties of the 80 kW and the 200 kW systems differentiate, slightly different low level control systems were implemented for the processes.

4.1 Fuzzy control

As the properties and the dynamics of the 80 kW system were observed, it was concluded that the effects of typical fuel feed disturbance were significant. As a result, the temperature, the O_2 and the CO signals varied substantially also in case of large pile (Fig. 1). Based on process experience and earlier reported results [4], it was concluded that heavy dynamics affect the combustion. As the feedforward compensation can not be implemented due to lack of fuel flow measurement, the compensation has to be made by feedback control. Unfortunately, feedback control actions cannot be started before the disturbance is already affected the process [12]. Hence, as the temperature measurement starts to go down, the size of the fuel pile has already decreased. Therefore, fast and powerful control is required to compensate these disturbances. Fuzzy control is suited for this process, because its structure is flexible. Hence, nonlinear fuzzy control of Mandani approach (e.g. [2]) based on temperature measurement was generated. A block diagram of the implemented low level direct control system is presented in Figure 3.

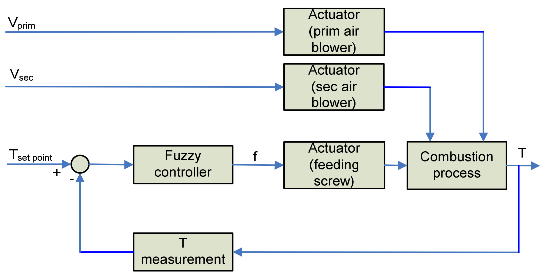

Figure 3: Low level feedback control system.

The idea of the fuzzy controller is to conclude the current behaviour and near future trend of the temperature signal. This is done by comparing the measurement signal with the temperature set point. The set point is desired temperature at a selected measurement point in prevailing conditions, which is in this control structure given by the system operator. The fuzzy controller infers the compensation requirement of fuel feed based on temperature error signal (*e*), which is the difference of temperature set point and measurement signal, and its rate of change (Δe). These are divided into five regions. Therefore, there are 25 rules that define the status of the temperature. Based on these rules the inference is made between five compensation levels, whether to keep the normal feeding level or to change it. Descriptions of the rules are presented in Table I. A detailed description of the fuzzy controller is presented in [3].

As the fuel feeding disturbance starts to affect the process, normally the temperature measurement signal goes down rapidly, bottoms out and finally after the disturbance is over it starts to go up slowly. The idea of fuzzy system is that the steeper the decline, the bigger the compensation. Therefore, forceful compensation is made straight after it is concluded that there is a severe temperature drop due to fuel feed disturbance. When the temperature decline is slowing down, fuel increase is subtracted. Finally, when the bottom of the temperature is reached, the fuel feed is kept at constant normal level. As the affect of the disturbance is to be over, the temperatures start to go up. This means, that the process has started to recover. At this point, extra fuel is not fed anymore to avoid over compensation.

Table I: Rules of fuzzy controller. Vertical heading stands for error signal (*e*) and horizontal heading for rate of change of error signal (Δe). Headings: N=negative, P= positive, S=small, L=large, Z=zero. Content: S=subtract, A=add, B=base, S=small, L=large. E.g. If *e* is Positive Small AND if Δe is Positive Large THEN Add Large.

e/Δe	NL	NS	Z	PS	PL
NL	SL	SL	B	B	B
NS	SL	SS	B	B	B
Z	B	B	B	B	B
PS	B	B	B	AS	AL
PL	B	B	AS	AL	AL

Thus, the basic idea of the fuzzy controller is to increase significantly the fuel feed after temperature drop. Additionally, when the process has started to recover, the fuel feed is kept at normal level. This kind of nonlinear control actions can not be implemented with a standard PID controller. If it was used instead of the fuzzy controller, the fuel feeding compensation would be done also when the process is starting to recover. That kind of operation causes overcompensation. As this should be avoided, the PID controller has to be tuned so slow that the compensation at a point, when it is needed the most, is insignificant.

As the temperatures decreased due to fuel feeding disturbance, the heat release went down as well. This describes, that the level of pyrolysis and especially char combustion stages have decreased. Because extra fuel is fed to the burner straight after the temperature drop by the control system, there is more fresh fuel in the pile compared to the case that there is no compensation. Naturally, it takes some time for the stages of combustion to stabilize to their normal level, as there are strong couplings between the sub processes, e.g. [4]. Thanks to the presented feedback control, the size of the pile is increased. This prompts the process to recover and not to be that vulnerable to next conceivable disturbance.

Figure 4 presents a process experiment made with the 80 kW system with large fuel pile and with the fuzzy control. First figure indicates the temperature measurement from combustion chamber and its set point. Second figure depicts the CO level, and third picture illustrates the percentage level, which describes the operation time of the fuel feeding screw compared to overall time. Moreover, third picture indicates the moments when the grate sweeping occurs. It can be seen, that the controller has increased the fuel feed at points when the temperature is much lower than the set point. Moreover, there are small indications of slight overcompensation.

Figure 1 compares the behaviour of the test run presented in Figure 4 with the case with no control actions. There are also corresponding distributions from a similar test run with small pile. As it can be seen, the effect of the fuzzy control is not significant compared with the case without feedback control and with small pile. However, the tails of the distributions are though cut, which is important for stable power production. In the case of large pile, the fuzzy control moves the temperature distribution to higher temperatures. Additionally, oxygen distributions are transferred a significant amount to lower oxygen levels. As CO levels have not changed too much, the efficiency with fuzzy control has increased with no expense.

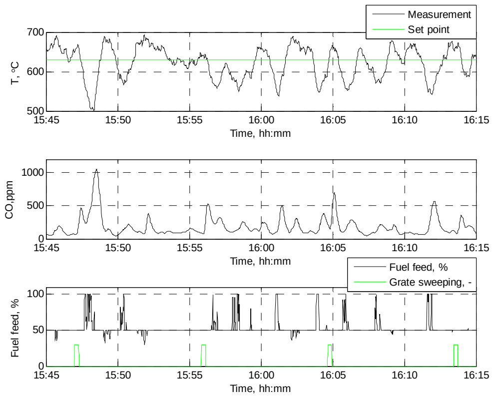

Figure 4: Test run with fuzzy control and with large pile made with 80 kW wood chip burner with stem chips with moisture content of 25 %. First figure indicates temperature measurement from combustion chamber and its set point. Second figure represents CO emissions reduced to 10 % O_2. Third figure illustrates percentage level, which describes the operation time of the fuel feeding screw compared to overall time. Additionally, third picture indicates moments of grate sweeping.

4.2 Fuzzy and integral control in parallel

As the properties and dynamics of the 200 kW system was observed, it was concluded that the disturbances in the fuel feed were different compared with the disturbances of the 80 kW system. This is a result of different kind of fuel storages. The one used with 200 kW system was 24 m^3 in volume. Despite of the long and two phase feeding screw and rod dischargers, the fuel feed was not stable. In fact, the fuel pile in the storage did not elapse equally. Typically some time after filling the storage, the fuel bed above the screw was gone and there were a lot of fuel in both sides of the storage. The fuel in storage behaves as function of type, size and moisture content of the fuel. Altogether, the fuel feed fluctuated with heavier dynamics and smaller in size compared with corresponding of the 80 kW system. Hence, an integral controller was set in parallel with the retuned fuzzy controller. It provides the control system to follow the slow fluctuations of the system, as the purpose of the fuzzy controller is to compensate the fuel feed only momentarily. Moreover, the integral controller provides the possibility for the system to follow the operator defined temperature set point. This can be seen in Figure 5. First figure illustrates the temperature measurement and its set point. Second figure indicates the inverter frequency. The peaks of fuel feeding frequency are due to the fuzzy controller and the quietly changing frequency is due to the integral controller.

The significance of the fuzzy controller in the 200 kW system is smaller than in the 80 kW system, because passive stabilization in the 200 kW system operates well. This is because the fuel feed is more even in relation to the size of the fuel pile compared to corresponding of the 80 kW system. It is positive, however, that the fuzzy controller exists when a sudden drop in fuel feed occurs.

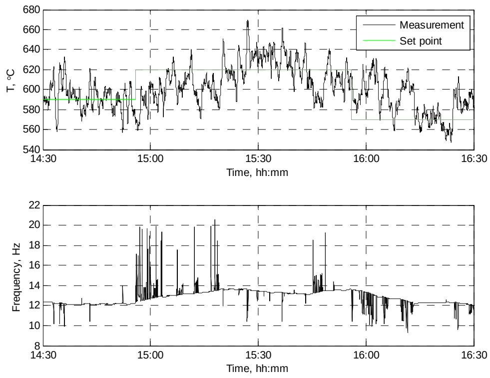

Figure 5: Step response of temperature set point made with the 200 kW burner with forest chips with moisture content of 26.5 %. First figure illustrates temperature measurement from the upper part of furnace and its set point. Second diagram presents inverter frequency.

5 ACTIVE HIGH LEVEL CONTROL

An essential part of the low level control described in chapter 4 is the selection of appropriate temperature set point. It depends e.g. on boiler geometry, the type and location of the temperature sensor, power level, fuel moisture and chip size, boiler temperature, fouling level of the boiler and draft. Finding the suitable set point defines the behaviour of the system. If the set point is too high, too much fuel is fed to the burner. This results in high emissions and low efficiency. On the other hand, if the set point is too small, enough fuel is not provided. As a result, power generated goes down and emissions increases due to too high excess air.

The low level control system stabilizes the combustion by fuel feed. If the primary and secondary air feeds are kept constant, changing the temperature set point changes the excess air level. Therefore, oxygen measurement by lambda sensor provides important knowledge about the temperature set point. Hence, Figure 6 presents a block diagram of the cascade control system, which resets the appropriate temperature set point by lambda measurement. The inner or secondary loop consists of the control system presented in chapter 4.2. The outer or primary controller to control the oxygen level of combustion by lambda measurement is presented a round the secondary loop. Moreover, the grate sweeping compensation described in chapter 3.2 is presented in the figure.

The system is run by adjusting the primary and secondary air feeds to suitable levels. At the same time, the power level is set, as the cascade control loop settles the fuel feed to balance with the air feeds. Then, the desired oxygen set point to the system is set. The appropriate oxygen set point is e.g. a function of fuel moisture [11] and chip size, power level and system structure. The oxygen controller finds the suitable temperature set point by oxygen error signal, which is the difference of the set point and the measurement. As the temperature set point is defined automatically by the primary control loop, the uncertainty of what to choose as temperature set point, e.g. due to the location of the sensor, the combustion conditions or the system structure, is mainly vanished. Therefore, any representative temperature measurement is suited for the control purposes. This is extremely beneficial, when the control system is adapted to different combustion systems.

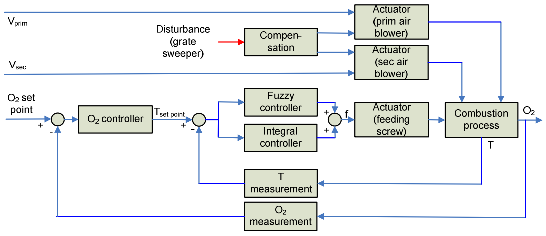

Figure 6: Cascade control loop, in which primary control loop is the O_2 control loop and the secondary loop is the temperature control loop. Air feeding signals are user defined, and air feed ratio is changed to compensate for the disturbances generated by the grate sweeping.

The cascade control is suitable with processes where there are multiple measurements and one actuator. Additionally, there should be long delays or time constants. Therefore, it is reasonable to adapt the cascade control with the combustion application. The idea of cascade control is that the secondary controller compensates the disturbances before they affect the most important quantity of the system. This is then controlled by the primary control loop quietly. The rule of thumb is that time constants of primary control loop must be at least 5 times longer than with secondary loop [12].

Figure 7 introduces preliminary results of a control test made with the 200 kW system at produced power level of 140 kW. The oxygen controller was implemented with an integral controller. Before the experiment, the cold system had been started up, and after the combustion temperatures were at normal range, the active control was turned on. The time constant of the temperature controller was some 20 minutes and with oxygen controller some 125 minutes. Primary and secondary air feeds were constants, but the primary air was decreased and secondary air was increased around grate sweeping for compensation purposes. Meanwhile, the control system was switched off. First figure illustrates the temperature measurement from the upper part of furnace and its set point. Second figure presents lambda measurement and its set point. Third figure introduces the fuel feeding frequency. Fourth figure illustrates primary and secondary air flows, and fifth figure shows produced CO emissions.

It can be concluded from Figure 7, that the control system was able to decrease the oxygen level to its set point. This was achieved by increasing the temperature set point, which the temperature measurement followed fairly well. Despite of the decreased oxygen level, the CO emissions decreased as well. Therefore, efficiency was increased and emissions subtracted. At the end of the test the integral part of the fuel feeding frequency was at the same level than at the beginning of the test. Therefore it can be concluded, that the fuel energy feed varied during the test.

The benefit of the presented control system is that when the cascade control system has found the suitable temperature set point and if there are no major disturbances, e.g. fuel remains the same, the primary loop can be switched off. This means that the lambda sensor can be taken away from the flue gas channel, as the secondary loop presented in chapter 4 maintains the temperature set point. When there will be a significant change in the process, the lambda sensor is installed back to the process for a few hours, and a new temperature set point is obtained. In this way, the worst conditions, e.g. start ups, shut downs and pilot flame situations, can be avoided. As a result, the lifetime of lambda sensor can be extended substantially. Meanwhile, active feedback control is used to get proper efficiency and low emissions.

6 CONCLUSION

In this paper, a control concept in order to reduce the effect of fluctuation of the fuel feed was introduced. The task of the control system is to maintain the fuel feed at a desired level after a change in the combustion conditions. Additionally, temporary fluctuations of the degree of filling of feeding screw are compensated. As the control concept is not dependent on the design of the combustion system, the concept is adaptable to present systems.

The approach was to produce a multilevel feedback control concept for wood chip combustion. In this concept, the low level control system controls the fuel feed by a temperature measurement from the upper part of combustion chamber. Its purpose is both to compensate for the temporary fluctuations of fuel energy feed and to adjust the fuel feed to a desired level in order to maintain the desired combustion temperature. Then, the upper level control algorithm defines the temperature set point value and hence the operation regions for the low level control algorithm by lambda measurement. The low level system is robust and working whenever the burner is operating in normal operation range. The upper level control system is active only when the combustion conditions change substantially. As a result, when the lambda sensor is taken a way from the exhaust gas duct when it is not active, and it is exposed to combustion conditions only occasionally. This increases the lifetime of the lambda sensor substantially.

The goal of the control system was to minimize the generated CO level. As there is no CO measurement available in the system, it has to be estimated. Therefore, knowledge of the behaviour of CO levels as function of excess air level is exploited. As a result, the control concept complies with soft sensor approach. Moreover, when the lambda feedback is switched off, the oxygen level is estimated by temperature measurement. This can be interpreted as soft sensing as well.

The low level control system was tested with the 80 kW and the 200 kW commercial wood chip fired heating systems. Additionally, the high level control system was tested with the 200 kW system. The process experiments indicated that the high level control system was able to adapt to varying combustion conditions and to maintain low emission levels. Additionally, the low level control system was able to prevent a heat output level drop in case of a sudden decrease of output of the fuel feeding screw of the 80 kW system.

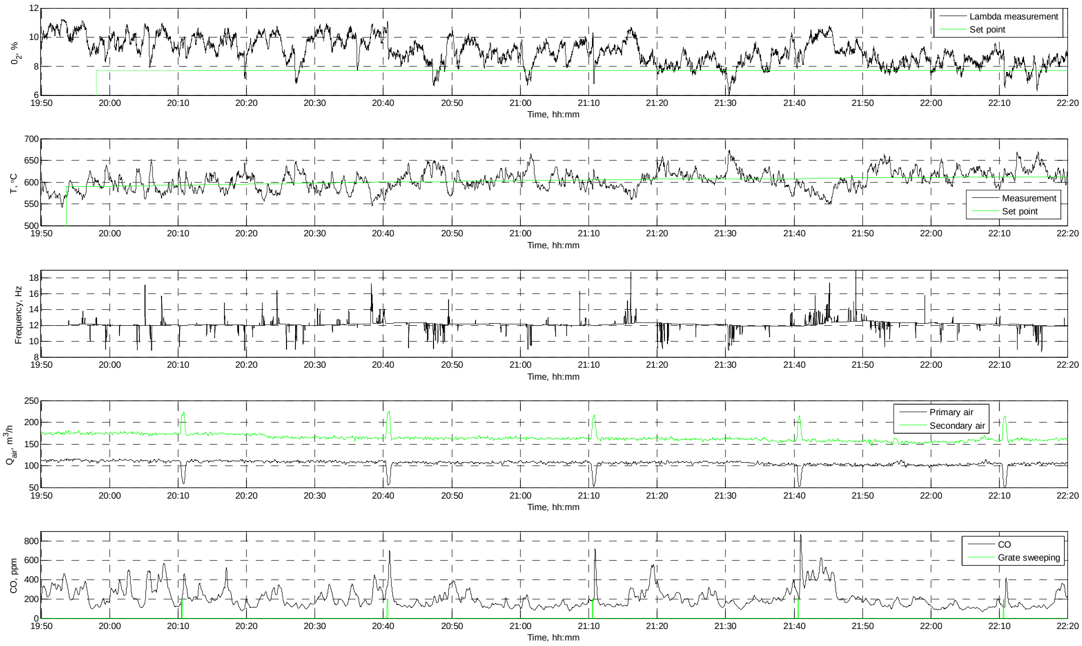

Figure 7: Test run with high level control system, which was carried out with the 200 kW burner with whole tree chips with moisture content of 33.5 %. At the experiment, active control was turned on after start up of the system. First figure illustrates the temperature measurement from the upper part of furnace and its set point. Second figure presents lambda O_2 measurement and its set point. Third figure introduces the fuel feeding frequency. Fourth figure illustrates primary and secondary air flows. Fifth figure shows CO emissions reduced to 10 % O_2 and moments of grate sweeping.

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Control Strategy for Small-Scale Wood Chip Combustion

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Abstract: The purpose is to control small-scale (< $1MW_{th}$) wood chip combustion in an inexpensive and durable way. Therefore, a hierarchical control concept is presented. The main task of the fuel feed control system, which is based on temperature and lambda measurements, is to settle the fuel feed to air feeds and to compensate for the temporary fluctuations in the fuel feed. The task of the air flow control is to set the primary and secondary air flows suitable for the power level and for the fuel moisture content. Test results of a 200 kW commercial system are presented. The process experiments indicate that the high level control system is able to adapt to varying combustion conditions and to maintain low emission levels. The control concept is adaptable also to existing systems.

Keywords: Combustion control, cascade control, fuzzy control, sensors, biomass, wood chips

1. INTRODUCTION

By combusting wood in the form of pellets, chips and logs, inexpensive and CO_2 neutral energy can be exploited. Therefore, significance of small-scale (10–1000 kW) biomass fired systems have increased over the last years. However, wood chip combustion in small scale is challenging due to extensive process fluctuations. The main source of fluctuations is irregular fuel feed. This is largely due to the variation in the degree of filling of the feeding screw. Additionally, the energy density and moisture content of the chips may vary significantly. These variations disturb the combustion, with the result of increased emissions, loss of efficiency and fouling of heat surfaces and sensors. Therefore, active control actions have to be made to compensate for the fuel feed fluctuations. However, to maintain the inexpensiveness of small-scale combustion systems also with better controllability, instrumentation should be kept on reasonable level. Moreover, robustness of sensors used must be such that the sensors last in the challenging combustion environment without defects or drifting. This work aims to provide an inexpensive and comprehensive control solution for these challenges also to existing combustion systems.

Small-scale wood combustion produces significant amount of fine particles and hence causes health hazards (Tissari *et al.*, 2007). Good combustion in CO and OGC (organic gaseous compound) point of view also reduces fine particle emission compared to the poor combustion (Tissari *et al.*, 2007). The CO and OGC emissions correlate well with each other as a function of excess air in the small-scale combustion systems (Eskilsson *et al.*, 2004). Hence, the natural goal of the control system is to minimize the CO emissions. However, the optimum in the emission point of view is not exactly the same as in the efficiency point of view (Ruusunen, 2006), because the efficiency optimum is got when the CO and OGC emissions are slightly increased due to lack of excess air. Therefore, enough excess air must be provided to reduce emissions with price of lower efficiency. On the contrary, NO_x emissions slightly increase as the excess air increases (Eskilsson *et al.*, 2004). Altogether, a suitable excess air level for the combustion system must be found and maintained at every heat output level in order to satisfy these conflicting requirements.

Lambda sensor is a widespread sensor used for feedback control in modern wood chip fired systems. However, the durability and long-term accuracy of the lambda measurement might not be optimal, especially if the sensor is exposed to highly unclean gas. This is in particular the case with discontinuous combustion with iterative start-ups, shut downs and pilot flame (Tissari, 2007). Hence, the better the quality of combustion, the longer lifetime is expected for the sensor.

Temperature measurements are common as a part of combustion control system in wood pellet fired systems, as temperature measurement is a reliable and inexpensive measurement. Its measurement signal has a good negative correlation with the flue gas oxygen content, if suitable amount of excess air is guaranteed. Unfortunately, the temperature measurement signal does not describe reliably the absolute value of the oxygen content. This is the case if the fuel quality and especially the moisture content (Ruusunen, 2008) of the fuel vary. Therefore, the temperature measurement by itself does not suit with the wood chip combustion as well as for the wood pellet combustion. In an earlier work (Korpela *et al.*, 2008), a soft sensor (e.g. Ruusunen & Leiviskä, 2004) framework was presented, in which the positive properties of temperature and lambda sensors were joined. The paper also covered passive stabilization methods and a low-level control strategy for the fuel feed control. This paper, instead, focuses on how to utilize the low-level system as a part of a comprehensive control strategy including fuel and air feed controls.

2. EXPERIMENTAL SET-UP

Combustion tests were carried out with a commercial system including a Säätötuli 200 kW stoker burner, which is not originally equipped with feedback combustion control. The burner is designed primarily for wood chip combustion, but it can also be used with other solid biomass fuels as well. Therefore, it is equipped with grate sweepers. Grate sweepers are metal rods, which are used to move the ash away from the grate and to equalize the fuel pile. Grate sweeping, however, causes significant disturbances to combustion, which can be e.g. compensated by reducing the primary air and increasing the secondary air around the sweeping (Korpela *et al.*, 2008). Therefore, compensations were used at trial runs illustrated in this paper. The idea of compensation is to damp momentarily the speed of pyrolysis and to provide extended amount of secondary air for increased amount of combustion gases due to the sweeping. As the grate sweeping compensation interfere the operation of a feedback control system, the control has to be locked during and straight after the compensation.

Two separate blowers fed primary and secondary air to the burner. Primary air was fed trough the grate upwards. Secondary air was fed from the roof downwards, from the back of the burner to boiler direction and from the sidewall to the opposite wall. The walls and the roof of the combustion space of the burner were made of paste. The fuel feed was realized continuously with an inverter control. The burner was installed in a commercial Arimax Bio 250 SP boiler with nominal capacity of 250 kW. A 24-m^3 fuel storage was equipped with back and forth moving rod dischargers. The system was pressure controlled by pressure measurement and by exhaust fan to a fixed 25 Pa underpressure level.

A control and measurement system was implemented in the LabVIEW environment. Some measurements were collected with a DT9806 data acquisition system. Some instrumentation of the commercial installation based on OMRON logic was utilized via an OPC connection. Flue gas analysis was made with Testo 330-2 flue gas analyzer, which was equipped with O_2, CO and NO measurements. 1.5 mm thick K type sensors for temperature measurements and a lambda system by Motec PLM for O_2 measurement were used. Additionally, air flow velocity sensors by Produal IVL 10 in air feed pipes were used. The velocity measurement values from the middle of the pipe were compensated to effective velocities according to the flow profile (e.g. Halttunen, 2007).

3. LOW LEVEL CONTROL

Korpela *et al.* (2008) presents a low-level control system based on temperature measurement from the upper part of combustion chamber. The goal of the low-level control system is to stabilize the fuel feed in prevailing conditions. In the case of typical fuel feeding disturbance, less fuel is fed to the burner compared to the normal level. As a result, the size of the fuel pile on the grate decreases and the combustion starts to fade. This can be observed e.g. with temperature measurements. As the temperature measurement signal starts to go down, the size of the fuel pile has already decreased. Therefore, fast and powerful control is required. Hence, nonlinear fuzzy controller of Mandani approach was generated. A block diagram of the implemented low-level control system is presented in Fig. 1. In addition, the grate sweeping compensation described in chapter 2 is included.

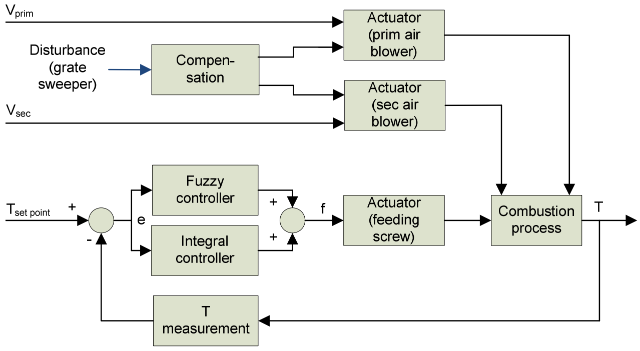

Fig. 1. Low level control loop, in which fuzzy controller and integral controller are in parallel. Air feeding signals are user defined, but air feed ratio is changed to compensate for the disturbances generated by the grate sweeping.

The fuzzy controller infers the compensation requirement based on temperature error signal and its rate of change. These both are divided into five regions, so there are 25 rules that define the status of the temperature. Based on the rules, inference is made between five compensation levels, whether to keep the normal feeding level or to change it. Descriptions of the rules are presented in Table 1. A detailed discussion of the fuzzy controller is presented in Korpela *et al.* (2008).

Table 1. Rules of the fuzzy controller. Vertical and horizontal headings stand for error signal (*e*) and its rate of change (Δ*e*), respectively. Headings: N=negative, P=positive, S=small, L=large, Z=zero. Content: S=subtract, A=add, B=base, S= small, L=large. E.g. If *e* is Positive Large AND if Δ*e* is Positive Small THEN Add Large.

e/Δe	NL	NS	Z	PS	PL
NL	SL	SL	B	B	B
NS	SL	SS	B	B	B
Z	B	B	B	B	B
PS	B	B	B	AS	AL
PL	B	B	AS	AL	AL

As the fuzzy controller compensates for the fast and intensive fuel feed changes, it is beneficial to set an integral controller in parallel with the fuzzy controller. It provides the control system to follow the slow fluctuations of the system. Additionally, the integral controller provides the possibility for the system to follow the operator defined temperature set point.

4. HIGH LEVEL CONTROL

4.1 Operation principle

An essential part of the low-level control is the selection of the appropriate temperature set point, which depends on several factors (Korpela *et al.*, 2008). The set point defines the operation point of the system. If the set point is too high, too much fuel is fed to the burner, and vice versa.

When the primary and secondary air feeds are kept constant, changing the temperature set point changes the excess air level, as the low-level control stabilizes the combustion by fuel feed. This feature enables the oxygen measurement by lambda sensor to provide fundamental knowledge about the suitability of the current temperature set point. Hence, Fig. 2 presents a block diagram of a cascade control system, which resets the appropriate temperature set point by lambda measurement. The primary controller to control the oxygen level is presented around the secondary loop of Fig. 1.

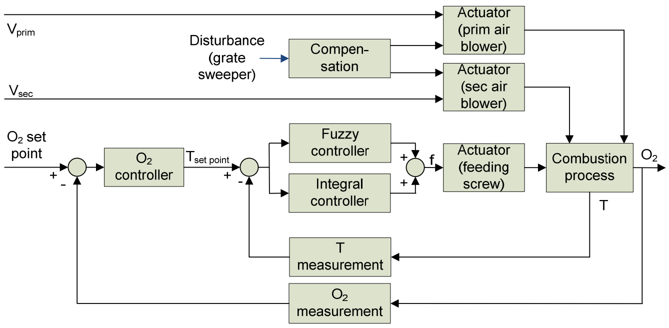

Fig. 2. Cascade control system. (Korpela *et al.*, 2008)

As the temperature set point is defined by the primary control loop, the parameters affecting the temperature set point, such as sensor location, combustion conditions and system structure, are mainly cancelled. Therefore, any representative temperature measurement is suitable for the control purposes. This is highly beneficial, when the control system is adapted to different combustion environments.

Cascade control is suitable with processes where there are multiple measurements and one actuator. There should also be long delays or time constants. Hence, combustion is a good application for the cascade control. The idea of the cascade control is that the secondary controller compensates for the disturbances before they affect the most important factor of the system controlled by the primary control loop.

The system is run by setting the desired oxygen set point and adjusting the primary and secondary air feeds to suitable levels. At the same time, the desired power level is roughly set, as the cascade control loop settles the fuel feed to balance with the air feeds. Hence, the goal of the control system is to maintain the power level at every combustion condition with low emissions and high efficiency. This includes also the cases when the fuel flow capacity of the fuel feeding screw is reduced for some reason, which would lead to power reduction without suitable compensation. Uninterrupted power production is vital for the end users, because the purpose of combustion systems is to produce heat in a reliable way.

When a significant change to the desired power level is made, the controllers are locked and manual step changes to fuel and air feeds are made to get new rough states. After a transient, the controllers are unlocked to find the optimum state for prevailing conditions. With this arrangement, the system can adapt to the heat demand, which enables longer operation periods and decreased amount of undesired start-ups and shutdowns. Care must be taken, that there is enough combustion air present also during transients. An approved solution for this is the air and fuel feed control used in power plants (e.g. Kovács & Mononen, 2007). When the power level is increased, air feed is increased first. On the other hand, when the power level is reduced, the fuel feed is reduced first. This assures that there is always enough excess air present, which provides proper combustion also during transients.

Stable underpressure in the combustion chamber enables stable combustion conditions (Kovács & Mononen, 2007). Hence, draft control assists the control system for good performance. If there is no such control, the produced power level floats with draft conditions. During high draft the air fans produces increased air flow levels and therefore higher heat power compared to normal draft, as the oxygen controller increases the fuel feed. On the contrary, during poor draft the power level is restricted because of reduced air flows. Problems will arise, if the draft conditions fluctuate faster than the control system has got time to adapt to the changes. In these cases, there will be increased emission and efficiency losses. The system might even start to oscillate, if the frequency of draft change is undesired for the system. All of these can be avoided by properly implemented draft control.

The appropriate oxygen set point depends on several issues. Combustion of wood with high moisture content requires larger portion total amount of air compared to fuel with low moisture content (Yang *et al.*, 2004), so with moist fuel the oxygen set point must be higher than with dry fuel. Additionally, the power level and system structure affect the set point. The optimal oxygen level decreases as the power level increases due to improved mixing of unburnt gases and secondary air. In addition, there is a structure defined oxygen limit with every system. When the limit is undercut, the low emission level is lost, so there should be large enough safety margins that the limit is never broken.

Air staging also has a significant impact on the behaviour of the control system. Even if the oxygen content of the flue gas is desired, the control system might not operate well if the air staging is improper in relation to the fuel moisture content. Therefore, the moisture content information is required, as it is the main parameter in defining the air staging ratio (Ruusunen, 2008) in general. More primary air is needed relatively as the fuel moisture content increases (Yang *et al.*, 2004; Ruusunen, 2008). An empirical suggestion is that the percentage of primary air compared to total amount of air is roughly the same as the fuel moisture content. The air staging has an effect also to emissions. Wiinikka & Gebart (2004) concluded that the total emissions of particles can be minimized in small-scale biomass combustion by minimizing the combustion temperature in the fuel-bed and maximising the temperature in the secondary combustion zone. This can be adapted by proper air staging, which also reduces NO_x emissions (e.g. Eskilsson *et al.*, 2004).

The more information there is on hand for the control system, the better it can be optimized. This applies especially with the fuel moisture content information. A rough estimate can be provided by the user. This is realistic in particularly with heat entrepreneurs, who get the information from the fuel supplier. Still, it would be by far beneficial if the information could be received automatically. Ruusunen (2008) presented an indirect temperature measurement based real time fuel moisture content estimator for grate combustion. After model calibration, the fuel moisture content estimate enables on line control of air staging, which results in improved system performance as a part of this control system, too.

The operation range of the control system of Fig. 2 is limited to normal combustion range. This means that the cause effect directions might change if the state goes too far from the normal range. This covers e.g. very high or very low oxygen levels. If the operation point of the system is lost for some large disturbance, the control system might not be able to recover the process to normal operation region. These cases must be taken into account by defining the region where the system may act. If these limits are exceeded, the interlocking and forced control must provide safe state of the system.

4.2 Case examples

Fig. 3 present responses to a step change in oxygen set point, in which primary and secondary controllers had been stabilized before the step change. The oxygen controller was implemented as an integral controller. The time constants of the temperature and oxygen controllers were some 20 and 125 minutes, respectively. Primary and secondary air feeds were constants, but primary air was reduced around grate sweeping while the control system was inactive. The first graph illustrates oxygen measurement by lambda sensor and its set point. The second graph presents the temperature measurement from the upper part of furnace and its set point. The third graph introduces the fuel feeding frequency. The peaks are due to the fuzzy controller and the slowly changing basic frequency is due to the integral controller. The fourth graph describes the primary and secondary air flows, and the fifth graph shows CO emissions and times of grate sweeping.

It can be concluded from Fig. 3 that the control structure is able to change the operation point due to the change in the oxygen set point. As the set point was increased, the oxygen controller started to decrease the temperature set point. This, in turn, reduced the fuel feed. The temperature measurement followed its set point quite well, as the fuzzy controller took actions when there were significant fluctuations due to the unequal fuel feed. Moreover, it can also be noticed that the basic level of CO was good. However, there were a few severe CO peaks, which were largely the results of grate sweeping. As only the primary air was reduced around grate sweeping to cut down the speed of pyrolysis, the amount of secondary air was not sufficient for clean combustion. Therefore, the reduction of primary air by itself is not a sufficient action to prevent CO peaks caused by grate sweeping.

Next, Fig. 4 presents a challenging test run at power level of 140 kW, in which constant oxygen set point of 7.9 O_2 % is kept. In this case, the conditions for good combustion were particularly challenging because of fuel behaviour in the storage. Even though the fuel storage was half-full and there were rod dischargers in the storage to equalize the fuel pile, the pile did not elapse equally. As a result, the fuel feeding screw in the storage was at times revealed, which led to even more fluctuating fuel flow than normally. The controllers and their tunings as well as the air feeds were the same as in the previous case, except that the secondary air was increased around grate sweeping.

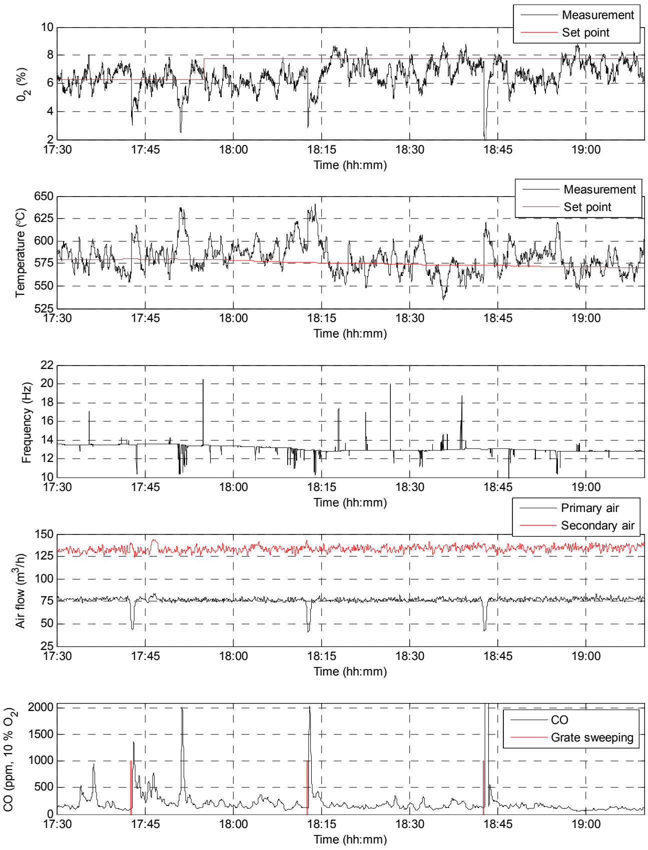

Fig. 3. Step responses to oxygen set point change with forest chips and with moisture content of 36 %. 1) Lambda measurement and its set point. 2) The temperature measurement from the upper part of furnace and its set point. 3) Fuel feeding frequency. 4) Primary and secondary air flows. 5) CO emissions (10 % O_2) and moments of grate sweeping.

It can be seen in Fig. 4 that at the beginning the oxygen level was around its set point and temperature measurement was above its set point. After the fuel feed reduction by the temperature controller, the temperature level found its set point, but the oxygen level rose instead. Therefore, it can be concluded that the primary and secondary controllers were not yet stabilized. Moreover, the fuel feeding screw in the storage was revealed occasionally. This led to high oxygen level and was slowly compensated by the cascade control, which increased the fuel feeding frequency. Additionally, the operation interval of rod dischargers was manually increased significantly during 11:32-11:45. As a result, the capacity of the feeding screw increased, with the effect that the oxygen level went down and the temperature level rose at time 11:55-12:10. However, the control system observed this and compensated the change. Unfortunately, the CO measurement was serviced at time 11:51-11:58. Due to the lower oxygen level compared to normal operation, it is likely that there were CO peaks during that time. In general, the CO level was rather low. This was even the case after the grate sweepings, so added secondary air was able to compensate for the undesired grate sweeping effect at this operation condition. Altogether, the control system handled this extreme case well and the desired power level was maintained. The control system settled the oxygen level to the set point, whereas the temperature measurement followed its set point quite well.

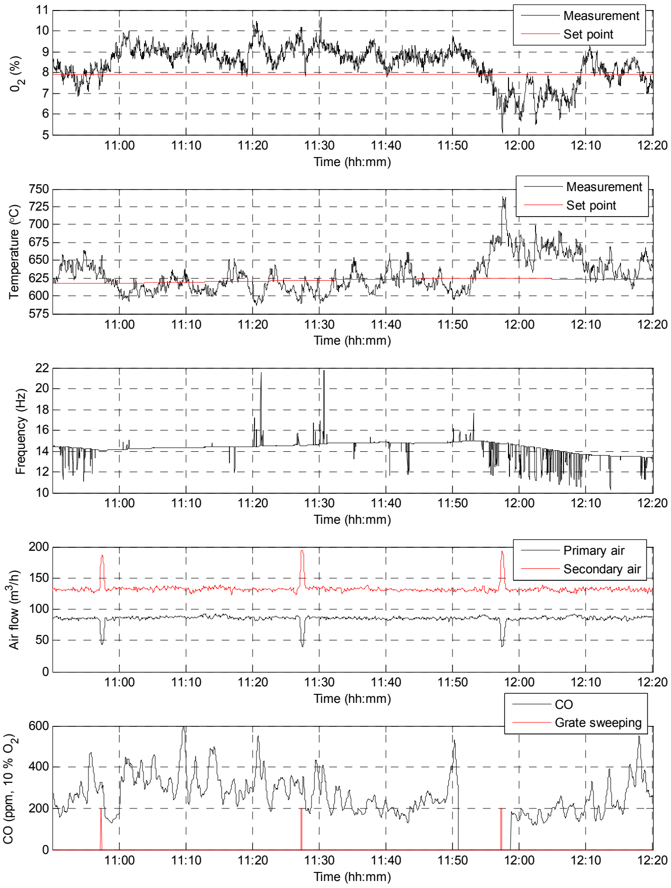

Fig. 4. A test run with the high level control system and with whole tree chips with moisture content of 33.5 %. Explanations of figures are similar to those in Fig. 3.

In a third case example, at time 12:18 of the case presented in Fig. 4, a change to fuel type was made. The half full fuel storage with whole tree chips with moisture content of 33.5 % were filled by stem chips with moisture content of 45,9 %. During the test, all the controls were similar to those in the previous cases, as the moisture content of the second fuel was expected to have a moisture content of some 40 %. Some 20 minutes after the fuel addition an impact could be seen. The oxygen level remained stable but it was a bit above the oxygen set point, so the oxygen controller increased the temperature set point moderately. However, the temperature started to oscillate dramatically a bit over the set point, and the fuzzy controller tried to compensate for the fluctuation forcefully. Additionally, the integral part of temperature controller reduced rapidly the basic fuel feeding frequency. This was the result when a 2-meter high wet fuel bed in the store tightened the fuel at the bottom, so the fuel flow capacity of the screw increased substantially compared to partly revealed screw. However, after some 40 minutes oscillation, the temperature settled down close to its set point. Still, the operation of the system was undesired, as the CO emissions increased slowly to 3000 ppm (10 % O_2). This indicates that even though there was enough excess air, the air staging was not suitable for such a wet fuel, as the amount of primary air compared to total amount of air was some 40 %. Due to the lack of primary air, the firing rate was too low for the burner. Hence, the grate surface of the burner became too small, and unburnt chips fell to the bottom of the combustion chamber. This also explains the accumulated CO emissions. As a conclusion, the control system was not able to handle the case due to improper air staging. Hence, it is by far essential that the air staging is reasonable for the fuel moisture. One should though remember that there is no sense in combusting such a wet fuel in this scale as was used in the test.

4.3 Benefits

The main benefit of the control system in addition to clean combustion, high efficiency and moderate instrumentation is the maintained power also in constantly varying conditions. Another benefit is that when the cascade control system has found the suitable temperature set point and if there are no major disturbances expected, e.g. fuel and power level remain the same, the primary loop can be switched off. This means that the lambda sensor can be taken away from the flue gas channel, as the secondary loop presented in Fig. 1 maintains the temperature set point to get proper efficiency and low emissions. After a significant change in the process conditions, the lambda sensor is put back to the process for a few hours, and a new temperature set point is obtained. In this way, the worst conditions for the sensor, e.g. start ups, shut downs and pilot flame situations, can be avoided. Then, the lifetime of lambda sensor can be extended substantially.

Additionally, it is highly beneficial that the control system is robust for different sensor installations and system structures. E.g., measurements presented in Fig. 3 and Fig. 4 are from separate trial run sessions, in which temperature sensor locations were slightly different. Still, the system operated well with the same set-ups in both cases. As the control concept is not dependent on the design of the combustion system, the concept is also adaptable to present systems.

4.4 Extended control strategy

Determination of air feeds and the desired power level as well as significant power level changes were done only manually in the trial runs. However, Fig. 5 presents a block diagram, in which the air feeds are set automatically. The fuel feed control loop is the same as in Fig. 2. Above that, there is a control loop for produced heat power, for which power set point and an estimate of the fuel moisture content are set. Based on this input information and system structure, the total amount of air is calculated. The power controller then defines the primary and secondary air flow requirements by moisture content estimate. It is worthwhile to set air flow measurements to both air feed cannels to enable air flow controls which set the air flow levels reliably despite of the nonlinear process and of the changes in process conditions. As in the manual case, the cascade control loop settles the fuel feed to balance with the air feeds. Then the control system balances the process to the desired heat output level, while the major power chances are handled in the way described in chapter 4.1. Simpler structure with less instrumentation is possible but also with reduced system performance.

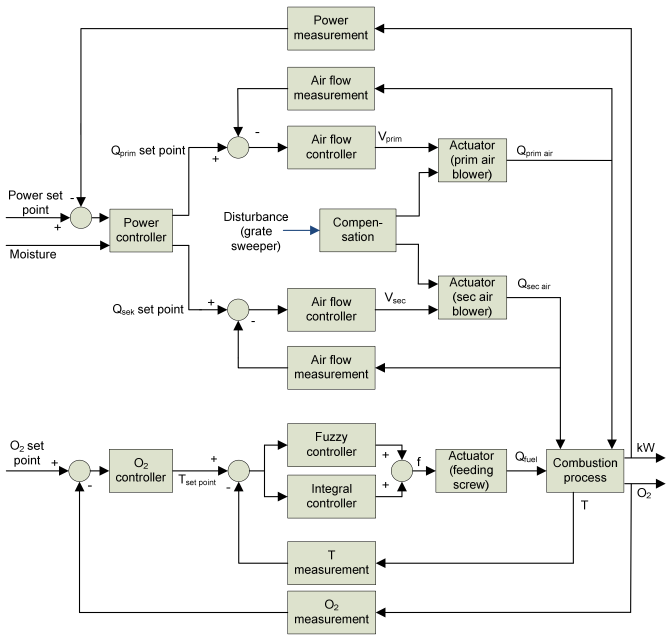

Fig. 5. High-level control system extended by power control.

5. CONCLUSIONS

In this paper, a hierarchical control concept in order to reduce the effect of fluctuation of the fuel feed is presented. The main task of the fuel feed control system is to settle the fuel feed to air feeds and to compensate for the temporary fluctuations in the fuel feed. The task of the air flow control is to set the primary and secondary air flows suitable for the power level and for the fuel moisture content. The air staging plays a major role in the performance of the presented control system, so suitable air staging must be guaranteed. As the control concept is not dependent on the design of the combustion system, the concept is adaptable to present systems.

The main benefit with the system is maintained power also in varying conditions. It is advantageous that the lambda measurement provides fundamental knowledge about the suitability of the temperature set point of the low level control system. An advantage is the possibility to take the lambda probe away from the flue gas channel, when the cascade control system has found the suitable temperature set point and when there are no major disturbances expected. Then the secondary loop maintains the temperature set point to get proper efficiency and low emissions. In this way, the worst conditions for the sensor can be avoided and lifetime of the lambda sensor can be extended. Most importantly, the control system provides high efficiency and clean combustion with moderate instrumentation.

Test results of a 200 kW commercial system were presented. The process experiments indicate that the high level control system is able to adapt to varying and challenging combustion conditions and to maintain low emission levels.

The future work covers long-term performance monitoring of the control system (Fig. 5) in a commercial system. This will also include reference trials with conventional control structures e.g. discussed by Korpela *et al.* (2009).

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Indirect NO_x emission monitoring in natural gas fired boilers

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ABSTRACT

New emission regulations will increase the need for inexpensive NO_x emission monitoring solutions also in smaller power plants. The objective in this study is to find easily maintainable and transparent but still valid models to predict NO_x emissions in natural gas fired hot water boilers utilizing existing process instrumentation. With a focus on long-term applicability in practical installations, the performance of linear regression is compared in two municipal 43 MW boilers with three widely used nonlinear methods: multilayer perceptron, support vector regression, and fuzzy inference system. The linear models were the most applicable providing the best estimation results (relative error of <3% in all cases), generalizability and simplicity. Therefore, the approach fulfils the requirements of the Industrial Emission Directive and is valid to be applied as a soft sensor in PEMS[1] applications in practise. However, each boiler model should be identified individually.

1. Introduction

There is an increasing demand to protect the environment from harmful emissions. One of the main sources of air pollution are combustion processes, which emit sulphur dioxide (SO_2), particulate matter, carbon monoxide (CO) and dioxide (CO_2), unburned hydrocarbons (C_xH_Y), and nitrogen oxides (NO_x). NO_x emissions are considered as primary pollutants, since they can cause health issues in addition to environmental problems, e.g. photochemical smog, acid rain, tropospheric ozone and ozone layer depletion (Skalska, Miller, & Ledakowicz, 2010).

As energy production is a major source of emissions, authorities have set further tightening emission limits to power plants. In the European Union (EU), flue gas emissions, i.e. SO_2, NO_x and dust, are restricted by the Industrial Emission Directive (IED, 2010), which came into effect in 2016. It is applicable in all existing power plants exceeding 50 MW. Additionally, the combination of plants where flue gases from multiple individual plants with rated thermal input over 15 MW could be discharged through a common stack are considered as a single combustion plant and their capacities are combined when calculating the total thermal input. This aggregation rule extended the scope of the IED to combustion plants with rated thermal power between 15 and 50 MW. Especially in Nordic countries, these <50 MW boilers typically have low operation hours. They are typically remotely operated and built for peak load and reserve capacity generation in district heating networks. Their role, however, might change in the future, as district heating networks and their components become more intensively interlinked with renewable energy generation systems.

According to the IED, the concentrations of SO_2, NO_x and dust in flue gases must be measured continuously in all combustion plants exceeding total thermal capacity of 100 MW. Otherwise these emissions (and, CO for gas fired plants) must be measured periodically at least once every 6 months. However, the IED provides an alternative to discontinuous SO_2 and NO_x measurements through other procedures if they are verified and approved by a competent authority. Such procedures must rely on CEN or other international standards, which ensure the provision of data of scientific quality.

There are three options to monitor flue gas NO_x emissions from a combustion unit, i.e. by periodic measurements, CEMS (Continuous Emission Monitoring System) or PEMS (Predictive Emission Monitoring System). Periodic measurements are typically performed with calibrated equipment and conducted by an emission-testing laboratory with moderate costs. However, it is not guaranteed that the emission levels are valid in actual operation between the campaigns. As illustrated e.g. by Korpela, Kaivosoja, Majanne, Laakkonen, Nurmoranta, and Vilkko (2016), heat only boilers may increasingly be operated with fast power transients to stabilize the district heating networks when nearby combined heat and power (CHP) plants contribute to balancing of the

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[1] Predictive Emission Monitoring System.

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electric power system. In these cases, the periodic measurements are not able to determine the actual NO_x emissions (although this is not yet required in IED). In CEMS, the emission monitoring equipment is installed on-site and is active during plant operation. CEMS provides online and actual information on emissions, when maintenance and calibrations are conducted according to standard procedures. However, purchase and maintenance costs of CEMS are relatively high, especially compared to their benefits in boilers that have low power outputs and few operation hours. PEMS combines the positive properties of the former methods, as PEMS is a software based monitoring system, which utilizes existing process measurements and calculation models to estimate power plant emissions. There is no accepted CEN standard for PEMS at present but preparation is under way by CEN/TC 264/WG 37.

Indirect measurements, such as those calculated in PEMS, require a model to be driven with the online measurements. The model can be based on first principles and the physical properties of the boiler, measurement data correlations, or the combination of them. Derivation of an accurate first principle model for NO_x emissions is a complex task due to several factors, for example, complex nitrogen reactions. Hence, data based models are dominating in NO_x emission estimation. The purpose of NO_x emission estimation is primarily to study and predict the emissions in different operating conditions from process perspective, to derive indirect NO_x emission monitoring solutions to provide analytical redundancy to online measurements, or to estimate the emissions when no NO_x measurement is available. Numerous data based NO_x emission models have been presented in literature for various combustion applications (e.g. pulverized coal boilers, fluidized bed boilers, grate boilers, gas boilers, gas turbines, engines) in various power ranges and fuels (e.g. coal, biomass, waste, oil, and gas). These aspects significantly affect NO_x emissions and therefore also NO_x emission estimation. These NO_x models typically utilize existing process measurements. The amount, quality and type, and the maintenance procedures of the measurements that can be utilized in NO_x estimation applications are dependent directly or via environmental permits on the power rating of the plant, its location and the operation purpose (e.g. hot water or steam only, power generation). Therefore, the variety of applied modelling methods in data based NO_x estimation is vast, covering linear multivariate regression and nonlinear multivariate methods, such as radial basis function (RBF), multilayer perceptron (MLP), partial least squares (PLS), least squares support vector machine (LSSVM), Fuzzy Inference Systems (FIS), Kohonen's self-organizing maps (SOM), and so on. The NO_x models are mainly static, but dynamic models also exist when the dynamics have a significant role in NO_x formation.

Data based models are, in general, only valid in the operating conditions which exist in the identification data used in their training. Therefore, the collection of the training data should be carefully considered. The data for model derivation can be generated by measuring normal operation of the combustion plant, by conducting separate trial runs to stimulate the processes, or by simulating the process with some other models. The first approach typically requires input data collection over a long period; however, the data may then not cover all potential operating conditions. Separate trial runs may improve this situation significantly, but the amount of data collected with this approach is usually much smaller than in the case of online process data collection. In the third approach, the input data to the models may be derived from complex combustion models, e.g. Computational Fluid Dynamic (CFD) models, but this approach is hardly a general solution in PEMS applications. In this study, separate and comprehensive trial runs were conducted to enable a reliable identification of the models. The models were validated by data collected from normal process operation but with increased excitement of the processes by frequent set point changes. This allows the performance of the models to be evaluated in realistic conditions, which is a prerequisite for the presented approach.

In summary, there are numerous approaches and NO_x models for different kinds of combustor applications. Selection of suitable NO_x modelling methods is case specific taking into account all relevant aspects determining the appropriate modelling approach for the task. This paper focuses on indirect NO_x emission estimation in natural gas (NG) fired boilers. The applicable literature on the topic is reviewed next. In Iliyas, Elshafei, Habib, and Adeniran (2013), a three-dimensional (3D) CFD model for a 160 MW gas boiler was developed to produce data for computational NO_x and O_2 sensors. The system utilized 6–8 input variables and RBF and MLP neural networks, of which the RBF model with six input variables performed best (Ferretti & Piroddi, 2001) utilized a 3D CFD model and developed a neural network-based strategy utilizing two different learning strategies to NO_x emission estimation for an oil and methane fired 320 MW thermal power plant. Eng-genes and MLP neural networks were applied to the same power plant by Li, Peng, Irwin, Piroddi, and Spinelli (2005), utilizing Arrhenius type equations in a semi-empirical model. The last two papers utilized cell temperatures derived with the CFD model as model inputs, which are usually not available in real systems (Li et al., 2005). Another semi-empirical model was presented in Bebar, Kermes, Stehlik, Canek, and Oral (2002), where simplified kinetic equations utilizing six input variables describing the formation of nitrogen oxides were developed for a testing facility. There, the average estimation error was 9.1%, with the maximum of 25%. In another study, a NO_x soft sensor for NG fired water tube boiler was developed by Shakil, Elshafei, Habib, and Maleki (2009). This model utilized static and dynamic neural networks. A principal component analysis (PCA) was used to reduce model inputs from 9 to 6, and genetic algorithms were used to identify the system's time delays. The estimation accuracies of 83% and 99% were obtained with static and dynamic models, respectively. In another case, application of linear models was studied with full or limited operation regions (Korpela, Kumpulainen, Majanne, & Häyrinen, 2015) and linear and non-linear models were compared (Kumpulainen, Korpela, Majanne, & Häyrinen, 2015) in natural gas fired 43 MW hot water boilers.

Though linear models were considered in the last two articles, the literature on prediction of NO_x emission in NG combustion is focused on nonlinear and multiple input variable models. These models can provide quite accurate NO_x predictions but are arguably not generally applicable nor inexpensive solutions to PEMS applications. As this paper is a significant extension to the last two articles, there are no other published NO_x models meeting the objectives of this paper. The objective of this study is to evaluate the accuracy, generalizability and long-term applicability of indirect NO_x estimates in existing NG fired boilers, in order to apply the methods in practise in a cost effective way. For the study, trial runs were conducted with two similar 43 MW NG fired hot water boilers. The studied boilers are structurally relatively simple with a single burner with fixed air distribution simplifying the modelling task. The goal is to find maintainable and transparent but still valid models for NO_x estimation and to evaluate the performance in varying operating conditions. Requiring easy maintainability and transparency promotes the application of simple models, e.g. linear regression models, which require tuning only a few parameters. As the performance drop cannot be too significant, the simple models have to be compared with models that are more complex in order to estimate the differences in performance. Hence, the linear multivariate regression models are compared with commonly used nonlinear models, which are identified with automatic procedure without any manual fine-tuning. Additionally, the number of input variables and selection of data sets are examined together with model sensitivity analysis.

2. NO_x formation, control and identification

The abbreviation NO_x refers to nitrogen monoxide (NO) and nitrogen dioxide (NO_2), which are present in the flue gas because of chemical reactions of nitrogen and oxygen. Approximatively 95% of the NO_x emitted from combustion processes consists of NO and c. 5% of NO_2. As the majority of NO reacts to NO_2 in the atmosphere, the environmental effects are practically the same for both of the NO_x components (Van Loo & Koppejan, 2008), and hence the emission limits for NO_x are typically set for NO_2, e.g. in IED.

This section provides some background information about NO_x formation. Primary reduction methods are also briefly discussed, as these methods are actively in use and they provide information on which parameters need to be considered while predicting the NO_x emissions. Additionally, identification of NO_x emissions is discussed. In-depth presentations of NO_x formation and control can be found from literature, e.g. from Hill and Smoot (2000), and Skalska et al. (2010), respectively.

2.1. NO_x formation mechanisms and primary reduction methods

Element nitrogen contributing to NO_x emissions originates from two sources, i.e. bound organic nitrogen from fuel and elemental nitrogen (N_2) from air. Based on these nitrogen sources, nitrogen oxides are formed in combustion by four different mechanisms: (1) *fuel NO_x* mechanism (2) *thermal NO_x* mechanism, (3) *prompt NO_x* mechanism, and (4) via nitrous oxide (N_2O). Fuel NO_x is formed in reactions after the release of fuel bound nitrogen when the fuel is heated during volatilization, and is therefore to major extent dependent on the content of chemically bound nitrogen in the fuel. Fuel NO_x is mainly reduced by providing a fuel rich combustion environment by air or fuel staging in the primary combustion zone. Thermal *NO_x formation* requires sufficiently high temperature (>1300 °C) and residence time for dissociation of the atmospheric diatomic molecules N_2 and O_2. These can, for example, be reduced by lowering reaction times at high temperatures and especially by reducing the peak temperatures below the threshold, e.g. by favouring long and radiative flames, recirculating flue gas, reducing air preheating, injecting water or steam, and by reducing excess air (Kilpinen, 2002). Prompt NO_x formation takes place in reactions of atmospheric nitrogen and hydrocarbon radicals in fuel-rich regions. The mechanism is less dependent on temperature and significantly faster than thermal NO_x (Turns, 2000). NO_x formation via N_2O produces NO_x from atmospheric nitrogen. The mechanism is significant with high excess air and pressure, and low temperature (Kilpinen, 2002; Turns, 2000).

2.2. NO_x emissions in natural gas fired burner

Combustion system design, fuel type, process operation and prospective NO_x abatement techniques significantly influence NO_x emissions (Bělohradský & Kermes, 2012; Habib, Elshafei, & Dajani, 2008; Ilbas, Sahin, & Karyeyen, 2016; Skalska et al., 2010; Skryja, Bělohradský, Hudák, & Jurena, 2015). When analysing one specific boiler, the interest focus on the dominating NO_x formation mechanism. In NG fired boilers, the contributions of prompt and N_2O based NO_x mechanisms are typically less than 5% each (Kilpinen, 2002). Nitrogen included in the NG is in elementary form (N_2), which behaves similarly to atmospheric nitrogen (Kilpinen, 2002), and therefore fuel NO_x formation is insignificant in NG combustion. However, the presence of chemically bound nitrogen in the gaseous fuel influences the formation of fuel based NO_x (Skryja, Bělohradský, & Hudák, 2014). This must also be considered if other gases than pure NG are combusted and especially if the fuel quality changes. The dominant NO_x formation mechanism in NG combustion is the thermal one (Turns, 2000). However, the dominant mechanism may change depending on the operating point, so the trial runs for NO_x identification must be designed with care.

In thermal NO_x formation, the primary variables on NO_x yields are time, temperature, and oxygen availability (Turns, 2000). Therefore, any actions affecting flows and especially flame temperatures (e.g. via fuel power, air distribution, active flame cooling, air preheating, and boiler water temperature) or flue gas oxygen contents must be considered. Potential primary NO_x control methods aim at preventing the formation of NO_x emissions through these means. The potential methods include low-NO_x burner structures, reduction of excess air, air or fuel staging, water or steam injection, and flue gas recirculation. Therefore, the NO_x control actions are only relevant to the indirect NO_x emission estimation if they affect the combustion conditions actively. In these cases, the effect of these control variables must be included in NO_x models. Secondary NO_x reduction methods, such as selective catalytic and non-catalytic reduction systems (SCR, SNCR), that aim at reducing already produced NO_x emissions have not been applied, at least yet, to boilers of the considered category.

2.3. NO_x emission identification

When identifying a NO_x emission model based on measurement data, it is vital to consider all the affecting variables. Ferretti and Piroddi (2001) concluded that NO_x correlations in literature can be expressed in general form:

$$[NO_x] = f(p, \tau, T, \lambda), \tag{1}$$

where NO_x emissions are expressed as a function of pressure, residence time, temperature and excess air ratio, of which the first three are related to fuel flow rate and therefore to fuel power. Depending on the structure of the plant however, the number and quality of measurements and controllable parameters may vary significantly. Fig. 1 presents a general framework for NO_x estimation with various affecting controllable and uncontrollable variables, though some other variables may exist especially in large power plants. In practise, some of the measurements may be missing or otherwise unavailable. In that case, the control signals of actuators can be utilized instead, but then the potential nonlinearity of the characteristics of the actuator is not included in the NO_x model. Additionally, it should be noted that not all the variables are free variables, in other words, they might be controlled or linked to other variables e.g. by a control chart linkage. It is beneficial to conduct initial tests systematically and then to analyse the effect of predetermined variables on NO_x emissions, which is illustrated e.g. in Bělohradský and Kermes (2012) and Skryja et al. (2015). After the main affecting input variables are known, the identification and validation tests can be conducted. However, if the boiler or burner are modified or the operation strategy of the boiler changes significantly, the process should be thoroughly identified again.

3. Test setup and trial runs

The test plant was a municipal 258 MW_{fuel} back-up heating plant in Helsinki, Finland. The plant consists of six 43 MW_{fuel} hot water boilers connected to a common stack. The plant is a remotely operated back up and peak load plant. Typical annual operation hours of the boilers are relatively low, but still the plant is a solid part of the district heating network of Helsinki. Three of the boilers can be equipped with either NG or heavy fuel oil (HFO) burners and three with only HFO burners. The trial runs presented here were conducted with two NG fired boilers (i.e. Boiler A and B). All the boilers are identical, and the burners (one at a time in a boiler) are located at the ceiling of the vertical combustion chamber with downward flames. The gas burners were originally similar, but due to ongoing burner modifications, they were slightly dissimilar with respect to air feed structure. Therefore, the NO_x emissions of the burners behave to some extent differently and represent two similar but not identical cases. Both burners had fixed air distribution structure that can be changed only mechanically. NG came from Siberia, Russia, via gas pipe. The nitrogen content of the NG is in elementary form (N_2) and is less than 1% of the gas volume.

The trial runs were conducted during four separate measurement campaigns with similar outdoor conditions. Measurements were provided by the normal measurement setup present in each boiler, including fuel flow, flue gas O_2 content, temperatures of flue gas, feed water, return water, and boiler room, and pressures of combustion chamber and combustion air. Additionally, a portable flue gas analyser was used that consists of (a) Horiba PG-350 SRM portable flue gas analyser with NO_x, SO_2, CO, CO_2 and O_2 measurements, (b) gas conditioning, drying and sampling system PSS-5, and (c) portable gas sample probe PSP4000-H. The data from separate sources, i.e. the automation system and external NO_x analyser, were synchronized and combined to a data set

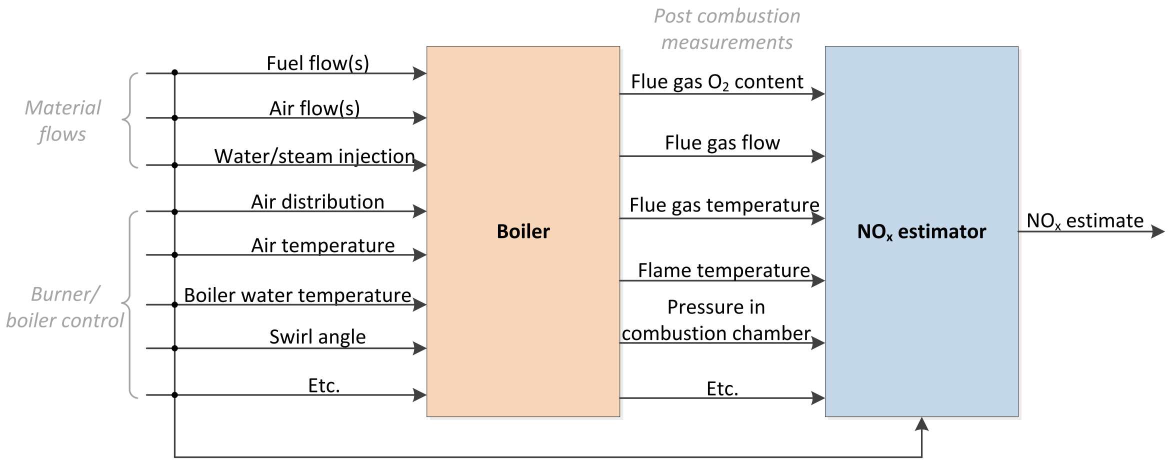

Fig. 1. A generic framework for NO_x estimation.

with 15-second sampling interval. Due to the standard procedure of drying of sample gas that is fed to the analyser, the analyser measured the gas properties (i.e. O_2, CO & NO_x) from dry flue gas (marked as dry basis, d.b.). In comparison, the fixed O_2 sensors of the boilers measured oxygen content directly from moist flue gas (marked as wet basis, w.b.). The difference between dry and moist flue gas contents depends on the fuel hydrogen content and is $X_{d.b.} = 1.233\ X_{w.b.}$ for NG in stoichiometric conditions, i.e. no excess air, but the factor 1.233 is lowered when the oxygen excess is increased. This fraction is included in the parameters of the data based models, but it should be kept in mind when interpreting the O_2 levels from different measurements. Additionally, the gas properties are converted by standard procedure to represent the emission levels in reference O_2 level, which is calculated by

$$f_{O_2} = \left(20.95 - X_{O_2,measured,\ dry}\right) / \left(20.95 - X_{O_2,reference}\right). \tag{2}$$

$X_{O_2,reference}$ refers to O_2 reference, a fuel dependent parameter which is 3% for gaseous fuels. In summary, the calculated NO_x estimates are presented in the form that is applied in the IED, i.e. [mg NO_2/N m^3, O_2 = 3%, d.b.], where N m^3 stands for normalized volume in standard temperature and pressure, i.e. $T = 0$ °C & $p = 101\ 325$ Pa. The emission values required by the IED are hourly averages, but here the applied sampling and estimation interval was 15 s and no averages were calculated. This approach was used to study the momentary emission conditions in the process and to evaluate how correctly the method is able to estimate the emissions in all the relevant process conditions.

The manipulated variables of the boilers are fuel flow (controlled primarily based on power requirements), airflow (controlled in relation to fuel flow and is fine-tuned based on flue gas O_2 content), and boiler-water recirculation flow (controlled by flue gas temperature and boiler return water temperature that is 60 °C). Combustion air is taken from the boiler room without air preheating, except that the incoming air to the boiler room is heated to be clearly above 0 °C. Hence, the combustion air temperatures are typically in the range 5–15 °C. The temperature of feed water to the district heating network varies between 110–120 °C, but is typically controlled to 110 °C. The pressures of combustion air and combustion chamber are measured but their values are fixed in relation to the NG flow, so they are not independent variables in practise. To conclude, as the boiler water and combustion air temperatures have very limited operating ranges, air distribution is mechanically fixed and there is no water injection to boilers, the only controllable parameters of the boiler are air and fuel flows. The gas flow directly determines the fuel power in NG combustion. Within a fuel power level, alterations to the airflow are followed by changes to flue-gas oxygen contents. Therefore, the fuel flow and flue-gas oxygen content are of special interest when conducting the tests. This is also supported by the NO_x theory presented in Section 2 and the results from preliminary tests, which have been excluded here for convenience. However, other variables, for example, flue gas temperature, pressure in combustion chamber, or return water temperature, might fluctuate and have an effect on NO_x emissions. However, as these variables cannot directly be affected, the identification of their contribution is more difficult to determine. Still, their contributions are studied in Section 5.4.

For NO_x model identification, two separate trial runs were conducted with both boilers: *identification* and *extra validation* runs. The identification runs used constant power levels within the normal operating ranges. They are referred to as *train* sections as they relate to model training. At every power level, air feed steps to vary oxygen levels were performed exceeding the typical operating regions. The sections of constant power levels were used for identification of the NO_x models. The power transition sections, called *test* sections, were run in normal automation mode with power level set point changes and with constant O_2 set points. The test sections were used for validating the model performance within the identification day. The ultimate target is that the trial runs in practical cases could be conducted in a day for each boiler and contain both identification (i.e. *train*) and validation (i.e. *test*) sections. In this work, however, extra validation runs with both boilers were conducted in order to estimate repeatability, the effect of varying process conditions, and the contribution of normal automatic operation in contrast to the manual runs. These extra validation runs were executed in normal automation mode, i.e. feedback control loops were active, with set point changes to flue-gas oxygen content and to fuel power in Boiler A and heating power in Boiler B. The trial runs of Boiler A took place on adjacent days with similar winter conditions. The trial runs of Boiler B, however, were conducted in winter (identification run) and in autumn (extra validation run) with a 7-month time difference. The processes were unchanged between the runs. Only the boiler under study was in operation during each run, all the others were shut down, except in the beginning of the identification run of Boiler B.

In the identification runs, step changes to air feed were conducted at different power levels in manual mode. The responses to fuel flow and flue gas oxygen content, which are the process measurements used for model inputs, are presented for Boilers A & B in left of Figs. 2 and 3, respectively. As the lower heat value of the NG is 36 MJ/N m^3, the constant fuel powers represent 25.0, 35.5, and 18.5 MW for Boiler A and 37.4, 30.4, 24.6, and 17.2 MW for Boiler B. Oxygen level 2.2% O_2 (w.b.) is a typical set point used in remote operation.

The extra validation runs of Boilers A and B are presented in Fig. 2 and Fig. 3 (right). The runs were conducted in normal automation mode, and the changes to process states were conducted by fuel power and O_2 controller set point changes. With Boiler B, the values of the controlled variables fluctuated significantly during the trial run, due to exceptionally high heat power and temperature fluctuations in the

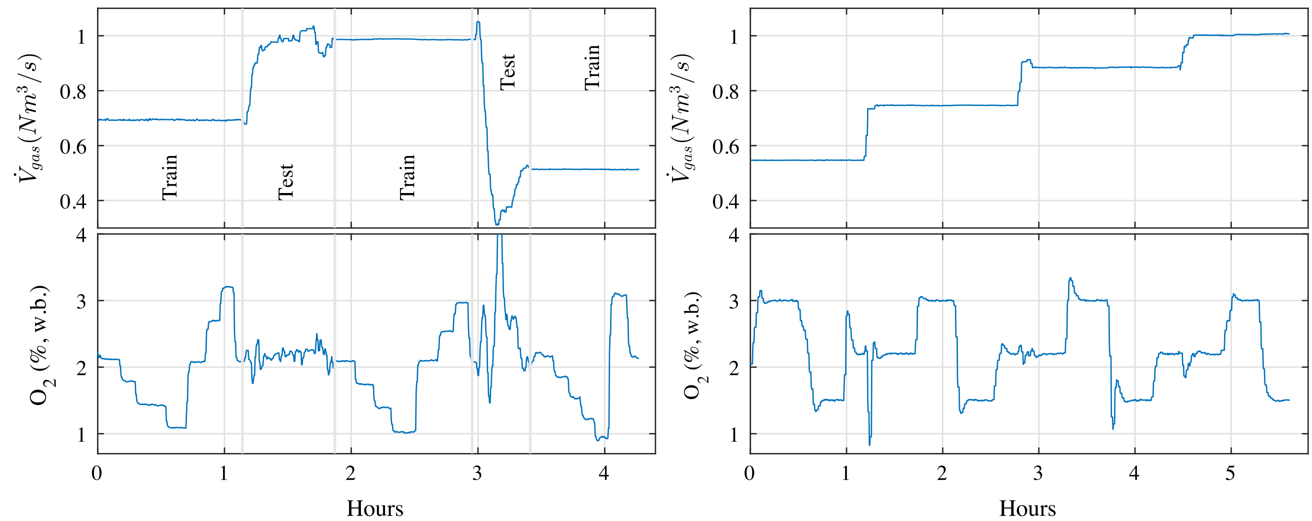

Fig. 2. Measured model inputs of Boiler A in the identification run (left) and extra validation run (right), i.e. gas flow (top) and moist flue-gas oxygen content (bottom).

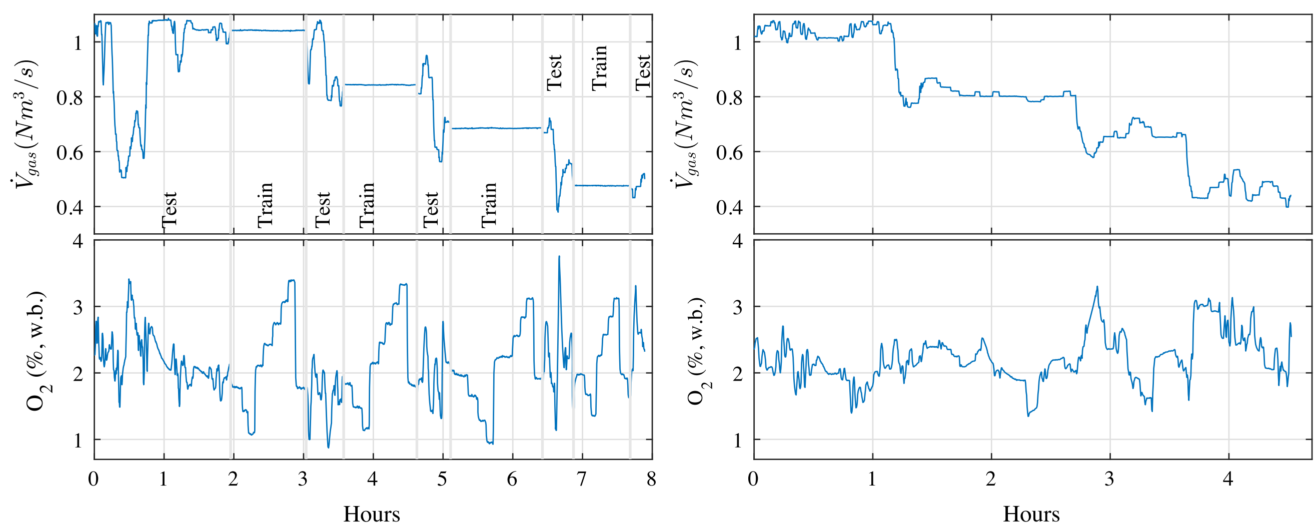

Fig. 3. Similar to Fig. 2 in case of Boiler B.

district heating network and limited control performance of the boiler. Therefore, the run is operated in close to extreme operating conditions, which would indicate that if the NO_x estimation succeeds in the run, it is expected to perform at least as well in normal operation conditions.

Figs. 4 and 5 present scatter plots of NO_x and CO emissions as a function of flue-gas oxygen contents for Boilers A and B, respectively. Fig. 4 illustrates that the NO_x data points at small and medium power levels are linear and almost linear at high power level. However, the respective plot of Boiler B in *Fig.* 5 indicates that the NO_x data points are almost linear at two of the lowest power levels, but significant nonlinearity and some variance can be seen at two of the highest power levels and especially at oxygen levels higher than 3.0% (d.b.). Therefore, it is expected that linear models are not fully applicable in the whole oxygen range in the case of Boiler B.

The typical set point for O_2 used in normal remote operation is 2.2% O_2 (w.b.) which corresponds to 2.7% (d.b.). Therefore, CO scatter plots presented in Figs. 4 and 5 indicate that there is potential to reduce the oxygen set point without the threat of increasing CO, which would be beneficial from the perspective of efficiency, NO_x emission level, and NO_x response linearity.

4. Methods

As was pointed out in the Introduction, quite a few data based modelling methods can be applied in NO_x emission estimation. The objective of this study was to find practical solutions for NO_x emission monitoring in the existing case processes in the long-term, which introduces additional requirements to the applied methods. In addition to prediction accuracy, the model must be reasonably straightforward to identify and maintain in varying process conditions, and the selected modelling methods should preferably be widely in use and easily available. Based on these criteria, four modelling methods were selected for the study, of which one is linear (affine) and the others nonlinear. Some other relevant methods may exist, but the selected methods should reveal most of the modelling potential. All the chosen methods are static since the dynamics of NG combustion is very fast.

The four applied methods are presented next. *Linear multivariate regression* is the most basic data based modelling method (Draper & Smith, 1998). It is straightforward to identify without iterative optimization of parameters and is easy to update and maintain. *Multilayer perceptron (MLP)* neural networks (Haykin, 1994) with one hidden layer containing a sufficient number of neurons provides a universal approximation. Hence, they are very commonly applied nonlinear regression models.

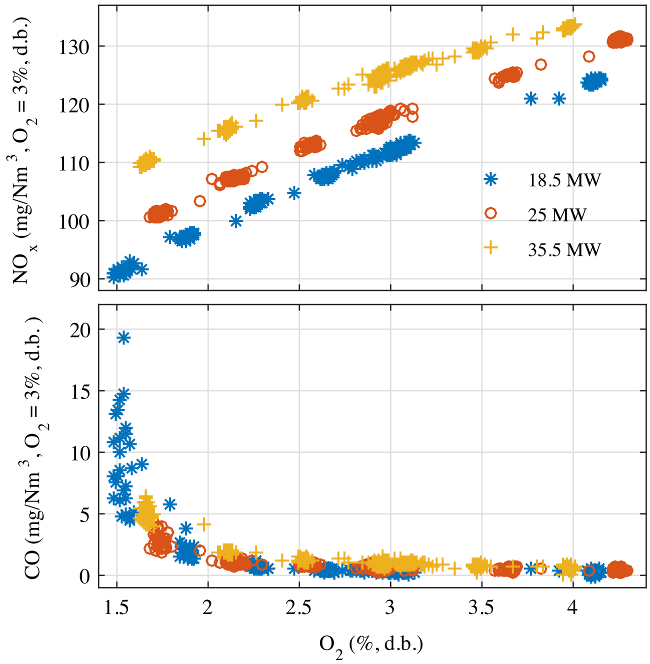

Fig. 4. Measured NO_x (top) and CO (bottom) emission of Boiler A as functions of O_2 level at constant power levels. The data is collected from the train sections of the identification run.

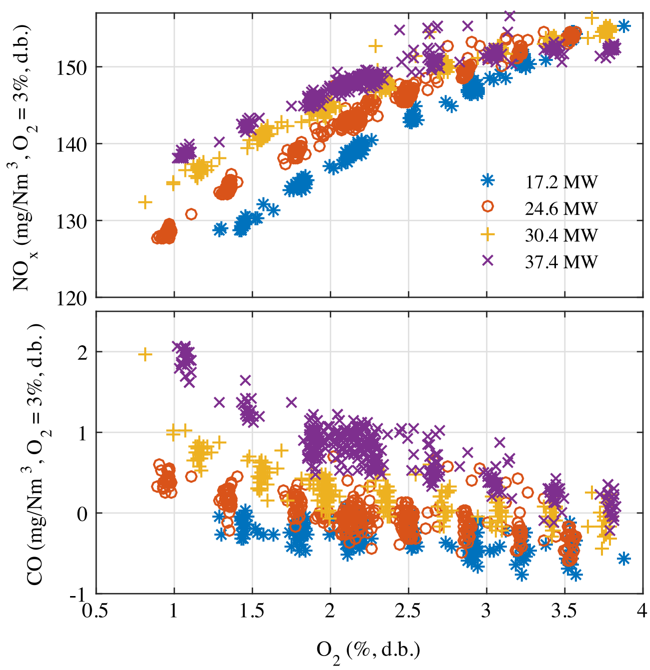

Fig. 5. Similar to Fig. 4 in case of Boiler B. The CO curve is slightly biased due to a calibration error.

In this work, the MLP networks were trained using the Levenberg–Marquardt method presented in Nørgaard (2003). *Fuzzy inference system (FIS)* of Sugeno type is commonly applied for nonlinear regression (Sugeno, 1985). The final output is a weighted average of the constant or linear output functions, weighted by the membership functions of the input variables. The membership functions can be identified from the data by ANFIS (adaptive-network-based fuzzy inference system), a hybrid-learning algorithm, which combines the least-squares method, and the backpropagation gradient descent method (Jang, 1993). In this study, an ANFIS model with linear output functions and bell-shaped membership functions were used for input variables. *Support Vector Regression (SVR)*, such as ν-SVR (Schölkopf, Smola, Williamson, & Bartlett, 2000), can be used for nonlinear modelling of continuous data. The parameter ν controls the number of support vectors in the model. In this study, radial Basis Function (RBF) kernels $K(\mathbf{x}_i, \mathbf{x}_j) = \exp(-\gamma\|\mathbf{x}_i - \mathbf{x}_j\|^2)$, $\gamma > 0$ were used, which is a versatile method and works well in most applications (Hsu, Chang, & Lin, 2016). For that, a software package LIBSVM (Chang & Lin, 2011) was used in this study.

It should be noted that the estimation results of MLP and FIS are to some extent random due to randomly selected initial values. Therefore, the modelling results of these methods might be slightly dissimilar when the identification is repeated. The models presented in this article were identified several times and the models converged well to similar results. In comparison, linear regression and ν-SVR provide deterministic estimates.

The performance of the NO_x emission estimates were analysed by comparing absolute and relative RMSE (Root Mean Squared Error) values, that are based on absolute (ϵ_i) and relative (δ_i) errors, expressed as

$$\epsilon_i \left[\text{mg/N m}^3\right] = \text{NO}_{x,est,i} - \text{NO}_{x,meas,i} \tag{3}$$

$$\delta_i \left[\%\right] = 100 \cdot \epsilon_i / \text{NO}_{x,meas,i} \tag{4}$$

$$\text{RMSE} \left[\text{mg/N m}^3\right] = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\epsilon_i^2} \tag{5}$$

$$\textit{Relative}\ \text{RMSE} \left[\%\right] = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\delta_i^2}. \tag{6}$$

where N denotes the number of samples.

5. Results

In this section, the NO_x models and their estimation results are presented. However first, the model derivation procedures, including model structure selections, are presented. The idea is that the NO_x emission models should be identified with standard procedures without any manual fine-tuning in order to enable straightforward implementation of PEMS applications by operators that might be unfamiliar with the modelling methods. In Section 5.1, the data is first scaled and then the structures of the nonlinear models with two input variables are detected by cross validations. After fixing the model structures, the NO_x models are identified and presented for Boilers A and B in Sections 5.2 and 5.3, respectively. Section 5.4 examines the effect of additional input variables with selected model structures. Section 5.5 discusses the selection of model identification data, and finally, Section 5.6 discusses the model sensitivity to errors in the measurements used as model inputs.

5.1. Data pre-processing and cross validation

The input variables were scaled before applying the nonlinear modelling methods. The normal operating range of each input variable was scaled to [−1 1]. The first part of the section concentrates on utilizing two model input variables that are fuel flow and flue gas O_2 content (w.b.). The selected operational ranges were [0 1.2] N m^3/s (corresponding to [0 43.2] MW) for fuel flow and [0 6]% for O_2. The target variable, NO_x was scaled similarly from operational range [70 180] mg NO_2/N m^3. In comparison, the linear multivariate regression models were identified with original non-scaled data.

In order to be applied generally and to avoid overfitting of the models, the optimal parameters for all nonlinear models were selected by cross validation with the training data sets. The optimal number of

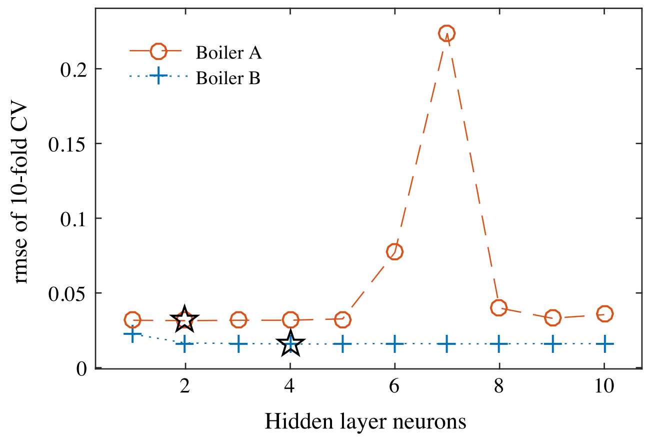

Fig. 6. Ten-fold cross validation errors of MLP.

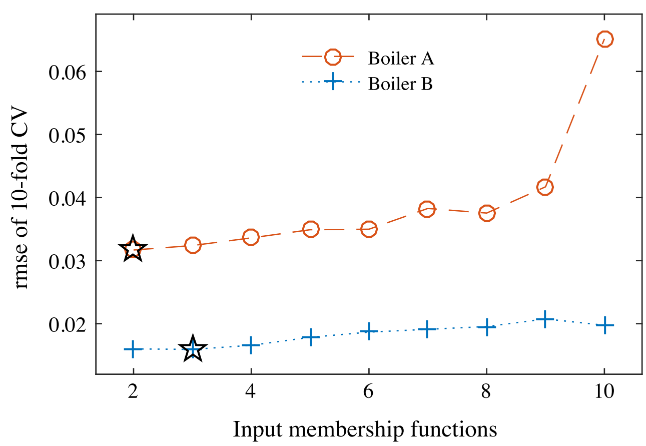

Fig. 7. Ten-fold cross validation errors of FIS.

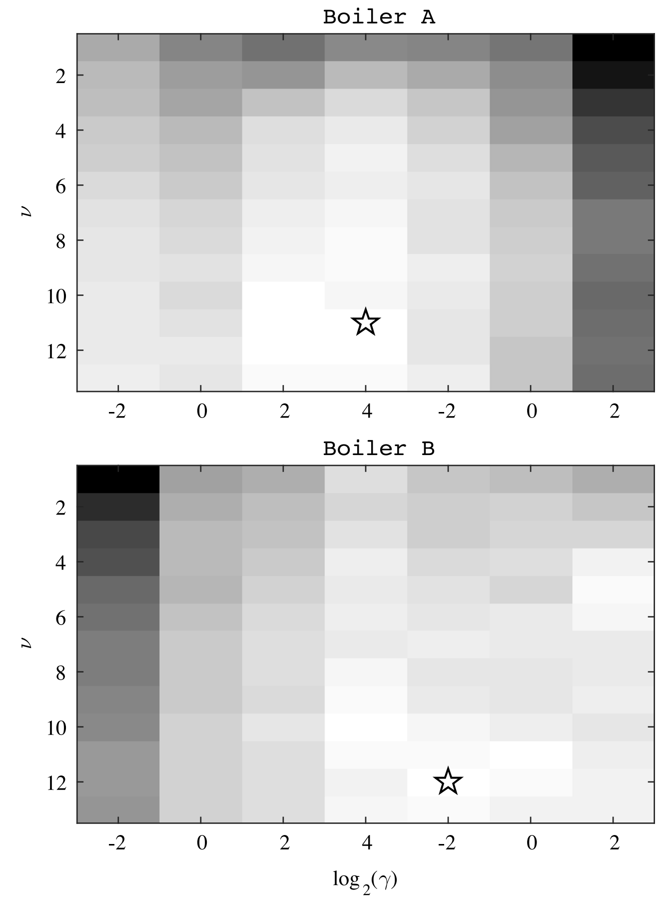

Fig. 8. Ten-fold cross validation errors of ν-SVR regression.

neurons in the hidden layer of the MLP network was determined by 10-fold cross validation, including ten Monte Carlo repetitions for each partitioning. Fig. 6 indicates that the minimum cross validation RMSE errors were achieved with two neurons for Boiler A and four neurons for Boiler B. The cases with 6 and 7 hidden layer neurons are examples where the model has been overfitted producing very high validation errors.

The numbers of bell shaped membership functions for inputs in the FIS were selected by ten-fold cross validation, including ten Monte Carlo repetitions for each partitioning. The minimum cross validation errors we achieved with two functions for Boiler A and three functions for Boiler B, which can be seen in Fig. 7.

The optimal values for the parameters ν and γ for ν-SVR were also selected by ten-fold cross validation. The cross validation errors are presented in Fig. 8, where the darker colours indicate higher error. The minimum error occurs for Boiler A with parameters $\nu = 0.7$ and $\gamma = 2$ (i.e. $\log_2(\gamma) = 1$), and respectively for Boiler B with parameters $\nu = 0.75$ and $\gamma = 4$ ($\log_2(\gamma) = 2$).

5.2. NO_x estimates with two input variables – Boiler A

Based on measured data, the following linear NO_x emission model [mg NO_2/N m^3, O_2 = 3%, d.b.] for Boiler A was identified:

$$NO_{x,est} = 13.8 \cdot O_2 + 29.6 \cdot \dot{V}_{gas} + 66.6. \tag{7}$$

where O_2 denotes measured moist oxygen content and $\dot{V}_{gas}$ gas flow to the burner as presented previously in Fig. 2. The respective measured and estimated NO_x emissions are presented in Fig. 9 along with MLP, SRV and FIS models identified in the previously described manner. In the figure, the training and testing sections of the identification run are separated by vertical lines. The linear model performs well in general but has some difficulties in the extreme O_2 levels, which is expected based on the scatterplot presented in Fig. 4. Other than that, all models have essentially equal performance. Notable differences are a slightly inferior performance of FIS in the first test section, and the peak in the second test section, which SVR fails to estimate. Still, the performance during the test sections is very similar to those of MLP and SVR. Therefore, the models are able to predict the NO_x emission response fairly well in all sections.

Fig. 10 presents NO_x estimates of Boiler A in the extra validation run. As can be seen, the linear model performs very well, except for minor biases. Both MLP and SVR perform generally even better, but they underestimate the NO_x level at the end of the run at the highest power level. The performance of FIS is inadequate, as there is a significant bias at all power and O_2 levels.

Fig. 11 sums up the estimation errors of NO_x models of Boiler A in the identification run (left) and extra validation run (right). The figures verify that the estimation errors are typically modest and significant biases exist only with FIS and at high oxygen contents with the linear model. However, there are some more or less significant error peaks in both runs, which occur during fast transients after the changes in control signals. Such errors, typically active for a few samples and usually followed by opposite error samples, are primarily due to a minor time shift between the portable gas analyser and process measurements. Thus, the two measurements represent slightly different process conditions. However, some faulty and especially opposite samples have a minor contribution to an hourly average that is applied in the IED. Typically,

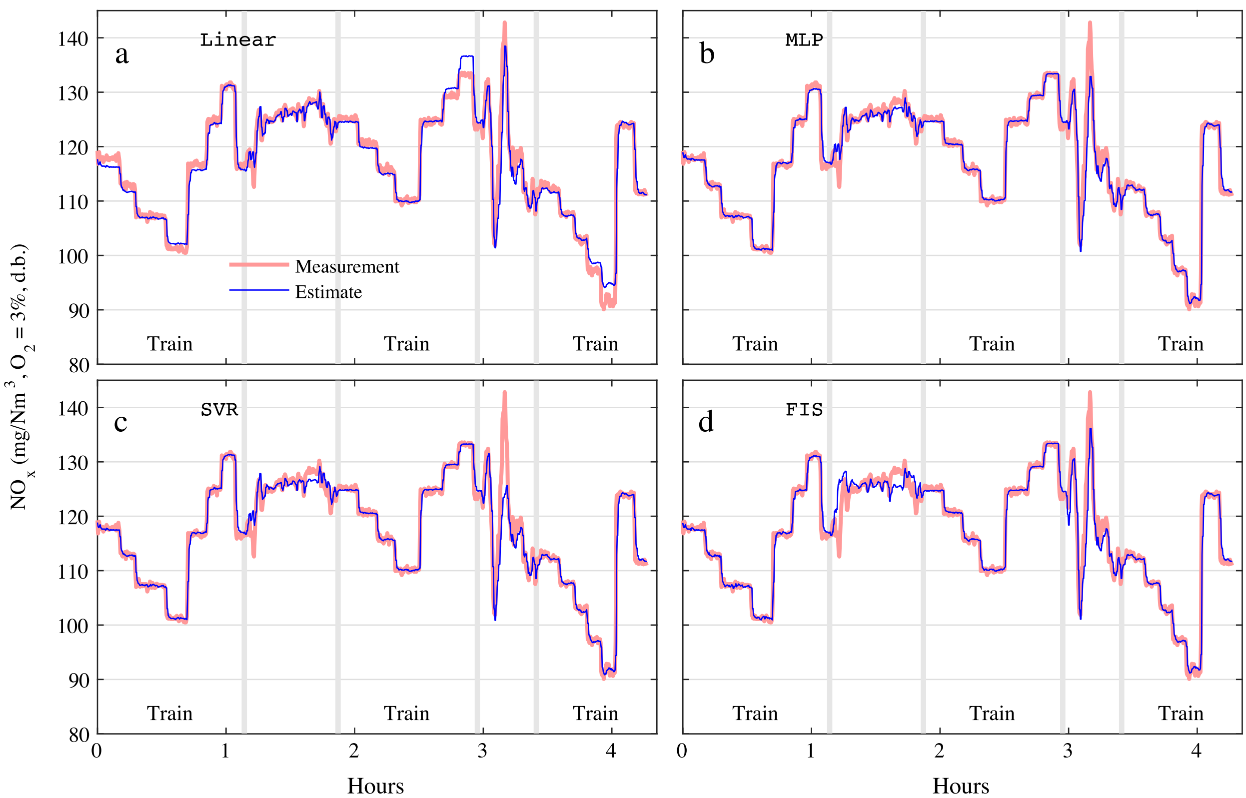

Fig. 9. NO$_x$ estimates of Boiler A in the identification run. Training sections are marked with 'Train', and the remaining sections are Test sections.

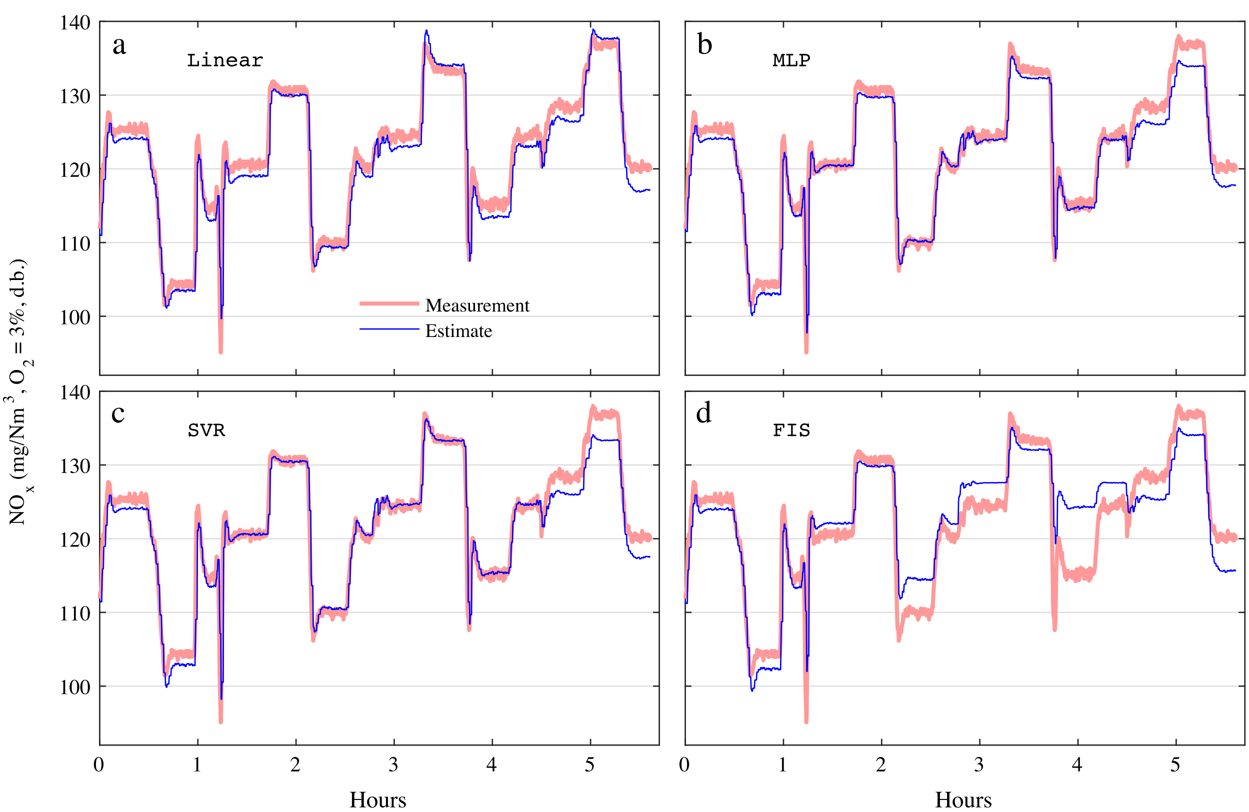

Fig. 10. NO$_x$ estimates of Boiler A in the extra validation run.

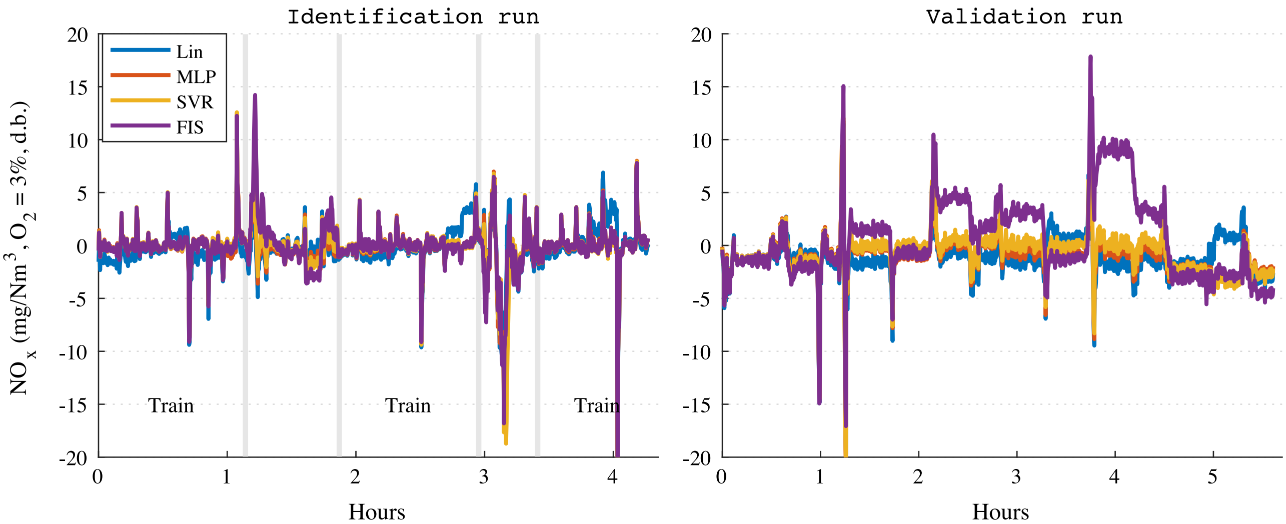

Fig. 11. Estimation errors of NO_x models of Boiler A in the identification run (left) and extra validation run (right).

Table 1
The absolute and relative RMSE values of Boiler A.

Model	Absolute RMSE (mg/Nm^3)			Relative RMSE (%)		
	Train	Test	Validation	Train	Test	Validation
Linear	2.03	2.65	2.27	1.78	2.16	1.91
MLP	1.71	2.90	2.21	1.46	2.33	1.86
SVR	1.71	3.57	2.25	1.46	2.76	1.88
FIS	1.70	3.42	3.89	1.45	2.80	3.35

Table 2
The absolute and relative RMSE values of Boiler B.

Model	Absolute RMSE (mg/Nm^3)			Relative RMSE (%)		
	Train	Test	Validation	Train	Test	Validation
Linear	2.26	2.70	3.80	1.58	1.84	2.70
MLP	0.86	2.35	5.08	0.60	1.58	3.58
SVR	0.86	2.22	5.10	0.60	1.49	3.60
FIS	0.85	7.72	9.30	0.59	5.28	6.48

boilers of this type are operated with slow changes in set points even in the new energy systems, indicating that the influence of such errors in normal operation should be insignificant.

Table 1 presents the absolute and relative RMSE values of Boiler A in train and test sections of the identification run and in the extra validation run. Based on the results, the linear model is the best in test sections and performs equally well in comparison to MLP and SVR in the extra validation run. The FIS fails in all test and validation sets. As a result, the linear model is the best two input variable model for Boiler A, predicting the NO_x emissions with a relative RMSE of 2.2% in the test section of the identification run and 1.9% in the validation run. The minor differences of the RMSE values in test and validation runs can be explained by different operating points and different operating conditions. Thus, the effect of additional input variables is presented in Section 5.4. Still, the linear model with two input variables performs very well in Boiler A, and can hence be utilized in PEMS applications.

5.3. NO_x estimates with two input variables – Boiler B

Based on measured data, the following linear NO_x emission model [mg NO_2/N m^3, O_2 = 3%, d.b.] for Boiler B was identified:

$$NO_{x,est} = 9.1 \cdot O_2 + 10.4 \cdot \dot{V}_{gas} + 117.4 \tag{8}$$

where O_2 and $\dot{V}_{gas}$ are presented in Fig. 3. The respective measured and estimated NO_x emissions are presented in Fig. 12 along with MLP, SRV and FIS models. As previously, the training and testing sections of the identification run are separated by vertical lines. All nonlinear models perform well in training sections. The linear model has difficulties in the first training section when both, the power and O_2, have the highest or the lowest levels as presented in Fig. 3. However, the performance during test sections is very similar to those of MLP and SVR. The first test section, when other boilers were also in operation, is best predicted by the MLP model. The performance of FIS is excellent in training sections, but the predictions fail totally at some points in all three test sections.

Fig. 13 presents the NO_x estimates of Boiler B in the extra validation run. The shapes of the estimates mostly equals the measurement apart from the FIS. However, all the estimates include noticeable and similar biases highlighted in Fig. 14, which presents the NO_x estimation errors of Boiler B. This indicates that the outdoor, process, or sensor conditions have slightly changed between the two trial runs conducted with a 7-month time difference. The cause for the change is examined in the next section by studying the effect of additional variables. However, such biases are easily removed by calibration of sensors if the process is not changed. This is especially the case with linear models, which require only few measurement points to find the new parameter values for the equations.

Table 2 collects the absolute and relative RMSE values of all distinct sections. The MLP and SVR provide the best estimates in test sections of identification run, but the linear model performs best in the extra validation run. Still, the modest bias and the relative RMSE of 2.7% after 7 months from identification in different operating conditions indicate that the modelling principle is robust.

As shown in Table 2, the linear model has the best generalization ability with respect to the extra validation run. However, the performance was lower in the test section of the identification run in comparison to MLP and SRV. As was already pointed out, and illustrated in Fig. 5, the largest estimation errors in test sections with linear model occurred with the largest oxygen contents at the highest power levels. In practise, however, these regions are not typically used due to emission and especially efficiency related aspects. Thus, the performance of the linear model could possibly be improved by excluding these sections from input data without significant impairing model utilization. A new linear model, excluding the time instants in training sections where the oxygen level exceeds 3.0% (d.b.) corresponding to 2.5% (w.b.), was calculated:

$$NO_{x,est} = 10.9 \cdot O_2 + 13.4 \cdot \dot{V}_{gas} + 112.0. \tag{9}$$

Fig. 15 presents the scatter plots of linear regression models with full (Eq. (8)) and limited (Eq. (9)) input data at four constant power

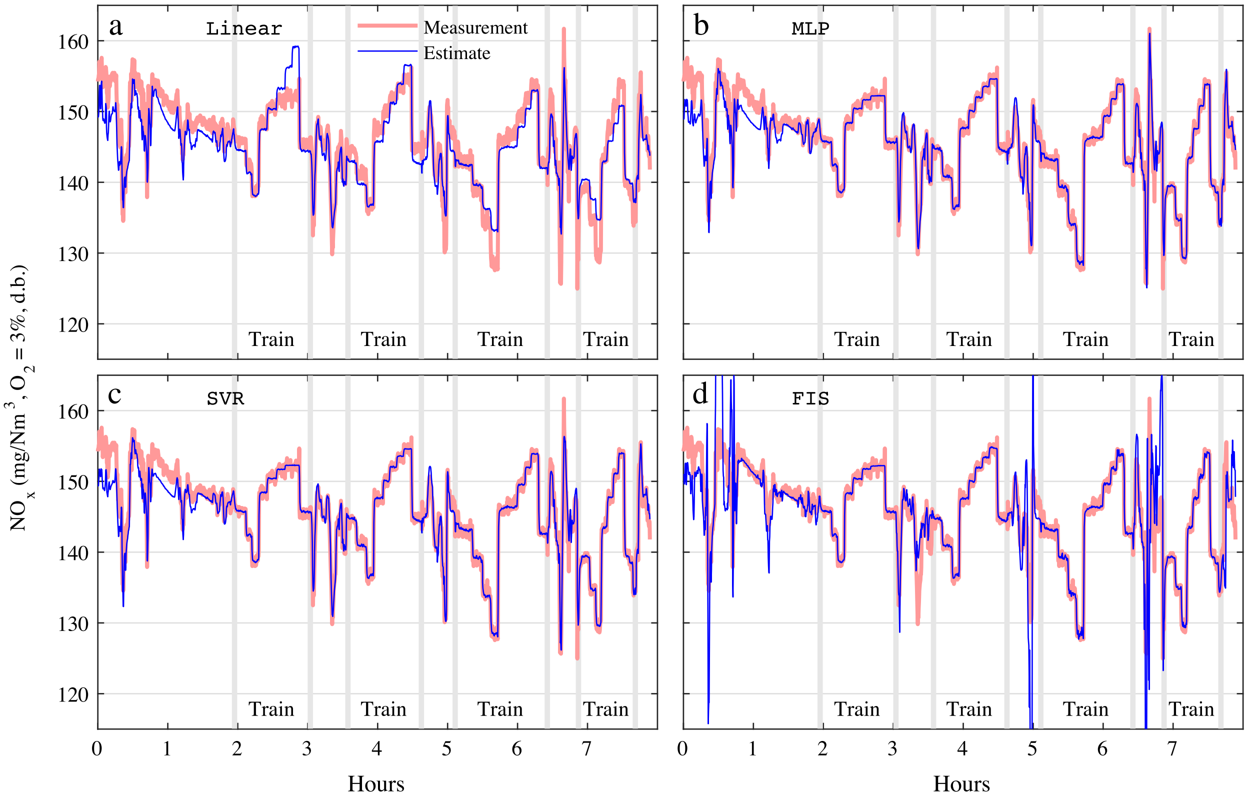

Fig. 12. NO_x emission estimates for Boiler B in the identification run. Training sections are marked with 'Train', and the remaining sections are Test sections.

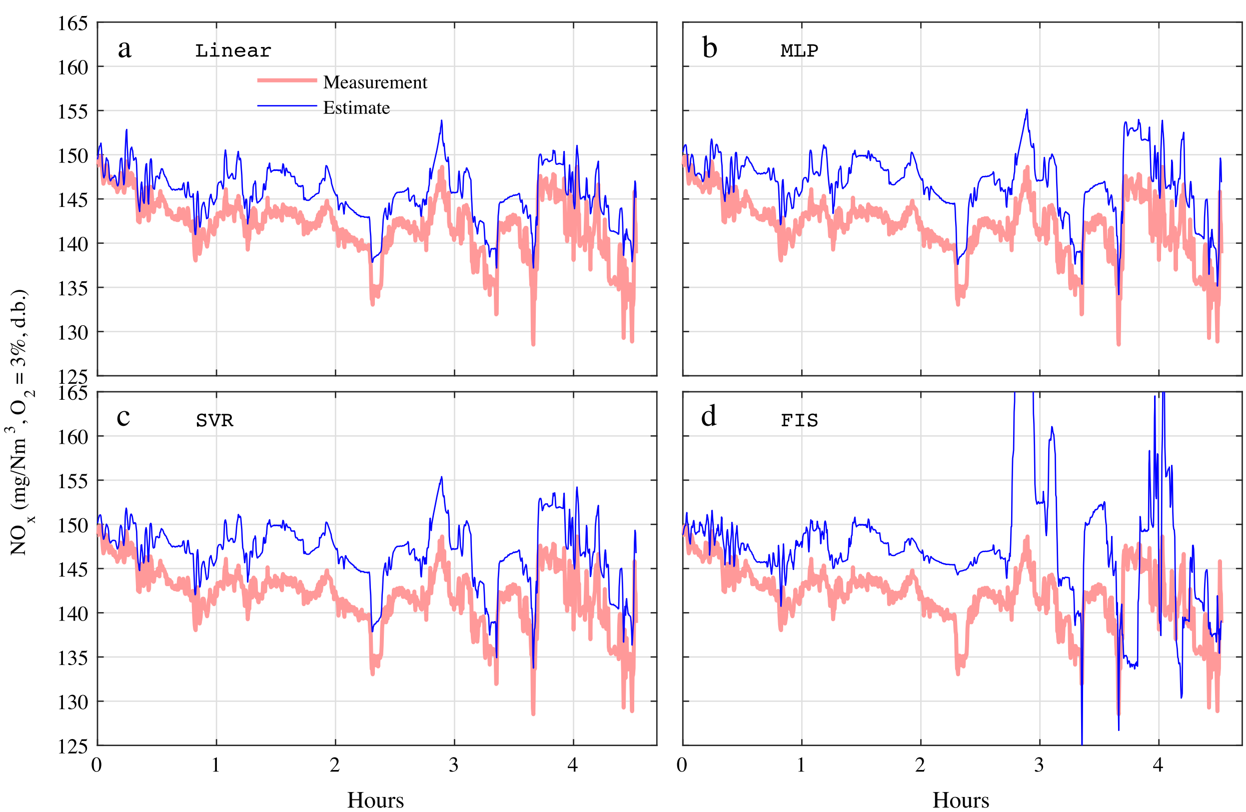

Fig. 13. NO_x emission estimates for the validation run of Boiler B.

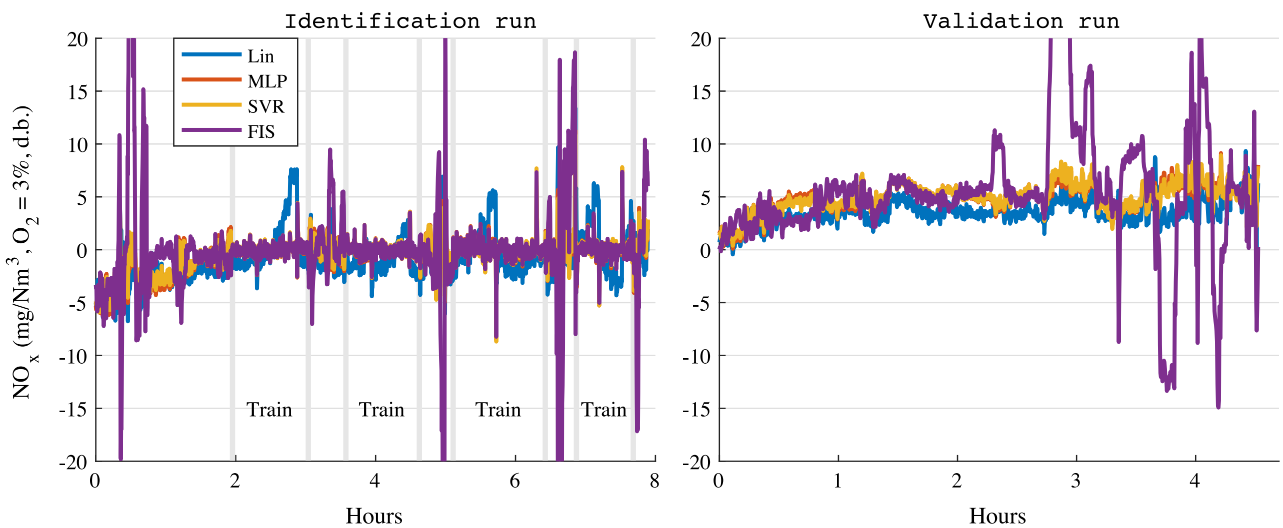

Fig. 14. Estimation errors of NO_x models of Boiler B in the identification run (left) and extra validation run (right).

Table 3
The absolute and relative RMSE values of models of Boiler B that have limited oxygen range.

Model	Absolute RMSE (mg/Nm^3)			Relative RMSE (%)		
	Train	Test	Validation	Train	Test	Validation
Linear, all	2.26	2.70	3.80	1.58	1.84	2.70
Linear, lim.	1.64	2.05	4.53	1.15	1.42	3.08
MLP, all	0.86	2.35	5.08	0.60	1.58	3.58
MLP, lim.	1.17	2.00	4.98	0.81	1.38	3.39

levels existing in training sections of the identification run. The figure illustrates that the model with limited range has a smaller constant parameter and steeper gradient, with the result that the measured samples fit better with the model than the one that also covers the highest oxygen levels. Therefore, it is expected that the model with limited oxygen range has a better performance at lower oxygen levels, although the difference between the model outputs is rather small. However, this benefit is not fully exploited in the extra validation run, as the run was conducted in a normal operating region avoiding the lowest oxygen levels.

Table 3 presents the RMSE values for the linear and MLP models both for the original (Data included: All) and reduced (Limited) training data. The results verify that reduced training data lowers the RMSE values especially with the linear model in the test section, but performance is lowered in the extra validation run partly due to different operating regions. The RMSE of the MLP is lower with the identification data as expected, but the performance improvement within the test section is negligible. Though not the case here, this indicates that limiting the operating region could improve the estimation performance with linear regression models in some cases.

In conclusion, the linear multivariate regression model performed the most consistently when identifying the NO_x emissions of Boiler B. The nonlinearity of NO_x response seen in Fig. 5 suggests the utilization of models with limited oxygen range, but this did not improve the estimation performance consistently. Therefore, simple linear model is the best. However, the constant bias of ca. 3 mg/N m^3 suggests that the two input variables do not fully explain the long-term NO_x emission behaviour. Hence, the next section studies the effect of additional input variables to the estimates.

5.4. NO_x estimates with additional input variables

In the previous sections, the performance of NO_x emission estimates was analysed with models with two controllable input variables. Next, the contribution of three additional and uncontrollable input variables is tested with linear multivariate regression and MLP using the same data as previously. The selected input variables are flue gas temperature, boiler feed water temperature and pressure in the combustion chamber. The input variables were scaled in the same way as the two initial input variables, thus the normal operating range of each input variable was scaled to [−1 1]. The operating ranges of these additional input variables were [70 200] for flue gas temperature (°C), [50 150] for boiler feed water temperature (°C), and [−10 20] for pressure (Pa) in the combustion chamber.

Linear stepwise regression was used to select input variables to the linear multivariate model. The O_2, fuel flow, and pressure of the combustion chamber were the first variables to be included in both boilers, respectively. For Boiler A, the remaining two input variables were not considered significant, resulting in a three input variable model. For Boiler B, the stepwise procedure included all five input variables. The identification procedure of MLP models was equal to the one with the two input variables. Ten-fold cross validation with ten Monte Carlo repetitions was performed to select the number of hidden layer neurons. For Boiler A, the best number of neurons was two for all the variable combinations. The minimum errors for Boiler B were achieved with four, three and three neurons for two, three- and five-input variable models, respectively.

Next the results for three combinations of input variables for both linear and MLP models are presented. The two input variable models with all data are equal to the ones presented in the previous sections, containing the fuel flow and O_2. The model with three input variables contains the pressure of the combustion chamber, and the model with five input variables includes the flue gas temperature and feed water temperature. The RMSE values of the results are presented in Table 4. With Boiler A, the additional input variables reduce the model performance of the linear model in test sections but slightly improve the performance in validation runs when three inputs are used. In comparison, the MLP results are poor, in particular with the test data with three input variables. This is due to two brief sections where the pressure of the combustion chamber is slightly higher than elsewhere but still well within the normal operating range. As a result, the NO_x estimates of these sections are out of the bounds, yielding very high RMSE values. The estimation performance is not significantly improved and the addition of extra input variables is not justified with Boiler A. With Boiler B, the additional input variables impair the estimation results of the linear model significantly in test sections but improve the performance noticeably in the extra validation run. On the other hand, the results of the MLP models of the test data outperform the linear model and even improve slightly with additional variables. However, the MLP presents

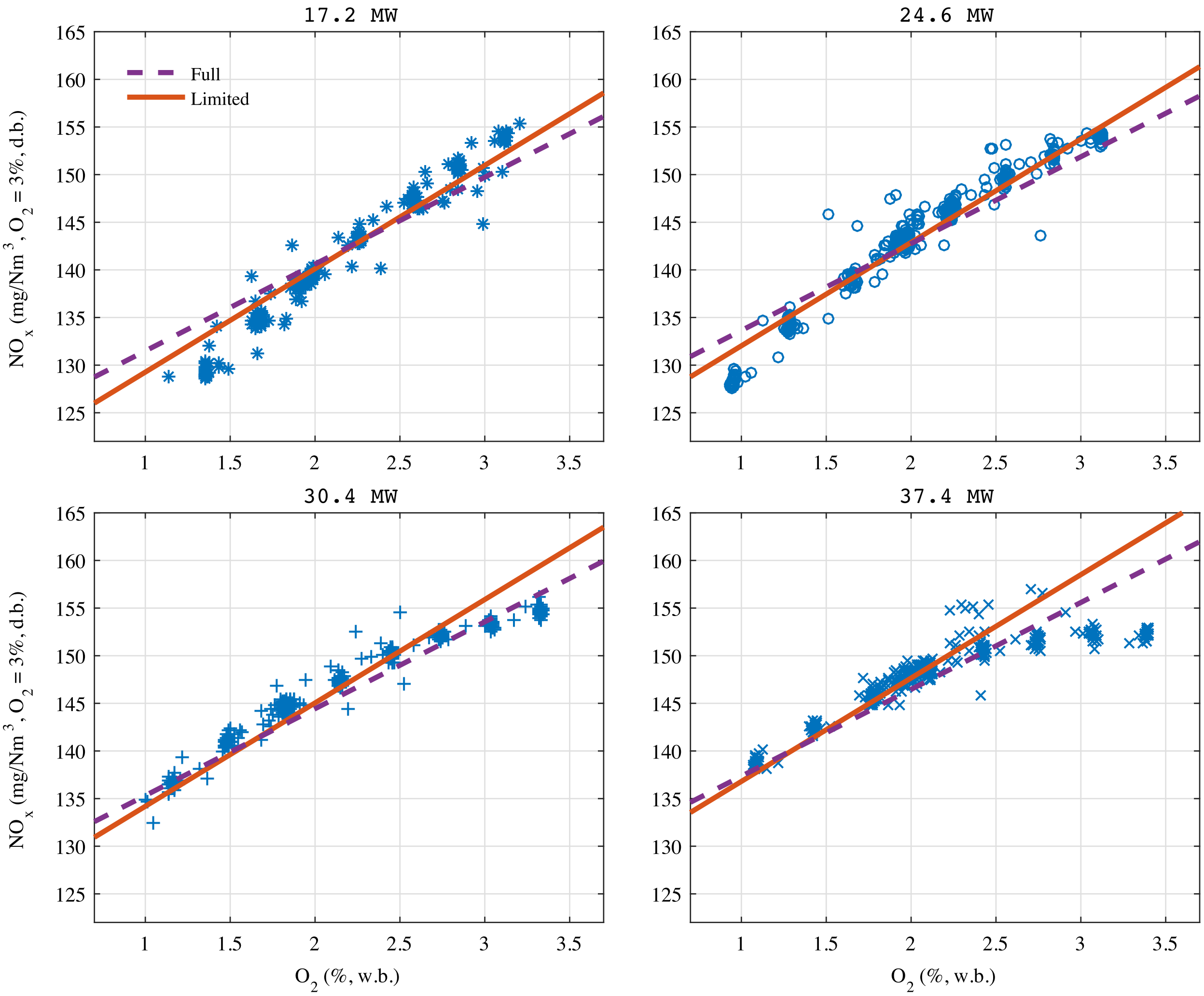

Fig. 15. Scatter plots of linear regression models with full (Eq. (8)) and limited (Eq. (9)) input data at four constant power levels existing in training sections of the identification run.

Table 4
RMSE (mg/Nm^3) values of models with 2, 3, and 5 input variables for linear and MLP models.

Model	Number of variables	Boiler A			Boiler B		
		Train	Test	Validation	Train	Test	Validation
Linear	2	2.03	**2.65**	**2.27**	2.26	**2.70**	**3.80**
Linear	3	1.99	3.01	**2.19**	1.89	4.40	**3.51**
Linear	5	1.92	3.51	**2.40**	1.79	5.01	**3.35**
MLP	2	1.71	2.90	**2.21**	0.86	**2.28**	5.05
MLP	3	1.59	38.0	5.98	0.84	**2.16**	5.53
MLP	5	1.56	3.56	3.19	0.81	**2.40**	5.80

poor results in the extra validation run and the performance is even worsened with the additional model inputs. Therefore, the additional input variables do not significantly improve the NO_x estimates, behave consistently nor clearly explain the bias in the validation run, so their addition to the models is not reasonable. Moreover, the addition of input variables may improve the estimation performance slightly or weaken it significantly depending on the case. In conclusion, the addition of variables should be considered only in special cases with special care.

5.5. NO_x estimates with extended input data

All the models presented so far have been identified based on data from training sections of the identification runs, as the idea was to cost effectively identify the models with training data and validate the model with test data from the same trial run. The results indicate that the nonlinear models do not generally improve the estimation results, but rather the opposite. However, due to the nonlinear behaviour of Boiler B, an additional calculation was performed. Here, the whole identification run, including the transients was used as identification data while the extra validation run data was used for validation. Table 5 presents the results, which indicate that the estimation results are worse when compared to the original procedure. Therefore, increasing the input data did not improve the estimation.

5.6. Model sensitivity analysis and sensor quality control

One important aspect when utilizing data based NO_x emission models in PEMS applications is the model sensitivity to measurement errors. If the uncertainty of the NO_x analyser is excluded, the model uncertainty

Table 5
The absolute and relative RMSE values of models of Boiler B identified with train and additional identification data (+).

	Absolute RMSE (mg/Nm^3)		Relative RMSE (%)	
	Identification	Validation	Identification	Validation
Linear		3.80		2.70
Linear +	2.30	4.49	1.59	3.18
MLP		5.08		3.58
MLP +	1.31	5.68	0.90	4.01

will originate from the error in the measurements used as model inputs. The uncertainty can originate from unfavourable sensor locations and from sensor fouling or wearing, or from random noise. The effect of location is primarily compensated for in model derivation if the sensor locations are fixed, however, the influence of sensor fouling or wearing on measurement error can change over time. In the presented cases, the measurements used as model inputs are fuel flow and flue gas oxygen content. When considering fuel flow measurements, the error of ±10% is not uncommon. The nominal power of both boilers is 43 MW, which corresponds to NG flow of 1.2 N m^3/s. Considering the linear regression models presented in Eqs. (7) and (8), such an error would contribute to the maximum error of $\epsilon_{\dot{V}_{gas},\text{Boiler A}} = 0.1 \cdot 1.2 \cdot 29.6 \approx 3.6\ (\text{mg NO}_2/\text{N m}^3)$ and $\epsilon_{\dot{V}_{gas},\text{Boiler B}} = 0.1 \cdot 1.2 \cdot 10.4 \approx 1.3\ (\text{mg NO}_2/\text{N m}^3)$ for Boiler A and B, respectively. Similarly, an error of 0.3 percentage points in oxygen measurement is possible between calibrations, which could contribute the errors by $\epsilon_{O_2,\text{Boiler A}} = 0.3 \cdot 13.8 \approx 4.1\ (\text{mg NO}_2/\text{N m}^3)$ and $\epsilon_{O_2,\text{Boiler B}} = 0.3 \cdot 9.1 \approx 2.8\ (\text{mg NO}_2/\text{N m}^3)$. The contribution of additional variables can be similarly examined. Thus, the influence of measurement errors on the linear models is relatively modest. However, even small errors may have a large influence when nonlinear models are used. This was illustrated in Section 5.4 where a small deviation in the pressure of the combustion chamber caused a significant error in the NO_x estimate. The total error can be calculated by summing the root mean squares of the error components, including the model errors.

The quality of measurements used in PEMS applications must be controlled regularly. Advanced sensor quality control procedures, e.g. as presented in Korpela and Suominen et al (2016) cannot be applied considering the cost effective requirements. Instead, the effect of measurement uncertainty can be handled by regular sensor calibrations and hardware or software redundancy, and monitoring of the process measurements and NO_x estimates compared to history data, e.g. Nikula, Ruusunen, and Leiviskä (2016). These actions are especially important in PEMS applications, where the NO_x models utilize process measurements that have not been previously actively maintained.

6. Discussions

The literature review proposes to use nonlinear models for NO_x monitoring that provide accurate NO_x predictions, which is supported by the complexity of NO_x formation. Sensors, including the ones used in model inputs, may drift in the long term, so operation personnel of the plants should be able to tune the PEMS software on demand. Nonlinear models are difficult to update, as the influence of parameter adjustments cannot be easily deduced. Therefore, automatic procedures should be favoured. However, because the behaviour of the processes changed slightly between the trial runs and process operating principle to another, so too good a model does not necessarily contribute to the best long-term generalization ability. Therefore, the models should be as simple as possible with good maintainability and transparency, especially when considering that the models should be identified and validated cost effectively.

In case there are excess of suitable and independent measurements in the process, the application of robust estimation methods is enabled. However, this condition was not met in the tested boilers. There is, though, a flue-gas temperature measurement available, whose signal typically correlates with O_2 measurement signal. However, the correlation is not consistent in this case, because the flue gas temperature is controlled by boiler-water recirculation flow. The situation with measurement redundancy could be improved if there were an additional O_2 measurement or airflow or flue-gas flow measurements present that could be used to improve the quality of measurements used as model inputs. However, the application of such methods do not remove the uncertainty of NO_x model in changing process conditions, and therefore they are not enough to guarantee the validity of the estimate. On the other hand, the adaptation of the model is hard to be convinced to the authorities, because the input–output relation is not predictable anymore.

The results presented in the previous sections indicate that linear regression models perform typically at least as well as the nonlinear models in both boilers. The linearity of the tested boilers can partly be explained by homogeneous fuel (NG), a simple burner structure, and especially the fixed air distribution structures. Still, some effort is required to apply linear models to almost linear processes. The nonlinearity must be carefully considered in the modelling stage by conducting trial runs that cover the full operating region for all the controlled input variables. Scatter plots (e.g. Figs. 3 and 4) can reveal nonlinearities easily and linear models can be tuned to consider limited operating regions, as was tested with Boiler B. If errors are small with relevant data, the model is able to predict NO_x behaviour and the model can be utilized in normal operation. If no process modifications are made, the linearity of the process should remain. Therefore, retuning linear models (e.g. after recalibration of sensors) is straightforward and can be conducted with a simple trial run with a few power and oxygen levels. Notably, constant biases in the whole operating region, which were noticed in the case of Boiler B, can easily be removed by correcting the constant parameter of the linear model by a measurement with two measurement points. This kind of model validation can be conducted after the introduction of the PEMS regularly with an interval of a few months with modest costs. Therefore, PEMS with the NO_x estimation model could be a cost effective solution. However, the results indicate that each boiler should be identified and modelled separately. This is understandable due to the sensitiveness of NO_x emission formation to burner and furnace structures, which is also in line with the results presented in Pulles and Heslinga (2004). Moreover, the combustion and hence NO_x emission formation is sensitive to changes from NG to biogas (Ilbas et al., 2016) and to potential enrichment of oxygen content in air (Riahi, Mergheni, Sautet, & Ben Nasrallah, 2016). Hence, if these kinds of changes are applied, the NO_x full modelling procedure should be redone.

If the performance of a linear model is substantially lower than that of some nonlinear one, there are still some options to avoid the usage of nonlinear models. This can be achieved e.g. by applying the model in a limited operating region, analysed in this paper in the case of Boiler B. Alternatively, piecewise linear functions could be applied, or alternatively a nonlinear polynomial could be used to model the curvature as seen in the scatter diagrams. On the other hand, the challenge is further increased when the number of controllable model inputs increases, as the length of trial runs is substantially lengthened, especially if the effect of the variables is nonlinear. Additionally, some excluded variables might also affect NO_x emission formation, even if the results in this case indicated that their contribution did not improve the estimation results consistently. Still, their role should be carefully considered if the long-term generalization ability of the model is not good enough. However, the cost reduction potential of PEMS is easily lost if the effort required to identify and maintain the models is substantially increased. Therefore, applying PEMS to relatively simple processes should be most beneficial.

7. Conclusions

This paper compared NO_x emission estimation models in two similar 43 MW natural gas fired hot water boilers. The models utilize online process measurements that are always available even in relatively low-instrumented set-ups. The objective of the work was to find maintainable and transparent but still valid models for NO_x estimation, in order to evaluate the potential of PEMS application for NO_x emission monitoring in long-term operation in practical installations. The performance of linear regression models was compared with widely used nonlinear models, i.e. MLP, SVR and FIS, which were identified with automatic procedures without any fine-tuning. Most of the analysis concentrated on the models with two input variables, i.e. flue gas oxygen content and fuel flow. They are in practise the only controllable variables affecting NO_x emissions in the tested and many similar boilers that now fall under the jurisdiction of the Industrial Emission Directive. Additionally, the influence of additional, uncontrollable input variables and selection of data sets was considered in order to determine the best available model. In the study, two separate trial runs with two different operating modes (manual and automatic) were conducted in order to evaluate the long-term operation of the boilers and hence the performance of the modelling approach.

The RMSE values indicate that the linear multivariate regression models have the most consistent long-term performance. The performance of MLP and SVR varied significantly between the boilers and the test sections. Despite the cross validation, the FIS was overfitted, performing very well with training sets but failing in the validation set. Its performance could probably have been improved by fine-tuning; however, this would violate the requirement for easy maintainability. The extra measurements increased the accuracy of the linear models to some extent in some cases but not consistently. In conclusion, the results indicate that the linear model performs nearly as well as the best nonlinear models with both boilers. If the performance of the model is good enough, the simpler model structure should be favoured, which also promotes the easy model maintainability. However, the results indicate that the identification and maintenance of the models must be conducted separately for each boiler due to the differences in burner structures and instrumentations. Moreover, when the process itself or its parameters are changed, the validity of the models should be carefully reconsidered.

In conclusion, linear models with two input variables presented the most feasible approach in PEMS applications to estimate NO_x emissions in the types of boilers considered here. As presented, these models were insensitive to simultaneous operation of multiple boilers and to significant drift in measurement error in long-term operation. The linear regression models provided accurate estimates with relative RMSE values of less than 3% in all the analysed cases, which is a good result also in comparison to previously published results. Online NO_x estimates provide reliable estimates of total NO_x emissions released in various operating conditions. This is a major benefit of PEMS applications and cannot be achieved with intermittent measurements carried out with portable NO_x analysers. Additionally, the estimates provide prospects to NO_x emission optimization in boiler operation. The proposed approach is best feasible for boilers in range 15–100 MW, as in that range continuous emission monitoring solutions are not required, the instrumentation level is generally low and the process designs are typically relatively simple. Naturally, with more available instrumentation and more complex processes and hence more degrees of freedom, the feasibility of the solution should be reconsidered, especially if the model accuracies are not at an adequate level.

Additionally, the NO_x estimates derived with the method can be used to improve the control of ammonia/urea dosing in SCR and SNCR (Selective (Non-) Catalytic Reduction) NO_x reduction method, if further tightening emission limits require such actions to be applied also in such boilers in the future.

Despite the four separate trial runs, future work should include long-term verification of the models in various weather conditions. Additionally, the effect of fuel quality changes due to changed gas type e.g. via LNG or upgraded biogas in NG network, should be researched, especially if PEMS is to be widely applied. Moreover, the approach could be tested in other types of boiler setups.

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Online monitoring of flue gas emissions in power plants having multiple fuels

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Abstract: This paper introduces an online monitoring application for flue gas emission measurements. The monitoring is conducted by analytical redundancy by estimating the monitored measurement variables. The estimated variables are CO_2, H_2O, flue gas flow and combustion air flow. Additionally, SO_2 content in the flue gas can be estimated with certain limitations. The monitoring method is based on physical combustion modeling and is therefore boiler structure and fuel independent. The model is valid for multiple fuels as long as the fuel flow measurements, fuel properties and flue gas O_2 measurement are available. The estimates can further be improved by flue gas CO measurement. The monitoring method was successfully tested in an industrial wood, peat, bark and slurry fired power plant. The results verify that the method is able to automatically separate sensor faults and process disturbances.

Keywords: Process monitoring, estimation, mass balance, power plant, sensor diagnostics, flue gas

1. INTRODUCTION

There is an increasing demand to protect environment from harmful emissions. As energy production is a major source of harmful emissions, authorities have set further tightening emission limits also to power plants. In European Union, the flue gas emissions, i.e. SO_2, NO_x and dust, are restricted e.g. by Large Combustion Plant (LCP) directive, Integrated Pollution Prevention and Control (IPPC) directive and their future replacement Industrial Emission Directive (IED) that is coming into effect in 2016. In parallel, European Union Emission Trading System (EU ETS) aims at reducing greenhouse gas emissions, especially CO_2 emissions. These directives and systems not only control the emission levels but also set requirements for the reliability of emission measurements in power plants. Therefore, the reliability of emission measurements is getting an increasing attention in the future.

The required measurement reliabilities of emission monitoring systems are described in (EN 14181) by Quality Assurance Levels (QAL) 2–3 and in Annual Surveillance Tests (AST) procedures. There, the correctness of measurements is assured by regular calibrations carried out by external specialists. However, the reliability of sensors might be deteriorated e.g. due to fouling and wearing, and without any actions these inaccuracies might not be observed for a while. Therefore, quality control of emission sensors should also be carried out between the calibrations to provide environmentally efficient operation of the combustion processes.

Fault detection procedures applied in sensor diagnostics are based on redundant information where the readings from the monitored sensors are compared with reference values. The reference values can be generated either by hardware redundancy from redundant sensors or by analytical redundancy generated by models. Hardware redundancy in emission measurements is hardly a solution mainly due to high investment and maintenance costs. Therefore, analytical redundancy is preferable if it is able to provide decent estimates. The analytical redundancy can be generated by data based models or physical models. In flue gas emission monitoring, there are some publications of data based emission estimates, e.g. Ruusunen & Leiviskä (2004); Ruusunen (2013), Yap & Karri (2011) and Shakil *et al.* (2009). Additionally, there are quite a few publications covering monitoring of NO_x emissions and emission monitoring of internal combustion engines, which are out of scope of this article. However, the validity and applicability of data based models are often case and fuel specific and require maintenance. On the other hand, there are physical combustion models, which are typically based on energy and and/or mass balances and are used to estimate some features, especially fuel moisture contents or heating values. However, to authors' knowledge there are no publications covering emission monitoring based on physical combustion models that are fuel quality and quantity independent.

After the redundant information for sensor signal is generated, the inconsistency between actual measured data and reference data indicates fault either in the diagnosed signal or some value used in the generation of the reference information. The faulty signal is identified by generating a model chain where redundant information is generated by using different measurements as source data and the inconsistency appears in so called parity relations where the faulty signal is applied. The estimates can also be utilized in data reconciliation applications, e.g. presented in Huovinen *et al.* (2012).

This paper introduces an online monitoring method for flue gas emission measurements. The monitoring is conducted by analytical redundancy by estimating the monitored measurement variables. The combustion air flow estimate and flue gas estimates (CO_2, H_2O, SO_2, and flue gas flow) are based on physical combustion modelling. The model is derived to be applicable with multiple fuels to gain applicability in challenging and versatile combustion environments. The method was successfully tested in an industrial wood, peat, bark and slurry fired boiler, and the results are presented and commented after model derivation.

2. MODELLING OF THE COMBUSTION

In this section, the model for estimating the combustion variables is presented. The model is derived to be applied with multiple fuels to gain generality and exploitability. The foundation of the model is element balance equations that can be solved analytically. Unfortunately, some effort is needed to scale the measured and a priori information to required forms and to calculate the estimates from these scaled variables. After that, however, the estimates provide physically relevant information that connects several separate measurement signals to form an entirety. The analytical solution enables exploitation of the method with minor calculation power in any real computational environment.

The idea of the combustion model is to calculate the desired estimates according to measurement and a priori information. The main a priori information for this model are fuel chemical compositions, which are expressed in form of $C_xH_yO_zN_vS_w$, where C stands for element carbon, H hydrogen, N nitrogen, and S sulphur. Moreover, the fuel moisture and ash contents must be known for all fuels. When this a priori information is gathered together with fuel flow measurement and flue gas oxygen measurement information, which is one of the most reliable flue gas measurements and inexpensively duplicable, the main components of flue gas flow can be estimated. Moreover, the estimates can be further improved by CO measurement that reduces the proportion of CO_2 in the flue gas.

The principles of equations presented in this section can be found in books covering combustion, e.g. in Van Loo & Koppejan (2008), but according to author's knowledge, the derived analytical solution has not been published previously.

Table 1. Nomenclature

Symbol	Description	Unit
n	Amount of substance	mol
M	Molecular mass	kg/mol
m	Mass	kg
p	Pressure	Pa
R	Universal gas constant	J/(mol·K)
ρ	Density	kg/m^3
T	Temperature	°C
$r_{F,k}$	Ratio of molecular flow of fuel k over molecular fuel flow	-
x	Molecular ratio of C to C	-
y	Molecular ratio of H to C	-
z	Molecular ratio of O to C	-
v	Molecular ratio of N to C	-
w	Molecular ratio of S to C	-
r_{Air}	Oxygen-to-fuel mole ratio	-
λ	Molecular air factor	-
η	Proportion of water vapour in air	-
γ	Molecular ratio of H_2O to combustion	-
X	Volume ratio	-
φ	Measured air moisture content	-

Table 2. Indexes

Symbol	Description
k	Fuel k, i.e. $k \in \boldsymbol{N}$
daf	Dry, ash free
st	Stoichiometric
FG	Flue gas
l	Gas component, i.e. $l =$ O_2, CO
NTP	T = 0 °C & p = 101 325 Pa
me	Measurement
est	Estimate

2.1 Balance equations

The main chemical reactions in combustion environment having over stoichiometric conditions can be presented as

$$C + O_2 + 3.76 \cdot N_2 \rightarrow CO_2 + 3.76 \cdot N_2 \quad (1)$$

$$C + 0.5 \cdot (O_2 + 3.76 \cdot N_2) \rightarrow CO + 1.88 \cdot N_2 \quad (2)$$

$$2 \cdot H + 0.5 \cdot (O_2 + 3.76 \cdot N_2) \rightarrow H_2O + 1.88 \cdot N_2 \quad (3)$$

$$S + O_2 + 3.76 \cdot N_2 \rightarrow SO_2 + 3.76 \cdot N_2. \quad (4)$$

Based on the chemical reactions (1–4), the main flue gas components are carbon dioxide (CO_2), water (H_2O), nitrogen (N_2) and sulphur dioxide (SO_2). Typically, some carbon monoxide (CO) is also present due to incomplete combustion despite the excess air feed which can be seen in oxygen (O_2) content in the flue gas. By combining this information, the overall chemical reaction formula of combustion of multiple fuels ($k \in \boldsymbol{N}$) can be described as

$$\sum_k \left(r_{F,k} \cdot C_{x_k} H_{y_k} O_{z_k} N_{v_k} S_{w_k} \right)$$
$$+ r_{Air} \cdot (O_2 + 3.76 \cdot N_2 + \eta \cdot H_2O) + \gamma \cdot H_2O \rightarrow$$
$$b \cdot CO + c \cdot CO_2 + d \cdot H_2O + e \cdot O_2 + f \cdot N_2 + h \cdot SO_2, \quad (5)$$

of which some of the symbols and indexes are described in Table 1 and 2, respectively. The parameters b, c, d, e, f, and h determine the molecular proportions of the flue gas, and their values are solved later in this section. Ashes, dust and unburned material are not stated in (5) but must be considered when measured and a priori information is converted to required form of (5). From (5), the element balance equations for C, H, O, N, and S, can be described, respectively, as

$$\sum_k \left(r_{F,k} \cdot x_k \right) - (b + c) = 0 \quad (6)$$

$$\sum_k \left(r_{F,k} \cdot y_k \right) + 2 \cdot r_{Air} \cdot \eta + 2 \cdot \gamma - 2 \cdot d = 0 \quad (7)$$

$$\sum_k \left(r_{F,k} \cdot z_k \right) + r_{Air} \cdot (2 + \eta) + \gamma$$
$$-(b + 2 \cdot c + d + 2 \cdot e + 2 \cdot h) = 0 \quad (8)$$

$$\sum_k \left(r_{F,k} \cdot v_k \right) + 2 \cdot 3.76 \cdot r_{Air} - 2 \cdot \mathrm{f} = 0 \quad (9)$$

$$\sum_k \left(r_{F,k} \cdot w_k \right) - \mathrm{h} = 0 \quad (10)$$

In (10) it is assumed that all the sulphur is reacted to SO_2. The validity of this assumption is process and process condition dependent, i.e. any SO_2 removal actions deteriorates this approach. However, this parameter can be omitted by setting w_k to zero.

From (5), the concentrations of O_2 and CO in the flue gas can be represented by molecular ratios

$$X_{O_2} = e/(b + c + d + e + f + h) \quad (11)$$

$$X_{CO} = b/(b + c + d + e + f + h). \quad (12)$$

The equations (11–12) can be fixed with the flue gas composition measurements by balances

$$X_{O_{2,me}} - X_{O_2} = 0 \quad (13)$$

$$X_{CO,me} - X_{CO} = 0 \quad (14)$$

which actually connects the balance equation (5) to reality.

By solving the equations (6–10) and (13–14) simultaneously while setting the other variables as parameters, the formulas for flue gas coefficients, i.e. parameters b, c, d, e, f, and h, and therefore flue gas composition and oxygen-to-fuel mole ratio r_{Air} can be calculated analytically. The analytical solution as such provides mathematically exact results, but the calculation results, however, are not necessarily correct due to incorrectness of input parameters and assumptions made when deriving the calculations.

2.2 *Calculation of model input parameters*

In this subsection, the input parameters needed to exploit the balance calculus are presented. The molecular flow of fuel k over total molecular fuel flow can be presented as

$$r_{F,k} = \dot{n}_{k,daf} / \sum_k \dot{n}_{k,daf}, \quad (15)$$

where

$$\dot{n}_{k,daf} = \dot{m}_{k,daf} / M_k, \quad (16)$$

in which $\dot{m}_{k,daf}$ can be calculated by reducing the respective fuel moisture and ash contents from the measured fuel mass flows. The molecular mass M of fuel k can be calculated by

$$M_k = x_k \cdot \mathrm{M}_C + y_k \cdot \mathrm{M}_H + z_k \cdot \mathrm{M}_O + v_k \cdot \mathrm{M}_N + w_k \cdot \mathrm{M}_S. \quad (17)$$

The external moisture content that is fed to the boiler in the form of fuel moisture and steam from soot blowing system can be considered as

$$\gamma = \sum_k \left(r_{F,k} \cdot n_{H_2O,k} / n_{C,k}\right) + r_{steam}, \quad (18)$$

where $n_{H_2O,k}$ is the molecular amount of water in 1 kg of moist fuel k and $n_{C,k}$ is the respective amount of carbon. Additionally, the r_{steam} stands for relative amount of soot blowing steam compared to total molecular fuel flow, which can be presented as

$$r_{steam} = \dot{m}_{steam,me} / \left(\mathrm{M}_{H2O} \cdot \sum_k \dot{n}_{k,daf}\right), \quad (19)$$

where $\dot{m}_{steam,me}$ stands for measured mass flow of steam fed to the boiler.

The air humidity can be taken into account by calculating the molecular ratio of air moisture to dry air by equation

$$\eta = (\varphi \cdot p_h') / (p_{tot} - \varphi \cdot p_h'), \quad (20)$$

where φ is measured air moisture content, p_h' saturation pressure of water vapour in measured combustion air temperature, and p_{tot} measured pressure of moist air.

2.3 *Model outputs: Combustion air*

In this subsection, the combustion air estimates that can be generated based on element balance calculus are derived. The stoichiometric (*st*) air requirement of fuel k can be expressed as

$$r_{Air,st,k} = x_k + y_k/4 + w_k - z_k/2. \quad (21)$$

Then, the overall excess air ratio can be calculated as

$$\lambda = r_{Air} / \sum_k r_{Air,st,k}. \quad (22)$$

The dry air and air moisture mass flows can be calculated by equations

$$\dot{m}_{air,dry} = 4.76 \cdot r_{Air} \cdot M_{air} \cdot \sum_k \dot{n}_{k,daf} \quad (23)$$

$$\dot{m}_{air,H_2O} = \eta \cdot r_{Air} \cdot M_{H_2O} \cdot \sum_k \dot{n}_{k,daf}, \quad (24)$$

whose sum is the total moist air mass flow. Next, the mass flow can be converted to volume flow by multiplying it with relevant gas density derived from ideal gas law, i.e.

$$\rho_{gas} = p_{gas} \cdot M_{gas} / \left(R \cdot \left(T_{gas} + \mathrm{T}_{\mathrm{NTP}}\right)\right). \quad (25)$$

Finally, the volume flow of combustion air can be estimated by equation

$$\dot{V}_{Air,est} = \dot{m}_{air,dry} / \rho_{Air} + \dot{m}_{air,H_2O} / \rho_{H_2O}. \quad (26)$$

2.4 *Model outputs: Flue gas properties*

In this subsection, the flue gas estimates that can be generated based on element balance calculus are derived. The main outputs of the combustion model are the flue gas compositions and flue gas volume flow. The flue gas composition can be solved from equations (13–14) and (27–30)

$$X_{CO_2,est} = c/(b + c + d + e + f + h) \quad (27)$$

$$X_{H_2O,est} = d/(b + c + d + e + f + h) \quad (28)$$

$$X_{N_2,est} = f/(b + c + d + e + f + h) \quad (29)$$

$$X_{SO_2,est} = h/(b + c + d + e + f + h). \quad (30)$$

Additionally, the mass flows (kg/h) of flue gas components can be calculated by equations

$$\dot{m}_{CO} = b \cdot M_{CO} \cdot \sum_k \dot{n}_{k,daf} \quad (31)$$

$$\dot{m}_{CO_2} = c \cdot M_{CO_2} \cdot \sum_k \dot{n}_{k,daf} \quad (32)$$

$$\dot{m}_{H_2O} = d \cdot M_{H_2O} \cdot \sum_k \dot{n}_{k,daf} \quad (33)$$

$$\dot{m}_{O_2} = e \cdot M_{O_2} \cdot \sum_k \dot{n}_{k,daf} \quad (34)$$

$$\dot{m}_{N_2} = \mathrm{f} \cdot M_{N_2} \cdot \sum_k \dot{n}_{k,daf} \quad (35)$$

$$\dot{m}_{SO_2} = h \cdot M_{SO_2} \cdot \sum_k \dot{n}_{k,daf}. \quad (36)$$

The total flue gas volume flow (Nm^3/h) can be calculated by

$$\dot{V}_{FG,est} = \sum_l \dot{m}_l/\rho_l, \tag{37}$$

where l includes CO, CO_2, H_2O, O_2, N_2, and SO_2.

2.5 Converting the estimates to measurement formats

Before comparing the derived estimates with respective process measurement information, the estimates must be converted to standard forms. These standard gas compositions are component specific. For H_2O, there is typically no conversion, so the estimate is valid as such, i.e.

$$X_{H_2O,est,norm}(\%) = 100 \cdot X_{H_2O,est}(-). \tag{38}$$

The O_2 is typically presented as volume concentration in dry flue gases according to equation

$$X_{O_2,est,norm}(\%) = 100 \cdot X_{O_2,est}(-) \cdot f_{H_2O}, \tag{39}$$

where

$$f_{H_2O} = 100/\left(100 - X_{H_2O,est,norm}\right). \tag{40}$$

The other gas components are typically normalized to some reference O_2 content, i.e. $X_{O_{2,ref}}(\%)$. According to IED directive, the standardised O_2 content is 6 % for solid fuels, 3 % for combustion plants other than gas turbines and gas engines using liquid and gaseous fuels, and 15 % for gas turbines and gas engines. The O_2 normalization can be made

$$f_{O_2} = \left(20.95 - X_{O_2,est,norm}\right)/\left(20.95 - X_{O_{2,ref}}\right). \tag{41}$$

The CO_2 and N_2 proportions can be then normalized as

$$X_{l,est,norm}(\%) = 100 \cdot X_{l,est} \cdot f_{H_2O} \cdot f_{O_2}, \tag{42}$$

where l includes CO_2 and N_2. The rest of the estimated gases are typically presented in the form of mg/Nm^3, which can be achieved by equation

$$X_{l,est,norm} = \theta_l \cdot X_{l,est} \cdot f_{H_2O} \cdot f_{O_2}, \tag{43}$$

where l includes CO and SO_2 and θ_l stands for gas specific unit conversion coefficient.

The flue gas volume flows are typically normalized as

$$\dot{V}_{FG,est,norm} = \dot{V}_{FG,est}/f_{H_2O}. \tag{44}$$

3. ESTIMATION RESULTS

The theory presented in Section 2 was tested in an industrial installation. This section introduces the setup briefly and concentrates on estimation results.

3.1 Process description

The test process was an industrial 200 MW$_{th}$ BFB (Bubbling Fluidized Bed) boiler producing energy for a paper mill. The main fuels of the boiler are woody biomass, peat, bark and slurry. The woody biomass consists mainly of chipped logging residues, wood, stumps, and saw dust. The bark and slurry comes from the neighbouring paper mill. Roughly 2/3 of the slurry is primary waste and 1/3 biological waste from waste water purification process.

There are a 2000 m^3 storage for woody biomass, a 2000 m^3 storage for peat and a 5000 m^3 storage for bark at the site. The storages also stabilize fuel quality changes. After these storages, there are two parallel 100 m^3 fuel feeding silos before the boiler, which are fed from fuel specific storages and through a slurry flow line from the waste water treatment process. All the fuel mass flows are measured separately before the fuel feeding silos, and these measurements are used as model inputs. With typical fuel mixtures, the capacity of the silos provides some 30–40 minutes operation at full boiler load.

Emission monitoring system of the plant and respective measurements fulfil the requirements of LCP directive.

3.2 Trial run setup

There are four types of fuels involved in the process, i.e. wood, peat, bark and slurry. Table 3 presents fuel element compositions that are used in the calculations, which are taken from literature and fit within the ranges that are typically presented for such fuels. Fuel moisture contents are rough estimates of typical values at the plant, and these values also fit with the literature values. Fuel compositions and especially moisture contents, however, are known to vary to a significant extent from fuel batch to another, but the average values tend to remain somewhat stable primarily due to stabilizing effect of fuel storages. Therefore, all the values of Table 3 are kept constant during the estimation period.

Table 3. Fuel element compositions and moistures

Element composition (m-%, d.b.)	Wood	Peat	Bark	Slurry
C	49.8	53	57.5	45
H	6.4	5.5	7.1	5.75
S	0.05	0.2	0.05	0.05
N	1.45	1.7	0.5	0.4
O	41.8	34.1	32.35	28.8
Ash	0.5	5.5	2.5	20
Water	50	50	60	77

The estimations and subsequent calculations were carried out in Matlab© environment. These results were conducted off-line, but the calculations can as well be done on-line.

3.3 Estimation results

Next is presented estimation results in a case that lasted 1 000 hours. The time resolution of calculations was 1 hour. Fig. 1 describes the basic conditions during the period. Upper diagram points out the estimated fuel power during the period, which was calculated indirectly from steam power. The graph illustrates that fuel power was mainly some 50–75 % of boiler nominal capacity. Lower figure presents the estimated fuel power proportions of the four fuel feeds. It can be seen that woody biomass dominated the fuel feed, slurry flow was minor but stable and the peat and bark flows fluctuated to significant extent.

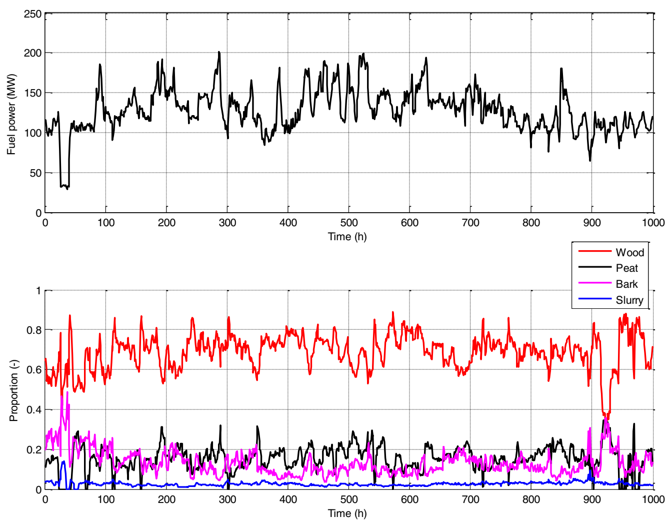

Fig. 1. Estimated total fuel power (upper) and proportions of fuel powers of total fuel power (lower).

Fig 2. illustrates flue gas O_2 and CO contents during the period. The raw measurements without compensations were fixed in equations (13) and (14). As the O_2 signal is uncompensated as such, the measured and estimated O_2 curves in Fig. 2 are the same. However, the measured and estimated CO signals differ slightly but to a noticeable extent due to errors in flue gas H_2O estimation that is used to compensate the CO estimate according to equation (40). Moreover, it can be seen that there is a significant raise in O_2 measurement at the beginning of the period which was caused by a process disturbance. The raise will affect the other estimates by oxygen compensation equation (41).

Fig. 3 and 4 demonstrate the estimation results. There, the flue gas moisture content compensations for estimated variables are calculated with use of flue gas moisture content estimate. Hence, an error in flue gas moisture content estimate will immediately disturb the other estimates accordingly. Fig 3. presents the measured and estimated air (upper) and flue gas (lower) flows.

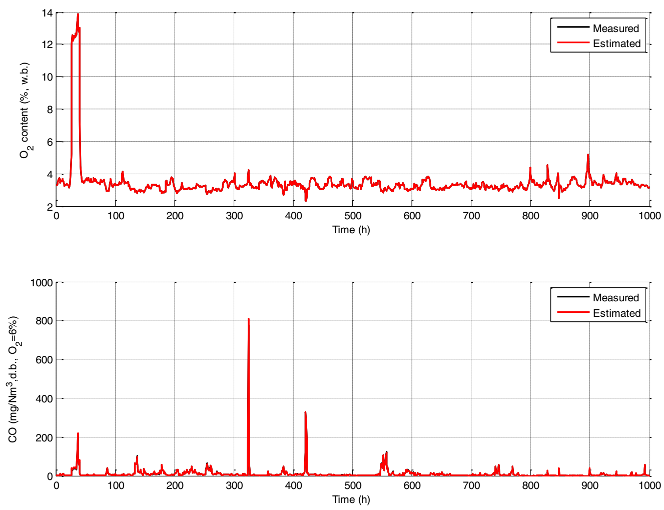

Fig. 2. Process measurements that are used as inputs in estimation calculus: O_2 (upper) and CO (lower).

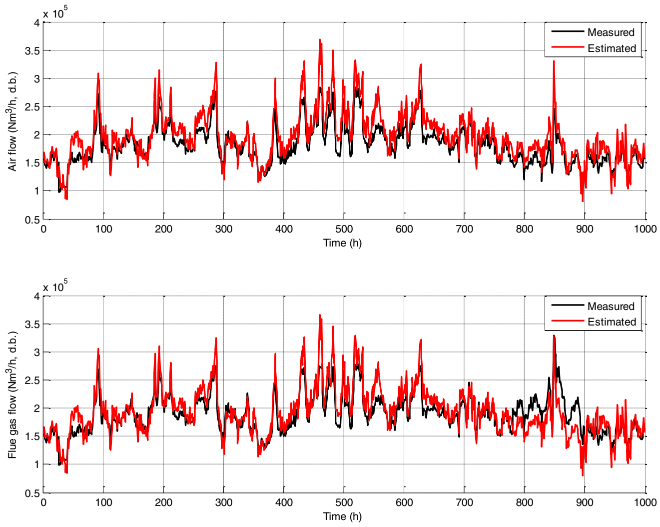

Fig. 3. Measured and estimated air (upper) and flue gas (lower) flows.

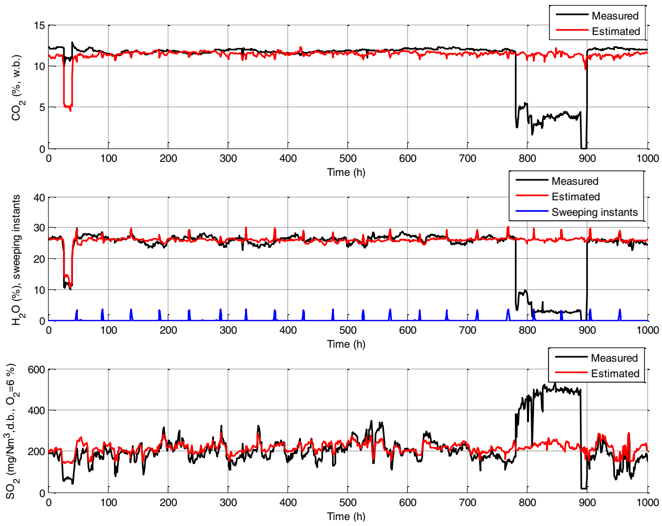

Fig 4. Measured and estimated flue gas CO_2 (upper), H_2O (middle) and SO_2 (lower) contents. Middle figure also shows time instants when steam assisted soot blowing was active.

It can be seen in Fig. 3 that the estimates fit quite well with the measurements. The most of the inconsistencies can be seen in both the air and the flue gas flows at the same time, which indicates that the actual fuel flows were different than measured. However, the similarity between air and flue gas flows is somewhat disturbed between time period 800–900, where the flue gas flow is significantly underestimated. The reason can be seen in Fig. 4, which demonstrates the measured and estimated flue gas contents, i.e. CO_2 (upper), H_2O in addition to boiler soot blowing instances (middle), and SO_2 (lower). There, the CO_2 and H_2O measurements drop significantly while the SO_2 peaks. This was caused by a failure in measurement device that provided the CO_2 and H_2O signals. As a result, the disturbed measurement signal also reflected to presented SO_2 signal via H_2O compensation. As can be seen, the estimates are likely to provide somewhat correct estimates also during the failure, which is highly beneficial from plant operation, diagnostics and emission reporting point of views. It should also be noticed, that the estimations succeed to recognise the abnormal process behaviour at the beginning of the run by providing fairly correct estimates. This feature enables the plant operators to differentiate the sensor malfunctions and abnormal process behaviours.

4. DISCUSSION

The major benefit of the presented flue gas estimation model is that it enables to connect several measurements before and after the boiler to form an entirety, which enables on-line anomaly detection, sensor diagnostics and drifting prevention. These prospects can be achieved with any fuel combination, as long as fuel flows and their chemical compositions and moisture contents are known. The major drawback is that these values, i.e. fuel compositions and moisture contents, do change constantly. Fortunately, some of these changes can be recognised, as these effects are indicated in several variables. Additionally, the fuel storages stabilize fuel quality changes, but trends remain. Therefore, some adaptive feature would improve the performance of the proposed estimation model. On the other hand, fuel storages might also cause errors to estimates, as the volume changes in storages deteriorate the simultaneousness of measurement before and after the boiler. Indication of this behaviour can be seen when estimation errors in both flue gas and air flow estimates increase synchronously. This could also be taken into account by adding energy balance to the calculations.

It was pointed out that the presented estimation method is able to recognise process anomalies and sensor malfunctions. The sensor malfunctions can, however, occur also in sensors that provide inputs to the model. Additionally, the fuel element properties and especially fuel moisture contents might change. As the analytical solution provides mathematically correct results, the estimates satisfy the balances also with false information. As a result, all the estimates are incorrect with false input information. If the error in the input signal is significant, the disadvantageous effect can be seen as increased estimation error in several or all the estimated variables. False information in O_2 and CO measurements and fuel properties affect primarily the estimates about flue gas compositions whereas false information in fuel flows primarily disturbs combustion air and flue gas flow estimates. Still, the interpretation of results might require some expertise but the results indicate a change in some variables.

The estimates presented in this paper also benefit other emission variables (i.e. NO_x, HCl, etc.) which are typically monitored, presented, and supervised in normalized conditions by O_2 and H_2O compensations. Therefore, the monitoring of these compensation variables also increases indirectly the reliability of these reported emission measurements.

5. CONCLUSIONS

The need for monitoring is evident; process anomalies and sensor faults must be detected and identified. This paper presented a balance calculation method to estimate combustion air and flue gas flows and flue gas composition (CO_2, H_2O, SO_2, and N_2) in any over stoichiometric combustion environment having one or multiple fuels. Based on physical characteristics of combustion, the analytical solution provides interpretable results in various process conditions and low CPU requirement in computational environments. The method was tested in an industrial BFB boiler having wood, peat, bark, and slurry as fuels. The test results indicated the applicability of the method in this challenging process environment. Currently, the method is applied on-line at the power plant described in this article, and the method is to be applied at two boilers of a coal fired power plant and at a waste incineration plant in the near future. The method should, however, be further developed to adapt to significant fuel flow and especially fuel moisture content variations.

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Robust data reconciliation of combustion variables in multi-fuel fired industrial boilers

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ABSTRACT

This paper introduces an application of simultaneous nonlinear data reconciliation and gross error detection for power plants utilizing a complex but computationally light first principle combustion model. Element and energy balances and robust techniques introduce nonlinearity and the consequent optimization problem is solved using nonlinear optimization. Data reconciliation improves estimation of process variables and enables improved sensor quality control and identification of process anomalies. The approach was applied to an industrial 200 MW_{th} fluidized bed boiler combusting wood, peat, bark, and slurry. The results indicate that the approach is valid and is able to perform in various process conditions. As the combustion model is generic, the method is applicable in any boiler environment.

1. Introduction

Safe and sound operation of systems has a very important role in modern energy industry due to economic, environmental, and safety related aspects. The soundness of systems can be evaluated only if there is reliable information available about the state of the processes. This information is needed to enable optimum performance and to fulfill the requirements set by authorities. Development of process and operation strategies is based on information collected from running processes. Thus, correct decision making requires correct information, and actions based on false information can be expensive, and even dangerous. Furthermore, complying with permitted emissions levels and monitoring of cumulative carbon dioxide emissions must be based on reliable process information. Optimal operation of emission reduction systems such as filters, scrubbers, and converters should be based on reliable information about existing emission levels, and trading with carbon emission allowances is, as well, based on reliable definition of cumulative emissions. Today, a significant share of the electric energy market takes place in energy exchanges, where trading is based on the marginal costs of individual producers. The lowest bid gets the transaction. To be successful on these markets, the producers should have reliable information about the states and marginal production costs of their power generation systems. Thus, there is without a doubt a need for and value generated from on-time and reliable information from production systems.

Real industrial plant measurements are almost without exception corrupted by measurement noise and occasional gross errors. Malfunctions or incorrect calibration in sensor equipment may cause systematic errors or atypical statistical characteristics in the measured values and lead to suboptimal system operation, hazardous situations, and significant monetary losses. Sensor faults may be observable only intermittently or may require a plant wide analysis to uncover their sources which motivates the development of automatic monitoring systems. Power plants present a promising application area for automatic monitoring as they are large, consist of multiple interconnected subsystems, and economic volumes are high. Even a small improvement may have a great impact on the economic result. Unfortunately, the trivial solution to increase measurement reliability by adding extra measurements is often impossible due to economic reasons, so other solutions must be found. An alternative to hardware redundancy is analytical redundancy which utilizes existing process measurements, models, and data analysis to provide more insight into measurement reliability. The major drawbacks of this approach are model development and maintenance costs, which can to some extent be managed by employing generic combustion models. This approach is utilized in this article.

Model based Fault Detection and Identification (FDI) has been studied and developed actively since 1980s. The two main procedures for model based fault detection are dynamic observers and

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parameter estimation based methods often augmented with applications of artificial intelligence for fault identification. In observer based methods, estimated system state information is compared with measured information and in fault detection with system parameter estimation incipient faults are detected by repetitive identification of system parameters. These methods are documented in several books, e.g. (Chen & Patton, 1999; Gertler, 1998; Korbicz, Koscielny, Kowalczuk & Cholewa, 2004; Patton, Frank & Clark, 1989, 2000).

Power generation plants have been a common target for process diagnostics. This is motivated by the high reliability requirements set for energy production systems and remarkable monetary flows related to efficient operation. Early detection of incipient faults can prevent unexpected shutdowns and will help power system operators maintain the balance in the power system. Non-optimal operation of a power plant due to false information from unreliable or faulty measurements or defective process components will easily lead to hundreds of thousands of euros in extra annual operation costs. Examples of diagnosis applications in different kinds of power generation systems, such as steam boilers, thermal gasifiers, nuclear power plants, and wind turbines are reported in Majanne (2008), Majanne, Lautala and Lappalainen (1995), Majanne, Ruokonen, Kurki and Ala-Siuru (1992), Odgaard, Lin and Jorgensen (2008), Odgaard and Mataji (2008), Ruan and Fantoni (2002).

The origin of measurement errors can be determined by examining the statistical properties of received data and analyzing corrections made by data reconciliation procedures. Data reconciliation corrects process data using optimization methods to satisfy process constraints. The process model is defined in the form of equality and/or inequality constraints derived from conservation laws, equilibrium constraints, and physical process constraints. In other words, the process model defines the mass and energy balance of the system and takes into account the physical limitations of the sensors. The objective function weights corrections of the measured values by their reliability calculated from the measurement variance of normal operation.

The first steady-state data reconciliation method was proposed by Kuehn and Davidson (1961). The initial data reconciliation solutions relied on simple mass balances where the problem may be solved using linear programming. The iterative successive linearization method was first used to solve nonlinear reconciliation problems in Knepper and Gorman (1980), MacDonald and Howat (1988). Matrix projection, proposed in Crowe, Campos and Hrymak (1983), Crowe (1986), enabled the solution of further linear and nonlinear problems. These and other reconciliation methods have typically relied on the least squares objective function that has a prerequisite that gross errors must be detected and filtered out of measured data before the data reconciliation. A general review of data reconciliation and gross error detection methods may be found in Narasimhan and Jordache (1999).

The robust statistics methods of Huber (1981) have been applied to data reconciliation to overcome the need for iterative procedures which first remove gross errors and then perform the reconciliation. Simultaneous data reconciliation and gross error detection was first used in Tjoa and Biegler (1991) where the objective function was based on a contaminated Normal distribution and the ensuing problem solved using nonlinear programming. Different robust estimators and their feasibility have been examined in Albuquerque and Biegler (1996), Arora and Biegler (2001), Johnston and Kramer (1995). A comparative review of different estimators was presented in Özyurt and Pike (2004). Successful application of the robust estimators has been reported in Prata, Schwaab, Lima and Pinto (2010) using data from an industrial polypropylene reactor.

In power plant environments, data reconciliation has been applied in several cases. For example, Fellner, Cencic & Rechberger (2007) used data reconciliation to determine the fractions of biogenic and fossil matter in a waste to energy plant. Gulen and Smith (2009) derived a generic form for data reconciliation when mass, energy and/or momentum balances are available and demonstrated the method with simulated data from a single shaft combined cycle system. Heyen, Vrielynck and Kalitventzef (1998) used data reconciliation to improve data reliability for parameter identification in a power generation setting. Szega (2011) used a data reconciliation method to improve the reliability of measurement data in calculation of parameters characterizing the thermal process in a waste-heat boiler. Touš, Frýba and Pavlas (2013) utilized nonlinear optimization and data reconciliation to improve the evaluation of lower heating value of waste and efficiency evaluation. Huovinen, Laukkanen and Korpela (2012) present an on-line data reconciliation application used to estimate the reliability of measurements in the water-steam cycle of power plants. Jiang, Liu and Li (2014a), (2014b) demonstrated data reconciliation and gross error detection in integrated sensor and equipment performance monitoring with simulated data from the feed water heating system of a coal-fired power plant. Karlsson, Dahlquist and Dotzauer (2004) used data reconciliation and gross error detection with simulated data to correct the mass flow measurements from a bio-fuel fired heat and power plant. Martini, Sorce, Traverso and Massardo (2013) presented the application of data reconciliation and gross error detection to a microturbine-based test rig. Syed, Dooley, Carl Knopf, Erbes and Madron (2013) demonstrated the efficacy of data reconciliation and gross error detection in examples from gas turbine cogeneration systems. Valdetaro and Schirru (2011) used a robust data reconciliation method to select models, detect outliers and improve measurement data in a simplified thermal reactor using particle swarms. As a conclusion, most of these papers focus on limited sub-processes and mainly on the water-steam cycle of power plants.

In this paper, simultaneous nonlinear data reconciliation and gross error detection is applied to monitoring of combustion variables in a complex multi-fuel fired industrial fluidized bed boiler. Utilization of the method requires a mathematical model, which in this case is a first principle combustion model. The model is founded on element balance equations that are formed from the main chemical reactions taking place in combustion environments. Element balances have been utilized previously in some applications, especially in waste incineration applications, to estimate some interesting characteristics. Element balances have been utilized e.g. in estimation of fuel heating value by Fellner, Cencic and Rechberger (2007), Hsi and Kuo (2008), Van Kessel, Arendsen and Brem (2004), fuel burning rate (Hsi & Kuo, 2008), in separation of defined fractions of fossil organic and biogenic waste components (Fellner, Cencic & Rechberger, 2007), and in calculation of flue gas specific heat and specific exergy value (Coskun, Oktay & Ilten, 2009). For monitoring purposes it has been applied by Korpela, Björkqvist, Majanne and Lautala (2014) where element balance calculus was utilized for indirect online monitoring of flue gas CO_2, H_2O, and SO_2 concentrations in addition to flue gas and combustion air flows. In the model, the analytical solution of element balances enables computationally light numerical calculus, which is a prerequisite for computationally intensive nonlinear optimization required in simultaneous nonlinear data reconciliation and gross error detection. This paper extends the approach presented in Korpela, Björkqvist, Majanne and Lautala (2014) with an extended model and especially with adaptive features.

This work addresses the enhancement of an existing reconciliation system to simultaneous data reconciliation and gross error detection in combustion environment. The structure of the article is as follows. Section 2 presents the nonlinear optimization and robust estimators used in data reconciliation. Section 3 presents the derivation of the combustion model. The overall objective of the model derivation is to provide analytical redundancy by formulating estimates for every analyzed measurement or quantity. Section 4 illustrates the approach with a case study on an industrial 200 MW_{th} bubbling fluidized bed boiler using wood, peat, bark, and slurry as fuels. Section 5 includes the discussion, and Section 6 summarizes the article.

2. Nonlinear optimization and robust estimators in data reconciliation

In comparison to linear programming methods, nonlinear optimization allows for the direct solution of reconciliation problems which include nonlinear constraints without the need for approximation. Nonlinearities are, for example, present in energy balances if material flows and their temperatures are to be simultaneously reconciled. Nonlinear constraints additionally allow incorporation of more advanced process knowledge into the optimization problem directly. This knowledge may include processes such as cooling which may be directly defined as an inequality constraint between consecutive, in time or place, measurements. Nonlinear optimization problems have been hard to implement mainly due to requirements on computational power and the required computation times prohibiting real time use. With increasing availability of nonlinear optimization software and increases in computational power, nonlinear optimization can provide significant benefits. However, the applicability of nonlinear optimization is highly dependent on the computational solvability of the model. In the diagnostic method presented in this paper, the practical rationality is dependent on on-line computation in industrial environment and hence on the computational solvability of the model. Therefore the model formulation presented in Section 3 is crucial.

Data reconciliation deals with measurement errors which may be classified into random and gross errors. The first type is generally present in all process measurements. They are random and small in comparison and should not influence the performance of the control systems if the variance of the random error stays within allowable limits. Random errors are characterized by a probability distribution which is typically assumed to be a zero mean normal distribution. The performance of measurement devices may degrade, leading to increases in variance. Data reconciliation may be used to compare the realized error variances with the values given by the manufacturers of the measurement devices and possible specified operational limits. However, generally the evaluation of any measurement error variance through data reconciliation is susceptible to errors in the process models because the relative magnitude is small.

Gross errors are in practice comprised of either systematic errors or signal errors. Systematic errors are defined as either static measurement biases or time-varying trending biases. A typical source for the first type is calibration errors whereas calibration drifting leads to time-varying biases. By examining deviations from ideal mass/energy balances, data reconciliation provides an indication of the need for recalibration or maintenance.

Signal errors may be viewed as systematic errors though they are typically not consistent. They are especially troublesome for process control as they may be hard to detect and can influence process performance. Typical causes include instrument failure, transmission errors, and process errors such as leaks. Power plants may lack automatic supervision or reactionary methods for these types of errors especially in noncritical measurements (Laukkanen & Huovinen, 2011). Data reconciliation can be used to pinpoint the location of these errors.

Notably any measurement error should cause a deviation from the ideal mass/energy balance and should be detectable with data reconciliation.

2.1. Mathematical formulation

The robust estimators considered here belong to the class of M-estimators which are defined broadly as estimators providing the minima of sums of functions of the data. Functions are chosen in robust methods such that the estimators are not sensitive to gross errors. The generalized steady-state data reconciliation optimization problem, for some time instant n, has the general form:

$$\min\sum_i \rho\left(\frac{y_{i,n}-\hat{y}_{i,n}}{\sigma_i}\right)=\min\sum_i \rho(\xi_i) \tag{1}$$

$$s.t.\, f\left(\hat{\boldsymbol{u}},\hat{\boldsymbol{y}}_n\right)\le 0$$

$$g\left(\hat{\boldsymbol{u}},\hat{\boldsymbol{y}}_n\right)=0.$$

Here, ρ denotes the cost function defined by the chosen estimator. Further, $y_{i,n}$ denotes the measured value of the i^{th} variable. The variables $\hat{y}_{i,n}$ denote the reconciled values to be found which are collected into the vector $\hat{\boldsymbol{y}}_n$. Under ideal conditions, i.e. no gross errors, measurement errors are assumed additive, uncorrelated, and normally distributed with known standard deviation σ_i. The standard error is denoted ξ_i. The reconciled variables should minimize the sum of deviations from the measured values while still fulfilling the relevant process constraints. The constraints are described by the process model constraints f and g. Equality constraints generally describe the material and energy balances, and the inequality constraints are imposed by feasibility of process operation and physical limits. Any unmeasured variables or process parameters to be estimated are denoted with the vector $\hat{\boldsymbol{u}}$.

In the ideal case, without gross errors, the maximum likelihood estimator is the weighted least squares (WLS) estimate. The ρ function is then:

$$\rho(\xi_i)=\frac{1}{2}\xi_i^2, \tag{2}$$

Assuming measurements are independent, i.e. no cross correlations exist, each correction is weighted with the inverse of the variance meaning more reliable measurements will be corrected less and vice versa.

Different types of cost functions have been designed such as, for example, the Huber, Cauchy, Lorentzian, Contaminated normal, Tukey, and Hampel robust estimators. In this case, we only consider the Welsch estimator (Dennis & Welsch, 1978) . This is defined using the tuning parameter c_W and has the following form:

$$\rho(\xi_i,c_W)=\frac{c_W^2}{2}\left(1-\exp\left[-\left(\frac{\xi_i}{c_W}\right)^2\right]\right). \tag{3}$$

The value c_w=2.9846 is used to obtain 95% asymptotic efficiency on the standard normal distribution (Prata, Pinto & Lima, 2008). The efficiency roughly refers to how well the method performs under a known distribution and when errors differ from the known distribution.

The influence function is often used to evaluate the robustness of M-estimators (Hampel, Ronchetti, Rousseew & Stathel, 1986; Özyurt & Pike, 2004). It describes how data whose distribution differs from the ideal assumption affects the estimate. Fig. 1 shows the forms of the two ρ-functions and their influence functions for the standardized error. For large values of the standard error, the

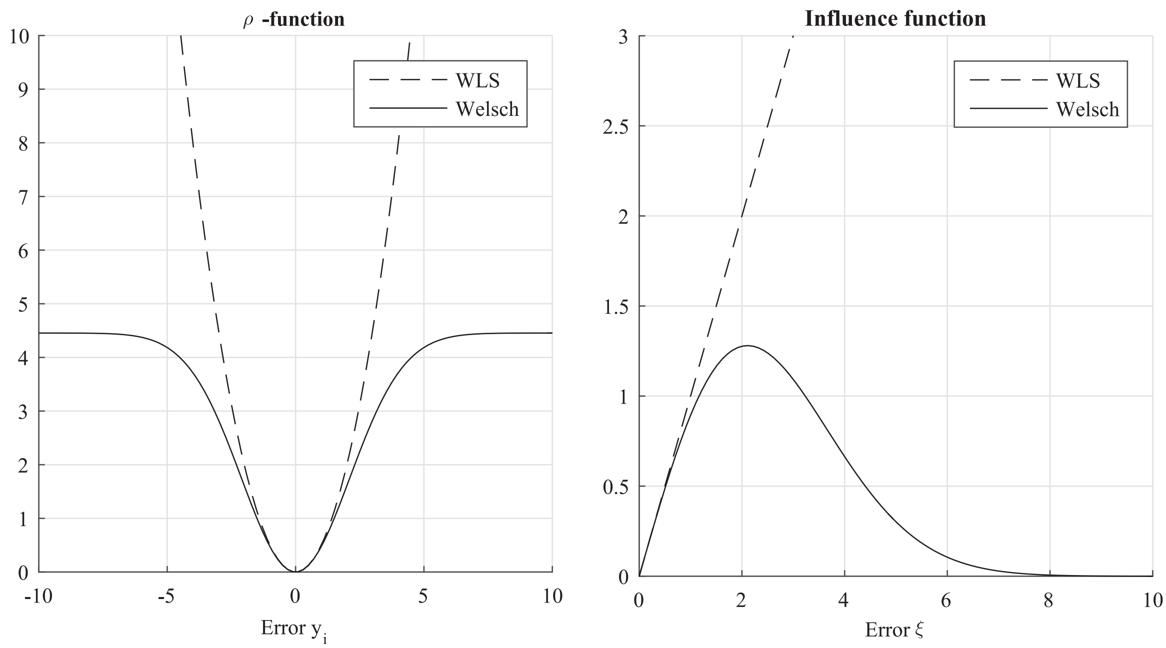

Fig. 1. ρ-function for one variable and influence function over the standardized error ξ for the weighted least squares (WLS) and Welsch-estimators.

influence function of the Welsch estimator approaches zero while for the WLS estimator the value is unbounded. Robustness requires a bounded influence function. The WLS influence function indicates that a large error in one variable will influence the other obtained values when using the WLS estimator. A large deviation in one variable causes other variables to compensate in the opposite direction. This effect is commonly referred to as smearing. In contrast, the influence function of the Welsch estimator indicates that after a certain point a gross error will not affect the other variables.

The Welsch estimator has been recommended and applied by Prata, Pinto and Lima, (2008), Prata, Schwaab, Lima and Pinto, (2010). A further practical justification for its use is the existence of a continuous derivative in terms of the objective function when performing optimization. The gradient can be used in many commercial optimization programs to significantly speed up computation.

2.2. Nonlinear data reconciliation example

Consider the following simple system where two material flows (indexes 1 and 2 below) at different temperatures are mixed and the ensuing material (index 3 and 4) is heated by a third flow (indexes 5 and 6) which does not mix with the combined flow. All flows and their temperatures are measured before and after mixing and before and after heating. The flows with their indexes are depicted below in Fig. 2.

The first equation below describes the summation of the two first flows which is required to be equal to the ensuing flow. The second and third equations are related to the fact that the combined flow and the heating flow must equal the flows leaving the heater. The variable m_i denotes the mass of a flow. The mass balances are:

$$m_1 + m_2 - m_3 = 0$$

$$m_3 - m_4 = 0$$

$$m_5 - m_6 = 0.$$

In the energy balance, the specific heat of all flows is assumed for simplicity to be equal and as such is left out below. Additionally, no heat is assumed to be lost. The mixing process defines the first equation below and the heating process the second. Energy exchanges must fulfill the following equalities:

$$m_1T_1 + m_2T_2 - m_3T_3 = 0$$

$$m_3T_3 + m_5T_5 - m_4T_4 - m_6T_6 = 0.$$

Each variable is measured directly and independently of each other with the following variances:

$$diag(\boldsymbol{\Sigma}) = [8, 6, 2, 2, 10, 12, 5, 5, 5, 5, 5, 5]^T,$$

where Σ denotes the combined covariance matrix and *diag* its diagonal elements. The variables are arranged such that the 6 mass flows are followed by the respective 6 temperatures. Measurement errors are simulated with normal distributions.

Fig. 3 shows a simulation illustrating the difference between the weighted least squares estimation, left, and robust estimators, right. Only the 6 mass variables are shown. After 50 time steps a bias is added to the fourth variable. When using the non-robust estimation technique, this clearly influences the reconciled values of the first and third variable indicating that such a gross error should be removed before reconciliation. When using the Welsch estimator, the correct variable m_4 is altered and the correction does not influence the other variables. Both examples were solved with Matlab's nonlinear optimization function *Fmincon* using an interior-point algorithm.

Notably, the reconciled values provided by data reconciliation fulfill the required balances and as such, assuming the model in

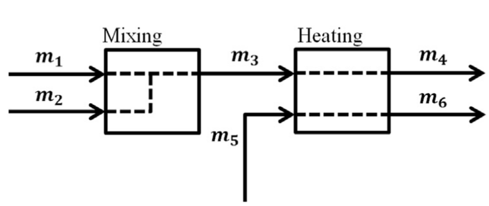

Fig. 2. Flow sheet of the example system with m_i denoting the i^{th} flow. Temperature of each flow is also measured.

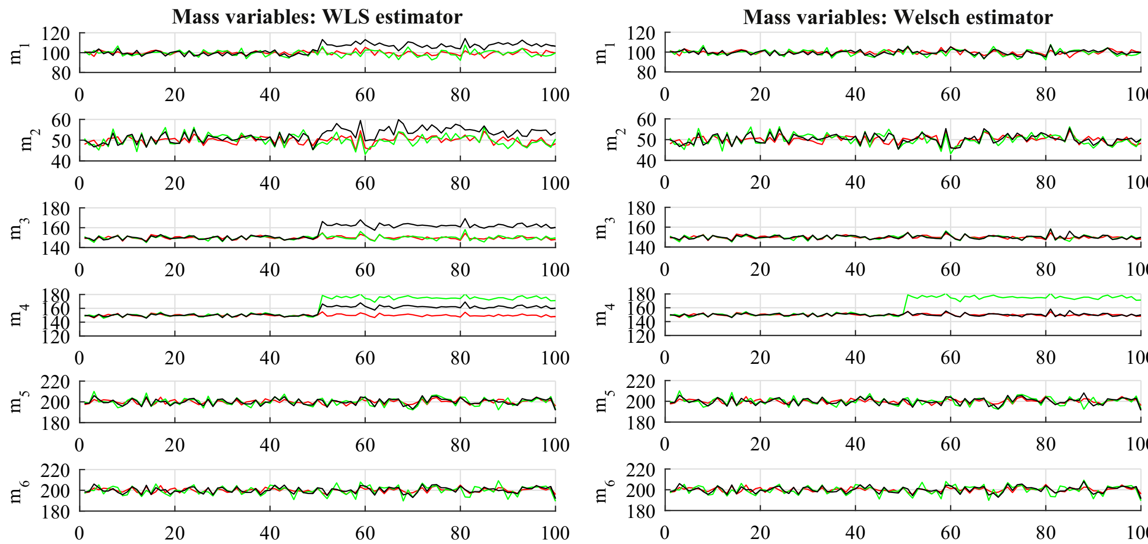

Fig. 3. Nonlinear data reconciliation with weighted least squares (left) and Welsch estimator (right). True data in red, measurements in green and reconciled values in black. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

use is well defined, will produce more trustworthy results. In this simulated case, it is also possible to compare the error of the reconciled values between estimators as the true values are known. In a longer test simulation of 200 time steps without gross errors, the mean squared error was reduced by 45–80% when comparing the reconciliation results of the WLS estimator to those provided by the Welsch estimator.

3. Modeling boiler process

In this section, the model for estimating the monitored variables is presented. The model focuses on combustion in boilers with over stoichiometric conditions (i.e. with oxygen excess) which excludes gasification and pyrolysis processes. The model is derived to be applied with multiple fuels and is as such boiler size and structure independent. However, utilization of the model requires some basic measurements which might not exist in small units or ones with modest monitoring requirements set by authorities. In Europe, all boiler units exceeding 50 MW_{th} fall under the jurisdiction of Industrial Emission Directive (IED, 2010) and have the required measurements to apply the main features of the method presented in this paper. The method is as such generic, but the configuration of every power plant is case specific.

The model merges several unreliable measurements and information into one analysis. In the estimation process, boiler inputs (i.e. fuel(s), combustion air, and sooting steam feeds) and outputs (flue gas and ash flows; exploited heat and heat losses) and their characteristics are measured or estimated. The foundation of the model is formed by the element balance equations that are derived from the main chemical reactions taking place in combustion environments. The element balances can be solved analytically, which enables their utilization in monitoring applications with only minor computational requirements. Additionally, the energy balance of the boiler is derived to provide additional measurement information from the water-steam portion of the boiler.

The overall objective of the modeling is to formulate estimates and then to derive balance equations for every analyzed measurement or quantity. The modeling procedure has two stages. In the first stage, the overall first principle combustion model, which is an extension of the model presented in Korpela, Björkqvist, Majanne and Lautala (2014), is derived. The model utilizes measurement and additional information and generates estimates for various variables: For the variables that have physical sensors the model provides analytical redundancy. This is used to generate balances in general form '*measurement–estimate*=0' that are utilized in Section 4. For variables without direct measurement the model provides additional information that can be utilized in numerous ways. In the second stage, the energy balance for the boiler is derived.

3.1. Element balance calculus

The first principle model is based on element and energy balance equations and a priori information. The main a priori information for the model is fuel chemical compositions (fuel ultimate analysis) expressed in form $C_xH_yO_zN_vS_wCl_o$, where x, y, z, v, w, and o represent the molecular ratio of the respective element to carbon, e.g. C_6H_{14} corresponds to $C_1H_{2.33}$. Additionally, moisture and ash contents, and higher heating value of the fuels (fuel proximate analysis) must be known for all fuels involved. Furthermore, potential inert material mixed with fuels, e.g. soil within biomass and unburnt material, can be taken into account when appropriate. Fuel chemical composition and the respective nomenclature are presented in Fig. 4. In this case study, fuel specific compositions of dry fuels and ashes are obtained from literature. In reality, these properties change but average values are utilized

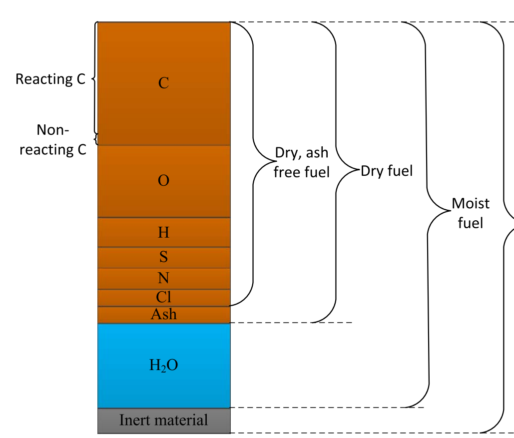

Fig. 4. Chemical composition of a fuel.

in this study. Inert material, e.g. rocks, dust, soil, and metal, are impurities within the fuels and are case specific, and any plant history data can provide information on these values. Additionally, fuel moisture contents of solid fuels may vary significantly and here case specific history values provide reasonable initial values which are altered in Section 4.

3.1.1. Element balance equations

The main chemical reactions in combustion environment in over stoichiometric (i.e. with oxygen excess) conditions can be presented as

$$C + O_2 + 3.76 \cdot N_2 \rightarrow CO_2 + 3.76 \cdot N_2 \tag{4}$$

$$C + 0.5 \cdot (O_2 + 3.76 \cdot N_2) \rightarrow CO + 1.88 \cdot N_2 \tag{5}$$

$$2 \cdot H + 0.5 \cdot (O_2 + 3.76 \cdot N_2) \rightarrow H_2O + 1.88 \cdot N_2 \tag{6}$$

$$S + O_2 + 3.76 \cdot N_2 \rightarrow SO_2 + 3.76 \cdot N_2 \tag{7}$$

$$N + 0.5 \cdot O_2 \rightarrow NO \tag{8}$$

$$N + O_2 \rightarrow NO_2 \tag{9}$$

Based on the chemical reactions (4–9), the main flue gas components are carbon dioxide (CO_2), water (H_2O), nitrogen (N_2) and sulphur dioxide (SO_2). Combustion typically takes place with excess air which is indicated by nonzero oxygen (O_2) content in the flue gas. Dry air contains ca. 21% of O_2 and 79% N_2, which means that 1 mole of O_2 carries with it 3.76 moles of N_2. Some carbon monoxide (CO) may also be present in the flue gas due to incomplete combustion. Nitrogen oxides (NO_x) are also present, of which the vast majority are in the form of nitrogen monoxide (NO) and some in the form of nitrogen dioxide (NO_2). In this approach, it is assumed for simplicity that all the NO_x emissions are in form NO.

In this study, the chloride of the fuels is converted to hydrogen chloride (HCl) by the reaction

$$H + Cl \rightarrow HCl \tag{10}$$

This is a rough estimate, which is somewhat valid when overall sulphur-to-alkane ratio is high enough and therefore only minor amounts of potassium chloride (KCl) is formed. The validity of the estimate is questionable, but is included in the model as it might provide information on boiler corrosion behavior (Nielsen, Frandsen, Dam-Johansen & Baxter, 2000). However, the estimated amount of HCl can be limited by reducing the amount of reacting chlorine.

By gathering the reactions (4–10)4 and considering the described limitations, the overall chemical reaction formula of combustion of multiple fuels ($k \in \mathbb{N}$) can be expressed as

$$\sum_k \left(r_{F,k} \cdot C_{x_k} H_{y_k} O_{z_k} N_{v_k} S_{w_k} Cl_{o_k} \right) + r_{Air} \cdot (O_2 + 3.76 \cdot N_2 + \eta \cdot H_2O) + \gamma \cdot H_2O \rightarrow b \cdot CO + c \cdot CO_2 + d \cdot H_2O + e \cdot O_2 + f \cdot N_2 + g \cdot NO + h \cdot SO_2 + i \cdot HCl \tag{11}$$

whose symbols and indexes are described in Tables 1 and 2, respectively.

The parameters b, c, d, e, f, g, h and i determine the molecular proportions of the flue gas. Ashes and other inorganic material, e.g. soil, and unreacted material must be excluded in (11). From (11), the element balance equations for C, H, O, N, S, and Cl can be described, respectively, as

Table 1
Nomenclature.

Symbol	Description	Unit
n	Amount of substance	mol
M	Molecular mass	kg/mol
m	Mass	kg
p	Pressure	Pa
R	Universal gas constant	J/(mol K)
ρ	Density	kg/m^3
T	Temperature	°C
$r_{F,k}$	Ratio of molecular flow of fuel k over total molecular fuel flow	–
u	Moisture content	–
x	Molecular ratio of C to C, i.e. $x=1$	–
y	Molecular ratio of H to C	–
z	Molecular ratio of O to C	–
v	Molecular ratio of N to C	–
w	Molecular ratio of S to C	–
o	Molecular ratio of Cl to C	–
r_{Air}	Air-to-fuel mole ratio	–
λ	Molecular air factor	–
η	Amount of moles of H_2O in air per mole of dry air	–
γ	H_2O-to-fuel mole ratio	–
X	Volume ratio	–
Y	Mass ratio	–
Φ	Air moisture content	–
$\dot{\varepsilon}$	Change rate of variable ε	1/h

Table 2
Indexes.

Symbol	Description
k	Fuel k, i.e $k \in \mathbb{N}$
daf	Dry, ash free
st	Stoichiometric
FG	Flue gas
l	Gas component, i.e. $l = O_2$,CO
STP	Standard temperature and pressure, i.e. $T = 0$ °C=273.15 K & $p = 101{,}325$ Pa
me	Measurement
est	Estimate

$$\sum_k \left(r_{F,k} \cdot x_k \right) - (b + c) = 0 \tag{12}$$

$$\sum_k \left(r_{F,k} \cdot y_k \right) + 2 \cdot r_{Air} \cdot \eta + 2 \cdot \gamma - (2 \cdot d + i) = 0 \tag{13}$$

$$\sum_k \left(r_{F,k} \cdot z_k \right) + r_{Air} \cdot (2 + \eta) + \gamma - (b + 2 \cdot c + d + 2 \cdot e + 2 \cdot h) = 0 \tag{14}$$

$$\sum_k \left(r_{F,k} \cdot v_k \right) + 2 \cdot 3.76 \cdot r_{Air} - (2 \cdot f + g) = 0 \tag{15}$$

$$\sum_k \left(r_{F,k} \cdot w_k \right) - h = 0 \tag{16}$$

$$\sum_k \left(r_{F,k} \cdot o_k \right) - i = 0. \tag{17}$$

In (16) it is stated that all the sulphur is reacted to SO_2. The validity of this assumption is process and process condition dependent, e.g. any SO_2 removal actions would invalidate the SO_2 estimate without affecting the other calculus. However, similar to HCl, this parameter can be altered by some additional information or omitted by setting w_k to zero. From (11), the concentrations of O_2, CO, and NO in the flue gas can be represented by molecular ratios in unit (–) as

$$X_{O_2} = e/(b + c + d + e + f + g + h + i) \tag{18}$$

$$X_{CO} = b/(b + c + d + e + f + g + h + i) \tag{19}$$

$$X_{NO} = g/(b + c + d + e + f + g + h + i) \tag{20}$$

The Eqs. (18–20) can be fixed with the flue gas composition measurements by balances

$$X_{O_2,me} - X_{O_2}=0 \tag{21}$$

$$X_{CO,me} - X_{CO}=0 \tag{22}$$

$$X_{NO,me} - X_{NO}=0. \tag{23}$$

The flue gas composition measurement values in Eq. (21–23) are used in uncompensated measurements conditions, i.e. in measured O_2, CO, and NO concentration and in moist gas presented in absolute units (–).

The Eqs. (12–17) and (21–23) form a system of 9 polynomial equations. The flue gas composition parameters, i.e. b, c, d, e, f, g, h and i, and oxygen-to-fuel mole ratio r_{Air} include 9 variables. When the other parameters are assumed to be known, the variables of interest can be solved analytically. The analytical solution can be formed with relevant software, e.g. MATLAB Symbolic Math Toolbox, and has to be done only once. After that, the solutions are expressed in terms of elementary functions that can be easily utilized in any calculation environment and require only minor computational power. The elementary functions of flue gas composition and air-to-fuel mole ratio are extensive as such and are omitted here for convenience. The computational lightness makes the model very applicable to the diagnostic methods proposed in this paper.

3.1.2. Calculation of input parameters of element balance model

In this subsection, derivation of the input parameters of the element balance model is presented. The most important input parameter is related to fuel qualities and their chemical compositions, whose definitions and presentations, unfortunately, differ in literature. Hence, fuel chemical composition definitions and the respective nomenclatures used in this paper are presented in Fig. 4.

The molecular flow of fuel k over total molecular fuel flow can be presented as (–)

$$r_{F,k} = \dot{n}_{k,daf}/\sum_k \dot{n}_{k,daf}, \tag{24}$$

where

$$\dot{n}_{k,daf} = \dot{m}_{k,daf}/M_k, \tag{25}$$

in which $\dot{m}_{k,daf}$ is dry ash free mass flow of fuel k. It can be calculated by reducing the respective fuel moisture, ash and inorganic contents from the measured fuel mass flows (Fig. 4). Such inorganic material might be e.g. soil that is mixed with solid biomass when handling the fuel in the fuel supply chain. Then, the molecular mass M of fuel k can be calculated by

$$M_k = x_k\cdot M_C + y_k\cdot M_H + z_k\cdot M_O + v_k\cdot M_N + w_k\cdot M_S + o_k\cdot M_{Cl} \tag{26}$$

where the molecular ratios (x_k, y_k,...) are based on reduced compositions. The external moisture content that is fed to the boiler in the form of fuel moisture and steam from the soot blowing system can be calculated with the following equation

$$\gamma = \sum_k \left(r_{F,k}\cdot x_k\cdot n_{H_2O,k}/n_{C,k}\right) + \dot{m}_{steam,me}/\left(M_{H2O}\,22c5 \sum_k \dot{n}_{k,daf}\right), \tag{27}$$

where $n_{H_2O,k}$ is the molecular amount of water in 1 kg of moist fuel k and $n_{C,k}$ is the respective amount of carbon. The ratio $n_{H_2O,k}/n_{C,k}$ is similar to scaling of fuel elements (e.g. $n_{H,k}/n_{C,k}$) and connects fuel moles and moistures. The latter term in (27) defines the relative amount of steam from soot blowing compared to total molecular fuel flow, where $\dot{m}_{steam,me}$ denotes the measured steam mass flow fed to the combustion chamber of the boiler.

The stoichiometric (st) air demand of fuel k can be expressed as

$$r_{Air,st,k} = x_k + (y_k - o_k)/4 + w_k - z_k/2. \tag{28}$$

Then, the overall excess air ratio (λ) can be calculated as

$$\lambda = r_{Air}/\sum_k r_{Air,st,k}. \tag{29}$$

The air humidity is taken into account by calculating the molecular ratio of air moisture to dry air by equation

$$\eta = (\varphi\cdot p_h')/(p_{tot} - \varphi\cdot p_h') \tag{30}$$

where φ is measured air moisture content, p_h' saturation pressure of water vapor at measured combustion air temperature, and p_{tot} measured pressure of moist air.

The dry air and air moisture mass flows can be calculated by equations

$$\dot{m}_{air,dry} = (1 + 3.76)\cdot r_{Air}\cdot M_{air}\cdot \sum_k \dot{n}_{k,daf} \tag{31}$$

$$\dot{m}_{air,H_2O} = \eta\cdot r_{Air}\cdot M_{H_2O}\cdot \sum_k \dot{n}_{k,daf} \tag{32}$$

whose sum is the total moist air mass flow. The mass flows can be converted to volume flows by multiplying them with respective gas densities derived from the ideal gas law, i.e.

$$\rho_{gas} = p_{gas}\cdot M_{gas}/\left(R\cdot(T_{gas} + T_{STP})\right) \tag{33}$$

where T_{STP}=273.15. Hence, the volume flow of combustion air can be estimated by equation

$$\dot{V}_{Air,est} = \dot{V}_{Air,est,dry} + \dot{V}_{Air,est,H_2O} = \dot{m}_{air,dry}/\rho_{Air} + \dot{m}_{air,H_2O}/\rho_{H_2O} \tag{34}$$

of which $\dot{V}_{Air,est,dry}$ is one of the variables that is reconciled in Section 4.

3.1.3. Calculation of output parameters of the element balance model

In this subsection, the flue gas estimates that can be generated based on element balance calculus are derived. The main outputs of the combustion model are the flue gas compositions and flue gas volume flow. The flue gas composition can be solved from Eqs. (18–20) and (35–39) in units (–)

$$X_{CO_2,est} = c/(b + c + d + e + f + g + h + i) \tag{35}$$

$$X_{H_2O,est} = d/(b + c + d + e + f + g + h + i) \tag{36}$$

$$X_{N_2,est} = f/(b + c + d + e + f + g + h + i) \tag{37}$$

$$X_{SO_2,est} = h/(b + c + d + e + f + g + h + i) \tag{38}$$

$$X_{HCl,est} = i/(b + c + d + e + f + g + h + i) \tag{39}$$

Additionally, the mass flows (kg/h) of flue gas components can be calculated by equations

$$\dot{m}_{CO} = b\cdot M_{CO}\cdot \sum_k \dot{n}_{k,daf} \tag{40}$$

$$\dot{m}_{CO_2} = c \cdot M_{CO_2} \cdot \sum_k \dot{n}_{k,daf} \tag{41}$$

$$\dot{m}_{H_2O} = d \cdot M_{H_2O} \cdot \sum_k \dot{n}_{k,daf} \tag{42}$$

$$\dot{m}_{O_2} = e \cdot M_{O_2} \cdot \sum_k \dot{n}_{k,daf} \tag{43}$$

$$\dot{m}_{N_2} = f \cdot M_{N_2} \cdot \sum_k \dot{n}_{k,daf} \tag{44}$$

$$\dot{m}_{NO} = g \cdot M_{NO} \cdot \sum_k \dot{n}_{k,daf} \tag{45}$$

$$\dot{m}_{SO_2} = h \cdot M_{SO_2} \cdot \sum_k \dot{n}_{k,daf} \tag{46}$$

$$\dot{m}_{HCl} = i \cdot M_{HCl} \cdot \sum_k \dot{n}_{k,daf} \tag{47}$$

Finally, the total volume flow (Nm^3/h) of the flue gas can be calculated by dividing the preceding equations by Eq. (33) with respective parameters and summing the flue gas components as

$$\dot{V}_{FG,est} = \sum_l \dot{m}_l / \rho_l \tag{48}$$

where l includes CO, CO_2, H_2O, O_2, N_2, NO, SO_2, and HCl. The density ρ_l is evaluated at standard temperature and pressure (0 °C and 1 atm).

Flue gas compositions are typically presented in standardized forms to unify interpretation. Therefore, the estimates must be converted to the standard forms before comparing the estimates with respective process measurements. This paper utilizes gas component specific unit conversions described in IED (2010), which are illustrated in Korpela, Björkqvist, Majanne and Lautala (2014).

3.2. Energy balance calculus

The determination of energy flows and hence the energy balance depends e.g. on boiler or block structure and is therefore case specific. A simple energy balance is presented in this section that is relevant to the case study presented in Section 4. An extension to this approach can be found e.g. from the European standard EN 12952-15. However, this energy balance formulation is not precisely based on the standard presentation as variations in fuel constituents (i.e. Fig. 4: Dry ash free fuel, ash, inert material and water) are taken into account such that the parameter alterations considered in Chapter 4 have as realistic an effect as possible.

3.2.1. Energy inputs to boiler

The most significant input power to boiler is fuel power, which can be presented (Raiko, 2002) as

$$\dot{Q}_{fuel,k} = \left(\left(q_{cal,k} - 21.96 \cdot Y_{H,k}\right) \cdot \left(1 - u_k\right) - 2.443 \cdot u_k\right) \cdot \left(1 - Y_{inert,k}\right) \cdot \dot{m}_{k,me} \tag{49}$$

where $q_{cal,k}$ denotes the gross caloric value of fuel k (MJ/kg), $Y_{H,k}$ mass ratio of hydrogen in dry fuel (–), u_k moisture content of fuel (–), $Y_{inert,k}$ inert material content of fuel (–), and $\dot{m}_{k,me}$ measured total fuel mass flow (kg/s). Sensible enthalpy of air can be calculated by

$$\dot{Q}_{air} = \left(c_{p,air}\left(T_{air,me}\right) \cdot Y_{air} + c_{p,H_2O}\left(T_{air,me}\right) \cdot \left(1 - Y_{air}\right)\right) \cdot \left(\dot{m}_{air,p,me} + \dot{m}_{air,s,me}\right) \cdot \left(T_{air,me} - T_{ref}\right), \tag{50}$$

where $c_{p,air}\left(T_{air,me}\right)$ and $c_{p,H_2O}\left(T_{air,me}\right)$ are heat capacity of air and air humidity as functions of temperature, and $\dot{m}_{air,p,me}$ and $\dot{m}_{air,s,me}$ measured primary and secondary air mass flows, respectively. Y_{air} denotes the mass ratio of dry air and moist air, which can be calculated as $Y_{air} = M_{air} / \left(M_{air} + \eta M_{H_2O}\right)$. Power input to the boiler by feed water flow can be expressed by $\dot{Q}_{FW} = \dot{m}_{FW,me} \cdot h_{FW}\left(T_{FW,me}, p_{FW,me}\right)$, where $\dot{m}_{FW,me}$ denotes measured feed water flow and h_{FW} feed water enthalpy which is a function of temperature and pressure.

3.2.2. Energy outputs from boiler

The main power output of the boiler is live steam flow presented as $\dot{Q}_{ST} = \dot{m}_{ST,me} \cdot h_{ST}\left(T_{ST,me}, p_{ST,me}\right)$, where $\dot{m}_{ST,me}$ and $h_{ST}\left(T_{ST,me}, p_{ST,me}\right)$ stand for measured live steam flow and enthalpy, which is expressed as a function of temperature and pressure. The flue gas heat loss $\dot{Q}_{FG}$ can be calculated based on flue gas measurements ($\dot{V}_{FG,me}$, $T_{FG,me}$, $X_{O_2,me}$, $X_{CO_2,me}$, $X_{H_2O,me}$, $X_{CO,me}$, $X_{NO,me}$, $X_{SO_2,me}$, $X_{HCl,me}$) and assuming that the rest of the flue gas is nitrogen ($X_{N_2,est}$). However, in this approach the estimated mass flows derived in Eqs. (40–47) are utilized as

$$\dot{Q}_{FG} = \sum_l \dot{m}_l \cdot c_{p,l}\left(T_{FG,me}\right) \cdot \left(T_{FG,me} - T_{ref}\right), \tag{51}$$

where $c_{p,l}\left(T_{FG,me}\right)$ is heat capacity of flue gas components as function of flue gas temperature and l includes CO, CO_2, H_2O, O_2, N_2, NO, SO_2, and HCl.

The boiler blow down loss $\dot{Q}_{BD}$ can be presented as $\dot{Q}_{BD} = \dot{m}_{BD} \cdot \left(h_{SS} - h_{FW}\right)$, where $\dot{m}_{BD}$ is mass flow of blow down steam (here assumed that $\dot{m}_{BD} = 0.01 \cdot \dot{m}_{FW}$) and h_{ss} is the enthalpy of the saturated steam in drum pressure. Boiler sooting steam loss can be stated as $\dot{Q}_{soot} = \dot{m}_{soot,me} \cdot \left(h_{ST,soot,est} - h_{FW}\right)$, where $\dot{m}_{soot,me}$ is measured sooting steam flow and $h_{ST,soot,est}$ estimated sooting steam enthalpy. Boiler ash and inert material loss $\dot{Q}_{Ash}$ is

$$\dot{Q}_{Ash+inert} = \left(\dot{m}_{Ash,est} + \dot{m}_{Inert,est}\right) \cdot \left(\left(c_{ash} \cdot \left(T_{Ash} - T_{ref}\right) + x_{UBC} \cdot H_C\right)\right) \tag{52}$$

where $\dot{m}_{Ash}$ is the mass flow of ash, c_{Ash} is the specific heat capacity of ash and inert material, x_{UBC} is the concentration of unburned carbon in the ash and H_C is the heat value of carbon. In this study it is assumed that inert material has the same heat capacity as ash, whose validity is case specific.

Boiler radiation and convection losses $\dot{Q}_{RC}$ can be estimated according to EN 12952-15 by definition $\dot{Q}_{RC} = C \cdot \dot{Q}_{max}^{0.7}$, where C is a boiler type specific coefficient (0.0113 for fuel oil and natural gas boilers, 0.220 for hard coal fired boilers, 0.0315 for brown coal and fluidized-bed combustion boilers) and $\dot{Q}_{max}$ for maximum heat power of the boiler.

3.2.3. Energy balance

The total energy balance can be stated as

$$\sum_k \dot{Q}_{fuel,k} + \dot{Q}_{air} + \dot{Q}_{FW} - \left(\dot{Q}_{ST} + \dot{Q}_{FG} + \dot{Q}_{BD} + \dot{Q}_{soot} + \dot{Q}_{Ash+inert} + Q_{RC}\right) = 0. \tag{53}$$

The energy balance must be adapted to every case process, but this balance is utilized in Section 4.

4. Case study

The theory presented in previous sections was tested on data from an industrial installation. Section 4.1 introduces the setup and calculation principles briefly. Section 4.2 describes examples with simulated and measured data in various operational conditions.

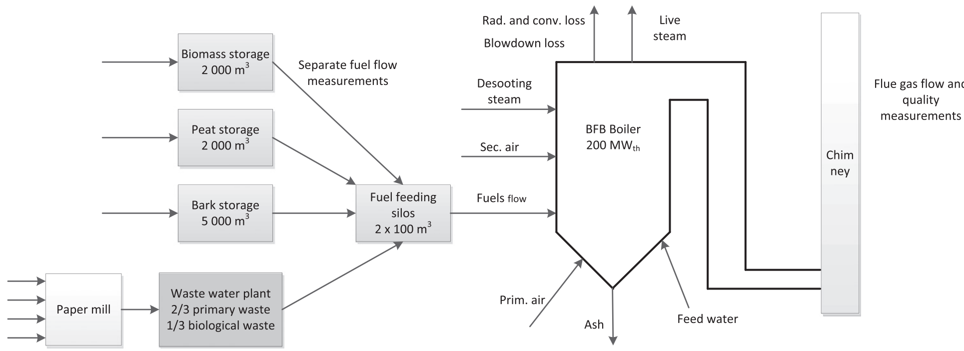

Fig. 5. Outline of the case process.

4.1. Process and case description

The test boiler is an industrial 200 MW_{th} BFB (Bubbling Fluidized Bed) boiler producing steam for a paper mill. The case process is presented in Fig. 5. The main fuels of the boiler were woody biomass, peat, bark, and slurry. The woody biomass consisted mainly of chipped logging residues, wood, stumps, and saw dust. The bark and slurry came from the paper mill. Roughly 2/3 of the slurry was primary waste and 1/3 biological waste from waste water purification process.

Fuel is fed from storage silos which include a 2000 m^3 storage for woody biomass, a 2000 m^3 storage for peat and a 5000 m^3 storage for bark at the site. After these, there are two parallel 100 m^3 fuel feeding silos, which are fed from fuel specific storages and through a slurry flow line from the waste water treatment process. These storages have the capacity to provide fuel for some 30–40 min operation at full boiler load. All the fuel mass flows are measured separately before the fuel feeding silos. The emission monitoring system of the plant and respective measurements fulfill the requirements of the Large Combustion Plant (LCP, 2001) directive.

There are four types of fuels used in the process: wood, peat, bark and slurry. Table 3 presents the fuel element compositions, fuel moisture contents and calorific values that were used in the case study. The conversion of mass fractions to fuel moles can be conducted with common practise of dividing 1 kg of “fresh” fuel to its elements (C, H, N…, H_2O, ash, inert material; Fig. 4) and calculating the mole fractions of the elements, e.g. mol H/(1 kg fuel). Total amounts/flows of the elements are then calculated by multiplying these fractions by the fuel amounts/flows, which are then utilized in equations presented in Section 3.1.

Fuel element compositions and calorific values presented in Table 3 are taken from literature. Moisture contents of wood, peat and bark are calculated from weighted average values from the 5 month period before the test case. Slurry composition and moisture content are averaged based on literature. Fuel compositions and especially moisture contents are known to vary to a significant extent from fuel batch to another, but the fuel storages stabilize the variation significantly. Therefore, fuel element compositions and calorific values presented in Table 3 were kept constant during the estimation period while moisture contents and inert material contents were varied, although the effect of inert material variation was noticed to be insignificant. As the calculation cannot differentiate from which fuel(s) the moisture content variation comes from, all the moisture contents were varied such that the assumed ratios hold.

The estimations and subsequent calculations were carried out off-line in Matlab© environment with hourly time averaged data. The analyzed case lasts 600 h (=25 days) and consists of two separate 300 h periods. The first period of 300 h covers normal process operation and also includes a period of minimum boiler load due to an interruption in paper machine operation (ca. at time interval 20–40 in Figs. 6 and 9). The second 300 h period (time interval 301–600) includes normal process operation and a failure in an emission measurement unit (ca. at time interval 380–500) which measures both CO_2 and H_2O. The time interval between these periods was 400 h of normal operation and is omitted here for clarity.

Table 3
Fuel element compositions, moisture contents and calorific values.

Element composition (m-%, d.b.)	Wood	Peat	Bark	Slurry
C	49.8	51	57.5	40.8
H	6.4	5.5	7.1	5.7
S	0.05	0.24	0.05	0.2
Cl	0.005	0.03	0.005	0.005
N	1.445	1.7	0.5	0.3
O	41.8	36.03	32.345	39.795
Ash	0.5	5.5	2.5	13.2
Water (%), initial values	45.7	48.0	60.0	77.0
Cal. Value (MJ/kg)	21.0	21.6	20.5	20

4.2. Description of balances

The foundation of the data reconciliation approach are balance equations that are in general form '*measurement* − *estimate* = 0'. In this case, selected balances were derived for dry flue gas flow, combustion air flow, and flue gas H_2O and CO_2 contents. Additionally, the power balance has a significant impact in this approach, but it is not based on one direct measurement but several indirect ones. Therefore, power balance was generated in form '*power input to boiler* − *power output from boiler* = 0', which is described in Eq. (53). Data reconciliation finds the correction to the selected variables which sets these equations to zero. In addition to these, the O_2, CO and NO balances defined in Eqs. (21–23) are also set to zero in element balance calculus, and so their effects are automatically included in the analysis.

Fig. 6 illustrates the original misbalances of the five balances before data reconciliation. It can be seen that with fixed fuel parameters and direct measurements the element balance calculus in general provide fairly accurate estimates. The most significant misbalances can be seen in CO_2 and H_2O balances in the latter portion during the sensor failure, and it should be noted that the disturbance in H_2O measurement also disturbs the flue gas flow balance due to moisture compensation. The other significant misbalance, close to the beginning of the time interval, occurs during the interruption in paper machine operation. The misbalance can be explained by possible unusual process operation or increased inaccuracy of measurements at low load. During the other time periods in normal operation the misbalances correlate significantly. For example, fuel power is incorrect when flue gas

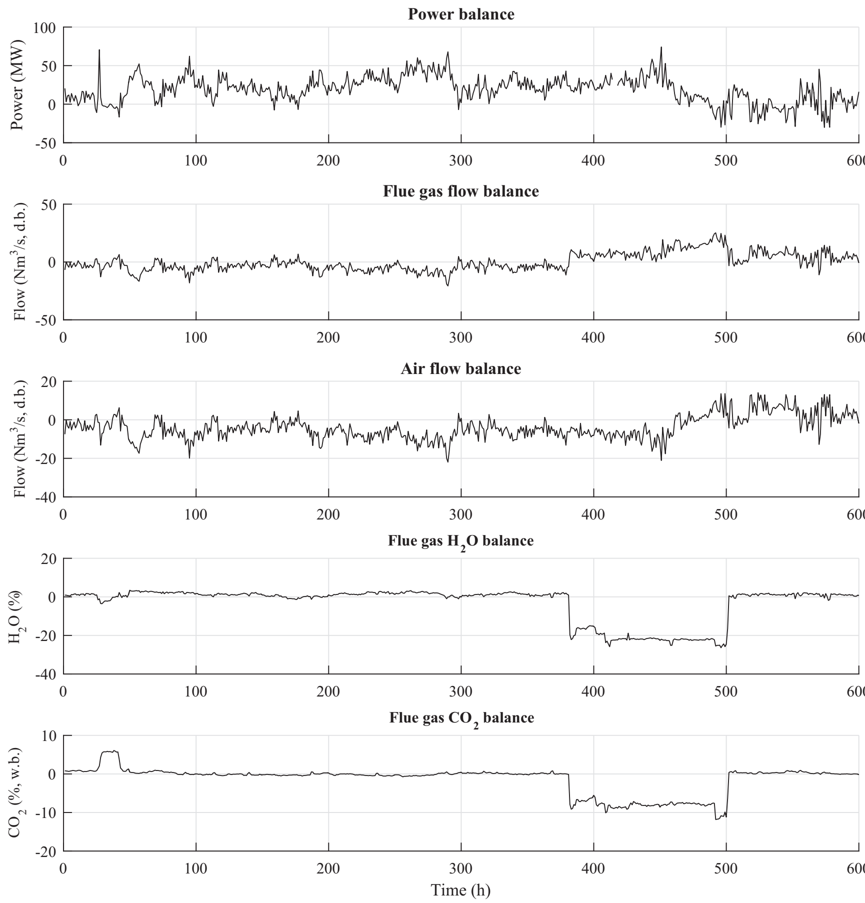

Fig. 6. Balance mismatch before data reconciliation.

moisture estimate or flue gas flow is incorrect. In the first case, the mismatch is likely caused by improper fuel moisture content estimates and in the second case variations in fuel flows. It should be kept in mind that the misbalance can also be caused by invalid initial values, process disturbance or sensor(s) malfunction.

Fig. 7 illustrates the sensitivity of the combustion model to variations in initial values and errors in key measurements. Hence, the figure provides an estimate as to the range of normal variation. Here, the estimates of fuel moisture contents and the measurements of fuel flows, flue gas flow, flue gas H_2O and CO_2 contents, and flue gas temperature were varied randomly $\pm 10\%$. Simultaneously, the measurements of flows, temperatures and pressures of feed water and live steam were varied randomly $\pm 2\%$. The figure presents the balances of Fig. 6 at normal conditions (time interval 200–300 in Fig. 6) and the highest and lowest estimates calculated with the varied inputs. The power balance indicates that the input power estimate is to some extent higher than the output power, which is an indication that the fuel(s) moisture contents are not high enough. This was verified by setting fuel moisture of wood to 50% which lowered the estimate by over 15 MW. Other balance errors are close to zero and indicate the sensitivity to model input errors. Most interestingly the $\pm 10\%$ variations in fuel moistures affected the flue gas H_2O estimate $\pm 5\%$. The CO_2 range was small because the fuel chemical compositions were fixed in the study.

4.3. Description of nonlinear data reconciliation calculus

The nonlinear data reconciliation calculus sets the five balances presented in Fig. 6 to zero by varying the selected variables presented in Table 4 such that the variables with high variance are more prone to be corrected. In this study, the variances were calculated from process data on selected time periods that had reasonably steady state and undisturbed conditions. However, some tuning was required as the directly calculated variances also include process variations. Ideally, they should only describe measurement error variance. Therefore, some expert knowledge was required to estimate the relative reliability of different measurements. In addition to variables and variances, Table 4 presents the pre-set minimum and maximum limits for the reconciled estimates. These constraints are utilized in Eq. (1).

The variable *Total fuel H_2O flow* in Table 4 includes the fuel moisture of all the four fuels. Thus, the calculation alters the total amount of incoming water in fuels. Moisture estimates are used to calculate the water amount which allows for separation of dry fuel flows and fuel moistures. After the total water in fuels is altered, the moisture content is recalculated and then used to calculate the balanced values. From the perspective of process operation, it is irrelevant which fuel moisture is altered as long as the variation in moisture content is relatively small, i.e. the fuels are transferrable and behave normally in storages. It would, however, be beneficial to separate the different moisture contents, but this is not possible with the available data.

In addition to the variables of Table 4, several measurements (e.g. feed water temperature) referenced in model derivation in Section 3 and mainly utilized in the power balance were also altered in the analysis. Their variations in data reconciliation, however, were negligible, primarily due to their high relative reliability and therefore they were kept unaltered in the following case. In some circumstances, however, they could provide more insight to the analysis.

Before the real case, a simulated case is presented in Fig. 8 to

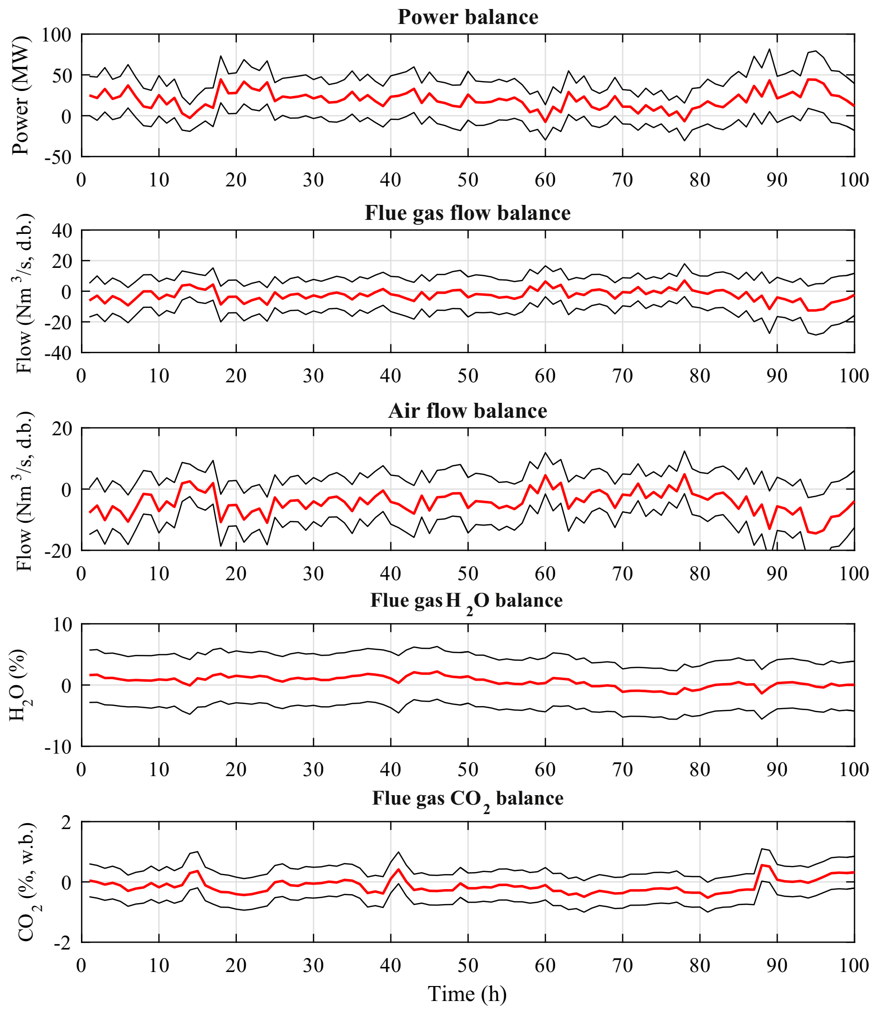

Fig. 7. Balance mismatch before data reconciliation (red) and minimum and maximum values (black) of simulated estimates with variations in initial values and errors in key measurements that presents the sensitivity of the combustion model to changes in assumed values. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 4
Varied variables and their variances and pre-set limits.

Description	Variance	Limits [min, max]	Units
Fuel flow, wood	0.70	[0, 30]	kg/s
Fuel flow, peat	0.40	[0, 12]	kg/s
Fuel flow, bark	0.40	[0, 10]	kg/s
Fuel flow, slurry	0.40	[0, 5]	kg/s
Flue gas O_2 content	0.060	[2, 10]	%
Flue gas H_2O content	5.31	[12, 35]	%
Flue gas CO_2 content	0.227	[10, 15]	%
Flue gas flow	7.40	[20, 120]	Nm^3/s
Primary air flow	6.95	[14.9, 33]	Nm^3/s
Secondary air flow	1.31	[0, 55]	Nm^3/s
Total fuel H_2O flow	1.50	[0, 15]	kg/s
Live steam flow	3.22	[0, 70]	kg/s

illustrate the performance of the presented robust data reconciliation method. The figure presents the simulated and reconciled values of selected variables: fuel flow of wood, peat, bark and slurry; flue gas O_2, H_2O and CO_2 contents; flue gas, primary and secondary air flows; and total fuel moisture and live steam flows. Here, an operating point, dotted line, which fulfills the assumed balances, is first chosen and replicated over the time horizon. Errors are introduced to the O_2, H_2O, CO_2, and flue gas flow variables. The errors are defined as trends to illustrate deviation in both directions and are allowed to overlap. Especially the error in the O_2 variable has a nonlinear effect on the considered balances. Some simulated noise is added to all variables with variances as one tenth of the variance presented in Table 4 in the case of real data. The simulated noise variance is lowered in this case as no process variance is present and otherwise it would mask much of the effect of the introduced trending errors. The introduced errors are correctly identified. The primary air flow is erroneously corrected in two positions, where at least the first correction is likely caused by the nonlinear effects of the flue gas O_2 and its interplay with the CO_2 variable. Despite that, this example points out the exploitability of the method in simulated environment.

Fig. 9 presents the case with the real process data. The figure includes measured and reconciled values of selected variables that are fuel flow of wood, peat, bark and slurry; flue gas O_2, H_2O and CO_2 contents; flue gas, primary and secondary air flows; and total fuel moisture and live steam flows. Additionally, measured and estimated flue gas SO_2 and HCl contents are presented. The uncompensated estimates (Eqs. 38 and 39) of SO_2 and HCl contents have been calculated with fixed sulphur and chlorine contents without data reconciliation, but the compensated estimates have been calculated with reconciled compensation measurements (O_2, H_2O) and with reconciled fuel flows. The SO_2 and HCl estimates challenge the assumptions made in the model derivation. Still, these measurements and estimates provide more insight to the

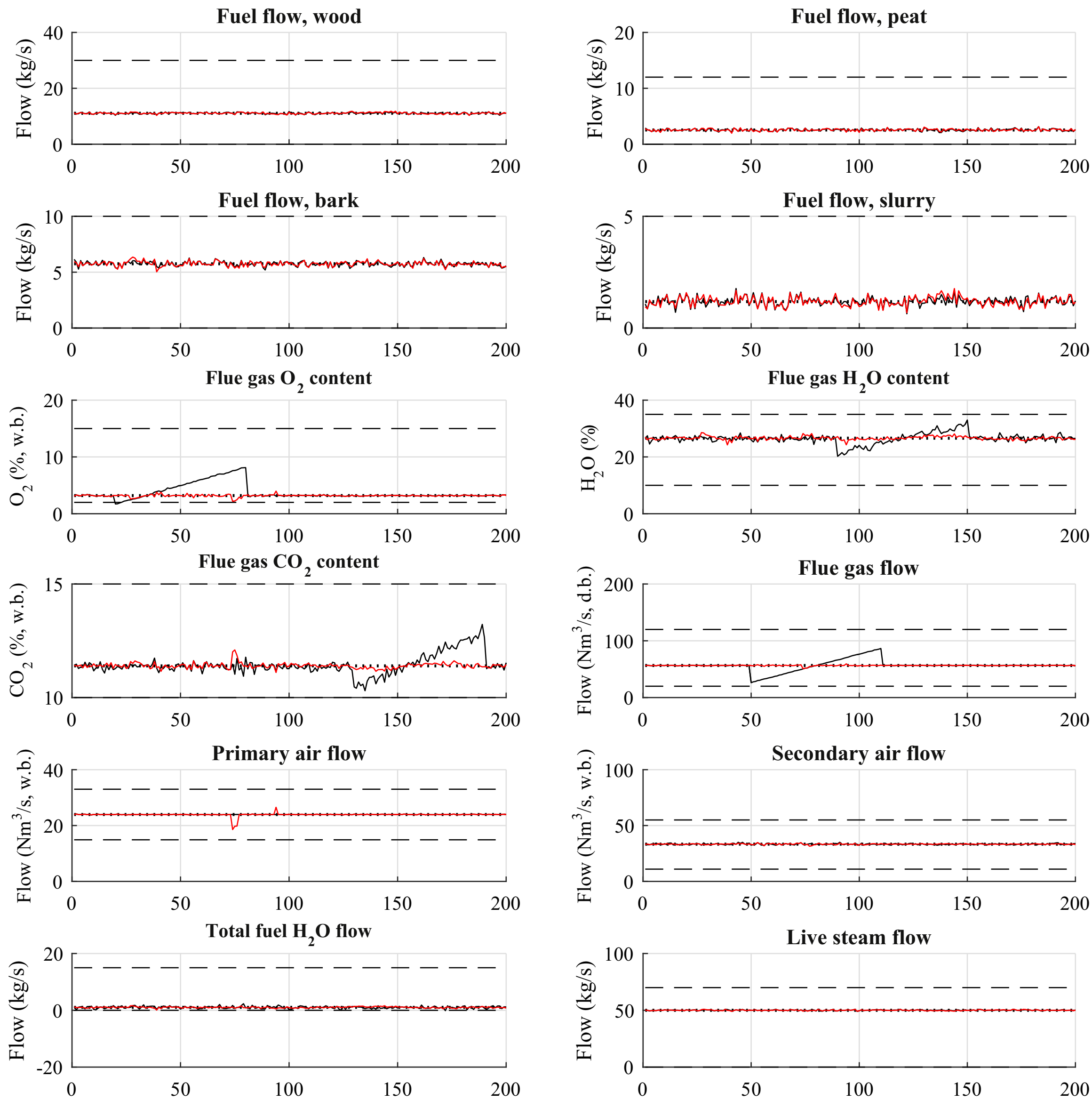

Fig. 8. Simulated errors in the O_2, H_2O, CO_2, and flue gas flow variables in a single process state. Reconciled values (red line), simulated measurement values including errors (black line) and the used true operating point (dashed line). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

analysis as individual flue gas measurements should react similarly in varying process conditions (flue gas flow, O_2, H_2O). Therefore, they are presented here with the reconciled variables.

Three different periods are analyzed: normal operation period (consists of several parts), the minimum power operation period and the sensor failure period. In normal operation periods the reconciled estimates are fairly similar to the measurements, so significant adjustments are not typically needed. The fuel flows behave identically though slurry flow is altered somewhat more than the others due to its distinct properties compared to the other fuels. The largest alterations in normal process operation are with flue gas H_2O contents and total fuel H_2O flows, which indicate fuel moisture content variations. This is expected as the fuel qualities and especially fuel moisture contents are known to vary significantly. This provides valuable information as flue gas H_2O variations also disturb the other measurements via moisture compensation. Altogether, the reconciled estimates behave well and consistently in normal process operation, which is a prerequisite for the application of the method.

In normal operation, the SO_2 estimate exceeds the measurement slightly but in general follows the same trends. The overestimation of SO_2 of flue gas indicates that all the sulphur in the fuels was not converted to SO_2 or the sulphur content of some of the fuels were overestimated. However, the estimate provides some relevant redundancy to the measurement, which indicates, at least, some change. The HCl estimate, on the other hand, diverges more from the measured values, and the trends of the signals are occasionally different. At the end of the period the trends of the HCl estimate and measured value are the same but the estimate includes major bias. An explanation to this behavior could be fuel quality changes, or HCl sensor drifting. Unfortunately, the reason behind this bias could not be verified from the plant.

In Fig. 9 the boiler is at minimum load during time the intervals 20–40 due to an interruption in the paper machine. The minimum load operation of a boiler is not a process disturbance as such but it has several features that are different compared to normal operation. During minimum load operation, most of the flows are small and channeling of gases might be emphasized which disturbs the gas measurements. Additionally, small flows decrease the accuracy of flow measurements. Moreover, the boiler might be

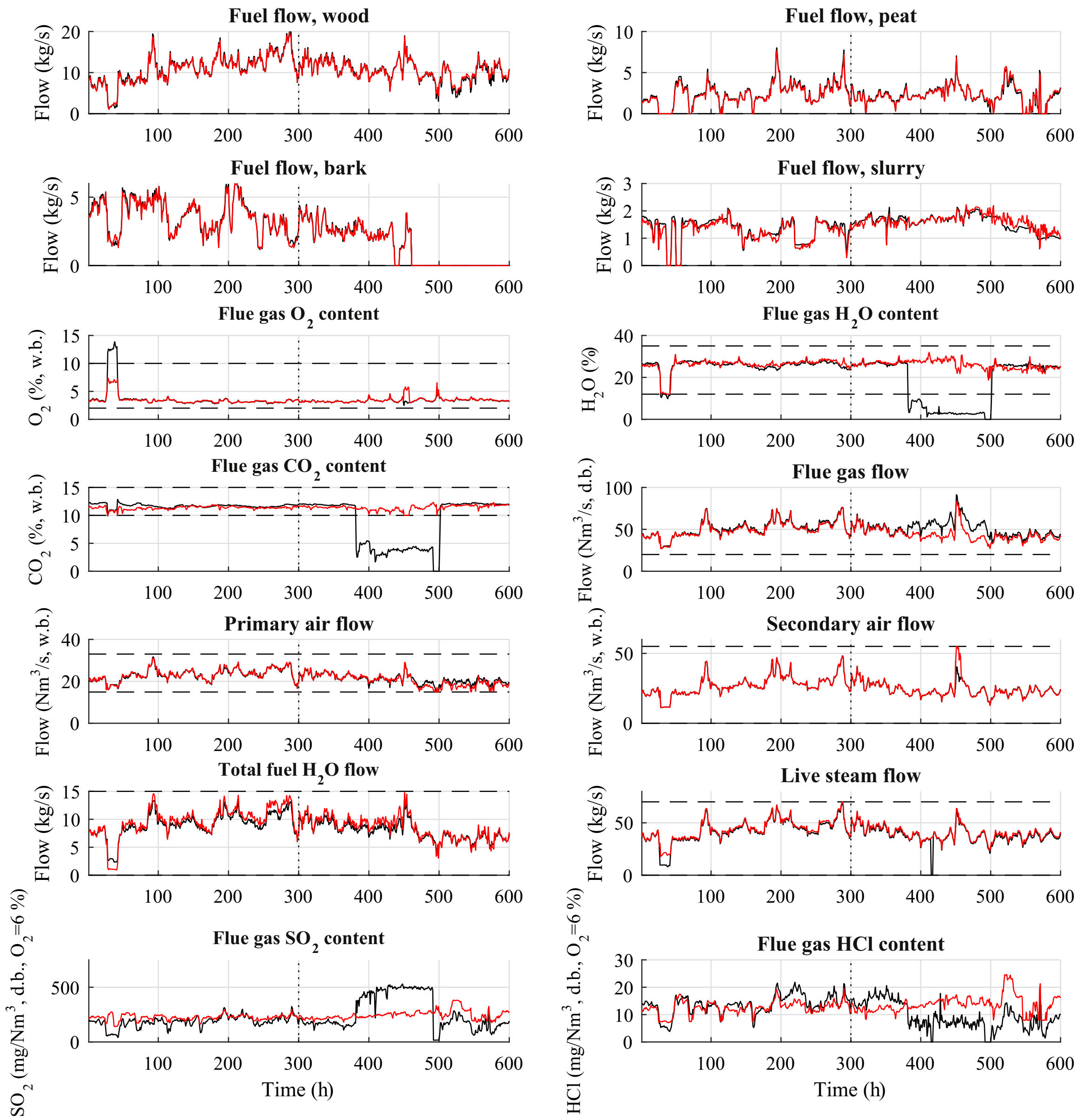

Fig. 9. Measurements (black solid line), reconciled estimates (red solid line), and upper and lower limits (black dashed line, presented only if they are within the range) of monitored variables. Data reconciliation affects flue gas SO_2 and HCl estimates only indirectly. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

run in an untypical fashion to avoid boiler shutdown. Therefore, minimum load operation is very different to normal operation and provides insight into the performance of the model and data reconciliation in challenging operation environments. During the period, the most significant alteration takes place in flue gas O_2 estimate. The O_2 peak can be seen as a dive in O_2 compensated measurements. However, the reconciliation cuts the O_2 peak significantly, to which the other variables react to varying degree. It seems that the cut is too large, but the final conclusion is hard to judge based on this data only. As a conclusion, the reconciliation operates here fairly reasonably but more tuning should be done in the low load operation range.

The measurement equipment measuring H_2O and CO_2 contents of the flue gas malfunctions during the time steps 380–500. From the reconciliation point of view two distinctive failures occur at once as there is no indication that these measurements are conducted with the same measurement unit. The H_2O sensor malfunction disturbs several other measurements due to moisture compensation. The reconciliation is able to calculate plausible estimates for all the measurements during the sensor failure verifying the method's ability to deal with gross errors. The differences between measured and reconciled values exceed significantly the uncertainties caused by normal variations in Fig. 7 and indicate that the H_2O and CO_2 measurements are the cause of the balance mismatch. This case points out the exploitability of the method in industrial power plant environment.

5. Discussions

The proposed robust data reconciliation method in its current form cannot separate the effect of similar variables, e.g. fuel moisture contents of distinctive fuels or primary air from secondary air. Different fuel flows can be separated to some limited extent. However, in practice the method balances the total amounts and the error when correcting the wrong measurement is in this case small. Fuels with more distinctive qualities, e.g. biomass and coal, would allow for more reliable differentiation of different fuel flows.

In the analysis, it was discovered that the role of inert material is small. With this measurement set-up, there is no way to separate inert material flow from error in fuel flow measurement. In some cases, the inclusion of inert material could provide assistance especially if the verified inert material variations are significant. In other cases it could be set to zero or some other constant value.

The key assumption in the element balance model is that the balance holds at least for gaseous compounds. Unfortunately, this might not always be the case as gas leakages might occur in boilers, but typically these leakages are minor. However, leakages in rotary air preheater can be significant, especially with defective seal settings. In this case, the measured oxygen content is higher after the air preheater than before it. As the estimated air flow is assumed to be only combustion air, the air flow is overestimated compared to measured combustion air flow. Fortunately, oxygen content of flue gas is typically measured at both sides of rotary preheaters for monitoring purposes, so the leakage can be easily taken into account and the estimates are not corrupted.

Not all the sulphur is reacted to SO_2 according to reaction (7), as part of the sulphur will react to sulphite (SO_3) or some other compounds. Therefore, the SO_2 estimate should be seen as a maximum value of SO_2 emission, if such reductive pathways are not considered in input parameter selection as inert sulphur. Similarly, all the chloride is not reacted to HCl according to Eq. (10), as some chloride will react with alkali metals, especially potassium (K) and sodium (Na), especially when the overall sulphur content of fuel mixture is low. Therefore, the SO_2 and HCl contents in the flue gas are related. As the alkali chlorides are a major contributor of boiler corrosion, the estimated maximum HCl concentration and the respective measurement values and their differences could provide valuable information on combustion conditions with various fuel mixtures and corrosive combustion conditions. Still, the validity of these estimates is somewhat lower than that of the other presented estimates, so interpretability and therefore applicability of the presented estimates is of special concern. Fortunately, these estimates can easily be ignored by setting w_k and o_k as zero for all the fuels, e.g. in case that desulphurization actions reduce the SO_2 content in the flue gas.

In the presented approach, first principle models and process measurements were utilized. The benefit of this approach is that information from several sensors is connected by the model to form an entirety that can be analyzed as one. When utilizing the approach with first principle models and process measurements, several process details must be considered, e.g. sensor locations, units, compensations, and major dynamics. Therefore, the approach requires some effort, especially compared to data based models. However, when the configuration is finished, the approach provides relevant information regardless of process states and changes in the process. When the effort is made, the combination of estimates and measurements enable extended monitoring prospects that provide insight to process behavior, which can be used in several applications in process and sensor monitoring.

The estimates presented in this paper also benefit other emission variables which are typically monitored, presented, and supervised in normalized conditions by O_2 and H_2O compensations. Therefore, the monitoring of these compensation variables also increases indirectly the reliability of these emission measurements.

6. Conclusions

In this paper, an application of robust nonlinear data reconciliation to a multi-fuel fired industrial fluidized bed boiler was presented. The robust method allows for direct calculation of reconciled values and identification of gross errors simultaneously. Nonlinear calculation allows for use of nonlinear balance equations, which are present in most power plant environments, without the need for approximations. The prerequisite for the successful application of the calculation is a computationally light model that enables the efficient utilization of nonlinear optimization techniques that require iterative calculation. This requirement was satisfied with the element balance model presented in this paper as the element balances can be solved analytically. The combustion model allows fuel flows and other inputs to be connected to the outgoing gas flows and their properties, which is very useful in power plant applications. In future, the lightweight models can enable calculation of results in real-time.

The method was shown to be able to cope with different operating cases. The considered cases are especially interesting as estimates in power plant environments often depend on measurement equipment and measured variables which are not critical to operation and may not be maintained with the same diligence. Notably, the method enables the separation of abnormal operation points from abnormal states caused by malfunctioning sensors. In the analysis, three different cases were analyzed. The first case consisted of normal process operation where reconciled values match the expected measured values. In the second case with minimum load operation, the reconciliation of flue gas O_2 content may be dubious but is hard to judge from the data. However, other measurements and estimated values are within normal operation indicating no faults in sensor equipment. Further modeling or tuning of optimization parameters may be required to enable the full use of the method in abnormal operating points. In the third case where data includes H_2O and CO_2 disturbances known to be caused by a malfunctioning sensor unit, the method was able to identify the correct reconciliation. These results would allow operators to identify and find the cause of the malfunction.

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Monitoring of spraying in semi-dry desulfurization processes in coal fired power plants

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Abstract: The overall objective of the study is to improve usability and efficiency of desulphurization processes by providing assistance for plant operators by indicating arising issues. This paper introduces an indirect method to monitor spraying in semi-dry desulphurization processes, which is based on energy balance and first principle models. The method can e.g. be used to estimate flue gas exit temperature of the rector, which is the main control variable in the process, and slurry flows to reactors. The temperature estimate indicates what should be the exit temperature if spraying is functioning properly. The method was tested with process data collected from an industrial power plant, and the simulation results state that the method is able to predict the reactor exit temperature by error of typically less than few degrees Celsius regardless of the process state.

Keywords: Process monitoring, emissions, power plant, diagnostics, sulphur dioxide, desulfurization

1. INTRODUCTION

There is an increasing demand to restrict polluting emissions to environment. One harmful emission is sulphur oxides (SO_x), of which vast majority is sulphur dioxide (SO_2) that has unfavourable health and environmental effects. SO_2 emissions are formed primarily in combustion of fuels that contain sulphur, i.e. coal and heavy fuel oil, and in some industrial processes. In such combustion applications, the vast majority of sulphur oxidises, and the amount of SO_2 emissions is dependent on the fuel consumption and fuel sulphur content (Flagan & Seinfeld, 1988). Currently in European Union, the combustion originated SO_2 emissions exceed emission standards even with low sulphur coals. Therefore, SO_2 reduction methods have been applied since 1980's after the first SO_2 emission limits were set for coal fired power plants (Miller, 2011). Lately, the SO_2, NO_x and dust emission limits are further tightened from current Large Combustion Plant directive (LCP; 2001/80/EC) to Industrial Emission Directive (IED; 2010/75/EU), which will come into effect in 2016 for existing power plants. According to IED, the SO_2 emission limits will be lowered for existing large scale coal fired power plants from 400 to 200 mg/Nm^3. In several EU countries, the new emission limits are applied step wisely according to transitional national plans under IED to moderate investment burden. In parallel, after the release of new LCP BAT (Best Available Technology) document new requirements are expected to adopt in EU after a few years. As the sulphur content of inexpensive coals is not likely to decrease, the new emission limits are met only with more effective sulphur removal in existing desulphurization processes or with new installations. As costs are high with new installations, operational improvements in existing systems are extremely beneficial.

There are a few types of post combustion flue gas desulfurization (FGD) techniques. The second most applied method worldwide after wet scrubbing is based on spray dry or semi-dry absorption method which was applied intensively in the 1980's (Córdoba, 2015); (Jamil *et al.*, 2013). There, slurry constituting of water, calcium hydroxide $Ca(OH)_2$ and recycled reaction products are used for sulphur removal. The economic background of the method is effective recycling of end product in the process, which causes, unfortunately, several dynamical issues. The challenge with the process is a slow and nonlinear response from manipulated variables to the controlled process state variables. It may take hours before the results of the control actions made to the chemical feeds and flow rates will be seen in the states of the process. Furthermore, the origin of the detected behaviour of the process is often unclear; the reason can be found inside the desulphurization plant or it can be found in the operation of the combustion process as changed flue gas properties. This uncertainty causes easily problems, because the FGD process is sensitive to defective control actions which contribute to limited performance and might even lead to unexpected shut downs of the whole system caused e.g. by clogging of the lime slurry lines, spraying nozzles or by overloaded mixers. As spray-dray absorption type FGD can remove 85–90 % of SO_2 emissions (Jamil *et al.*, 2013) and more than 97 % of fine particle emissions from the flue gas flow escaping the coal fired boilers (Saarnio *et al.*, 2014), the ensuring of proper functioning of FGD process is a necessity. At the same time, the penetration of intermittent renewable energy sources (e.g. wind and solar power) set new dynamical requirements to conventional power plants that also flue gas cleaning processes must tackle. Additionally, co-combustion of biomasses, e.g. wood pellets, along with coal set new requirements also for flue gas cleaning processes (Judl *et al.*,

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2014). Hence, securing reliable operation efficiencies of sulphur removal processes are getting increased attention, and indirect monitoring can provide assistance in this task.

The monitoring methods require a model, which can be based on data or first principle models. The former approach is applied for FGD's e.g. by (Nikula *et al.*, 2012); (Nikula *et al.*, 2013). There are quite a few publications covering first principle modelling of spray dry absorption process, e.g. (Brogren & Karlsson, 1997); (Scala *et al.*, 2004); (Bandyopadhyay & Biswas, 2007); (Marocco, 2010). However, most of the models are phenomenal studies of processes made from process research perspective. Instead, the objective of this paper is to present a first principle model based monitoring method that utilize process measurements to provide additional and redundant information that can be compared with other measurements and hopefully used to assist the plant personnel in day-to-day optimization of the process. First draft of the approach was presented in (Korpela *et al.*, 2015), which is improved here. In the present approach, the special concern in process operation is with the slurry injection, where the spray nozzles (Fig. 1) have a tendency to get clogged up and/or forming obstructions that hinders efficient spraying. In those cases, the droplets are so large that the droplet falls to the bottom of the reactor with several undesired effects, of which the most negative is lowered SO_2 removal. Unfortunately, it cannot be concluded directly if the spraying is functioning adequately or not at all the nozzles. Therefore, an indirect monitoring method of slurry injection was developed, which is described in this paper. The method was developed for Salmisaari power plant (Power Plant) located in Helsinki, Finland. Still, the approach is generic and can be applied in any spray dry absorption process.

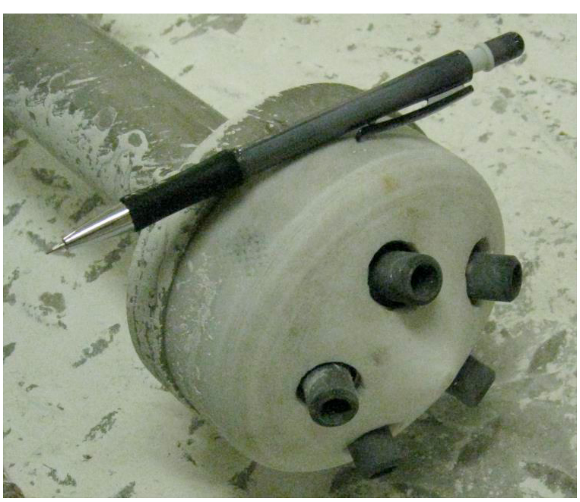

Fig. 1. Nozzle head with five nozzles in Power Plant.

2. SPRAY DRY ABSORPTION PROCESS

Fig. 2 presents a scheme of a spray dry absorption type desulphurization process. There, slurry constituting of water, calcium hydroxide $Ca(OH)_2$ and recycled reaction products is used for sulphur removal. In the process, slurry suspension is injected by compressed air through nozzles (Fig. 1) into reactor towers, where acid components of the flue gas, i.e. SO_2 and HCl, are rapidly absorbed into the alkaline droplets to form calcium sulphite ($CaSO_3$), sulphate ($CaSO_4$) and calcium chloride ($CaCl_2$) while the water of the slurry vaporizes. The main overall reactions in the reactor are (Córdoba, 2015); (Flagan & Seinfeld, 1988)

$$Ca(OH)_2 + SO_2 + H_2O \rightarrow CaSO_3 \cdot 2H_2O \quad \text{(R1)}$$

$$CaCO_3 + SO_2 + 2H_2O \rightarrow CaSO_3 \cdot 2H_2O + CO_2 \quad \text{(R2)}$$

$$CaSO_3 \cdot 2H_2O + 0.5O_2 \rightarrow CaSO_4 \cdot 2H_2O \quad \text{(R3)}$$

$$Ca(OH)_2 + 2HCl \rightarrow CaCl_2 \cdot 2H_2O, \quad \text{(R4)}$$

where the phrasing '$\cdot H_2O$' stand for chemically bound water. With appropriate control of gas distribution, slurry flow rate and droplet size, the droplets are dried by the time they reach the flue gas exit near the bottom of the reactor tower. Some of the dried products, that contain desirably maximum proportion of end products $CaSO_3$, $CaSO_4$ and $CaCl_2$, minimum amounts of reactive $Ca(OH)_2$ and calcium carbonite ($CaCO_3$); and water and ash, fall to the bottom of the reactor, while most of the solid particles moves along with the flue gas to bag filters. The filter fabric slowly collects the reaction products, and SO_2 removal continues there if the moisture content of the flue gas is at adequate level. Ultra sound and compressed air pulses can be used to shake the reaction products to the bottom of the fabric filter units. After that, most of the solid products are recycled to the slurry production system and the rest is discarded as unusable end product. At the end, the purified flue gas flows out to chimney via an exhaust gas fan.

The slurry injection is controlled in a way that the moisture content of the flue gas is within desired range that the sulphur removal continues at the surface of the bag filters. In practice, this is implemented by controlling the temperature of the flue gas at the bottom of the reactor by slurry flow injection.

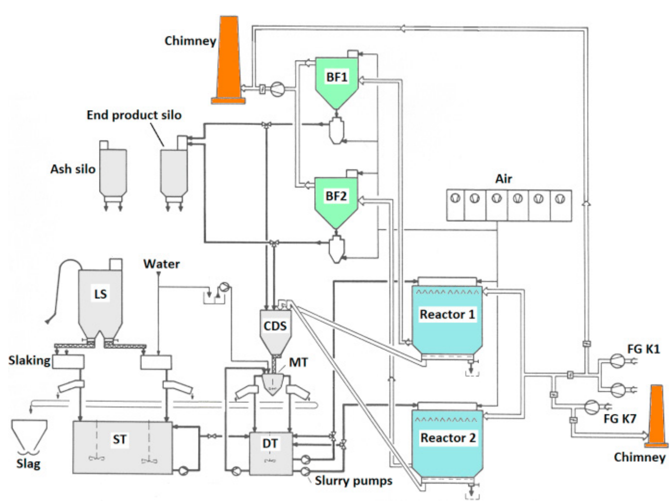

Fig. 2. FGD in Power Plant. Abbreviations: FG ≡ flue gas, BF ≡ bag filter, CDS ≡ circulating dust silo, MT ≡ mixing tank, DT ≡ dosing tank, ST ≡ storage tank, LS ≡ lime storage.

3. MODELLING OF SULPHUR REMOVAL

The proposed method to monitor functioning of spraying is based on energy balance. The fundamental idea is that by estimating the flows, contents and temperatures of injected flue gas, slurry and compressed air, the energy balance of the reactor can be calculated. With the balance, flue gas exit temperature of the rector, which is the main control variable in reactor control, can be estimated. The calculated temperature estimate indicates what should be the exit temperature if spraying is functioning as desired. If the spraying is not functioning properly, the model output should differ from the measured values. E.g. if the droplet sizes are too large, the temperature estimate should be smaller than the measured value indicating that the water in the slurry has not vaporized efficiently. Alternatively, the balance can be used to estimate the required slurry flows.

The challenge with this approach is, however, that there are a lot of variables that have an effect on flue gas and slurry flow compositions, but quite few of them are typically measured before the FGD. Therefore, several variables must be estimated based on measurement information and some additional information. In this approach, only first principle models are utilized. This chapter describes model derivation.

3.1 Material flows into desulphurization reactors

3.1.1 Flue gas flow

The main input material flow to FGD is flue gas from a power plant. The Power Plant constitutes of two boilers; boiler K1 is a steam boiler with capacity of 160 MW_{el} and 300 MW_{th}, and boiler K7 is a hot water boiler with capacity of 180 MW_{th}. In normal operation conditions, the flue gases from these boilers are mixed before conduction to the FGD. The main fuel of the boilers is pulverized coal, and heavy fuel oil is used as an auxiliary fuel. Moreover, boiler K1 has recently started wood pellet co-combustion, which is e.g. discussed in (Judl *et al.*, 2014). The boilers are under LCP and IED directives and EU Emission trading system (ETS), e.g. (Majanne *et al.*, 2014), so the flue gas properties are measured thoroughly. However, these measurements are located after the FGD in the stacks (Fig. 3), so there are only sensors prior to FGD that are used for process control. Therefore, detailed flue gas properties of the boilers, especially of K1, must be estimated.

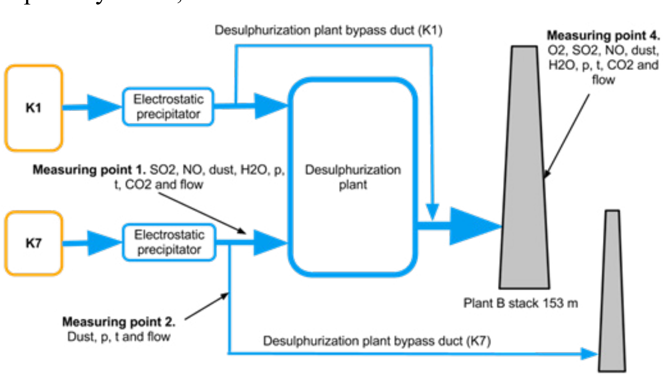

Fig. 3. Locations of flue gas measurements (Majanne *et al.*, 2014) in Power Plant utilized in monitoring for LCP and IED directives and emission trading system.

Flue gas flows and compositions can be estimated e.g. by a combustion model presented in (Korpela *et al.*, 2014) by applying the model to Power Plant with two boilers (K1 & K7) and three fuels (coal, heavy fuel oil, and wood pellet). There, fuel and prospective soot blowing steam flows and flue gas oxygen measurements are utilized for both boilers separately. Additionally, fuel chemical compositions must be known, at least to some detail level. Air properties (temperature, pressure and humidity) can also be taken into account. With this measurement information, flue gas compositions and flows of a single boiler can be estimated. These flue gases can then be summed, and the total flue gas flow and properties can be estimated.

There are two parallel reactor towers (R1 & R2) in FGD and the total flue gas (FG) flow is divided between them according to counter pressure conditions. Therefore, flue gas mass flow into each reactor r = R1,R2 can be estimated by

$$\dot{m}_{FG,r} = \frac{\sqrt{\Delta p_r}}{\sqrt{\Delta p_{R1}}+\sqrt{\Delta p_{R2}}} \cdot \dot{m}_{FG,tot}, \quad (1)$$

where $\dot{m}_{FG,tot}$ is the total flue gas mass flow estimate and Δp_r the pressure difference in the induct of the reactor r. Heat content of the flue gas to reactor r can be stated as

$$\dot{Q}_{FG} = \sum_i c_i\, \dot{m}_{FG,r,i} \cdot (T_{FG} - T_{ref}) \quad (2)$$

where c_i stand for heat capacity, T_{FG} flue gas temperature and T_{ref} reference temperature (zero in this approach). i includes flue gas components CO, CO_2, H_2O, O_2, N_2, SO_2 and HCl. Flue gas temperature before the reactors is typically 120–150 °C (Javanainen, 1989), so heat capacity values of flue gas components at temperature 135 °C are used in the model.

3.1.2 Slurry flow

The slurry is mixed in dosing tank (Fig. 2), and in steady state the slurry (SL) flow to reactor r can be expressed as (Javanainen, 1989)

$$\dot{m}_{SL,r} = \dot{m}_{milk,r} + \dot{m}_{RCP,r} + \dot{m}_{CL,r} + \dot{m}_{water,r}, \quad (3)$$

where *milk* stand for lime milk (water, fresh $Ca(OH)_2$ and some $CaCO_3$) from slaking process trough storage tank, *RCP* recycled solid product (H_2O, $Ca(OH)_2$, $CaSO_3$, $CaSO_4$, $CaCO_3$, $CaCl_2$, and ash; marked as *k*) from circulating dust silo (CDS), and *CL* extra $CaCl_2$ (not presented in Fig. 2). The composition of slurry is controlled such that density of slurry suspension ρ_{susp} is at desired level, typically 1200 kg/m^3. The denser the slurry suspension, more $Ca(OH)_2$ is fed to reactors, which then promotes SO_2 removal. However, there is an upper density limit c. 1250 kg/m^3, and higher densities contribute to undesirable practical issues that e.g. deteriorate pumping of slurry. In practice, slurry composition is such that the amount of recycled solid end product in the slurry is maximized, and amount of fresh lime milk is controlled such that desired flue gas SO_2 concentration after the FGD is reached. Water is fed to the dosing tank to control the slurry density.

The density of slurry $\rho_{m,SL}$ in the dosing tank and volumetric slurry flows $\dot{V}_{m,SL,r}$ to reactors r are measured, which can be utilized to separate solid and liquid parts of the slurry feeds. The mass ratio of solid material over total suspension can be estimated by equation (Javanainen, 1989)

$$x_{solid} = \frac{\rho_{solid}(\rho_{m,susp} - \rho_{H2O})}{\rho_{m,susp}(\rho_{solid} - \rho_{H2O})}, \quad (4)$$

where $\rho_{m,susp}$ is measured suspension density and ρ_{H2O} density of liquid water. In this case, density of solid substances involved are within range 2230–2330 kg/m^3, so it is estimated that average density of solid particles ρ_{solid} is 2300 kg/m^3. When $\rho_{m,susp}$ is equal to $\rho_{m,SL}$, solid material and water flows to reactor r can be stated as

$$\dot{m}_{SL,solid,r} = x_{solid} \cdot \dot{m}_{SL,r} = x_{solid} \cdot \dot{V}_{m,SL,r} \cdot \rho_{m,SL} \quad (5)$$

$$\dot{m}_{SL,H2O,r} = (1 - x_{solid})\,\dot{m}_{SL,r} = (1 - x_{solid}) \cdot \dot{V}_{m,SL,r} \cdot \rho_{m,SL}. \quad (6)$$

In the analysis, the flow $\dot{m}_{SL,solid,r}$ is divided to components k according to lime milk and recycled end product ratio. In calculus, typical compositions of recycled end product and lime milk compositions are utilized, but these estimates can be adjusted based on laboratory analysis results.

Heat power of slurry flow can be formulated as

$$\dot{Q}_{SL,r} = \sum_k c_k\ \dot{m}_{SL,k,r} \cdot (T_{SL} - T_{ref}) - \dot{m}_{SL,H2O,r} \cdot \Delta H_{vap}, \quad (7)$$

where the latter part considers liquid water in the slurry that vaporizes in the reactors, as ΔH_{vap} stand for heat of evaporation of water.

3.1.3 Air flow

Slurry suspension is injected into the reactors by compressed air through the nozzles. Heat content of air can be formulated as

$$\dot{Q}_{air,r} = c_{air}\dot{m}_{air,r} \cdot (T_{Air} - T_{ref}), \quad (8)$$

where $\dot{m}_{air,r}$ stand for air flows to the reactors and T_{air} air temperature. However, due to modest air flows to reactors the term $\dot{Q}_{air,r}$ has negligible effect on energy balance.

3.2 Material flows out of desulphurization reactors

The total heat content of the products exiting the reactor can be stated as

$$\dot{Q}_{out,r} = \sum_l c_l\,\dot{m}_l \cdot (T_{exit,l,rr} - T_{ref}) - \sum_l \dot{n}_l\,\Delta H^0_{f,l}, \quad (9)$$

where l covers solid and gaseous components, i.e. CO, CO_2, H_2O, O_2, N_2, SO_2, HCl, H_2O, $Ca(OH)_2$, $CaSO_3$, $CaSO_4$, $CaCO_3$, $CaCl_2$, and ash. The output temperatures of the reactors are typically controlled to be 75 °C, so respective c_l capacities at the temperature are used in the analysis. However, reaction enthalpies $\Delta H^0_{f,l,}$ of the reactions are assumed to be minor compared to heat content of material streams, so for monitoring of flue gas exit temperature and flue gas flow they can be omitted. When the chemical reactions are ignored, the chemical compositions of mass flows are the same as into the reactors, and the output flows of the reactors are flue gas flow to bag filters and solid mass flow to circulating dust silo. Additionally, it is assumed that all the solid and gaseous components l are at the same reactor exit temperature $T_{exit,r}$.

3.3 Energy balance

Flue gases are cooled in spray dry absorption reactors nearly adiabatically (Javanainen, 1989). Therefore, by assuming adiabatic conditions in the reactor, ignoring reaction enthalpies and combining equations 2, 7, 8 and 9, the total heat flows in and out of reactors r can be stated as

$$\dot{Q}_{in,r} = \dot{Q}_{FG,r} + \dot{Q}_{SL,r} + \dot{Q}_{air,r} = \sum_i c_i\,\dot{m}_{FG,r,i} \cdot (T_{FG} - T_{ref}) + \sum_k c_k\,\dot{m}_k \cdot (T_{SL} - T_{ref}) - \dot{m}_{SL,H2O} \cdot \Delta H_{vap} + c_{air}\dot{m}_{air,r} \cdot (T_{Air} - T_{ref}). \quad (10)$$

$$\dot{Q}_{out,r} = \sum_l c_l\,\dot{m}_l \cdot (T_{exit,l,rr} - T_{ref}) \quad (11)$$

The energy balance is formulated as $\dot{Q}_{in,r} - \dot{Q}_{out,r} = 0$, which can be utilized in many ways. In this context, the balance is used to solve the output temperatures of the reactors $T_{exit,r}$ or volumetric slurry flows $\dot{V}_{m,SL,r}$, which can be solved analytically e.g. with Matlab Symbolic Toolbox™.

4 MONITORING OF SO_2 REMOVAL

Fig. 4 presents a case example with 5 day period (120 hours). The simulation was conducted in Matlab Simulink™ environment with actual operational process data in typical plant operation during heating season. In the case, boiler K1 is run by coal almost at full load (Fig 4.1). Meanwhile, boiler K7 was started at the beginning of the period and flue gases of K7 are directed to FGD after 2 hours (Fig. 4.2). After full load operation, the boiler power of K7 was reduced before shut down at the end.

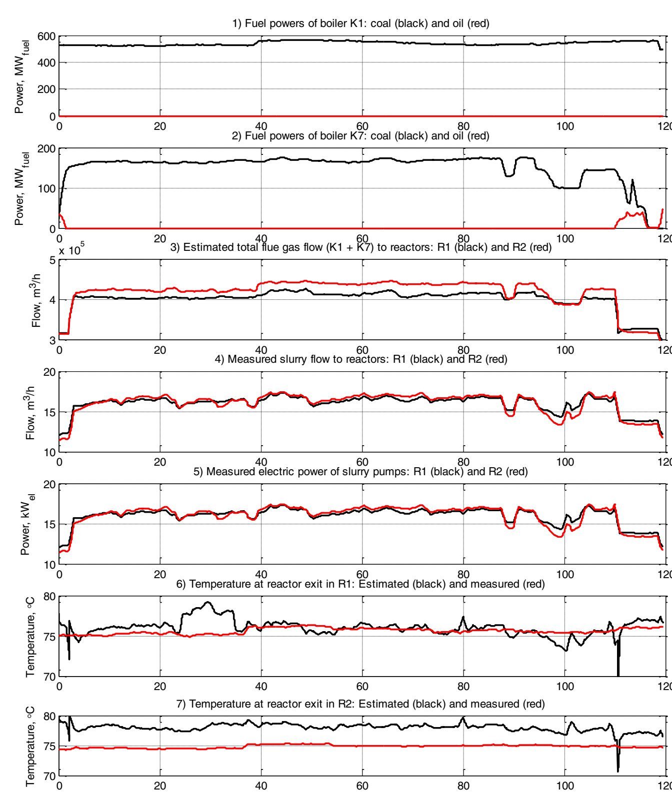

Fig. 4. Simulation with process data. There is a simulated error in Fig. 4.6 at period 25–35 that presents situation when 4.4 % of the water in the slurry to R1 does not vaporize.

The Fig. 4.3 indicates that there is a pressure misbalance between the reactors and the flue gas flow to R2 exceeds the flow to R1 by almost 10 %. The measured slurry flows (Fig. 4.4) and slurry pump powers (Fig. 4.5) react similarly but by varying degree. As a result, temperature estimate and measurement at reactor R1 (Fig. 4.6) fit well with each other, beside an simulated error at period 25–35 (h) that illustrates a situation when 4.4 % of the water in the slurry does not vaporize. The simulated error corresponds to a situation that two nozzles of total 45 nozzles in 9 nozzle heads are not spraying the slurry in small droplets but instead outputs the slurry as suspension flow that do not vaporize. Temperature estimate at R2 (Fig. 4.7) differ from measurement on average of 3 °C. The difference between the measurements can be due to measurement inaccuracies or process behaviour. As the slurry and flue gas compositions are the same for both reactors and the same temperature drop in the reactor is achieved with roughly the same slurry flows, it is likely that at least one of the pressure measurements that are used to separate the flue gas to reactors are biased, or alternatively, there is an error in one of the slurry flow measurements. Still, the estimates fit fairly well with the measurements in normal conditions. Most importantly, the simulated error illustrates that the method is able to alert if there is something unexpected happening in the process.

In the analysis, the estimated trends can be compared with the measurements and between the two parallel and similar reactors to gain indication of changes at the reactors. This is demonstrated in Fig. 5 which presents a relative performance index, which is ratio of temperature drop in the reactors per measured slurry flow to reactors. The index roughly estimates the effects of spraying per sprayed amount of slurry. As a relative index, much of possible un-modeled and/or unknown phenomena are negated due to the fact that both of the reactors operate under similar circumstances.

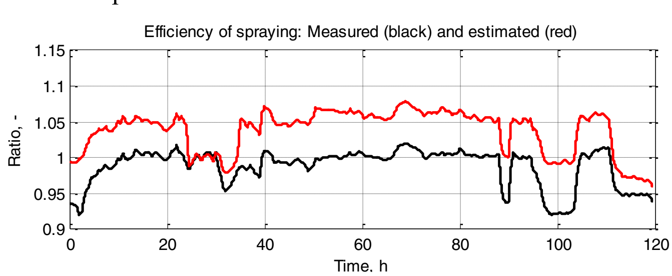

Fig. 5. Performance index: Efficiency of spraying.

On the other hand, energy balance can be utilized e.g. to calculate the required slurry flows $\dot{m}_{SL,r}$ that produce the measured flue gas exit temperatures of the reactors. This calculus can e.g. be used to trace malfunctions in slurry flow measurements, pumps or density measurement in dosing tank.

5 DISCUSSION

In the presented approach, only first principle models and process measurements were utilized. The benefit of this approach is that information from several sensors is connected to form the estimates, but the drawback is that inaccuracies in measurements affect the estimated result. Therefore, the method also monitors the measurement system and possible abnormal situations can also be explained by non-optimal measurement performance. Still, the method is very general because it has no special tuning parameters for different boiler configurations or operation conditions. This is very beneficial, as e.g. coal types and power levels with two boilers vary constantly. In addition to that, the process operations and therefore estimation challenges are further increased after the application of wood pellet and coal co-combustion with varying degree. As the monitoring method uses only measurements and general process information, the method should work without significant modifications also in the new operation environment.

When utilizing the approach with first principle models and process measurements, several process details must be considered, e.g. sensor locations, units, and compensations; major dynamics involved e.g. with storages (fuel silos, tanks in the FGD process); and main control structures and principles. Therefore, the approach requires quite a lot of effort in the implementation phase, especially when compared to data based models. However, when finished, the approach provides relevant information regardless of process states and changes in the process. As a result, it is case specific when to adapt the approach, but when the effort is made, the combination of estimates and measurements enable extended monitoring prospects that provide more insight to process behaviour that can be used in several applications, such as in process and sensor monitoring. The method can be further upgraded with some feedback mechanism (e.g. with Kalman filter or nonlinear data reconciliation) to improve the convergence of estimates and to reduce the sensitivity of estimates to model accuracy.

6 CONCLUSIONS

This paper presented an indirect method to monitor functioning of spraying of calcium slurry in the flue gas desulphurization (FGD) process. The method is based on the energy balance and first principle models, which were utilized due to lack of measurements before the FGD. With the method, flue gas exit temperature of the rector, which is the main control variable in reactor control, was estimated. The calculated temperature estimate indicates what should be the exit temperature if slurry injection to reactors were in order. The method was applied in a coal fired power plant. The results verify that the method is able to predict the reactor exit temperature by error of typically less than few degrees Celsius regardless of process state. Hence, the simulation results verified that the method is able to provide indication of deficit in spraying efficiency, which can be e.g. utilized in process monitoring.

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