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Model-based Fuel Flow Control for Fossil-fired Power Plants

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Model-based fuel flow control for fossil-fired power plants

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Contents

Abstract

The European liberalized energy market promotes cheap and reliable electricity generation. At the same time, governmental policies aim to lower the environmental impact of such production, encouraging generation from renewable energy sources, such as wind turbines. Unfortunately the production from such sources may vary unpredictably meaning that the desired level of generation cannot always be achieved upon request. On-demand production from controllable units, such as thermal power plants, must change quickly in order to ensure balance between consumer demands and electricity generation.

Coal-fired power plants represent the largest reserve of such controllable power sources in several countries. However, their production take-up rates are limited, mainly due to poor fuel flow control. The project aims to analyze the difficulties and potential improvements in the control of the coal grinding process, to allow more flexible production from these units. In order to do this, a suitable coal mill model is derived and validated. The model describes the coal circulation inside a mill, the fuel flow, and the heat balance. The model is used to derive a suitable stabilizing control law based on Lyapunov theory, which turns out to optimize a generalized performance index. The controller is verified through simulations and it is compared to a well-tuned PID-type controller used in the industry, and shown to give improvements.

In addition optimal supervisory control of coal mills and oil flow to the burners is investigated. This is a problem of scheduling continuous producers with discrete phases of operation. The phases are event-driven and they are governed by time and production constraints. Two solution approaches are studied: mixed integer linear programing and priced timed automata. Qualitative analysis of both approaches is performed based on a number of case scenarios showing that a combination of both methods could be advantageous. Finally, a supervisory control strategy for the fuel system in a thermal power plant is outlined and discussed.

Synopsis

Det liberaliserede europæiske energimarked fremmer billig og pålidelig elforsyning. Samtidig forsøger statslige institutioner at sænke energiforsyningens indvirkning på miljøet og fremme produktion fra vedvarende energikilder såsom vindmøller. Uheldigvis kan produktionen fra sådanne kilder variere uforudsigeligt, hvilket betyder, at den ønskede effekt ikke altid er tilgængelig. Dette medfører at nu-og-her produktionskapacitet fra kontrollerbare enheder, såsom termiske kraftværker, hurtigt skal kunne aktiveres for at sikre balance mellem forbrug og produktion.

I de fleste lande i det nordlige Europa udgør kulfyrede kraftværker p.t. den største reserve af sådan kontrollerbar kapacitet; men disse værkers evne til at køre hurtigt op og ned i last er begrænset, primært på grund af dårlig kontrol over brændselsindfyringen. Dette projekt har til formål at analysere vanskeligheder og mulige forbedringer i reguleringen af kulmøllerne der håndterer indfyringen på førnævnte kraftværker, for derigennem at sikre en mere fleksibel produktion fra disse enheder. For at opnå dette, er en regulerings-egnet kulmølle-model udledt og valideret. Modellen, som er baseret på varme- og massebalance, beskriver kulcirkulationen inde i en mølle og brændselsflowet ud af møllen. Modellen er brugt til at udlede en stabiliserende kontrol-lov baseret på Lyapunov teori, der viser sig at optimere et generelt performance-index. Regulatoren er testet gennem simuleringer og sammenholdt med en veltunet PID-regulator, og viser sig at have bedre performance

Herudover er optimal supervisory control af kulmøller og olie-flow til brænderne blevet undersøgt. Dette er et skeduleringsproblem, hvor kontinuerte producenter skeduleres i diskrete operationsfaser. Faserne er eventdrevne og underlagt tids- og produktionsmæssige constraints. To mulige løsninger er blevet undersøgt: Mixed-integer linear programming og priced timed automata. En kvalitativ analyse af begge fremgangsmåder er foretaget på basis af en række scenarier, og indikerer at en kombination af begge metoder kunne være fordelagtigt. Til sidst skitseres og diskuteres en overordnet kontrolstruktur for brændselsindfyringen i et termisk kraftværk.

Nomenclature

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m_c Mass of unground coal on the table [kg]

m_{pc} Mass of pulverized coal on the table [kg]

m_{cair} Mass of pulverized coal carried by primary air [kg]

w_c Mass flow of raw coal to the mill [kg/s]

w_{pc} Mass flow of pulverized coal [kg/s]

w_{out} Mass flow of pulverized coal out of the mill [kg/s]

w_{ret} Mass flow of coal returning to the table [kg/s]

w_{air} Primary air mass flow [kg/s]

Δp_{pa} Primary air differential pressure [mbar]

T_{in} Primary air inlet temperature [°C]

T_{out} Classifier temperature (outlet temperature) [°C]

Δp_{mill} Pressure drop across the mill [mbar]

E Power consumed for grinding [%]

E_e Power consumed for running empty mill [%]

ρ_m Coal moisture [%]

L_v Latent heat of vaporization [J/kg]

C_s Specific heat of a substance [J/(kg ^{o}C)] (s: {air, water, coal})

Acknowledgements

I can no other answer make, but, thanks, and thanks.

William Shakespeare

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1 Introduction

Contents

The European energy market undergoes significant changes during the recent years. Technological changes are necessary due to new governmental policies enforced in many countries. Their goal is to ensure low production costs through competition between utility companies (market liberalization), and at the same time to reduce the environmental impact of the generation (market regulation). Sustainable energy sources, such as sun radiation, water flow or wind are highly desired to be used in the future instead of fossil-fired power plants. Before this goal is achieved, the role of conventional power plants is changing, and efforts are made to improve many aspects of such plants. Due to growing share of electricity generation from uncontrollable energy sources, such as wind power, the conventional plants need to ensure the balance between production and consumption.

This introductory chapter gives motivation for the research project based on problems experienced in the energy industry. The state of the art is described to explicate the considered problem especially in terms of physical design of the studied system, the roots of the problems, as well as the previous developments in the area. Lastly, possible directions for improvements are indicated and the scientific hypothesis is formulated.

1.1   Electricity generation

A liberalized energy market allows free competition between utility companies pressing them to improve production efficiency in order to reduce costs. At the same time regulations enforce strict laws which demand environment friendly production. These actions stimulate technological changes in the energy sector, which aim to significantly improve this industry.

The number of wind turbines and small combined heat and power (CHP) units, which co-generate electricity and district heating, is constantly increasing. Mølbak [2002] mentions that in Western Denmark such non-controllable power capacity increased from 20% in 1980 to 70% in 2001. A sudden decrease in energy production for example from wind parks must be compensated by other (controllable) units, such that the balance between generation and consumption is restored. Such compensation is called load balancing of the grid. We associate a term *safety* of the grid to a situation where the balancing can be ensured at all times, and there is no risk of brownouts when supplies fall below demands, or blackouts when supplies fail completely.

By *flexibility* of the grid we understand the ability to sustain and handle load variations caused by changes in the generation or demands. Mølbak [2002] remarks that the load-following capability of controllable plants becomes crucial and it is the most important issue in plant control nowadays. This means that it is necessary to secure a backup capacity of generation which is used when customer demands increase. Backup *capacity* relates to the ability of increasing the electricity production quickly, such that the balance is sustained. The necessary capacity can be obtained from hydro power, which in many countries is limited due to the landscape, or thermal power plants. With increasing integration of wind generation on the electricity grid, an important objective for many conventional plants becomes to adjust the power production quickly, that is ensure the flexibility of the grid. Studies by Weber et al. [2006] show that at a certain level further increase of wind power leads to fuel saving, but it does not lead to significant reduction in the thermal power plant capacity, which needs to be used when supply from other sources decreases.

According to Mølbak [2010], the balancing problem can be divided into power balancing and energy balancing problems. The division is depicted in Figure 1.1, showing an actual wind park shut-down, which may be caused by malfunction or simply due to wind speed decrease.
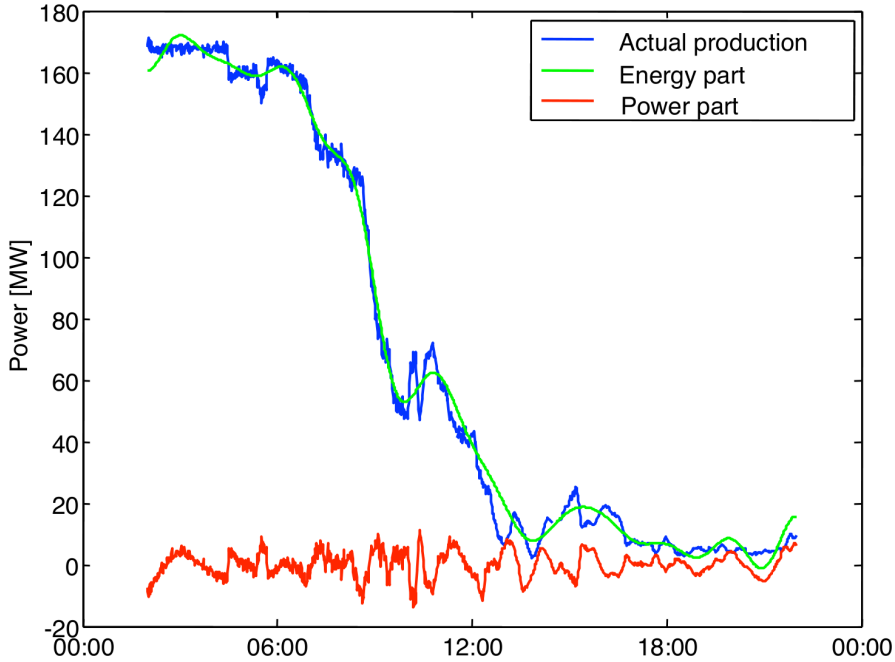
Figure 1.1: Measured power generation from a wind park during a shut-down and the division into power and energy balance [Mølbak, 2010].

In Denmark, the energy balance is ensured by day ahead *Elspot*[1] and intra-day *Elbas*[2] power markets that operate with 24 and 1-2 hours time horizons respectively. Those markets, which are based on forecasts, make sure that a sufficient number of economically sound units are committed to electricity generation. When the wind speed is low, the controllable units and international purchases provide the required production capacity.

A company called *EnergiNet.dk*[3] is responsible for the quality of electricity, which we called the power balance. In order to fulfill this task it contracts ancillary services, that reserves and regulates power, from utility companies. The *Manual Regulation Reserve* operates with 45 minute horizon ensuring response in $5-15$ minutes, and they are contracted for long

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[1]http://www.nordpoolspot.com/trading/The_Elspot_market/
[2]http://www.nordpoolspot.com/trading/The-Elbas-market/
[3]http://www.energinet.dk/EN/Sider/default.aspx

periods of time with utility companies. Additionally *Primary Regulation Reserve* and *Automatic Regulation Reserve* supported by *Frequency Control*, are fast response control capabilities that ensure the precise balance [Bülow, 2006].

Recent advances in control of wind parks are driven by the desire to incorporate the renewable energy into power balancing systems. By adjusting the pitch angle of blades in wind turbines at a wind farm, it is possible to control the overall power and the quality of the generated electricity. It is hoped that in the future such parks will be able to balance the production power. Even in the cases where (nominal) installed generation capacity of wind parks exceeds demands, there might be situations where it is not possible to ensure grid balance if the wind speed is very low. In this case low wind speed means simply that the controllable units must be used. If the change of the wind speed is sudden and significant, the intra-day markets need to ensure the balance. Improved flexibility of power generating units lowers the complexity of such a process and ensures higher safety of the grid. This means that more renewable sources can be incorporated safely in the grid.

1.1.1   Importance of thermal power plants

Thermal power plants are responsible for significant parts of electricity generation throughout the world. With the constantly increasing generation from renewable forms of energy their role remains valuable, but the operation conditions are changing. The emphasis is on the dynamical properties of power plants, as they need to assure the balance between generation and consumption on the grid, especially in the countries where hydro power cannot be used. This means that for thermal power plants, it becomes more important and economically beneficial, to allow for effective production controllability [Edlund et al., 2008]. Improvements of the existing technologies are required to ensure better flexibility of the grid and reduction of emissions, thus performance optimization of individual thermal power plants is crucial.

Coal-fired units are widely used mostly due to low cost, and because the resources of coal are large, which allows production for many years [Flynn, 2003]. Coal units are prevalent in many countries, hence, it is desirable to improve their operation and efficiency. In particular, units that utilize coal grinders are of high interest as the fuel flow can be adjusted relatively quickly, however, the complicated nature of the pulverization process is a

bottleneck that could be improved.

1.2   Coal-fired power plants
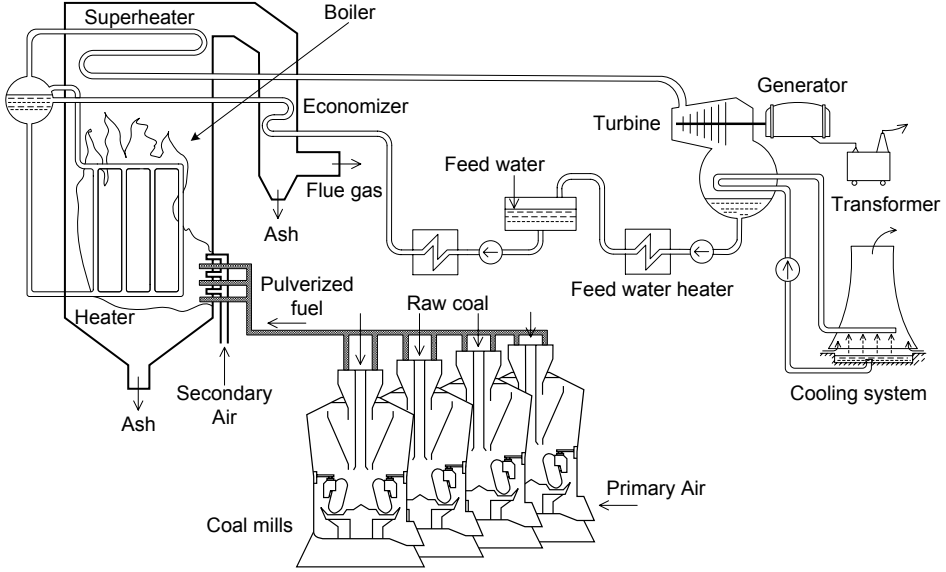
Figure 1.2: Simplified schematics of power production process in conventional power plant fired with pulverized coal [based on Laudyn et al., 2007].

The core element of thermal plants is the steam generator called *boiler*. Its characteristics influence the plant operation and the maximum generated power. The principle of operation is relatively simple; a controlled water flow in the pipes installed in a boiler is heated up and steam is produced.

There are two distinctive boiler designs used [Kitto and Stultz, 2005]. The most common and simple is equipped with a steam drum, which is the fixed point of steam separation from water (as depicted in Figure 1.2). The other type of design, where the exact point of water and steam separation is unknown, is called once-through steam generator.

Boilers are also categorized with respect to the layout proposed by the inventor, for example Lamont, Benson, Sulzer, or Ramzin boiler [Laudyn et al., 2007]. Another distinctions are associated with the steam generation,

namely the temperature of generated steam (superheated or not), or the pressure of operation (subcritical or supercritical, where boiling no longer occurs due to high pressure, i.e. above 22.1 MPa) [Kitto and Stultz, 2005; Laudyn et al., 2007]. For example, many of the modern Benson boilers are supercritical once-through superheated steam generators.

Thermal plants are categorized with respect to the fuel used to heat up the boiler, that is fossil fuels, biomass or nuclear reactions. In fossil fueled plants the combustion and flue gas cooling processes occur in boiler's *furnace* equipped with a set of burners located such that the flames heat up the boiler uniformly. It should noted that certain plants allow changing fuels, for example oil and pulverized coal, which gave rise to a study on optimal fuel selection [Kragelund et al., 2010b,c].

Figure 1.2 shows a simplified schematic of a conventional power plant equipped with a steam drum boiler with superheater and economizer fired with pulverized coal. The principle of the Benson boiler design is very similar. It has the superheater and economizer, but the water instead of circulating in the boiler passes through the pipes only once, changes into steam, and finally expands in the high pressure turbine.

The turbine is typically divided into three parts: high-, mid-, and low-pressure. Similarly, the superheater consists of a few levels in which the steam is superheated.

The role of the economizer is to preheat the feed water using the lower temperature flue gas, such that the maximum heat is recovered, making the steam generation process more effective.

An additional element that is sometimes used, but is not included in Figure 1.2, is called a reheater. The steam that flows from the higher pressure turbine to the lower pressure turbine, passes through the boiler, extracting additional heat from the flue gas.

After passing through the turbines, the steam is condensed. The resulting water is cooled down in water towers or in large water reservoirs, such as the sea, a bay, lake, or river. The turbine is mounted to the shaft of a rotating generator, which is connected to the grid through a transformer.

1.2.1 Plant control

There are four control modes typically employed in power plants [Kitto and Stultz, 2005]. We discuss them briefly in order to indicated the influence of fuel control on the overall plant operation.

Boiler-following control

The firing rate of the boiler is controlled to follow the turbine response. The turbine control valve is positioned according to the megawatt load to provide adequate generation, while the boiler control adjusts the steam production to restore appropriate throttle pressure. As a result of such control, the load response is very fast, but the throttle pressure control is less stable.

Turbine-following control

This control mode is opposite to the previously described; the turbine response follows the boiler response. The firing rate is controlled according to the megawatt load, causing changes in the throttle level. The position of the turbine's control valve is adjusted such that generated power is appropriate. The response of such a system is rather slow, however, the variance of the generated steam pressure is lowered.

Coordinated boiler turbine control

A combination of the two previously discussed control modes, which minimizes the disadvantages while preserving the advantages of both methods. Megawatt load and throttle pressure are jointly controlled by the boiler and turbine. This yields a stable steam pressure while achieving relatively fast load response. The control of the turbine valve provides fast response; at the same time pressure set point is adjusted by the load error. When the nominal steam pressure is achieved the turbine control valve is restored.

Integrated boiler turbine-generator control

In this mode the ratios of inputs, such as fuel flow to air flow, or fuel flow to feed water flow are controlled by the automatic load dispatch system to provide fast and efficient response.

From the analysis of the control modes it can be concluded that, to some extent, the boiler acts as a buffer with stored energy, which is then used in the turbine-generator system. Accurate fuel flow control allows fast megawatt response either indirectly by ensuring higher stability of the steam pressure variance in the boiler-following mode, or directly by contributing to the megawatt generation quickly in the turbine-following mode. This means that changes in the megawatt load can be compensated

more rapidly. We have defined this property as flexibility of the production. Moreover, better fuel flow control leads to higher efficiency of the plant due to lower energy waste in through the turbine valve and lower fuel consumption obtained from more precise control.

An important bottleneck in the operation of coal-fired power plants particular kind of plants, is the coal pulverization process, which gives rise to slow take-up rates and frequent plant shut-downs compared to the oil fired plants [Rees and Fan, 2003]. In typical coal fired power plants, there are 4-10 coal mills providing fuel to a boiler (Figure 1.2). The control problems arise from the lack of good sensors for measuring the output of pulverized fuel from each mill. The input mass flow of the raw coal to the mill is difficult to measure as well; typically, the conveyor belt speed is used for this purpose. Additionally the varying coal quality, e.g. Hardgrove Grindability Index (HGI) and moisture, of coal fed to the mills varies, and general mill wear causes parameter changes [Fan et al., 1997]. Due to these factors, control algorithms for the mills tend to be simplified and conservative, yielding poor performance when load demands change or when mills are started or shut down. The air and fuel ratio is difficult to control outside of the steady state operation, which leads to increased emissions. Advanced control strategies using pulverized fuel flow estimation or measurements could significantly improve the performance of plants; in fact performance close to oil fired power plants can be achieved with improved coal mill control according to [Rees, 1997]. Furthermore, the grinding process, which consumes a significant amount of energy, can be optimized, leading to more efficient generation.

1.3   Coal pulverization

Coal mills grind raw coal to dust, which is mixed with air in a suitable ratio, before being combusted in the steam-producing boiler furnaces. Because the coal dust is highly inflammable it cannot be buffered and must be used directly.

There exist a few types of coal pulverizers among which ball-race and vertical spindle roller types are the most often used. The principle of operation of both mills is similar, thus only the roller mill is described (Figure 1.3).

In the pulverization process, the raw coal is dropped from a bunker

Coal bunker

Fuel and air
mixture

Feeder belt

Rotating
classifier

Rollers

Primary
air flow

Grinding table
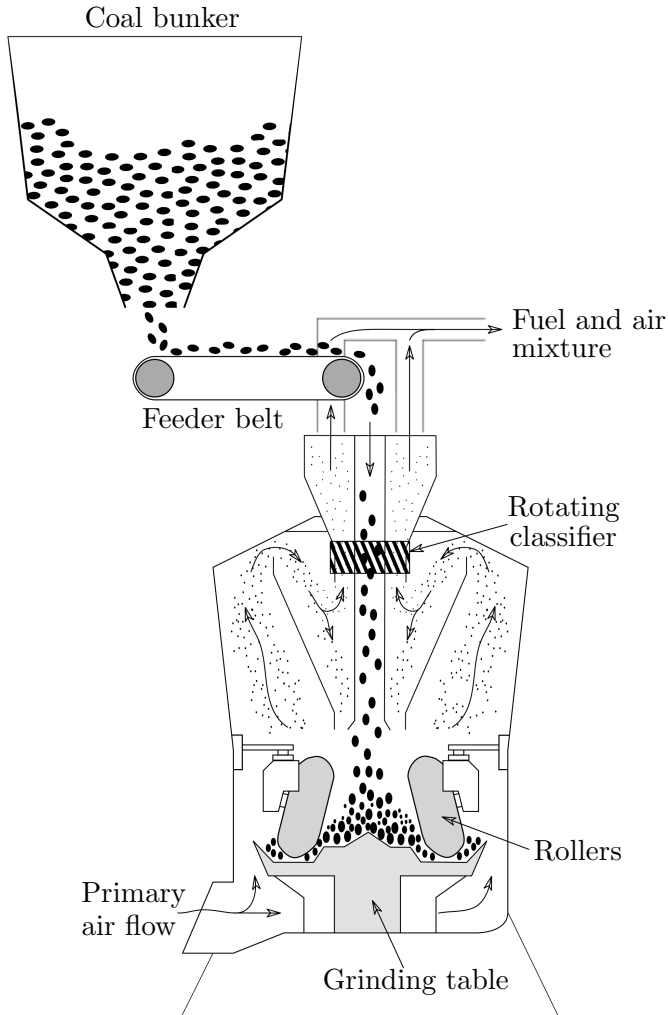
Figure 1.3: Overview of the coal pulverization process with MPS
type mill (air-swept, pressurized, vertical spindle, table/roller mill)
[Kitto and Stultz, 2005].

onto a feeder belt and it is transported to the coal mill. The mass feed
flow is controllable as the belt speed can be changed. The coal falls onto a
rotating table inside the mill. Rollers crush the coal into powder and the
fine particles are picked up by primary air, which enters the mill from the
bottom. The primary air is heated, such that it can dry the coal, which
initially contains water.

Coal particles are transported with the air upwards toward the outlet pipes. Heavy particles, whose size is too large, drop onto the table for regrinding. Often, an additional rotating classifier, constructed from a number of blades, is installed. Its role is to reject coal particles that would normally escape the mill. By controlling the angular velocity it is possible adjust the acceptable size of particles in the fuel flow.

The pulverization process is a highly nonlinear and uncertain process. The hope is that some of the problems related to the coal grinding can be alleviated with model based control [Andersen et al., 2006], especially with the more accurate fuel flow estimates.

Improved mill control is becoming feasible, because sensors for coal flow measurement from the mill to the furnace have become available on the market [Department of Trade and Industry, 2001; Laux et al., 1999; Blankinship, 2004]. Yet, the equipment tends to be expensive and requires frequent calibration, thus for some time it was not possible to use it directly for the control purposes. A recent study by [Dahl-Sørensen and Solberg, 2009] shows that it is possible to acquire good estimates of the pulverized fuel flow from such sensors by means of sensor fusion using Kalman filter techniques. In that work the authors combine information about the feeder speed with the available, but biased and unreliable pulverized fuel sensors in the Kalman filter design. They have successfully implemented and used the filter on all coal mills in two Danish power plants.

Let us study the state-of-the-art control of coal pulverization with raw coal flow feedback, in comparison to the controller with available fuel flow reference, based on the following example.

Motivating example - PID fuel control

The motivating example strives to demonstrate the room for improvements with the use of a more accurate control through the simulation study. As mentioned previously, due to the problems with unreliable and expensive fuel flow sensors, current control implementations use the feeder belt speed instead of the pulverized fuel measurement. Since the fuel flow is equal to the raw coal flow in the steady state, the control structure is justified, however, it yields poor performance. Fortunately, due to the recent advances in fuel flow estimation from biased sensors described by Dahl-Sørensen and Solberg, more accurate control techniques can be adapted. They have successfully implemented, in a Danish power plant, a PID-type controller with the obtained fuel flow estimate.

In the following example, the state-of-the-art and the improved PID-type controllers (both structures depicted in Figure 1.4) are compared. The controllers are tunned using the procedure implemented in MATLAB/SIMULINK; the obtained parameters are summarized in Table 1.1. They are simulated with a nonlinear model of a coal mill.
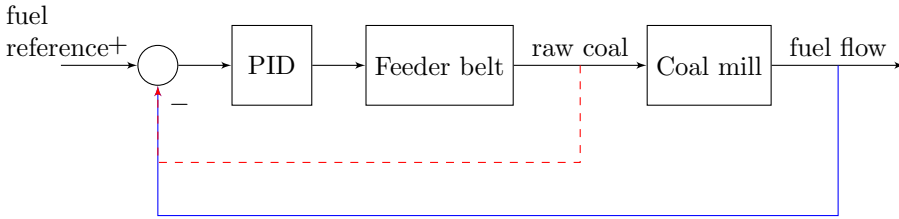
Figure 1.4: Two feedback variants analyzed in the motivating example.

	Fuel flow	Feeder belt
P gain	16.67	2.84
I gain	0.26	0.40
D gain	283.53	-7.50
D filter	14.58	0.38
back-calculation coefficient	0.02	0.02
overshoot	5.35 %	5.72 %
rise time	10.4 s	7.7 s
settling time	50.4 s	23.0 s

Table 1.1: Parameters of the PID controllers used in the comparison, and the corresponding system performance.

Looking only at the performance characteristics of both controllers one may have the impression that the controller with feeder belt feedback is superior. Such comparison is not viable because the controllers are tuned for different systems. As demonstrated in Figure 1.4, the PID controller that utilizes fuel flow measurement is tuned for the overall system (linearized around an operating point corresponding to the fuel flow of 7 [kg/s]), while the feeder belt PID is tuned only for the actuator dynamics.

To compare both controllers a test signal, consisting of various step and ramp elements is used. Simulations are performed with a nonlinear

model of the system, in a noise-free environment, and with actuators that exhibit saturation, hence, the controllers have an anti-windup strategy implemented [Kothare et al., 1994]. The results of the simulations are presented in Figure 1.5.

As can be seen from the plots, the fuel flow controller tuned for linearized system outperforms significantly the state-of-the-art control strategy used in plants. For the tested reference signal, the fuel flow error is reduced by half with the use of the fuel measurements. At the same time the required energy for grinding was reduced slightly (by 0.9 %). Such poor fuel control results in very conservative overall control of coal fired power plants. This is confirmed in practice by the fact that the same power plant fired with oil typically is allowed to handle two times steeper gradients than when fired with coal.

1.3.1 Supervisory control

The studied problem is not limited merely to the previously mentioned factors. There is a secondary top-level control problem that needs to be solved, since the grinding is performed on multiple mills. Depending on the megawatt load it is necessary to start or stop some of the pulverizers. The mills, however, demand special start-up and shut-down procedures which require time, they pose safety hazards, and lead to fuel waste. Operators, based on their experience and the maintenance schedules, decide when a certain coal mill needs to be running. Optimization of these routines, which leads to a supervisory controller design for the fuel system, motivates the study on possible solution approaches.

The complexity of the problem is very high. It belongs to the class of problems that in the literature is called $\mathcal{NP}$-complete (*nondeterministic polynomial*), which refers to problems for which deterministic polynomial execution time solution algorithms are not known. The existing solution methods to this problem suffer from so-called state explosion. This means that the algorithms have to search through a large number of possible configurations to find a solution, and there is no way of discarding intermediate configurations on the way. Nevertheless, it is interesting to compare some of the formulations to determine their characteristic features, and to judge the usability in this or similar contexts.

Scheduling problems occur in many applications, and have been investigated intensively from both theoretical and practical points of view [Panwalkar and Iskander, 1977; Rodammer and White, 1988]. The applications
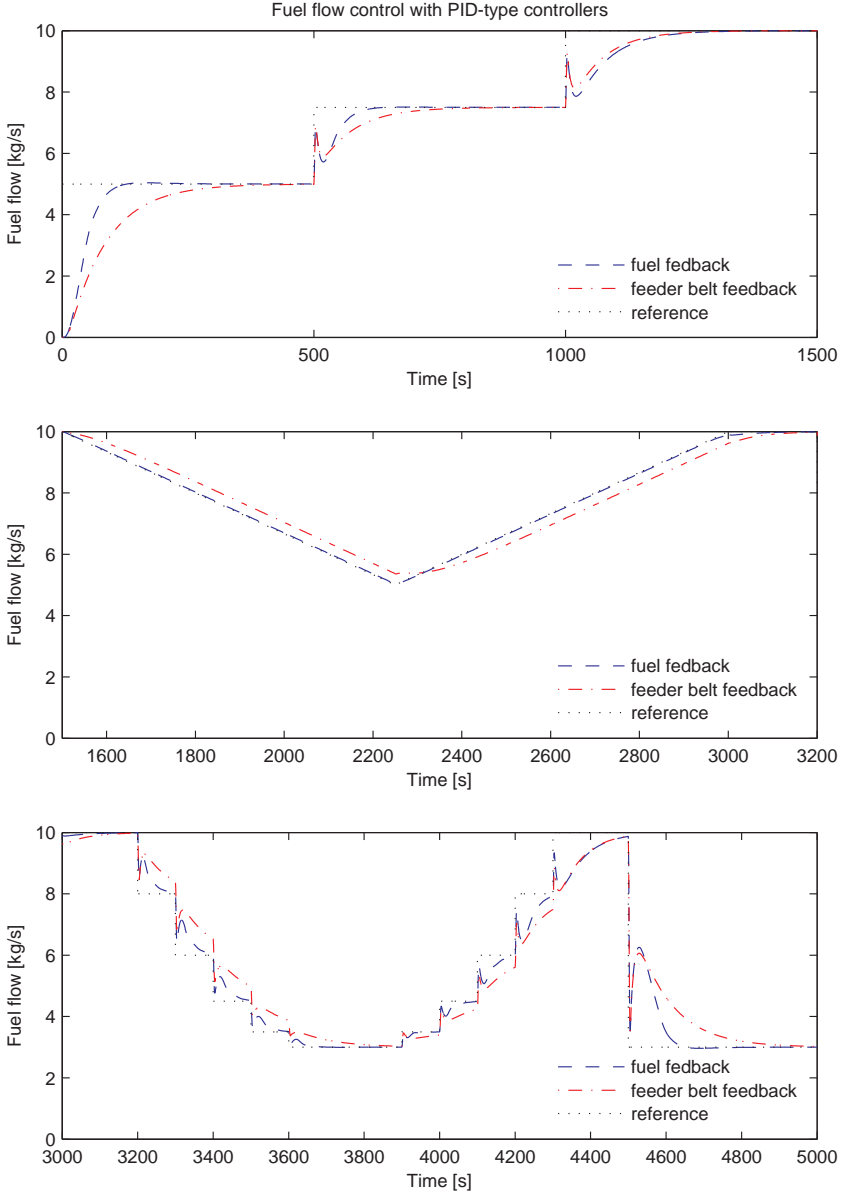
Figure 1.5: Motivating example for advanced control strategy of the fuel flow. Comparison of the present PID control with feeder belt feedback and the PID control utilizing fuel flow measurements.

are driven by desires to achieve favorable positions on the competitive markets or by the need to use limited resources efficiently. Scheduling problems
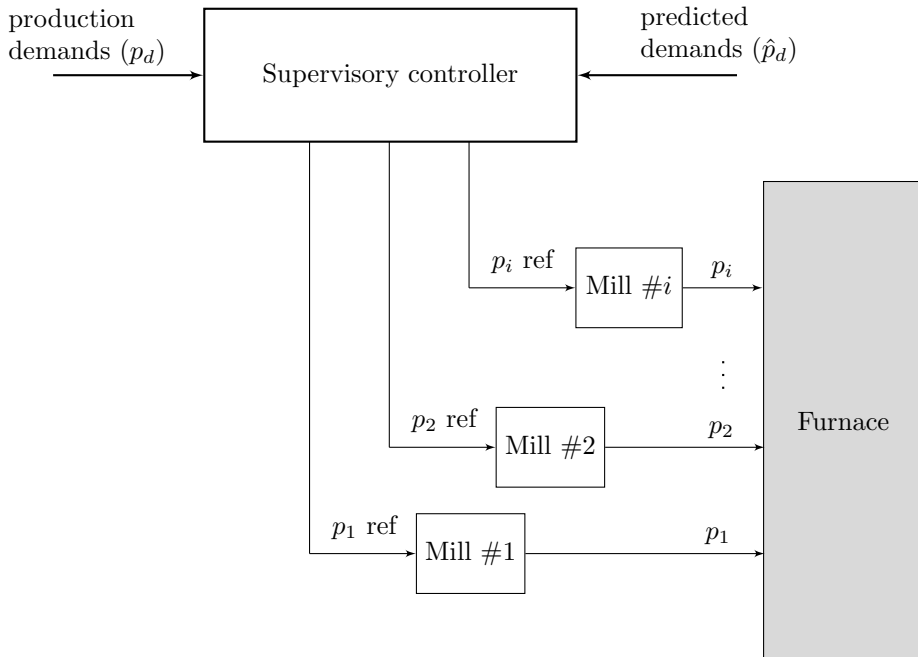
Figure 1.6: The supervisory controller is responsible for deciding, in an optimal way, the production levels for each coal mill, based on the predicted and actual production demands. It needs to account for distinct stages of operation, such as start-up and shut-down procedures.

tend to be quite different in nature, however, and thus solution techniques that are suitable for one class of problems may not be effective for others.

Probably the most widely investigated scheduling problems are *shop* problems (job-shop, open-shop, flow-shop) [Panwalkar and Iskander, 1977], scheduling of batch plants and crew assignment problems. In those problems, components are processed on machines to form a final product, chemicals are mixed according to the desired recipé, or people are assigned to machines or rooms. The class of problems we investigate in this paper has a different nature than these ones. Here, there is a number of *Producers* which continuously supply a product to the *Consumers*. The producers may be disabled, enabled or controlled, in order to fulfill the consumers' demands. The demands change over time, hence, it is required to adjust the production from producers accordingly. In order to minimize the cost of production and save resources, it is required that the producers are

scheduled for operation and controlled in an optimal way. It needs to be determined how many producers should be enabled, as well as, what should the production level from each of them be.

Two very important applications of this class of problems are found in the energy industry. The first is associated with the control of the production rate of coal mills in thermal power plants, while the second is encountered at the Transmission System Operator level, where in needs to be decided which units (power plants) should be committed for operation (the so-called Unit Commitment (UC) problem [Padhy, 2004; Salam, 2007]). Both problems have their own characteristics, but belong to the class of problems we investigate.

The objective for UC is to schedule an optimal configuration of power plants to ensure generation according to the demands. Plants have different costs of production, start up and shut down. Additionally there are restrictions on the minimum run time and the shut down time. UC is typically formulated as static optimization problem, and thus, it differs from the coal mill assignment problem, both, by taking into account the dynamics of the production, and the time scale.

Let us use the following quote from Rees and Fan [2003] as a concluding point of the introductory problem description and motivation

> *An area of power plant control that has received much less attention from modeling and control specialists is the coal mills. This is in spite of the fact that it is now accepted that coal mills and their poor dynamic response are major factors in the slow load take-up rate and they are also regular cause of plant shut-down.*

1.4 Scientific hypothesis

This section sums up previously discussed aspects of a problem met in energy industry in order to formulate a scientific hypothesis that is investigated through the dissertation.

Electricity production is a major environmental and economic factor which in recent years has been undergoing significant changes leading to complicated control and optimization problems. For various reasons, in many countries, the backbone of the production is still coal-fired power generation plants. It becomes safety-critical and economically beneficial to increase the flexibility of thermal power plant generation. There are

potentially significant improvements of the fuel system control in coal-fired units, which at the moment allow for limited power generation change rates largely due to poor coal grinding control. The coal dust from the mills is typically fed directly from mills to the burners instead of being stored due to risk of explosion.

To summarize, the motivation for the work comes from the energy industry that undergoes significant changes in these years. Two main areas of research are identified for which improvements are sought. Both of them deal with the fuel flow control in power plants which relates to the flexibility and efficiency of the electricity grid. The flexibility is crucial for increased wind power generation, and the fuel efficiency relates to decreased emissions and higher profits for the plant owners. From the control point of view two levels of operation are concerned – individual coal mill control and a top-level supervisory control of an assembly of mills.

The load following capabilities of coal fired power plants are directly linked to variable production capabilities of mills, thus, we state the hypothesis

> *The coal pulverization process, that affects the load following capabilities and efficiency of the considered class of power plants can be significantly improved by*
>
> I *applying more sophisticated control methodologies based on a suitable coal mill system model*
>
> II *introducing automated supervisory control of production rates and mill commissioning*

The following criteria for the hypothesis validation are considered

I A simulation study that compares a more sophisticated control strategy to the state-of-the-art PID-type control used in the industry. The performance of both controllers is measured with respect to

- *Fuel control performance* - measure of the integrated fuel error

- *Efficiency* - measure of the energy consumption used for grinding

- *Risk of choking* - measure of the amount of coal in the mill

- *Robustness* - evaluation of the other performance criteria for perturbed system parameters

using a representative reference test signal.

II This part of the hypothesis is validated by developing an algorithm that finds an optimal switching sequence for a number of mills and reasonable optimization horizon.

1.5   Contributions

A summary of the contributions of this work is listed below. It serves the purpose of giving an overview of the content presented in the thesis.

(1) Derivation of a coal mill model suited for control application as an extension of previous developments. The model includes heat balance and coal particle circulation in a mill, and has a reasonable number of model parameters. The varying angular velocity of the rotating particle classifier is included in the model, which affects the fuel flow and coal circulation. Differential Evolution (DE) algorithm is validated as parameter identification method for the model [Niemczyk et al., 2009].

(2) The model is validated using two types of coal mills. It is observed that the model captures the dynamics of both types well, in spite of being of low complexity, making it a good control-oriented model. The parameters found with the DE algorithm for the different pulverizers are similar, which is a good indication that the model and the identification method are suitable for the problem at hand [Niemczyk et al., 2011].

(3) State estimation and control methods for bilinear systems are applied to the investigated problem. Simulations of the proposed controller show that it is possible to achieve a more accurate and energy-efficient operation of the process, in comparison to a well-tuned PID-type control. A simulation-based parameter sensitivity analysis of both controllers is performed, showing that the performance advantages may be lost in case of poorly identified system parameters. On the other hand, the PID-type controller is very robust to parameter uncertainties [Niemczyk and Bendtsen, 2011].

(4) Stability of an augmented system composed of a bilinear and linear systems is investigated. Such structure corresponds to the coal mill controlled through actuators with linear dynamics. It is found that a

local coordinate transformation is nontrivial, however, it is proved that the control law for bilinear systems globally asymptotically stabilizes the augmented system provided certain requirements are satisfied.

(5) Optimal control problem based on Pontryagin's Maximum Principle is studied. The controller for the system with actuators is calculated, such that desired cost function, which corresponds to the verification criteria of the hypothesis, is minimized.

(6) Two formulations for optimal scheduling of continuous producers, such as coal mills, are discussed. The classical and well-known mixed integer linear programming (MILP) problem formulation is presented. Priced timed automata (PTA) model of the scheduling problem is developed, and used with a model checking tool, to find optimal results. Qualitative comparison study of both approaches is performed based on quantitative data obtained from solving the problem, for various production scenarios.

(7) A supervisory controller strategy, which generates schedules for the fuel system of a thermal power plant fired by pulverized coal and oil, is discussed as an extension of a knowledge base operator support system (KBOSS). The strategy is realized in a receding horizon fashion. Application related constraints are discussed. Suboptimal strategies for solving the problem are analyzed. Post-processing methods for improving the obtained schedules are described.

1.6 Overview of the remaining chapters

The second chapter relates our work to relevant results obtained previously in the research areas. In particular, literature on modeling and control of coal mills, and on optimization and supervisory control related to power plant fuel systems, are presented.

The next two chapters deal with the problem of modeling and control of a coal mill. A suitable mathematical model of the system is derived and validated against the collected plant data. Theoretical and practical aspects of control, such as stability, optimality, and control performance, are discussed in Chapter 4. In that chapter, we first consider a simplified model, which does not include actuator dynamics, and later we extend the study to the system with actuators.

Chapters 5 and 6 are devoted to the topic of optimal scheduling of continuous producers, with application to a supervisory control of a fuel system consisting of coal mills and oil injectors. Two problem formulations are presented and compared. Practical aspects of the supervisory control and receding horizon algorithm are discussed.

The outcome of the thesis is summarized in Chapter 7. The scientific hypothesis is verified, and the necessary steps, leading to improved power plant control, are described. Some of the interesting research directions, which could not be pursuit due to the time limitations, are discussed as perspectives.

Finally, the bibliographical list of cited publications is given. Additionally, the principles of Differential Evolution algorithm are described in the appendix.

2 Related work

Contents

In this chapter an overview of relevant results in the studied area is given. The chapter is divided into two main parts. First part presents development in the area of coal mill modeling and control. It includes an overview of the existing models which could potentially be useful in the area of automatic control, and presents the previously developed coal mill models.

Second part is devoted to related studies in the area of scheduling and supervisory control, from the application perspective and the employed methods.

The aim is to indicate relevant advances upon which this thesis is based. Some of the results are presented in more details along with the more detailed problem description in Chapters 3, 4, 5, and 6.

2.1   Control of a coal mill

This part describes historical development in the area of coal mill modeling and control. It should be noted that none of the authors of the referred publications use the accurate information obtained from the fuel flow measurements, as it is possible now thanks to Dahl-Sørensen and Solberg [2009]. In the related work the fuel flow is often estimated from other

measurements, for example oxygen concentration in the flue gas.

2.1.1 Modeling

In general, the existing models can be roughly divided into two categories, simulation models and control oriented models. In some cases the division is not very clear. Authors sometimes suggest model-based control strategies for relatively complex models. However, complicated models, with a large number of difficult to estimate parameters are generally not well suited for controller implementation in a power plant. They require implementation of accurate on-line parameter identification techniques, and they are difficult to tune by the plant crew, which needs to be done regularly. Therefore, there is a strong motivation for investigating an adequate, relatively simple model, with few parameters, as basis for development of advanced control strategies for individual mills.

Coal mill models can trace their roots back to the early 1940's where several groups of researchers worked on the mathematical modeling of mills and the development of grinding theory. The outcome of the early work on the subject is reviewed and compared by Austin [1971]. The purpose of that survey is to show similarities and differences between early modeling approaches and form a more uniform description. In order to do this, the author presents the model equations from various sources using common nomenclature. The main point of interest in this paper is mathematical description of coal size reduction as a rate process.

Neal et al. [1980] perform a frequency analysis of mill and boiler complex, and analyze its effects on the steam pressure. This leads to simple transfer function plant models. Similarly, Bollinger and Snowden [1983] perform an experimental study of a mill's transfer functions in order to devise feedforward controllers. The identification process was done for the transfer functions between coal flow, cold air mass flows, and hot air mass flows, to discharge temperature, and total air mass flow.

Detailed models of the coal pulverization process in a mill is presented by Austin et al. [1981, 1982a,b], Robinson [1985] and Corti et al. [1985]. These studies investigate the internal dynamics of the pulverizing process, i.e. coal breakage (particle distribution), pneumatic transportation and classification process.

Austin et al. in their series of papers (1981; 1982a; 1982b) analyze a ball-and-race mill. In the study they derive a detailed model based on a scale-up of the Hardgrove mill to an industrial mill.

Robinson [1985] classifies 15 particle sizes in six internal regions, leading to a detailed model composed of 76 ordinary differential equations. The model describes the physical phenomena associated with coal pulverization very well; however, due to its complexity it is difficult to use for control purposes.

Corti et al. [1985] develop a simulation model by treating breakage phenomena as a continuous process and introducing the concept of *breakage velocity*. Simulation models for steady and transient operations were also presented by Sato et al. [1996] and Shoji et al. [1998].

More control-oriented models have been presented by Kersting [1984], Fan and Rees [1994], Palizban et al. [1995], Rees and Fan [2003], Zhang et al. [2002] and Wei et al. [2007].

Kersting [1984] divides the process into three sub-models (grinding, pneumatic conveying and classification) and uses pressure drop measurements to validate the model.

Palizban et al. [1995] consider two sizes of coal particles in a mill. They consider mass balance only, and a static classification process. The derived model is seventh order nonlinear system with two inputs and two outputs. In addition to the model they have presented a Receding Horizon Control strategy for the mill.

Fan and Rees [1994]; Rees and Fan [2003] describe mass and heat balance as well as the grinding power consumption. The results of the work are very encouraging, although it is noted in Rees and Fan [2003] that very extensive parameter identification and verification is required, e.g. new and worn mills, various load conditions, various coal calorific values and moisture. These authors propose various control strategies including one that uses pulverized fuel flow measurements/estimates.

Zhang et al. [2002] and Wei et al. [2007] present a gray-box type model of a coal mill. They investigate only two particle sizes: raw coal and pulverized coal. The mass balance equations are similar to those by Palizban et al. [1995], but are further simplified. The advantages of their model are low order, fewer parameters with a suitable method for their identification, and the generic properties, i.e. similar types of mills might be described by the model.

Our modeling approach, which is presented in the next chapter, is inspired by Palizban et al. [1995] and in particular that of Zhang et al. [2002] and Wei et al. [2007]. We use the latest measurement technology for measuring pulverized fuel flow from mills for model validation. The resulting model should allow implementation of a multivariable control strategy,

which would improve the overall power plant control in the load balancing problem.

2.1.2   Controller design

Most of the existing mill controllers in the power industry are tuned based on the simplest first and third order models of the coal pulverization process [Austin, 1971; Neal et al., 1980; Bollinger and Snowden, 1983]. For a long time they performed sufficiently good in relation to the operating conditions of coal plants. With the new environmental regulations and market liberalization, the objectives have changes, and the control of power plant processes needs to be improved. According to Rees [1997] a performance close to that of oil fired power plants can be achieved with improved coal mill control. It should be noted that the large uncertainties associated with the pulverization are handled safely by PI controllers, and that such controllers are relatively easy to maintain.

In addition to the prevalent PID-type strategies implemented in plants, other control methods have been studied. Cao and Rees [1995], Cai et al. [1999], and Lu et al. [2002] propose various extensions of the classical controllers, such as decoupling controllers, utilizing fuzzy logic principles.

O'Kelly [1997] described a robust receding horizon controller based on a locally linearized models of the system, computed at each control iteration. He continuous the previous development on the model predictive control (MPC) by Palizban et al. [1995]. O'Kelly assumes that the pulverized coal flow measurements, mill differential pressure, and mill outlet temperature are available.

Rees and Fan [2003] discuss the most prevalent control strategies, namely PID-type controllers, for the coal mills, and investigate the advantages of fuel flow measurements, similarly to what we have done in the motivating example in Chapter 1.

Andersen et al. [2006] propose an observer based cascade control concept with the use of Kalman filter to estimate the pulverized fuel flow from the oxygen measurements of combustion air flow. They study the influence of such estimate on the power plant control, concluding that using such feedback gives better disturbance rejection capability.

2.2 Supervisory control of a fuel system

This part presents an overview of the related work in the area of a fuel system supervisory control in a thermal power plant.

2.2.1 Supervisory control

One of the objectives for the project is to investigate the potential improvements and automation of the switching strategy for the coal mills operating in a plant. Currently the number of mills in operation is decided by plant operators based on the predicted power generation. In a special case, when significant increase in megawatt load is expected compared to the predicted production demands, the Transmission System Operator (TSO) may ask the crew to start up another mill. The efficiency of the power plant is related to the number of mill-hours of operation needed to fulfill the production goals, as well as, the amount of fuel wasted in the start up and shut down sequences. The efficiency may be improved if precise information on the start and stop events is given to the operators for consideration. Moreover, the supervisory controller should decide, in an optimal way, about the coal flow set-points for each mill or any other fuel flow if it is available.

A knowledge based operator support system (KBOSS), which could be extended with the ability to inform and advise the plant crew about mill operation, is presented in Fan et al. [1997]; Rees and Fan [2003]. If the devised strategy is successful, it could directly act upon the mills, yielding more efficient and predictable control of the plant. The original KBOSS is designed to optimize the individual mill control, rather than the whole group of mills, thus, our methods for optimal switching could add value to the system.

An interesting results on optimal fuel selection in power plants has been published by Kragelund et al. [2010b,c]. In that work authors analyze situation where three different fuels with various costs and characteristics can be mixed. The goal is to choose the optimal mixture of fuels to maximize profits. Those results, however, differ from our approach, where distinct discontinuous phases of operation driven by events are analyzed. Therefore, different methodologies associated with discrete event systems need to be applied to our problem.

Supervisory control theory for discrete event systems is due to Ramadge and Wonham [1984]. The framework allows to generate the controller automatically based on formally specified requirements. The models and spec-

ifications are given in form of finite automata and the associated formal languages. There are two kinds of events that the plant exhibits, i.e. *controllable* and *uncontrollable*. The goal for the supervisor is to prevent the plant from entering into bad states which are either blocking states, from which desired states cannot be reached, or non-controllable states, that may generate uncontrollable events [Pinzon et al., 1999]. In our case, however, the supervisory controller has different objective. Instead of preventing certain actions we wish to find the optimal combination of events to guarantee that the overall production rate is satisfied at all time.

2.2.2 Optimal scheduling

The problem of optimal scheduling of mills for the supervisory controller driven by discrete events has not been studied in detail so far. Many solution methods have been studied for Unit Commitment (UC) problem, which shares some similarities, but is limited to static optimization. The approaches have been summarized in Padhy [2004] and Salam [2007]. In general, the methods fall in two groups based on the solution quality – optimal or suboptimal. The problem of finding the optimal solutions suffers from great complexity; it is $\mathcal{NP}$-complete, i.e., no polynomial-time solution algorithms exist. Guan et al. [2003] prove that the UC problem is $\mathcal{NP}$-complete by setting specific values for the problem and thus obtaining a well-known partition problem, which has this complexity. As a consequence, suboptimal methods are often employed in practice. Representatives of the first group are Dynamic Programming (DP) [Snyder et al., 1987; Hobbs et al., 1988; Al-Kalaani, 2009] and Mixed Integer Linear Programming (MILP) [Dillon et al., 1978; Carrion and Arroyo, 2006; Guan et al., 2003; Delarue and D'haeseleer, 2008] methods. Because of the computational burden associated with Dynamic Programming, the method is often adjusted and used to find near-optimal solutions, thus reducing the problem complexity. For the same reason MILP optimization can be stopped when the cost value is sufficiently close to the value of the relaxed problem, which becomes a Linear Problem (LP).

Another useful and commonly used method, which provides near-optimal results, is Lagrange Relaxation (LR). This approach benefits from relatively easy modeling possibilities and provides a quantitative measure of the solution quality [Guan et al., 2003].

Also, various heuristic and hybrid methods have been applied to UC throughout the years [Ouyang and Shahidehpour, 1990; Kazarlis et al.,

1996; Juste et al., 1999; Mantawy et al., 1999; Cheng et al., 2000].

In this thesis, we formulate the optimization problem using Quantitative Model Checking framework [Behrmann et al., 2005], which has its roots in the *theory of timed automata* [Alur and Dill, 1994; Bengtsson and Yi, 2004]. The timed automata framework has been applied to various job-shop and batch scheduling problems [Abdeddaïm et al., 2006; Behrmann et al., 2005; Subbiah et al., 2009; Larsen et al., 2001], but to the authors' best knowledge, such methods have not been used for the UC problem yet.

We compare the modeling effort and computational burden of QMC with the MILP formulation, which is the *classical* and well known approach. It is clear that both methods are applicable, so we cannot expect to find a winner. Our more modest hypothesis is that the performance of the methods depends very much on the profiles of the problem to be solved. Therefore the contribution is a qualitative study of both methods with the use of quantitative data obtained from carefully selected simulations.

An interesting approach for optimization of event-driven hybrid systems with integral dynamics is presented in [Di Cairano et al., 2009]. Di Cairano et al. introduce a class of systems called integral continuous-time hybrid automata (icHA). The proposed control strategy for such systems is based on model predict control principle, where the optimization problem is formulated as mixed-integer program. The systems are modeled as continuous time, however, the modes of operation can only change in discrete time, that is at sampling instances. This may lead to mode-mismatch errors, if the sampling time is relatively large, but on the other hand it helps to reduce pathological effects such as Zeno behavior. Although this description is very neat and fits our problem well, it was not analyzed in details due to time limitations of the project.

3   Coal mill model

Contents

The chapter presents development and validation of a coal mill model to be used for improved mill control, which may lead to a better load following capability of the power plants. The model is relatively simple, yet it captures all significant mill dynamics. The model is validated using data from four mills of two similar types produced by different manufacturers. In the validation, model parameters are estimated using an efficient evolutionary algorithm called Differential Evolution. The model parameters are similar and the simulation performance is satisfactory for all four mills, indicating that the model structure can be trusted.

3.1 Model characteristics

The model presented in this chapter is based on the assumptions from Rees [1997] and Ljung [2008]. Rees [1997] claims that it is not necessary to have a very accurate model of the process when using multivariable plant models or receding horizon control techniques for solving the load following problem. Additionally Ljung [2008] presents a measure of model fitness which combines both the chosen fit measure and a complexity penalty. According to the basic principle "Nature is simple", it is more likely that good performance will be achieved using a simple rather than a complicated model. Ljung gives the following requirements for a 'good' model must fulfill:

1. the model should agree with the estimation data,

2. the model should not be overly complex.

Besides the good performance of the model, which means that it represents the physical phenomena well, it is very beneficial for this particular application to:

3. have a universal description suitable for similar mill types from various suppliers, if possible,

4. allow easy estimation of mill parameters (preferably on-line due to mill wear).

The proposed model fulfills the above criteria. It is inspired by the model presented by Wei et al. [2007], but it differs significantly in certain key aspects, e.g. a rotating classifier is included and the mill temperature equation is based on first principles. The resulting model is a grey-box model based on physical knowledge and parameter identification methods.

A simplified design schematic of a so-called MPS mill sometimes called roller mill, and the corresponding nomenclature is presented in Figure 3.1, while the diagram in Figure 3.2 shows the particle circulation in the mill. The principle of operation can be summarized as follows. Raw coal is transported on a conveyor belt and dropped into the mill, where it falls onto a grinding table and is crushed by rollers. Primary air, blown from the bottom of the mill, picks up fine coal particles and transports them into the classifier section. Only the finest particles escape the mill, whereas the rest falls back onto the grinding table. For rotary classifiers, which

are constructed from a number of blades attached to a vertical axis of rotation, it is possible to control the angular velocity and thereby, if needed, increase the amount of coal escaping the mill quickly; one simply allows larger particles to pass through the classifier. The particles that drop onto the table are reground.
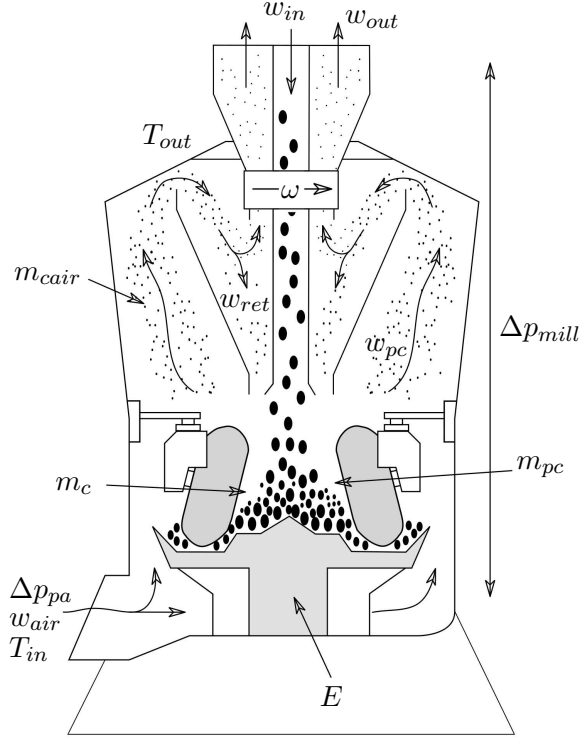
Figure 3.1: Overview of an MPS mill design (air-swept, pressurized, vertical spindle, table/roller mill) [Kitto and Stultz, 2005].

The equations have been derived mainly for nominal grinding operation of a mill, but they also capture the start up and shut down dynamics well. The main part of the model is the coal particle circulation, which is presented in Figure 3.2.

The following assumptions are made:

- Coal in the mill is either pulverized or unpulverized, i.e. different particle sizes are not considered. Variations of the mass of coal particles (e.g. depending on the moisture content) are not included in the

Raw coal in bunker

- ambient temperature T_a
- coal moisture ρ_m

Pulverized coal out of the mill

- outlet temperature T_{out}
- moisture evaporated

fuel flow

m_{cair} - mass of coal
suspended in air

pneumatic
transport

raw coal | large particles

grinding

m_c - mass of unpulverized
coal on the table

m_{pc} - mass of pulverized
coal on the table
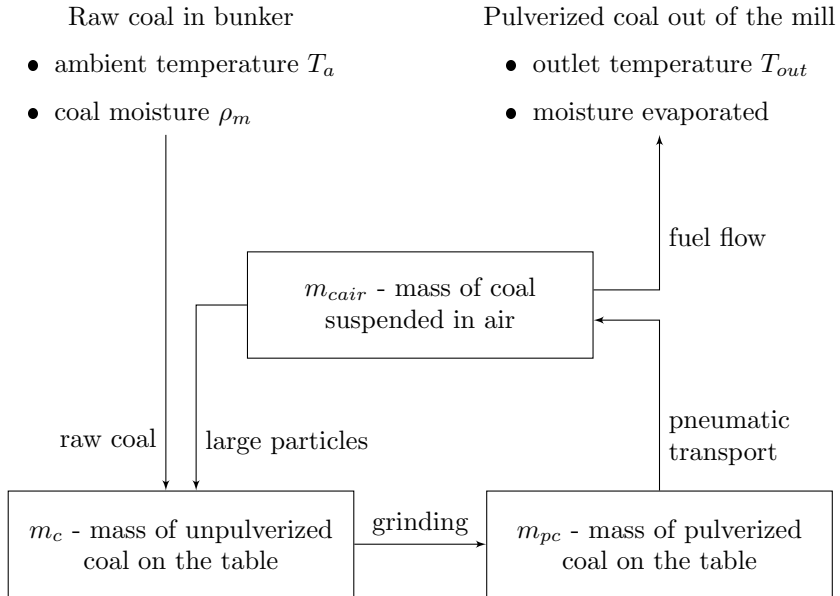
Figure 3.2: Coal particle circulation in a mill.

model.

- The temperature of the mill is assumed to be the same as the temperature of the classifier.

- Heat emitted from the mill to its environment is negligible.

- The mass change of coal causes insignificant change in the total heat capacity of the mill (k_{11}).

- The ambient temperature (temperature of raw coal entering the mill) T_a, coal moisture ρ_m and latent heat of vaporization L_v are known constants.

In the following sections the equations describing a coal mill, and a suitable parameter estimation procedure are presented. Parameter estimation is based on Differential Evolution algorithm [Storn and Price, 1995; Price et al., 2005; Feoktistov, 2006; Ursem and Vadstrup, 2003], which is described in Appendix A. Section 3.4 presents validation of the model against data obtained from mills utilized in Danish power plants.

3.2 Model equations

The mass of coal to be pulverized depends on the mass flow of the raw coal, w_{in}, the return flow of the particles rejected by the classifier, w_{ret}, and the grinding rate which is proportional to the mass of raw coal on the grinding table, m_c.

$$\frac{d}{dt}m_c(t) = w_{in}(t) + w_{ret}(t) - k_1 m_c(t) \tag{3.1}$$

The mass of pulverized coal on the table, m_{pc}, depends on the grinding rate and the amount of coal picked up by the primary air from the table, w_{pc}, (pneumatic transport).

$$\frac{d}{dt}m_{pc}(t) = k_1 m_c(t) - w_{pc}(t) \tag{3.2}$$

The mass of particles in the pneumatic transport upwards in the mill, m_{cair}, depends on the mass flow of coal particles picked up from the grinding table, the fuel flow out of the mill, w_{out}, and the return flow of rejected particles to the table.

$$\frac{d}{dt}m_{cair}(t) = w_{pc}(t) - w_{out}(t) - w_{ret}(t) \tag{3.3}$$

The mass flow of pulverized particles picked up by the primary air flow, w_{air}, to be transported towards the classifier is proportional to the primary air mass flow and the mass of pulverized coal on the table.

$$w_{pc}(t) = k_5 w_{air}(t) m_{pc}(t) \tag{3.4}$$

The mass flow of pulverized coal out of the mill is proportional to the mass of coal lifted from the table and depends on the classifier speed, ω.

$$w_{out}(t) = k_4 m_{cair}(t)\left(1 - \frac{\omega(t)}{k_6}\right) \tag{3.5}$$

where $0 < \omega(t) < k_6$. k_6 has the same unit as ω, making the term $\left(1 - \frac{\omega(t)}{k_6}\right)$ a dimensionless rating factor.

The mass flow of coal returning to the grinding table is proportional to the mass of coal in the pneumatic transport m_{cair}.

$$w_{ret}(t) = k_9 m_{cair}(t) \tag{3.6}$$

The pressure drop, Δp_{mill}, across the mill depends on the differential pressure of the primary air, Δp_{pa}, and the amount of coal suspended in the air. During normal operation, the mill pressure drop is predominately proportional to the primary air differential pressure and a small change in coal mass does not affect the pressure drop significantly. Also, when the coal mass becomes zero, the pressure drop also becomes zero. These conditions are guaranteed by the term $1 - e^{-k_8 m_{cair}(t)} \in [0, 1)$.

$$\Delta p_{mill}(t) = k_7(1 - e^{-k_8 m_{cair}(t)})\Delta p_{air}(t) \tag{3.7}$$

The power consumed for grinding is a sum of the power needed for rolling over raw and ground coal and the constant power need for running an empty mill (E_e).

$$E(t) = k_2 m_{pc}(t) + k_3 m_c(t) + E_e \tag{3.8}$$

Finally, the temperature equation is based on first principles (under the assumptions given above). The significant heat contribution comes from the primary air, moisture and coal flow into the mill ($C_{air}w_{air}(t)T_{in}(t)$, $\rho_m C_w w_{in}(t)T_a$, $C_c w_{in}(t)T_a$), and from grinding ($k_{10}E(t)$). The heat is used to evaporate moisture ($\rho_m w_{in}(t)L_v$) and raise the temperature of the coal and mill chassis to the outlet temperature ($C_{air}w_{air}(t)T_{out}(t)$, $C_c w_{out}(t)T_{out}(t)$).

$$\begin{aligned}
\frac{d}{dt}T_{out}(t) = \frac{1}{k_{11}} & [C_{air}w_{air}(t)T_{in}(t) + \rho_m C_w w_{in}(t)T_a \\
& + (1-\rho_m)C_c w_{in}(t)T_a - C_{air}w_{air}(t)T_{out}(t) \\
& - C_c w_{out}(t)T_{out}(t) - \rho_m w_{in}(t)L_v + k_{10}E(t)]
\end{aligned} \tag{3.9}$$

The resulting model is a fourth order nonlinear model of the form

$$\begin{aligned}
\frac{dx(t)}{dt} &= f(x(t), u(t)) \\
y(t) &= h(x(t), u(t))
\end{aligned} \tag{3.10}$$

with

$$x(t) = \begin{bmatrix} m_c(t) \\ m_{pc}(t) \\ m_{cair}(t) \\ T_{out}(t) \end{bmatrix}, u(t) = \begin{bmatrix} w_{in}(t) \\ w_{air}(t) \\ \omega(t) \\ T_{in}(t) \\ \Delta p_{air}(t) \end{bmatrix}, y(t) = \begin{bmatrix} w_{out}(t) \\ \Delta p_{mill}(t) \\ E(t) \\ T_{out}(t) \end{bmatrix} \tag{3.11}$$

and eleven tuning parameters $k_1, \ldots, k_{11}$. The state equations are

$$f(x(t), u(t)) = \begin{bmatrix} -k_1 x_1(t) + k_9 x_3(t) + u_1(t) \\ k_1 x_1(t) - k_5 u_2(t) x_2(t) \\ k_5 u_2(t) x_2(t) - k_4 \left(1 - \frac{u_3(t)}{k_6}\right) x_3(t) - k_9 x_3(t) \\ f_4(x, u) \end{bmatrix} \quad (3.12)$$

$$f_4(x, u) = \frac{1}{k_{11}} (C_{air} u_2(t) u_5(t) + \rho_m C_w T_a u_1(t) u_5(t) + (1 - \rho_m) C_c T_a u_1(t)$$

$$-C_{air} u_2(t) x_4(t) - C_c k_4 (1 - \frac{u_3(t)}{k_6}) x_3(t) x_4(t) - \rho_m L_v u_2(t) + k_{10} E)$$

and the output equations are

$$h(x(t), u(t)) = \begin{bmatrix} k_3 x_1(t) + k_2 x_2 + E_e \\ k_4 \left(1 - \frac{u_3(t)}{k_6}\right) x_3(t) \\ x_4(t) \\ k_7(1 - e^{-k_8 x_3(t)}) u_5(t) \end{bmatrix} \quad (3.13)$$

The mass flow of the primary air, w_{air}, is not a measured value; rather, it is calculated from the differential pressure of the primary air measured by a venturi sensor, taking into account the temperature of the air. Thus, w_{air} and Δp_{air} are not independent control inputs and for example Δp_{air} in equation (3.7) could be replaced by a mass flow of the air. For the sake of clarity, we have decided to present the equations in the more simple form, noting that the last input is dependent on the second input, and vice versa.

3.3 Parameter estimation

Identification of suitable model parameters is carried out by solving a nonlinear constrained optimization problem; the errors between the available mill measurements and the estimated values are used to determine the *fitness* of parameters.

There are eleven model parameters which take real values, hence $k \in \mathcal{K} \subseteq \mathbb{R}^{11} \backslash \{0\}$. We consider a functional $J : \mathcal{K} \to \mathbb{R}^+$, which is a measure of the parameters' fitness. Then the constrained optimization problem Feoktistov [2006] consists in finding a value of $k^\star \in \mathcal{K}$ that minimizes J.

$$k^\star \in \mathcal{K} : J(k) \geq J(k^\star) = J^\star \quad (3.14)$$

We use normalized signals from available mill sensors, that is power used for grinding, differential pressure across the mill, classifier temperature and pulverized coal flow, for the purpose of parameter identification. The available sensors of the pulverized fuel flow have bias errors and hence the information should be handled with special care. The signal is filtered and the mean values of the measured and estimated flows are subtracted. The fitness criterion is calculated from simulating model with the considered parameters and from the plant measurements according to the following formula

$$J = \frac{1}{N} \sum_{i=1}^{N} e^T(i) \mathsf{W} e(i) \tag{3.15}$$

where $e(i) = [e_1(i), \ldots, e_4(i)]^T$ is an error vector consisting of

$$e_1(i) = \frac{(w_{out,filt}(i) - \mu_{w_{out,filt}}) - (\hat{w}_{out,filt}(i) - \mu_{\hat{w}_{out,filt}})}{w_{out,max}(i) - \mu_{w_{out}}} \tag{3.16}$$

$$e_2(i) = \frac{\Delta p_{mill}(i) - \Delta \hat{p}_{mill}(i)}{\Delta p_{mill,max}} \tag{3.17}$$

$$e_3(i) = \frac{E(i) - \hat{E}(i)}{E_{max}} \tag{3.18}$$

$$e_4(i) = \frac{T_{out}(i) - \hat{T}_{out}(i)}{T_{out,max}} \tag{3.19}$$

with diagonal weighting matrix $\mathsf{W} \geq 0$, N is the number of samples, E_{max}, $\Delta p_{mill,max}$, $T_{out,max}$ and $w_{out,max}$ are the maximum measured values, $w_{out,filt}$ is the filtered signal of the pulverized coal flow and $\mu_{w_{out}}$ is its mean value.

The model is simulated using the continuous time description, and the cost function is calculated for a number of time samples.

An efficient type of Evolutionary Algorithm [Ahn, 2006; Rothlauf, 2006], known as Differential Evolution [Storn and Price, 1995; Price et al., 2005; Feoktistov, 2006] is applied to the problem. The Differential Evolution algorithm combines benefits of population-based algorithms (Evolutionary Algorithms) and gradient-based optimization methods. One of the advantages of the algorithm is that it requires only three control parameters: population size $\mathsf{P_S} \in \mathbb{Z}_+$, scaling factor $\mathsf{F} \in (0, 1]$ and crossover constant $\mathsf{C} \in (0, 1)$.

The population $\mathsf{P} = \{k^i\}_{i=1}^{\mathsf{P_S}}$ is a collection of $\mathsf{P_S}$ vectors $k = \{k_1, \ldots, k_{11}\}$, that is model parameters. Each element of the the population has a *fitness* value, $J(k)$. The parameter space $\mathcal{K}$ is explored based on special strategy,

which involves calculating gradients between individuals in the population, and applying crossover mechanisms, in order to find an optimal value to the problem.

3.3.1 Practical considerations

To achieve good results using Differential Evolution algorithms for the problem of parameter identification, it is necessary to consider a few important factors that may affect the procedure.

The authors of the algorithm propose to use the following control parameters as initial guess[1]: the population size P_S should be ten times the number of problem variables, k, the scaling factor $F = 0.8$ and the crossover factor $C = 0.9$. The algorithm is generally very robust to the selection of the control parameters, but the performance can be improved by tuning them appropriately. It is found that choosing $F = 0.35$ and $C = 0.2$ for the particular problem seems to give good results.

It is very important to specify the initial conditions for the simulations. Preferably, the system should be in the steady state at $t = 0$. Thus, the left hand sides in equations (3.1), (3.2), (3.3) and (3.9) are equal to zero and it is possible to calculate the initial values for the ordinary differential equations.

Additionally, a proper region for the parameter set $\mathcal{K}$, which bounds it away from unrealistic or unwanted values of the parameters, should be specified (e.g. all the values need to be positive, the grinding rate should not be too small, etc.). This prevents the DE algorithm from fitting the model output to the noise.

In general, proper plant excitation by valid selection of inputs gives a better chance to acquire valid and optimal model parameters. In case the plant inputs were poorly chosen it might be required to supervise the optimization routine and hand-tune some of the parameters. The result of such optimization does not guarantee that the model parameters are valid.

In this study measurements from one coal mill that was properly excited has been available (STV4); the other measurements mostly came from normal mill operation, thus finding optimal parameters for those mills was not fully automatic. The optimal parameters from the fully excited plant are used as a starting point for parameter identification of other mills. Additionally, the routine is supervised to prevent it from drifting very far from the initial values.

---

[1]http://www.icsi.berkeley.edu/~storn/code.html

In case of noisy and biased signals (e.g. measurements from pulverized fuel flow sensors), it might be required to pre-process them before the parameter identification is performed. In case of the fuel sensors the signal are filtered by a low pass filter, forth and back, to avoid introducing delays. Additionally, due to the measurement bias errors the mean values from both the measured and the model outputs are subtracted, thus emphasizing the dynamic performance of the model.

The weights W in equation (3.15) can be adjusted based on the quality of measurements (the more accurate measurements, the higher weight). In this work however, weights equal to one are chosen, as it is found that they do not influence the optimization process significantly.

3.4   Model verification

The process of model validation is performed in five steps for two different types of coal mills. Each step is described in a separate paragraph for clarity. The idea is to investigate how the model behaves when parameters change (for example due to mill wear) and how well the model describes other types of mills. The measurements used in this section were taken at Stigsnæs Power Station (STV) and Asnæs Power Station (ASV), located on Zealand, Denmark. In the STV plant there are four Babcock & Wilcox type 10E ball and race mills installed; in the ASV plant there are eight Loesche LM 19D vertical roller mills installed. The maximal capacity in terms of mass flow of pulverized coal of both types of mills is 10 [kg/s].

The measurements from mill one at plant STV are labeled STV1, measurements from mill three at ASV are labeled ASV3, etc.

Remark 1: *Offset in the pulverized fuel flow figure is made intentionally to separate the signals; steady state value of the model output is equal to steady state value of the raw coal input. The fuel sensors suffer from bias errors anyway.*

3.4.1   Primary data - STV4

The primary data for parameter identification comes from mill number four in the STV plant, where plant operators have applied various input steps to test the mill responses (Figure 3.3). This is the first verification step,
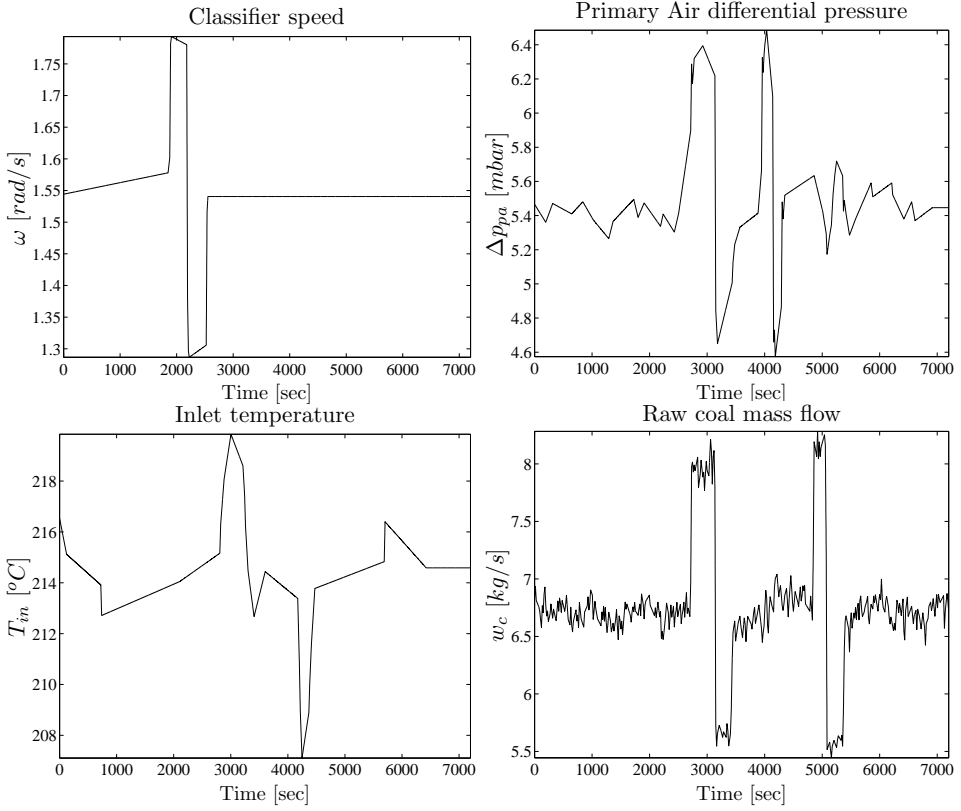
Figure 3.3: STV4 mill inputs; primary data for parameter identification.

which may indicate the potential quality of the model. Since the model is tuned and verified against the same data, a good fit does not guarantee that the model is valid for other regions of operation and combinations of inputs.

The comparison between measured outputs from STV4 and model is presented in Figure 3.4 and Figure 3.5. As can be seen, the performance of the model with properly tuned mill parameters is satisfactory. The mass flow of the pulverized fuel flow is represented very well; the captured dynamics are similar to those measured by the sensors and the steady state values correspond to the raw coal mass flow w_{in}.
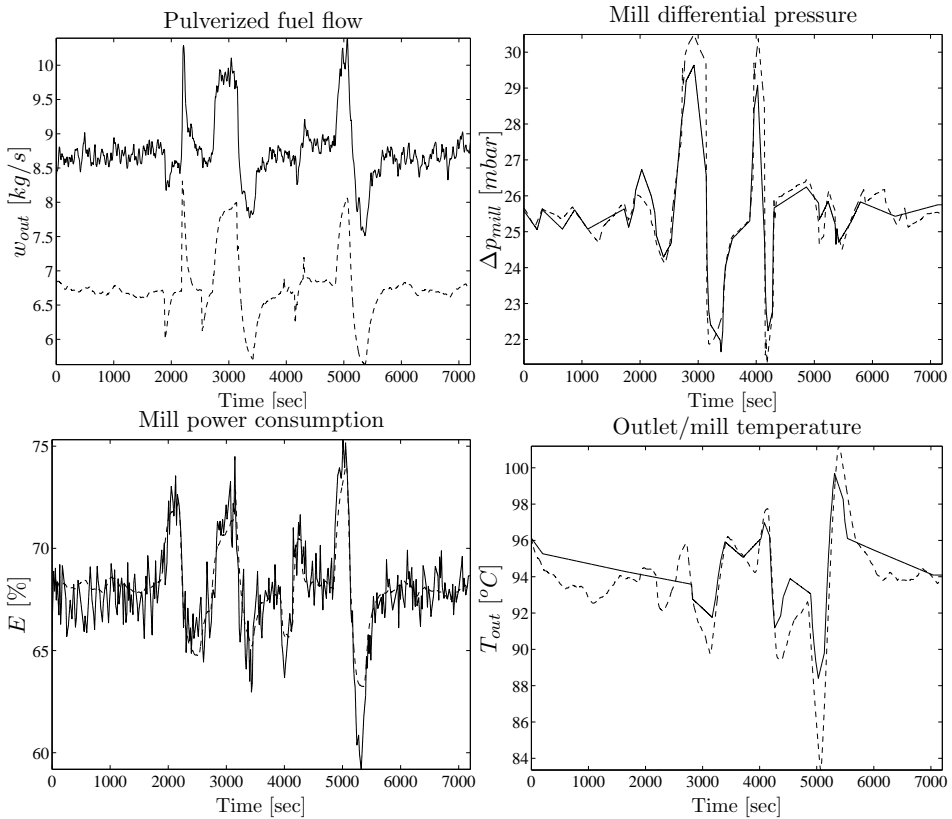
Figure 3.4: Comparison between model output and measurements (STV4); primary data for parameter estimation procedure. Solid lines are measured signals and dashed lines are model outputs.

3.4.2 Suboptimal parameters

In this test, the optimal parameters obtained for mill STV4 are used for simulating STV1 mill and the result is compared to the plant data. The aim is to validate how the model performs with suboptimal parameters. Afterwards optimal model parameters are found and compared to the previously used. Similar parameters for both mills indicate that the model structure is valid. The comparison between modeled system response with optimal and sub-optimal parameters, and the plant data is depicted in Figures 3.7 and 3.8.

The model outputs for mill STV1 with parameters from STV4 are presented in Figure 3.7. It is seen that the model captures the mill dynamics well, but there are bias errors. An optimal set of parameters improves

Figure 3.5: Pulverized fuel flow (STV4). Solid lines are measured signals and dashed lines are the model outputs. Additionally, the raw coal input flow is plotted with dotted line.
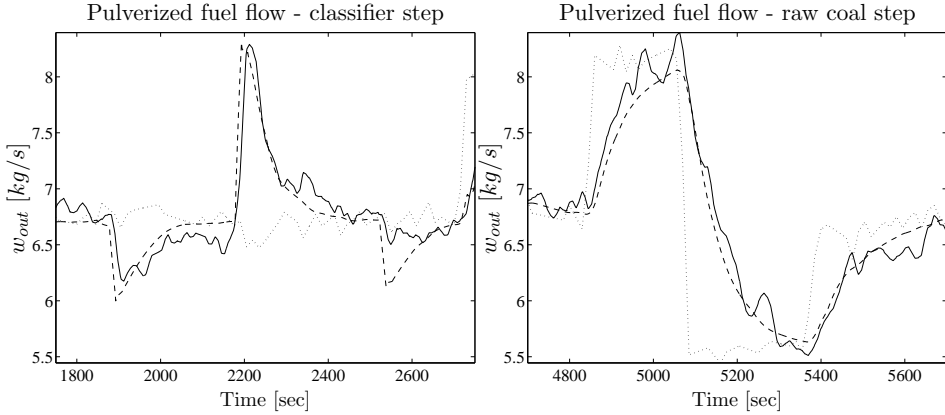
model output (Figure 3.8). The optimized STV1 model parameters are similar to the STV4 parameters (Table 3.1).

3.4.3   Different type of coal mill

The model is also validated with measurements from vertical roller mills from ASV power plant instead of ball and race mills (STV). This tests whether the model can be used with other types of mills. The validation is performed with optimal model parameters.

The dynamics during normal mill operation are captured well; the set of optimal model parameters is similar to those used in STV mills (see Table 3.1). The difference between measured and modeled response are plotted in Figure 3.9. The error amplitudes are small compared to the absolute values of the signals, and especially the pulverized fuel flow is modeled well.

3.4.4   Mill start up and shut down

The aim of this test is to check how well the pulverized fuel flow is modeled during the mill start up and shut down.

As can be seen from Figure 3.6, the dynamics in the measured pulverized fuel flow are reflected by the model and the steady state values of the raw coal flow are preserved. There is a small mismatch, around the 12'th minute, due to large classifier change, which is not
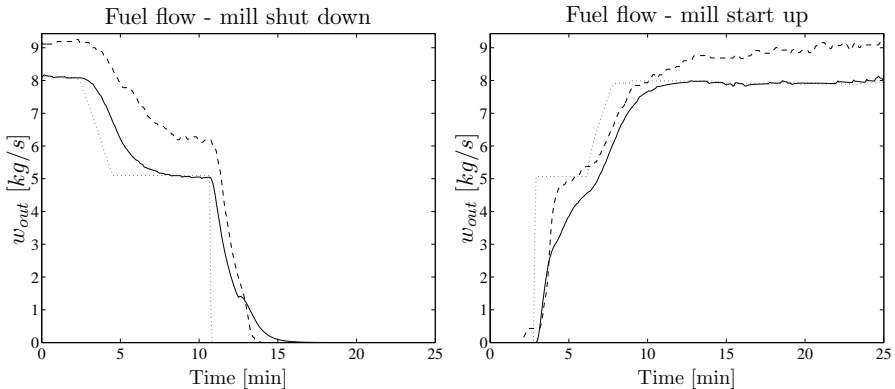
Figure 3.6: Pulverized fuel flow during mill start up and shut down (ASV5). The solid lines are the modeled outputs, the dashed lines are the measurements, and the dotted lines reflect the raw coal flow.

Parameter	STV1	STV4	STV4†	ASV1	ASV3
k_1	0.0423	0.0487	0.0487	0.0148	0.0424
k_2	0.0296	0.1409	0.1409	0.0034	0.0107
k_3	0.0403	0.0104	0.0104	0.0227	0.0315
k_4	0.8963	0.8148	0.8148	0.4463	0.4284
k_5	0.0040	0.0062	0.0062	0.0044	0.0013
k_6	2.3541	2.7855	2.7855	4.3156	3.1853
k_7	3.8751	4.8897	8.5450	9.1987	9.8809
k_8	0.1544	0.1710	0.0852	0.3356	0.3435
k_9	0.5586	0.5604	0.5604	0.6798	0.6371
k_{10}	8.2521	8.4325	8.4325	8.5000	8.3266
k_{11}	4.24×10^6	4.24×10^6	4.24×10^6	7×10^6	7×10^6
$T_a[^oC]$	10	10	10	10	10
$\rho_m[\%]$	7.2	6.8	10.9	11.4	11.1
$L_v[J/kg]$	2.5×10^6	2.5×10^6	2.5×10^6	2.5×10^6	
E_e	38.8	38.8	38.8	40	40
Q	0.3455	0.0923	0.1835	0.1160	0.1687

Table 3.1: Optimal model parameters $k^\star$ and constants found from the identification procedure and used for validation. STV4† corresponds to parameters of the fourth mill at STV after 6 months of operation.

3.4.5 Parameter change

Due to the mill wear, the parameters of mill are changing with time. The aim of this validation step is to analyze performance degradation over a period of six months; measurements from STV4 are available for this purpose.
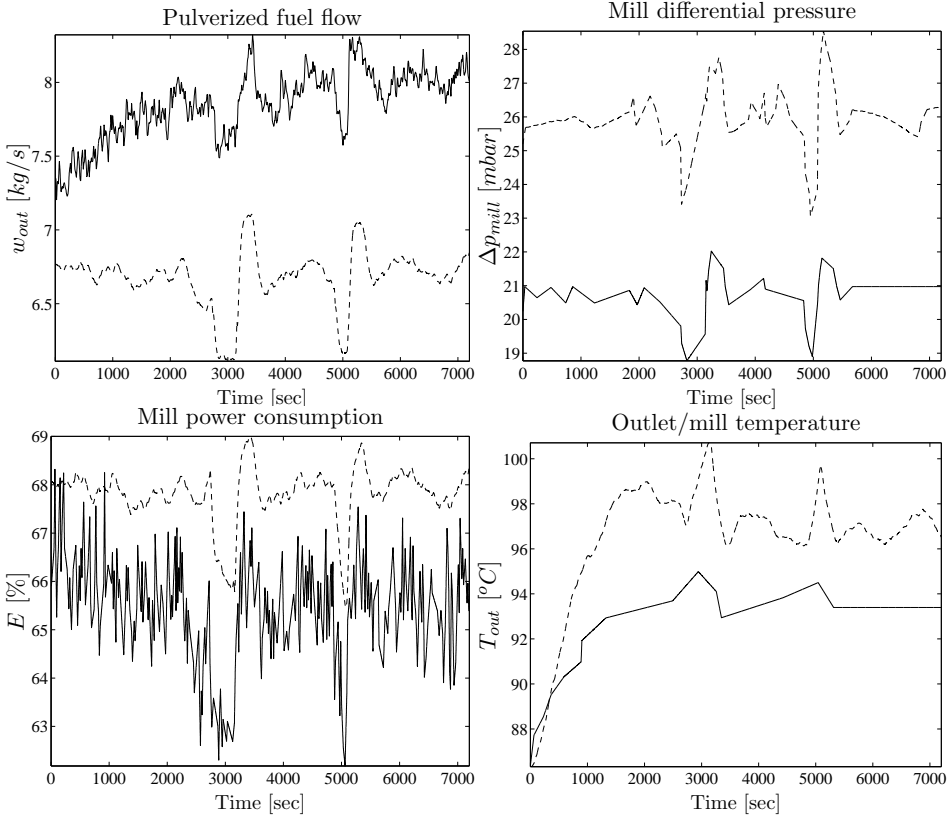
Figure 3.7: Comparison between model output and measurements (STV1) using suboptimal parameters; model coefficients k are found for mill STV4. Note: temperature affects the pulverized fuel flow measurements $(0 - 2500[sec])$.

Figure 3.11 depicts the new measurements, as well as the model outputs with old and new parameters. The measurements are taken during mill start up, which is a difficult situations for the model (Figure 3.10). It can be noticed that the very large classifier step, which is not a usual control action, is not represented very well by the model. The spike in pulverized fuel flow is captured, but it is more rapid than expected, and the return flow circulation to the grinding table is not quite large enough (as can be

seen from the energy consumption graph). Most of the old parameters can still be used, however. In the temperature model, it is enough to change the moisture parameter ρ_m; only the pressure equation requires new parameters. This indicates that, in general, the model is robust for a longer periods of time, however, the pressure equation parameters should be re-estimated periodically.
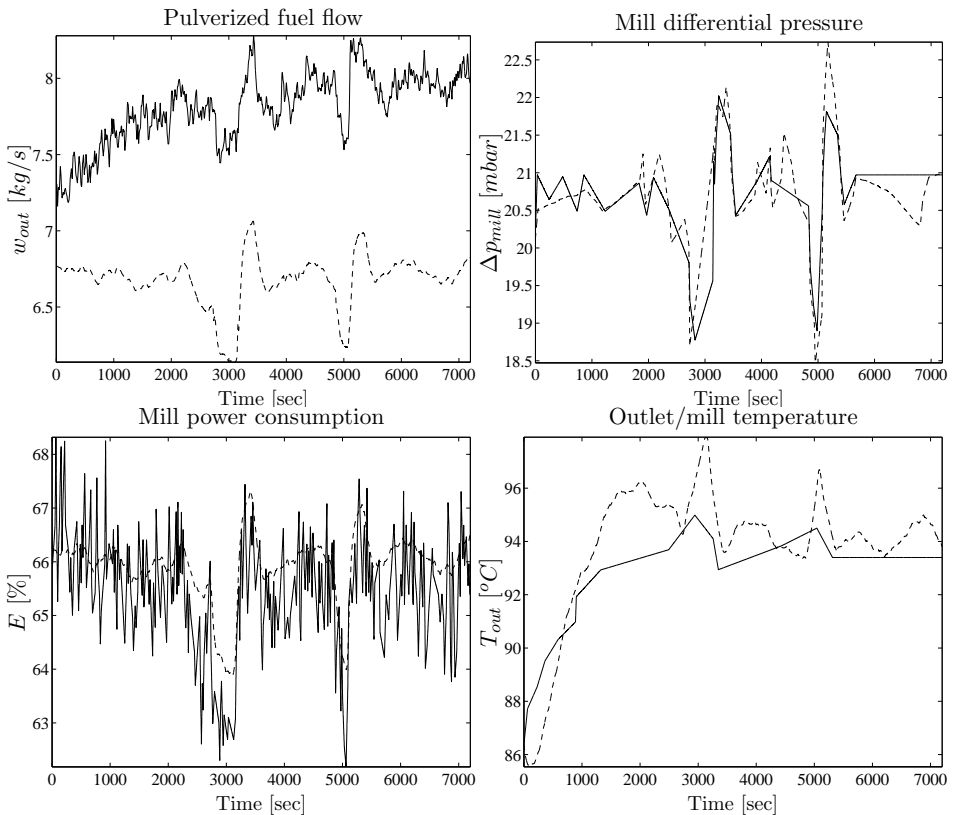
Figure 3.8: Comparison between model output and measurements (STV1). Solid lines are measured signals and dashed lines are the model outputs.
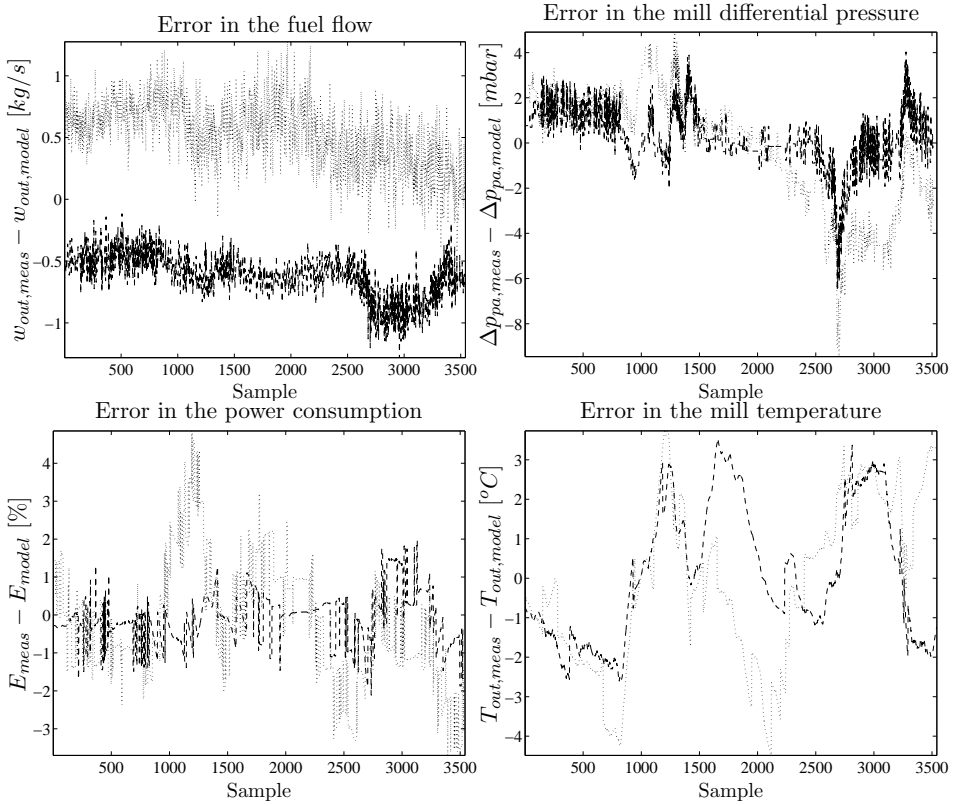
Figure 3.9: Differences between measured and modeled outputs of ASV1 (dashed line) and ASV3 (dotted line) during normal mill operation. Sampling time is 5 seconds.

Figure 3.10: STV4 mill inputs after six months of operation - mill start up and shut down; large classifier step should be noticed.

Figure 3.11: Comparison between model output and measurements (STV4) after six months of operation. Solid lines are m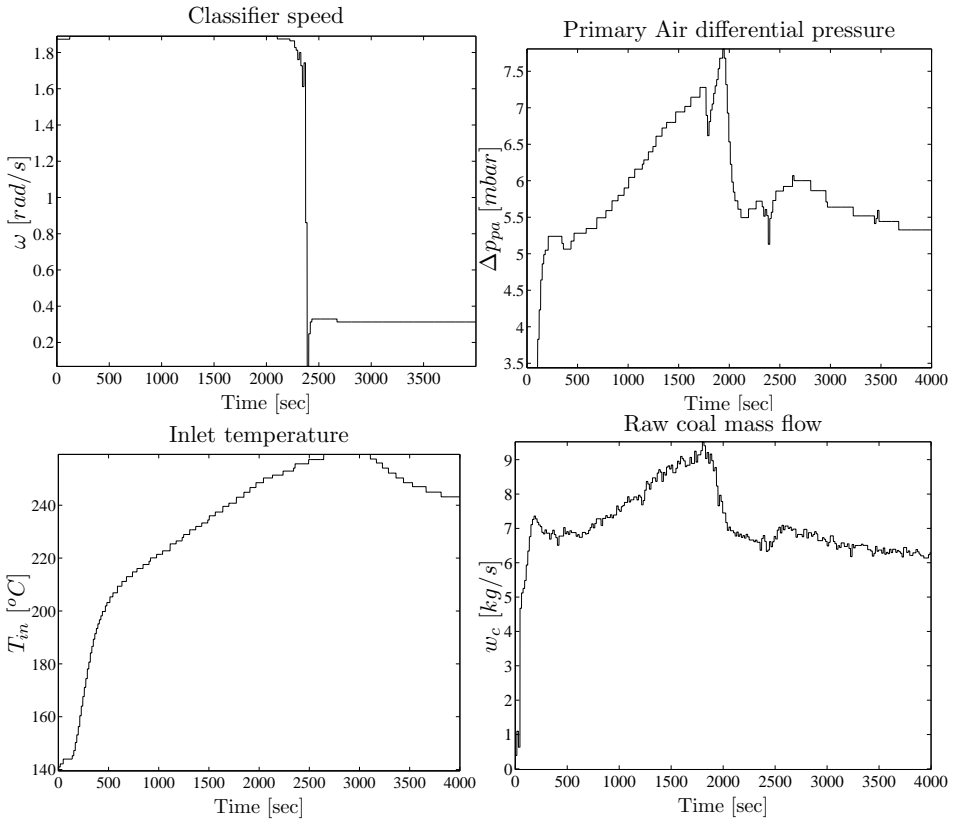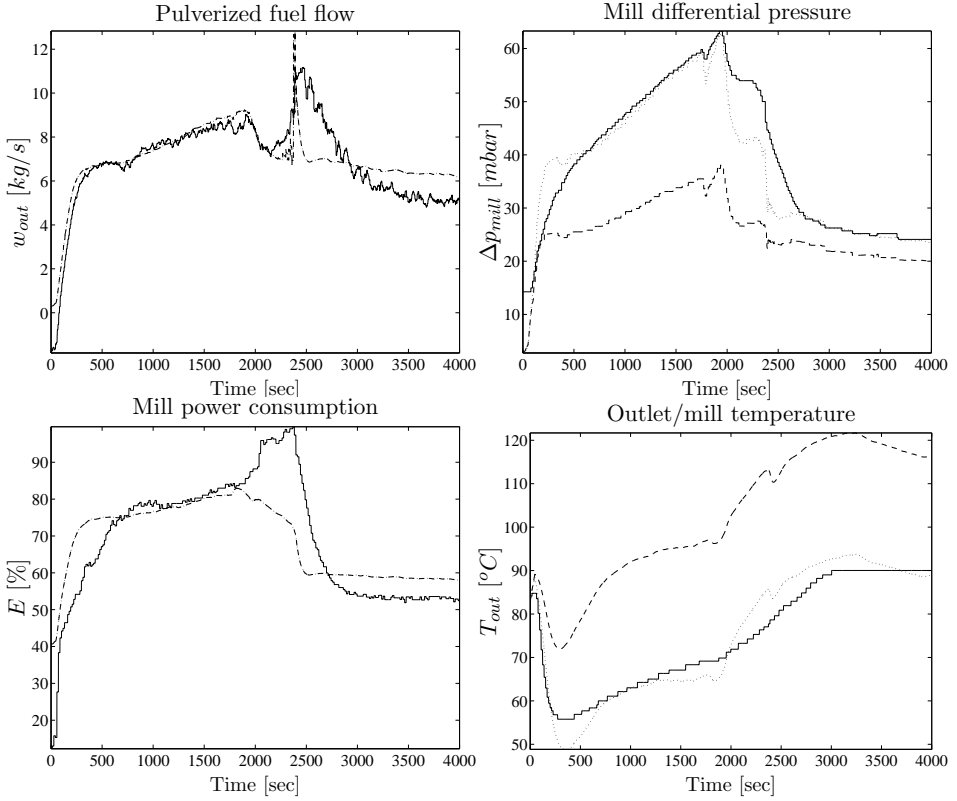easured signals, dashed lines are model outputs with old parameters, and dotted lines are model outputs with updated parameters.

3.5 Plant model

In this section we formulate the model to be used in the controller design. In particular, we are interested here in the coal grinding model

$$
\begin{aligned}
\dot{x}_1(t) &= -k_1 x_1(t) + k_9 x_3(t) + u_1(t) \\
\dot{x}_2(t) &= k_1 x_1(t) - k_5 x_2(t) u_2(t) \\
\dot{x}_3(t) &= k_5 x_2(t) u_2(t) - k_4 \left(1 - \frac{u_3(t)}{k_6} \right) x_3(t) - k_9 x_3(t)
\end{aligned}
\tag{3.20}
$$

Furthermore, we add a first order model of the primary air flow through the mill

$$
\dot{x}_4(t) = \kappa(-x_4(t) + u_2(t))
\tag{3.21}
$$

where $x_4(t)$ is the flow of the air at the mill outlet. The necessity for including the additional state is discussed later; it is motivated by the demand to control the fuel to air ratio.

The system can be written in a bilinear form

$$
\dot{x} = Ax + \sum_{i=1}^{m} u_i N_i x + Bu = Ax + \sum_{i=1}^{m} u_i \phi_i(x)
\tag{3.22}
$$

with

$$
\phi_i(x) = N_i x + B_i
\tag{3.23}
$$

where $x \in \mathbb{R}^n$ are the states, $u \in \mathbb{R}^m$ are the control inputs, $A \in \mathbb{R}^{n \times n}$, $N_i \in \mathbb{R}^{n \times n}$, $B \in \mathbb{R}^{n \times m}$, and B_i is the i-th column of matrix B.

In our case the states are

$x_1(t) = m_c(t)$ - mass of raw coal on the grinding table,

$x_2(t) = m_{pc}(t)$ - mass of pulverized coal on the grinding table,

$x_3(t) = m_{cair}(t)$ - mass of pulverized coal in pneumatic transport,

$x_4(t)$ - mass flow of primary air at the outlet,

and the inputs are

$u_1(t) = w_{in}(t)$ - mass flow of the raw coal,

$u_2(t) = w_{air}(t)$ - mass flow of the primary air,

$u_3(t) = \omega(t)$ - angular velocity of the classifier.

hence, we can write the system matrices as

$$A = \begin{bmatrix} -k_1 & 0 & k_9 & 0 \\ k_1 & 0 & 0 & 0 \\ 0 & 0 & -k_4 - k_9 & 0 \\ 0 & 0 & 0 & -\kappa \end{bmatrix}, \quad B = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & \kappa & 0 \end{bmatrix} \tag{3.24}$$

$$N_1 = 0, \quad N_2 = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & -k_5 & 0 & 0 \\ 0 & k_5 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}, \quad N_3 = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & \frac{k_4}{k_6} & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \tag{3.25}$$

Please note that the eigenvalues of the state matrix A are

$$\lambda_A = \begin{bmatrix} 0 \\ -k_1 \\ -k_4 - k_9 \\ -\kappa \end{bmatrix} \tag{3.26}$$

hence, it is not Hurwitz for $\kappa \in \mathbb{R}$, $k_i \in \mathbb{R}$, $i \in \{1, 4, 9\}$.

The objective for the controller is to ensure that the fuel flow attains the reference value quickly and with small overshoot, and that there is appropriate air flow through the mill. The second objective guarantees that the mill is adequately pressurized, and that the air to fuel ratio is not posing risk of explosion. In practice there is a carefully chosen load line, which characterizes the ratio between the coal flow and primary air flow [Kitto and Stultz, 2005]. In our work we kept the ratio constant; the value of $\rho_{af} = 2.5$ is chosen based on the available plant data.

3.5.1   Nominal operation

Before the design is carried out, the state equations are transformed to obtain a system with Hurwitz state matrix A. Such procedure simplifies further considerations. We use the fact, that prior to the mill operation, a start-up procedure is performed. During this procedure, the primary air is blown through the mill in order to heat it up and swipe out the remaining coal particles. The angular velocity of the classifier is controlled to the nominal value of operation. In the following discussions we use the term nominal inputs, for the preinitialized air flow and angular velocity, and we label them as $\bar{u}$. We choose the nominal inputs to be in the middle of the

operating region, that is $\bar{u}_2 = 17.5$ [kg/s] and $\bar{u}_3 = 1.5$ [rad/s]. New control inputs are thus

$$
\begin{aligned}
v_1(t) &= u_1(t) \\
v_2(t) &= u_2(t) - \bar{u}_2 \\
v_3(t) &= u_3(t) - \bar{u}_3
\end{aligned}
\tag{3.27}
$$

The operating ranges of the inputs are now

$$v_1 \in [0, 10] \qquad\qquad\qquad \text{[kg/s]} \tag{3.28}$$
$$v_2 \in [-17.5, 17.5] \qquad\qquad \text{[kg/s]} \tag{3.29}$$
$$v_3 \in [-0.2, 0.2] \qquad\qquad\quad \text{[rad/s]} \tag{3.30}$$

We rewrite the system as

$$
\dot{x} = Ax + \sum_{i=1}^{m} (\underbrace{u_i - \bar{u}_i}_{v_i} + \bar{u}_i)\phi_i(x) = \tilde{A}x + \sum_{i=1}^{m} B_i\bar{u}_i + \sum_{i=1}^{m} v_i\phi_i(x)
\tag{3.31}
$$

with

$$
\tilde{A} = A + \sum_{i=1}^{m} N_i\bar{u}_i =
\begin{bmatrix}
-k_1 & 0 & k_9 & 0 \\
k_1 & -k_5\bar{u}_2 & 0 & 0 \\
0 & k_5\bar{u}_2 & -k_4(1 - \frac{\bar{u}_3}{k_6}) - k_9 & 0 \\
0 & 0 & 0 & -\kappa
\end{bmatrix}
\tag{3.32}
$$

$$
\sum_{i=1}^{m} B_i\bar{u}_i =
\begin{bmatrix}
0 \\
0 \\
0 \\
\kappa\bar{u}_2
\end{bmatrix}
\tag{3.33}
$$

The derivative of the last state is affected by a constant term $\kappa\bar{u}_2$. Because it is a linear ordinary differential equation, we can removed it if we remember to compensate by subtracting such value from the reference signal; we change the equilibrium point of the independent state equation.

From now on we consider the above system with nominal inputs, which for the model parameters obtained in the previous chapter yields state matrix with negative eigenvalues. By abuse of the notation in the later considerations we write A instead of $\tilde{A}$.

3.5.2 Actuators

The model inputs, v_i, are in fact the quantities measured at the inlets, and due to actuator dynamics, they are not the control inputs. An adjustment

of the raw coal flow is not directly exerted on the due to the feeder belt dynamics. The same situation occurs in the primary air flow and angular velocity of the classifier. For this reason we augment the bilinear system with additional equations modeling linear actuator dynamics (first order systems).

$$\dot{z} = \bar{A}z + \bar{B}w = \begin{bmatrix} -\tau_1 & 0 & 0 \\ 0 & -\tau_2 & 0 \\ 0 & 0 & -\tau_3 \end{bmatrix} z + \begin{bmatrix} \tau_1 & 0 & 0 \\ 0 & \tau_2 & 0 \\ 0 & 0 & \tau_3 \end{bmatrix} w \qquad (3.34)$$

$$v = \bar{C}z \qquad (3.35)$$

We remark that the states of the actuators are measurable.

3.5.3 Reduced state observer

In the last section, before the chapter is concluded, we would like to describes a suitable state observer design procedure for bilinear systems, which is proposed by Derese, Stevens, and Noldus [1979]. This allows us to concentrate purely on the controller design in the next chapter.

Observer with bounded inputs

The considered observer is constructed in a similar way as the classical Luenberger observer. It consists of the system equations and a linear correction term (3.36). The block diagram of the observer is depicted in Figure 3.12.

$$\dot{\hat{x}}(t) = A\hat{x}(t) + \sum_{i=1}^{m} v_i(t)N_i\hat{x}(t) + Bv(t) + H(y(t) - C\hat{x}(t)) \qquad (3.36)$$

With the observation error defined as $e(t) = \hat{x}(t) - x(t)$ it is straightforward to see that

$$\dot{e}(t) = (A - HC)e(t) + \gamma(t) \qquad (3.37)$$

where $\gamma(t) = \sum_{i=1}^{m} v_i(t)N_i e(t)$ is an input dependent disturbance. We seek the upper bound on this term in order to prove the convergence of the observer in case of the largest admissible disturbance (3.38).

$$\gamma^T(t)\gamma(t) = e^T(t) \left(\sum_{i=1}^{m} v_i(t)N_i^T \right) \left(\sum_{i=1}^{m} v_i(t)N_i \right) e(t) \leq e^T(t)Se(t) \quad (3.38)$$
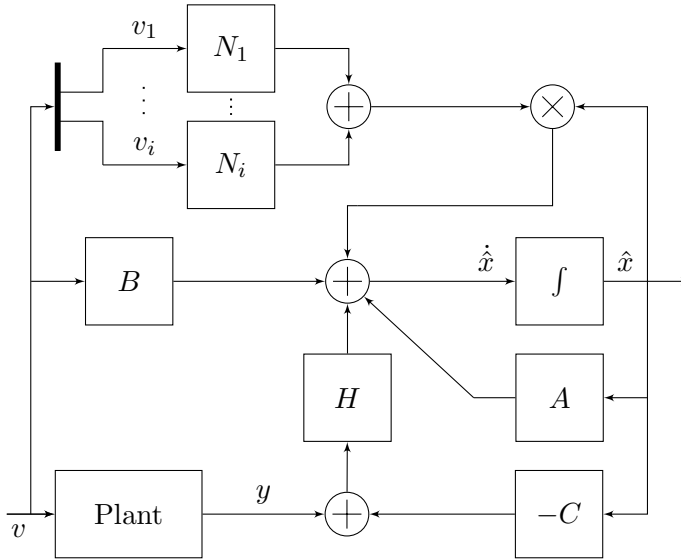
Figure 3.12: The block diagram of the state observer.

for all t, where $S = S^T \geq 0$ is a constant matrix.

The disturbance $\gamma(t)$ is input dependent, hence, it is necessary to determine the input bounds $v_i(t) \in [\underline{v_i}, \overline{v_i}]$, which in our case is known.

Convergence of the observation error (3.37) can be analyzed using quadratic Lyapunov function $V(e) = e^T(t)P_o e(t)$, with $P_o = P_o^T > 0$. The following condition needs to be fulfilled in order to stabilize the error dynamics to $e_0 = 0$

$$P_o(A - HC) + (A - HC)^T P_o + P_o^2 + S < 0 \tag{3.39}$$

Choosing the observer feedback matrix H to have the form

$$H = \frac{1}{2} P_o^{-1} C^T R_o \tag{3.40}$$

with $R_o = R_o^T > 0$ yields

$$A^T P_o + P_o A + P_o^2 + Q_o < 0 \tag{3.41}$$

with $Q_o = -C^T R_o C + S$. Equation (3.41) has the Riccati form. It can be written in standard linear matrix inequality form and solved efficiently [Boyd et al., 1994]

$$\begin{bmatrix} -A^T P_o - P_o A - Q_o & P_o \\ P_o & I \end{bmatrix} > 0 \tag{3.42}$$

In [Derese et al., 1979] authors demonstrate that it is sufficient to choose $R_o = \theta I$, with sufficiently large tunning parameter $\theta > 0$, for an exhaustive search of positive definite solutions for the chosen class of feedback matrices.

3.5.4   Implementation

A prerequisite for the observer design is that the pair of matrices A and C is observable. In our situation the output equation describing the power consumption (3.8) can remain almost unchanged, only the constant value E_e is subtracted. However, it is necessary to choose the second output carefully. The fuel flow equation (3.5) is nonlinear, and it is not possible to use it directly in the observer design, but the measurements can be used to obtain information on how much coal is accumulated in the mill according to (3.43).

$$
\begin{aligned}
m_t(\tau) &= \int_0^\tau (w_{in}(t) - w_{out}(t))dt \\
&= m_c(\tau) + m_{pc}(\tau) + m_{cair}(\tau)
\end{aligned}
\tag{3.43}
$$

and the chosen outputs have linear form

$$
\begin{aligned}
y_1(t) &= E(t) - E_e \\
y_2(t) &= m_c(t) + m_{pc}(t) + m_{cair}(t)
\end{aligned}
\tag{3.44}
$$

yielding the output matrix C

$$
C = \begin{bmatrix} k_3 & k_2 & 0 \\ 1 & 1 & 1 \end{bmatrix}
\tag{3.45}
$$

which together with the state matrix A forms an observable system.

Input dependent observer disturbance $\gamma(t)$ is calculated according to (3.38) by inputting the largest control values (3.28) to (3.28). As for the $\bar{N}_i$ matrices, the parameter uncertainties should be accounted for, and values corresponding to the largest eigenvalues should be chosen.

$$
S = \sum_{i=1}^{3} \sup_{v_i} v_i^2 \bar{N}_i^T \bar{N}_i \approx \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0.029 & 0 \\ 0 & 0 & 0.005 \end{bmatrix}
\tag{3.46}
$$

The observer parameter is chosen to be $\theta = 400$. Solving equations (3.41) and (3.47) the observer feedback matrix is determined to be

$$
H = \begin{bmatrix} -4.5 & 6.7 \\ 7.8 & 5.6 \\ -2.4 & 5.0 \end{bmatrix}
\tag{3.47}
$$

3.6 Chapter summary

The proposed model fulfills the criteria stated in Section 3.1, namely that it should capture the plant characteristics and at the same time it should not be overly complex to allow derivation of model-based control strategies. The validation has been performed for two different types of mills and various operating conditions, showing that the model is generic, and that it can be used for further investigations, that is design and comparison of controllers, which is done in the following chapter.

Moreover, it is identified that the coal circulation model has bilinear structure, which becomes nonlinear once the actuator dynamics are included. A suitable reduced state observer for the coal distribution in the coal mill, which will be used in the following chapter, is discussed.

4 Coal mill control

Contents

In this chapter we present a study of some problems associated with a coal mill control from theoretical and practical point of view. Strategies suitable to the considered problem are discussed and analyzed based on the model derived in the previous chapter. A more sophisticated control method based on stabilizing control law is compared to a PID-type controller, which is typically used in the industry, in order to determine whether it is beneficial to apply such strategies to improve performance of a power plant.

In the beginning of the chapter we present the previously established coal mill model written in the bilinear form. We slightly reformulate it to simplify further considerations. We present a state observer for bilinear systems, which suites our system. Then, we discuss the presence of actuator dynamics and their effect on the system.

We pose a general control problem for the augmented system. At first, a simplified problem with neglected actuator dynamics, is analyzed in terms

of stability, using Lyapunov's theory. Literature study on this topic shows that the considered class of stabilizing control laws minimizes generalized performance indexes. We verify the state observer and the stabilizing controller, with additional integral action, through simulations, using the plant model consisting of the coal mill equations and the actuator dynamics. We compare the proposed control strategy to a well-tuned PID-type controller, which utilizes fuel flow measurements.

Afterwards, the complete system with actuator dynamics is considered. Such system becomes nonlinear, hence, the stability result obtained previous needs to be verified. It is found that the previously used control law stabilizes the overall system provided certain conditions are satisfied. Although in the special case of coal mill control the feedback linearization could be used, it is beneficial to study the generalized systems.

Later, the optimal control of the mill with respect to a specific cost function (based on the verification criteria in the hypothesis), is calculated using Pontryagin's Maximum Principle. The idea is that the optimal controller, which has the lowest cost, can be compared with the previously established stabilizing law. The final result is still an open question due to the large computational power required by the adopted approach, nevertheless, the finding of the initial study are presented.

The last control aspects investigated in this chapter are concerned with the temperature control of a mill. In order to evaporate moisture from the coal efficiently, it is necessary to keep the mill temperature in certain range. For the studied mill type it is approximately 100 degrees Celsius. The temperature is controlled by adjusting the cold and hot air flows. As a result certain temperature of the primary air is achieved. At the same time, the total air flow must satisfy the air to fuel ratio. We show that adding second degree of freedom, that is the feed-forward term calculated based on the plant model, to the typical PID-type controller, reduces the mill temperature variance.

4.1 General problem description

We consider a system of the following form

$$
\begin{aligned}
\dot{x} &= Ax + \sum_{i=1}^{m} \phi_i(x) v_i \\
\dot{z} &= \bar{A}z + \bar{B}w = \bar{A}z + \sum_{i=1}^{m} w_i \bar{B}_i \\
v &= \bar{C}z
\end{aligned}
\tag{4.1}
$$

where $\bar{B}_i$ is the i-th column of matrix $\bar{B}$, $x \in X \subset \mathbb{R}^n$, $z \in Z \subset \mathbb{R}^m$ and $w \in W \subset \mathbb{R}^m$. In the sequel we assume that A and $\bar{A}$ are Hurwitz, $\phi_i(x)$ is continuous, X, Z are open, W is convex and compact, and generally refer to system (4.1) in the compact form

$$
\dot{\xi} = \mathcal{A}\xi + \sum_{i=1}^{m} \Phi_i(\xi)\nu_i
\tag{4.2}
$$

where

$$
\xi = \begin{bmatrix} x \\ z \end{bmatrix}, \quad \nu_i = \begin{bmatrix} 1 \\ w_i \end{bmatrix}, \quad \mathcal{A} = \begin{bmatrix} A & 0 \\ 0 & \bar{A} \end{bmatrix},
\tag{4.3}
$$

$$
\Phi_i(\xi) = \begin{bmatrix} \phi_i(x)z^T \bar{C}_i & 0 \\ 0 & \bar{B}_i \end{bmatrix} \in \mathbb{R}^{(n+m) \times 2}
\tag{4.4}
$$

with $\bar{C}_i$ the i-th row of matrix $\bar{C}$ written as a column vector.

Note that the model described in the previous chapter is of the above form, with $n = 4$ and $m = 3$.

We now proceed with the stabilizability analysis of system (4.2).

4.2 System without actuators

Let us first consider a simplified version of the system with no actuators dynamics. In this case the system consists of the first state equation in (4.1) only, and v_i are the control inputs. Hence, we consider the system

$$
\dot{x} = Ax + \sum_{i=1}^{m} v_i \phi_i(x)
\tag{4.5}
$$

Stability of such system can be analyzed by means of Lyapunov theory. We take the quadratic control Lyapunov function candidate $V(x) = \frac{1}{2}x^T P x$, with positive definite matrix $P = P^T$, obtained by solving $PA + A^T P = -Q$ for a given $Q = Q^T > 0$. Thus $V(x)$ is always greater than zero, except for $x = 0$, and radially unbounded. We calculate the time derivative, which yields

$$\dot{V}(x) = x^T P(Ax + \sum_{i=1}^m \phi_i(x)v_i) = -\frac{1}{2}x^T Q x + \sum_{i=1}^m x^T P \phi_i(x)v_i \qquad (4.6)$$

with positive definite matrix $Q = -PA - A^T P$. The first part in the above equation is always negative, except for $x = 0$. Furthermore, it is easily seen that choosing the feedback control law

$$v_i = -\alpha_i V_x(x)\phi_i(x) \qquad (4.7)$$

with $V_x(x)$ the gradient of the Lyapunov function $V(x)$ with respect to the state x; yields

$$\dot{V}(x) = -\frac{1}{2}x^T Q x - \alpha_i \sum_{i=1}^m [x^T P \phi_i(x)]^2 \qquad (4.8)$$

which is negative for all $x \neq 0$ when the scalar $\alpha_i \geq 0$. This means that the control law (4.7) globally asymptotically stabilizes system (4.5) at the origin.

Stabilizability (and optimality) of systems on the form (4.5) and control law (4.7) are studied in [Jacobson, 1976], [Tzafestas et al., 1984], and [Benallou et al., 1988]. We discuss those results as they are relevant to our problem.

Jacobson [1976] studies the problem of optimal stabilizing control law for the following system

$$\dot{x} = \sum_{i=1}^m \phi_i(x)v_i \qquad (4.9)$$

which are called homogeneous-in-the-input. This is a special type of the system (4.5) with matrix $A = 0$. From his work we learn that the control law

$$v_i = -[V_x(x)\phi_i(x)]^{\frac{1}{2p+1}}, \quad p \in \{0, 1, \ldots\} \qquad (4.10)$$

globally asymptotically stabilizes system (4.9). Moreover, the control law (4.10) minimizes the cost function

$$J = \int_0^\infty \left\{ q(x) + \frac{1}{2(p+1)} \sum_{i=1}^m v_i^{2(p+1)} \right\} dt \tag{4.11}$$

with

$$q(x) = \frac{2p+1}{2(p+1)} \sum_{i=1}^m [V_x(x)\phi_i(x)]^{\frac{2(p+1)}{2p+1}} \tag{4.12}$$

Later in his work, he extends the result to non-homeogenous systems

$$\dot{x} = f(x) + \sum_{i=1}^m \phi_i(x)v_i \tag{4.13}$$

and shows that the control law

$$v_i = -V_x(x)\phi_i(x) \tag{4.14}$$

globally asymptotically stabilizes the system (4.13) and minimizes the cost function

$$J = \int_0^\infty \left\{ q(x) + \frac{1}{2} \sum_{i=1}^m v_i^2 \right\} dt \tag{4.15}$$

with

$$q(x) = -V_x(x)f(x) + \frac{1}{2} \sum_{i=1}^m [V_x(x)\phi_i(x)]^2 \tag{4.16}$$

The system (4.5) is a special case of the non-homeogenous system studied by Jacobson, where $f(x) = Ax$, and the control law (4.7) is equivalent to (4.14) for $\alpha_i = 1$.

Benallou et al. [1988] show that the control law (4.7) with $\alpha_i = \frac{1}{r_i}$ and $\phi_i(x) = N_i x + B_i$ minimizes the following cost function

$$J = \frac{1}{2} \int_0^\infty \left\{ x^T Q x + \sum_{i=1}^m \frac{1}{r_i} [x^T P \phi_i(x)]^2 + v^T R v \right\} dt \tag{4.17}$$

where matrix R is diagonal with positive entries r_i; Q and P are positive definite matrices satisfying the Lyapunov equation

$$PA + A^T P = -Q \tag{4.18}$$

This is a special case of the result presented by Jacobson.

In their work, Benallou et al. [1988], compare the control law to the linear controller presented by Derese and Noldus [1980], which locally stabilizes bilinear systems. The globally asymptotically stabilizing controller outperforms the linear controller, in an example from Derese and Noldus [1980], due to the fact that it exploits the information about bilinear matrices N_i.

In contrast to the infinite horizon cost functions discussed before, Tzafestas et al. [1984] study finite time cost function with running and terminal costs

$$
\begin{aligned}
J = & \frac{1}{2} \int_{t_1}^{t_2} \left\{ x^T [Q(t) + \sum_{i=1}^{m} P(t)\phi_i(x) R_i^{-1} \phi_i^T(x) P(t)] x + v^T R v \right\} dt \\
& + x_f^T P_f x_f
\end{aligned}
\tag{4.19}
$$

with $\phi_i(x) = N_i x + B_i$, $x_f = x(t_2)$, matrices $P(t)$, P_f, and $Q(t)$ positive definite, and R diagonal with positive entries. The control law which minimizes the cost has the same form as Benallou et al. [1988]

$$
v_i = -\frac{1}{r_i} x^T P(t) \phi_i(x)
\tag{4.20}
$$

however, the matrix $P(t) = P(t)^T > 0$ is now a time dependent $n \times n$ matrix, which is obtained by solving the linear differential equation

$$
-\dot{P}(t) = A^T P(t) + P(t) A + Q - \sum_{i=1}^{m} P(t) B_i R_i^{-1} B_i^T P(t)
\tag{4.21}
$$

with $P(t_2) = P_f$.

The performance indexes J can be interpreted as an extension of the generalized quadratic cost in the linear case to bilinear systems. Such cost does not correspond to the performance criteria we have set up for our problem in the Introduction. Moreover, the stabilizing controllers are designed for system without actuator dynamics. In the sequel, however, we ignore this fact and we test the performance of the above control law on the full system (4.2) through simulations. Furthermore, the control laws will be evaluated with respect to the optimality criteria specified by the scientific hypothesis in Section 1.4.

4.3 Application to coal mill control

In this section we are discuss a special case of system (4.1) with parameters as in the modeling chapter, e.g. A and $\bar{A}$ are given by equations (3.32) and (3.34).

The evaluation criteria for the scientific hypothesis stated Section 1.4 allow to asses the quality of the mill control. The objective for the fuel controller is to ensure an adequate flow of the pulverized coal, while minimizing the power consumption of the machine, and reducing the risk of chocking when too much coal is stored inside the mill. We also demand that the air flow satisfies the air to fuel ratio, ρ_{af}. Hence, the following performance index

$$J = \frac{1}{2}(s_1 J_{fe} + s_2 J_E + s_3 J_c + s_4 J_{pa} + s_5 J_\nu) \tag{4.22}$$
$$= \int_0^{t_2} L(\xi(t), w(t), t)dt$$

where $s_i \geq 0$ are weights, and using the model equations (Section 3.5) we obtain the following elements of J

- *Fuel reference error*

$$J_{fe} = \int_0^{t_2} e_f^2(t)dt \tag{4.23}$$

  with $e_f(t) = w_{out}(t) - \bar{w}_{out}(t) = k_4(1 - \frac{\xi_7(t)+\bar{u}_3}{k_6})\xi_3(t) - \bar{w}_{out}(t)$, where $\bar{w}_{out}(t)$ is the desired fuel flow

- *Energy consumed for grinding*

$$J_E = \int_0^{t_2} (E(t) - E_e)dt = \int_{t_1}^{t_2} (k_3\xi_1(t) + k_2\xi_2(t))dt \tag{4.24}$$

  where E_e is the power required for turning an empty grinding table

- Total amount of coal in the mill during the operation *(risk of choking)*

$$J_c = \int_0^{t_2} \sum_{i=1}^{3} \xi_i(t)dt \tag{4.25}$$

- *Primary air reference error*

$$J_{pa} = \int_0^{t_2} \xi_4(t) - \bar{\xi}_4(t)dt \tag{4.26}$$

  where $\bar{\xi}_4(t)$ is the desired air flow through the mill

- *Input penalty*

$$J_\nu = \int_0^{t_2} (w(t) - \bar{u})^T R(w(t) - \bar{u}) \ dt \qquad (4.27)$$

where $R = \text{diag}[r_1, \ldots, r_m]$ is matrix of positive weights, and $\bar{u}$ are the nominal inputs, for example classifier speed equal to 1.5 [rad/s].

Here the input set W is described by (3.28) to (3.30) and the set $X \times Z$, containing coal mill and actuator states, is taken to be any open neighborhood of R_+^{4+3}.

In the sequel we verify that the control law from the previous section stabilizes the coal mill system with actuators. Moreover, the above performance index will be use as a measure of controller quality as the model-based control is compared with a PID-type controller.

For this analysis we are only interested in the coal circulation and the fuel flow, thus, we chosen $s_4 = s_5 = 0$. The full index will be used later in the study of optimality.

4.3.1   Proposed controller structure

We apply and test the control law (4.7), discussed in several variants before, to the system with actuators in order to compare it with a well-tunned PID-type controller. This should give us an indication whether the control law (4.7) is useful. Numerical values used in the simulations correspond to the STV4 coal mill found in the previous chapter.

The feedback controller (4.7) uses state information provided by the observer described in Section 3.5.3. Reference signals for the states are calculated from equations (4.28). The values are calculated for the steady-state operation and the desired fuel flow, $\bar{w}_{out}$.

$$\begin{aligned}
\bar{x}_3 &= \frac{\bar{w}_{out}}{k_4 \left(1 - \bar{u}_3/k_6\right)} \\
\bar{x}_1 &= \frac{k_9 \bar{x}_3 + \bar{w}_{out}}{k_1} \\
\bar{x}_4 &= \rho_{af} \bar{w}_{out} \\
\bar{x}_2 &= \frac{k_1 \bar{x}_1}{k_5 \bar{x}_4}
\end{aligned} \qquad (4.28)$$

where ρ_{af} is the air to fuel ratio at which the machine needs to operate to ensure proper air sweep of coal particles.

The integral control is added to remove the steady state error in the pulverized coal flow and the primary air flow. In case of the classifier it makes sure that the nominal angular velocity is restored. Due to actuator limitations it is necessary to introduce anti-windup strategies. The back-calculation method is used.

The overall structure of the system with controller is depicted in Figure 4.1.
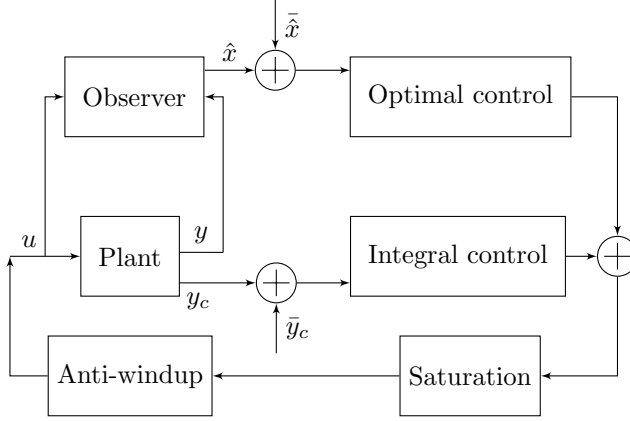
Figure 4.1: A block diagram of the proposed controller. y are the plant measurements, y_c are the controlled outputs, and $\hat{x}$ are the state estimates.

4.3.2 Controller verification

The controller parameters used for verification are summarized below. The gains of the integral action for the fuel flow, w_{out}, primary air flow, w_{air}, and classifier speed ω, are presented in Table 4.1.

$$Q = \begin{bmatrix} 10^{-4} & 0 & 0 & 0 \\ 0 & 2\ 10^{-4} & 0 & 0 \\ 0 & 0 & 1.5\ 10^{-2} & 0 \\ 0 & 0 & 0 & 4.89 \end{bmatrix} \quad (4.29)$$

$$R = \begin{bmatrix} 6.7\ 10^{-3} & 0 & 0 \\ 0 & 2.2\ 10^{-3} & 0 \\ 0 & 0 & 3.3\ 10^{-1} \end{bmatrix} \quad (4.30)$$

	w_{out}	w_{air}	ω
I gain	0.25	0.05	0.0001
back-calculation coefficient	0.04	0.02	0.0001

Table 4.1: Parameters of the integral control used with the optimal controller.

The PID-type controller is well-tuned around a realistic operating point (Table 4.2). The classifier speed in case of the PID-type controller is kept constant at the nominal speed of rotation.

P gain	6.75
I gain	0.10
D gain	33.23
D filter	14.58
back-calculation coefficient	0.01
overshoot	8.12 %
rise time	28.8 s
settling time	97.6 s

Table 4.2: Parameters and the performance with a linearized system of the PID controller used in the comparison.

The measurements and the inputs are affected by a white noise with standard deviations σ_i equal to half percent of the nominal value of the signal. The sample time of the noise generator is 10 seconds.

Performance with nominal parameters

Figures 4.2 to 4.4 depict the simulated fuel flow with both controllers, the reference signals, and the absolute error. The reference signal is chosen to consist of various step and ramp signals within the whole operating region.

From the plots it can be seen that the rise time of both controllers is nearly the same, however, there is no overshoot nor oscillations in case of the proposed controller. Lower grinding energy consumption is attributed to the fact of using varying classifier speed of rotation. This can be seen in Figure 4.5, where grinding power is reduced when classifier speed of rotation is lowered. The energy savings do not come freely; larger particles

Figure 4.2: Performance verification of the controllers – scenario 1. The simulations are performed in a noisy environment and with nominal values of parameters.

can escape the mill, hence the combustion might be less optimal, and most likely more ash is produced. The influence of lowering classifier's speed should be investigated in a plant where such strategy is planned.

The control inputs are depicted in Figure 4.6. The primary air flow is nearly identical for both controllers. The differences between the controllers are visible in the other two graphs. It can be noticed that the PID-type controller amplifies the noise more than the model-based controller. The last graph depicts the active classifier control versus nominal speed of rotation of the PID-type controller.

Performance with uncertain parameters

We use the Monte Carlo analysis to study the influence of model uncertainties (parametric sensitivity) on the control performance. In our case there are 9 model parameters, which are perturbed, and we run one thousand simulations. The obtained information helps us assess the performance
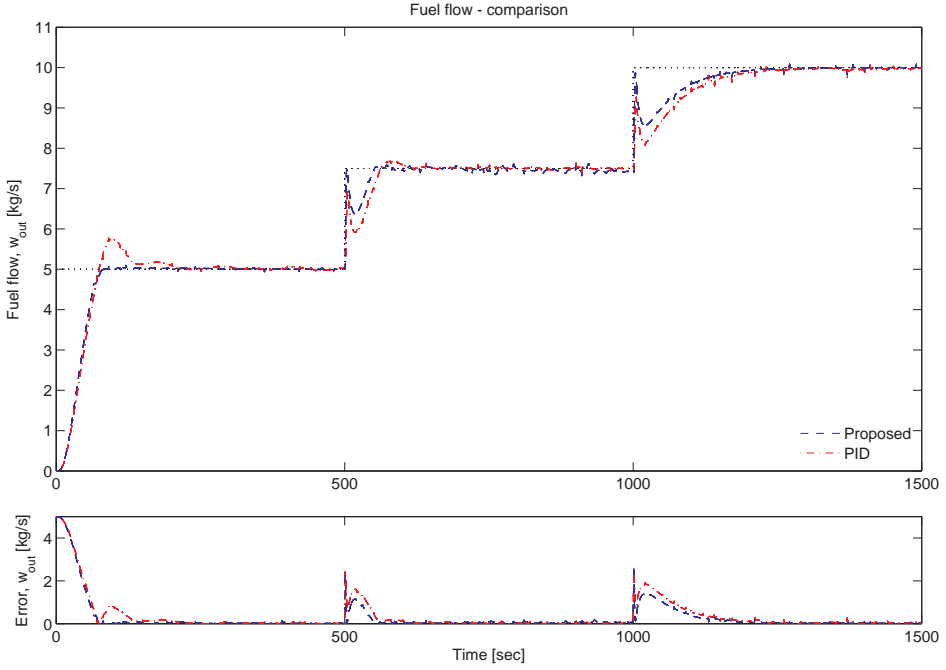
Figure 4.3: Performance verification of the controllers – scenario 2. The simulations are performed in a noisy environment and with nominal values of parameters.

of the controllers, but it also shows the potential applicability in a power plant; parametric uncertainties may pose significant problems in the control of coal mills and must be handled well.

The parameters are perturbed randomly with uniform distribution in the range of ± 10 [%] from the nominal values. Controllers operate in the same conditions, that is the same parameter perturbations and the same noise levels. We consider three performance criteria described previously: the fuel flow control quality, (4.23), the total amount of energy used for grinding, (4.24), and the risk of overfilling or mill choking, (4.25), which are now discretized with sampling time 1 second, and $t_2 = 5000$ seconds.

Numerical values of the indexes from 100 samples of the Monte Carlo analysis are depicted in Figures 4.7, 4.8, and 4.9, to give an overview of the distribution. The consistent performance of the PID controller is observed.

The results in Table 4.3 show the advantages of the proposed controller over the PID controller. For the tested scenario and the nominal parameters, the squared fuel error is reduced by more than a half. At the same
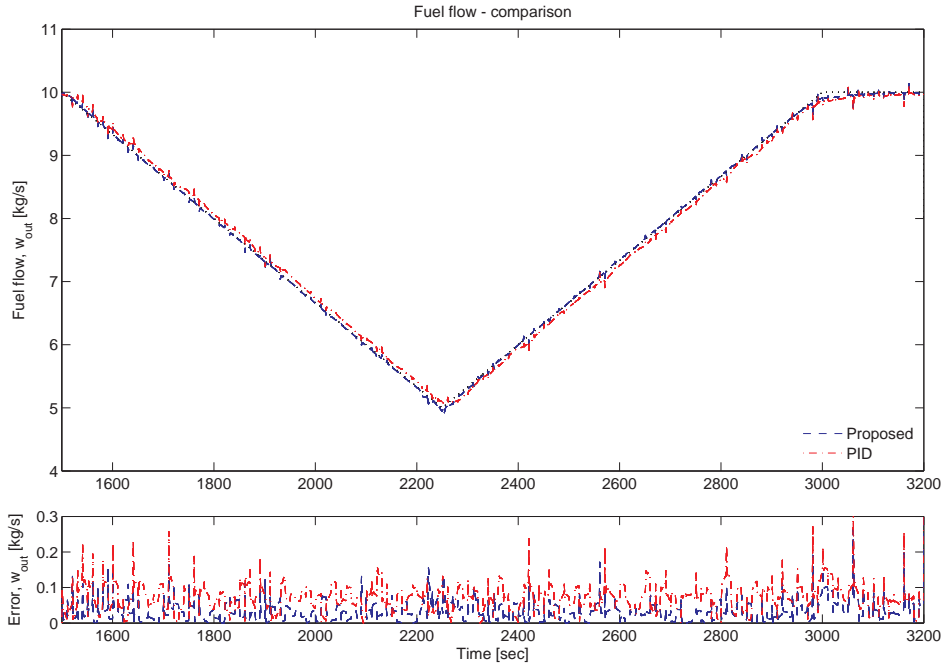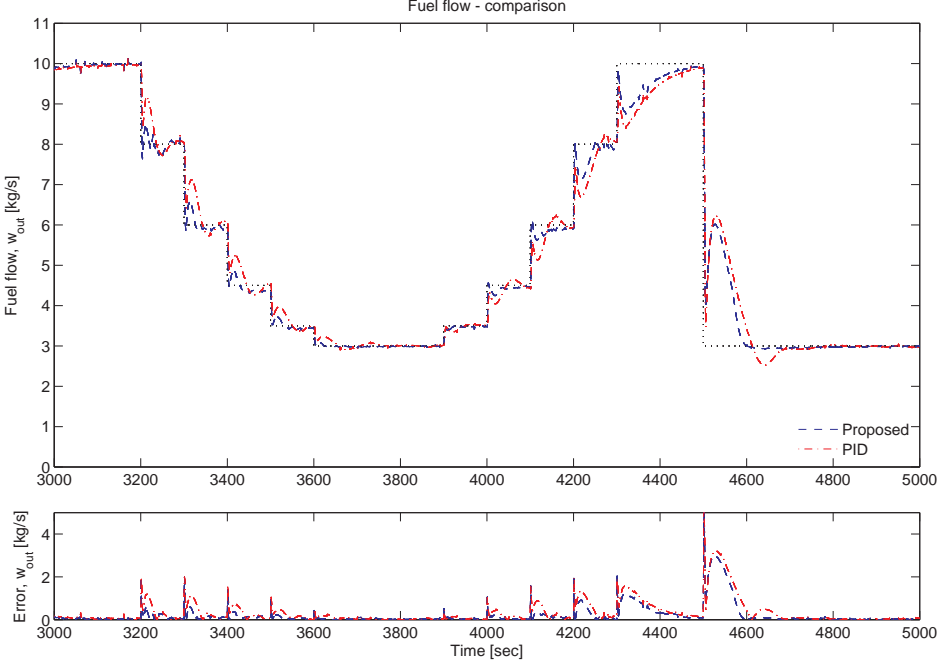
Figure 4.4: Performance verification of the controllers – scenario 3. The simulations are performed in a noisy environment and with nominal values of parameters.

time the energy consumption and the risk of choking are lowered.

On the other hand an advantage of the PID controller is its performance robustness in case of system's parameter changes. Even though the energy consumption and the amount of coal in the mill is always higher in case of the PID controller, in about 4.5% of cases the J_{fe} index is lower comparing to the proposed controller. Thus the maintenance of such controller in a plant should be relatively simple. The proposed controller should probably be implemented with an on-line parameter estimation/adaptation strategy, such that it automatically maintains the high quality performance.

Further simulation studies show that the PID-type controller can benefit from including the additional classifier control. It is suspected that the advantage of using the model-based controller over PID is more pronounce in case the bilinear terms, N_i, are large. In the considered example, the effects of bilinear terms were small, hence, linear control law can be used efficiently. On the other hand it is easy to construct a state observer for nearly linear systems.
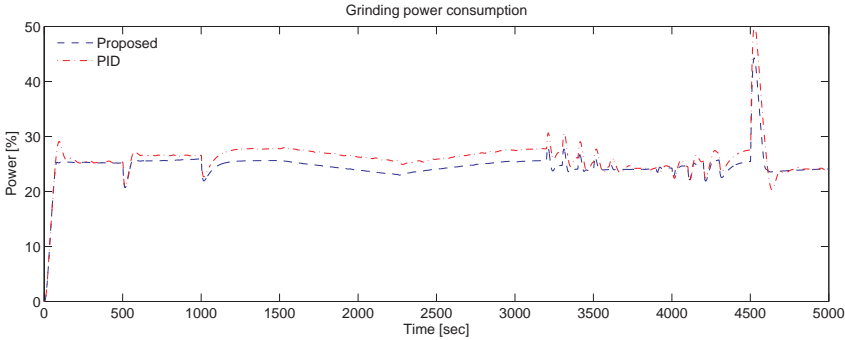
Figure 4.5: Grinding power consumption of the mill expressed in percentage of the maximum power. The proposed controller reduces the consumption thanks to active classifier control.

		J_{fe}		J_E		J_c	
		σ	μ	σ	μ	σ	μ
Proposed	nominal	1		1		1	
	uncertain	1.58	0.41	1.02	0.11	1.02	0.09
PID	nominal	2.16		1.06		1.07	
	uncertain	2.18	0.22	1.07	0.10	1.08	0.08

Table 4.3: Results of the performance analysis. The values are normalized with respect to the nominal performance of the proposed controller. Mean and standard deviation, σ, are calculated based on 1000 samples of Monte Carlo analysis with uncertain parameters distributed uniformly in range of $\pm 10\%$ from the nominal values.
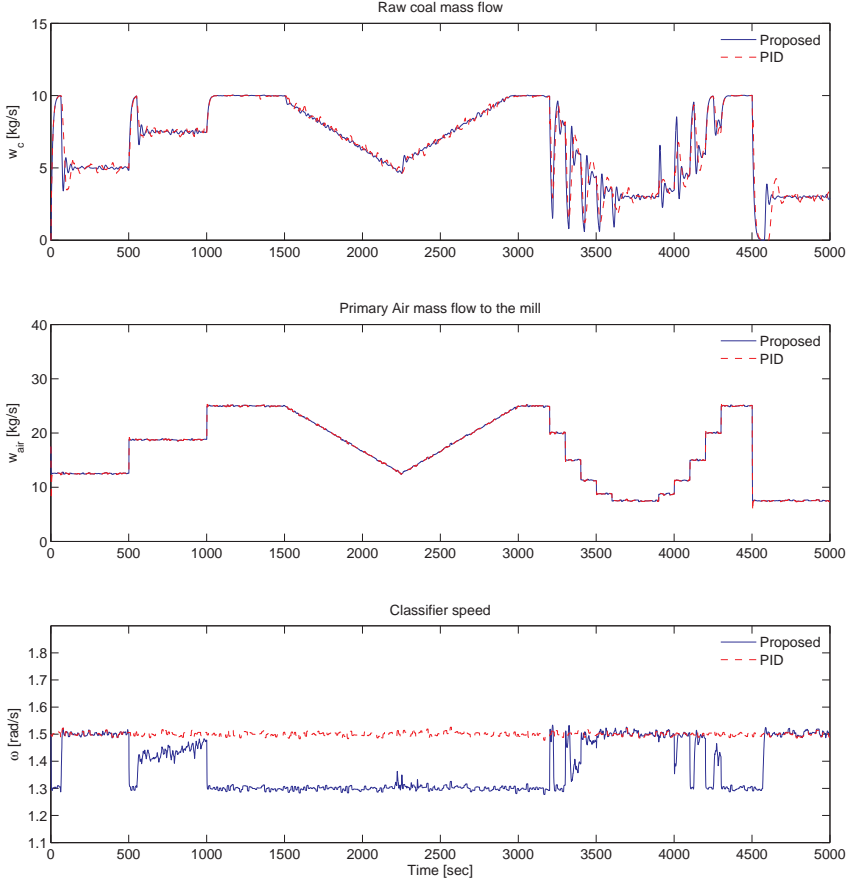
Figure 4.6: Control inputs applied to the system during the test scenario. Primary air flow inputs are almost identical.
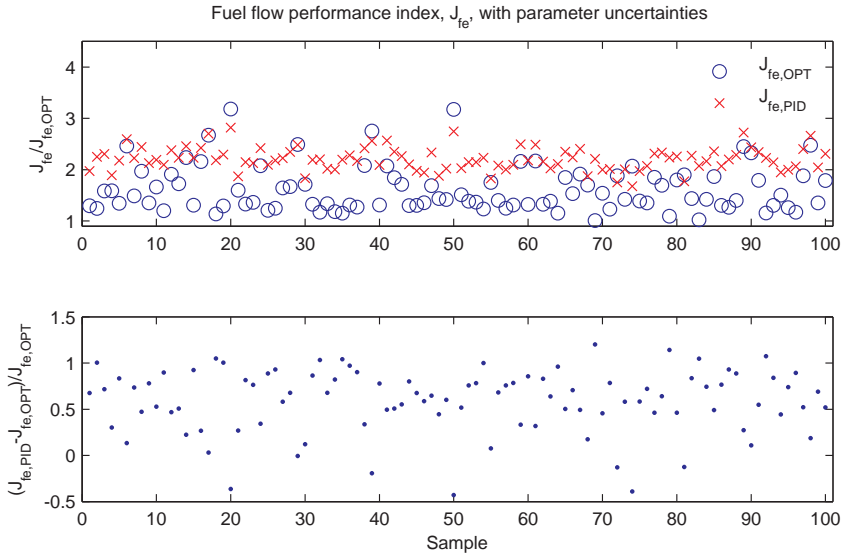
Figure 4.7: One hundred values of J_{fe} index (fuel error) from Monte Carlo analysis.
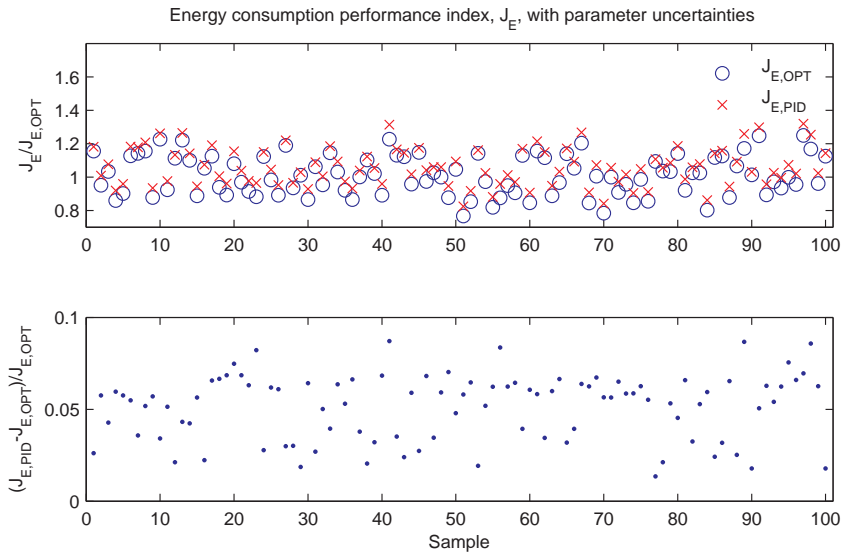
Figure 4.8: One hundred values of J_E index (grinding energy) from Monte Carlo analysis.
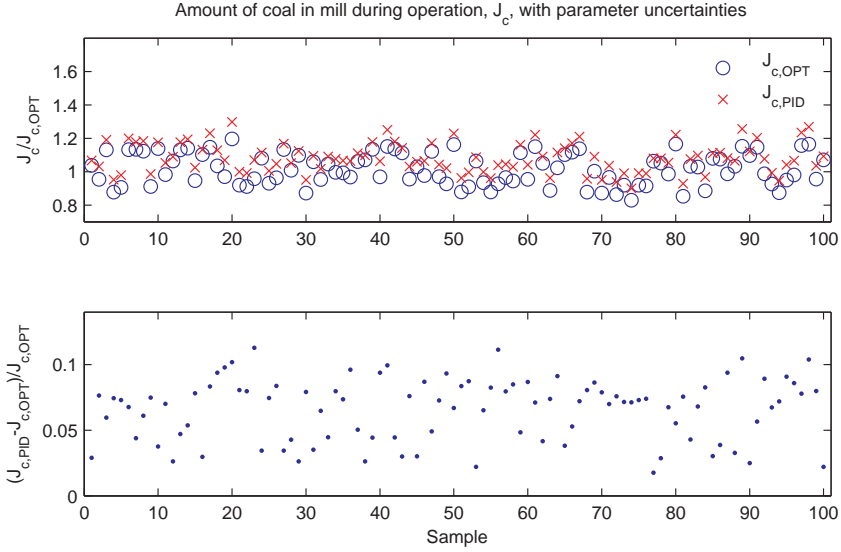
Figure 4.9: One hundred values of J_c index (amount of coal in the mill) from Monte Carlo analysis.

4.4 System with actuators

In Section 4.2 we discussed the problem of stabilization, and reviewed optimality results. For the coal mill the proposed controller (4.7) performs well in comparison to the PID-type controller with fuel reference, as seen in the previous section. In the simulations we have used the augmented plant model (4.2). Even though the performance in the simulations indicates stability, this cannot be guaranteed in general. In this section we verify that the control law (4.7) with $\alpha_i = 1$ is indeed stabilizing for the general system (4.2), in particular it guarantees stabilizability of the coal mill system.

Probably the first approach that comes to mind to derive a stabilizing controller for the coal mill with actuators (4.1), is to apply a local coordinate transformation, as described for example by Isidori [1995], which allows us to perform feedback linearization. We have analyzed the applicability of this method and the details of the derivation are included in Appendix B. Linear control techniques can be used for the linearized system, however, the stability of zero dynamics should be analyzed carefully. The applicability of the method is system related and we wish to find a more generic result.

4.4.1 Stabilizing controller

Inspired by the work of Kokotovic and Sussmann [1989] and Saberi et al. [1990] on stabilizing controllers for a class of nonlinear systems, we can show that the previously used control law stabilizes system (4.2) provided that $\alpha_i = 1$ for $i \in \{1 \ldots, m\}$, A and $\bar{A}$ are Hurwitz, and $\bar{B}^T \bar{P} = \bar{C}$. The Hurwitz assumption on $\bar{A}$ can be removed, however, then an additional term has to be included in the control law, as illustrated by the next proposition.

Proposition 1. *Consider the system (4.2). Assume that A is Hurwitz, that there exist $\bar{P} = \bar{P}^T > 0$, $\bar{Q} = \bar{Q}^T > 0$ and a controller $w = \bar{K}z + u$ such that $\bar{P}(\bar{A} + \bar{B}\bar{K}) + (\bar{A} + \bar{B}\bar{K})^T \bar{P} = -\bar{Q}$, and that $\bar{B}^T \bar{P} = \bar{C}$. Let $P = P^T > 0$ be the solution to the Lyapunov equation $A^T P + PA = -Q$ for some given $Q = Q^T > 0$. Let $\bar{K}_i$ be the i-th row of matrix $\bar{K}$ written as a column vector. The function $w(\xi)$ with coordinate functions*

$$w_i(\xi) = \bar{K}_i^T z - x^T P \phi_i(x), \ i = 1, \ldots, m \tag{4.31}$$

yields a feedback law $\nu(\xi)$ given by (4.3), which globally asymptotically stabilizes system (4.2) at the equilibrium 0.

Proof. Consider the following Lyapunov function candidate

$$W(\xi) = \frac{1}{2}\xi^T \mathcal{P}\xi \tag{4.32}$$

where $\mathcal{P} = \mathcal{P}^T = \begin{bmatrix} P & 0 \\ 0 & \bar{P} \end{bmatrix} > 0$.

The derivative of W along the trajectory is thus

$$\dot{W}(\xi) = \xi^T \mathcal{P}(\mathcal{A}\xi + \sum_{i=1}^m \Phi_i(\xi)\nu_i) \tag{4.33}$$

hence, using (4.31) we obtain after straightforward calculations

$$\dot{W}(\xi) = -\frac{1}{2}\xi^T \mathcal{Q}\xi + \sum_{i=1}^m (x^T P \phi_i(x)z^T \bar{C}_i + w_i z^T \bar{C}_i) \tag{4.34}$$

where $\mathcal{Q} = \mathcal{Q}^T = \begin{bmatrix} Q & 0 \\ 0 & \bar{Q} \end{bmatrix} > 0$. $\qquad \square$

Note that when $\bar{A}$ is Hurwitz $\bar{K}$ can be chosen to be zero. Hence, the control law (4.31) is identical to (4.7) under the assumption that $\bar{B}^T \bar{P} = \bar{C}$.

The above proof does not hold for control (4.7) with arbitrary α_i. It might be possible to alter the Lyapunov function candidate (4.32) to include additional terms, such that the more general controller guarantees stability. The task is left for future work. Hence, for the moment we conclude the controller (4.7) with $\alpha_i = \frac{1}{r_i}$, although performed well in the simulations, may not globally asymptotically stabilize the overall system.

4.5 Optimal control

In this section we return to the study of the coal mill system. We wish to use the Pontryagin's Maximum Principle to calculate the optimal controller for the optimization problem (4.22) with $\bar{w}_{out}(t)$ in (4.23) equal to the maximum fuel flow from the mill, hence, the Lagrangian L is autonomous. Furthermore, we let $t_2 = 500$ seconds and choose a fixed final condition on the state that corresponds to the steady state value obtained from using the stabilizing controller (4.7) described previously in the simulations. The reason for choosing t_2 and final condition as above is that the optimal control law gives possibility to evaluate the stabilizing controllers by comparing the performance indexes.

4.5.1 The necessary condition

For the coal mill system modeled in Chapter 3 and written in the form (4.2), we consider the optimization problem described in Section 4.3 with $\bar{w}_{out}(t)$ a constant (given by the fuel flow), $t_2 = 500$ seconds, and $\xi(t_2) = \bar{\xi}$ with $\bar{\xi}$ the steady state of the coal mill system when using the stabilizing control law (4.7).

Let notation be as in Section 4.3 and $\mathcal{W}$ denotes the set of bounded measurable functions $[0, 500] \to W$.

The considered optimization problem is of Bolza type, i.e.

$$\min_{w \in \mathcal{W}} \int_{t_1=0}^{t_2=500} L(\xi(t), w(t))dt \tag{4.35}$$

subject to

$$\dot{\xi}(t) = f(\xi(t), w(t)) = \mathcal{A}\xi(t) + \sum_{i=1}^{m} \bar{\Phi}_i(\xi(t), w(t)), \quad \bar{\Phi}_i(\xi, w) = \Phi_i(\xi)\begin{bmatrix} 1 \\ w_i \end{bmatrix} \tag{4.36}$$

with state, input, and terminal constraints

$$\xi(t) \in X \times Z, \ w(t) \in W, \xi(t_2) = \bar{\xi} \tag{4.37}$$

Define the Hamiltonian

$$H(\xi, w, p) = L(\xi, w) + p^T f(\xi, w) \tag{4.38}$$

Pontriagin's Maximum Principle for our particular optimization problem takes the following form [Cesari, 1983, Theorem 5.1.i].

Theorem 1. *Assume that there exists a bounded control $w^* \in \mathcal{W}$ with response ξ^* such that (w^*, ξ^*) is optimal for the problem (4.35)-(4.37). Then there exists an absolutely continuous vector function $p(t) = (p_1(t), \dots, p_n(t))$ such that, for almost every $t \in [0, 500]$,*

$$\dot{p}(t) = -\frac{\partial H}{\partial \xi}(\xi^*(t), w^*(t), p(t)), \quad p(0) = 0 \tag{4.39}$$

$$H(\xi^*(t), w^*(t), p(t)) = \min_{w \in W} H(\xi^*(t), w, p(t)) \tag{4.40}$$

$$\frac{d}{dt} H(\xi^*(t), w^*(t), p(t)) = 0 \tag{4.41}$$

We shall now calculate the optimal controller for our system and the cost function (4.22).

4.5.2 Optimal control of a coal mill

We apply 4.40 to derive the optimal control law

$$H(\xi^*(t), w^*(t), p(t)) = \min_{w \in W} H(\xi(t)^*, w, p(t)) \tag{4.42}$$

$$= F(\xi(t)) + \min_{w \in W} \{(w - \bar{u})^T R(w - \bar{u}) + p(t) \sum_{i=1} \bar{\Phi}_i(\xi(t), w)\}$$

$$= F(\xi(t)) + \min_{w \in W} \{\underbrace{(w - \bar{u})^T R(w - \bar{u}) + p_z(t)\bar{B}(w - \bar{u})}_{G(w)}\}$$

where $F(\xi(t))$ are the terms which do not contain w, $p_z(t)$ is the part of the co-state vector, $p(t)$, which corresponds to the actuator dynamics, and $\bar{u} = [0, \ 0, \ \bar{u}_3]^T$ is the desired nominal angular velocity of the classifier. Since G is a second degree polynomial in the variables w_1, w_2, w_3 with positive leading coefficients, the point w at which G obtains its minimum at time t is given as the solution to

$$0 = \nabla G(w) = 2(w - \bar{u})^T R + p_z^T(t)\bar{B} \tag{4.43}$$

which yields

$$w = -\frac{1}{2}R^{-1}\bar{B}^T p_z(t) + \bar{u} \tag{4.44}$$

Hence, the optimal controller is

$$w(t) = \arg\min_{w \in W} |w + \frac{1}{2}R^{-1}\bar{B}^T p_z(t) - \bar{u}| \tag{4.45}$$

4.5.3 Examination of a solution approach

The optimal control law requires the knowledge of $p_z(t)$, which in turns depends on the state $\xi(t)$. We encounter the typical optimal control problem, namely we know the final condition on the state $\xi(500)$ and the initial condition on the co-state $p(0)$. We cannot integrate ODE's (4.2), (4.39) with (4.45) forward or backward to find the solution trajectory, but we need to solve the two-point boundary value problem. Such problems can be solved numerically with the use of MATLAB's functions bvp4c and bvp5c. The differences between those methods are rather subtle; they relate to how the solution residual is controlled and how unknown parameters are handled. Both of them require good initial guess which is typically difficult to find.

In our case we could not find the appropriate starting point for the solver using ad-hoc methods, hence, we investigate a systematic method following similar study in case of linear system presented in [Kragelund et al., 2011]. The idea is to discretize the problem and use appropriate solver. We choose to use MATLAB's toolbox called YALMIP [Löfberg, 2004], which interfaces to various solvers. The problem is formulated as

$$\min_{w \in W} J = \sum_{k=0}^{t_2} L(\xi(k), w(k)) \tag{4.46}$$

such that

$$\xi(k+1) = (I + T_s\mathcal{A})\,\xi(k) + T_s \sum_{i=1}^{m} \left(\Phi_i(\xi) \begin{bmatrix} 1 \\ w_i(k) \end{bmatrix}\right) \tag{4.47}$$

with sampling time T_s.

Such discrete optimization problem is similar to model predictive control (MPC) with only one iteration and the time horizon 500 seconds. Two MPC problem formulations, explicit and implicit prediction form, are explained in YALMIP's manual[1]. In the explicit formulation the decision

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[1] http://users.isy.liu.se/johanl/yalmip/pmwiki.php?n=Examples.StandardMPC

variables are chosen to be the control inputs; the states and the cost are assigned iteratively in a loop. In the implicit formulation, the decision variables are declared to be the inputs and the states. System dynamics are modeled with equality constraints and the structure is exploited by the solver.

Contrary to [Kragelund et al., 2011], where linear system model was used, we were not able to reproduce similar result for our nonlinear system. With the implicit formulation we have encountered memory problems while trying to solve the problem on a designated application server with 8 GB of RAM. The explicit formulation requires less memory, however, it is still not possible to obtain the result due to segmentation fault encountered after a few hundred loops. We have used sampling time equal 1 second in case of the implicit formulation, while the explicit formulation requires 0.5 second sampling due to singularities while defining constraints on the states. In the former case the states are calculated backwards from the final condition and using sampled control inputs as decision variables.

Due to the difficulties with computational complexity, the problem remains open and it is left for future work.

4.6   Temperature control

In this section we would like to briefly study other control aspects of the coal grinding process, namely the temperature control that is the coal drying in a mill. We would like to analyze other benefits of model-based control.

Drying abilities of coal mills are very important as the raw coal entering the machine contains significant amount of water content, which needs to be evaporated. This process is disturbed in some of the plants and additional drying equipment needs to be installed, lowering plant's efficiency. High water content causes problems with mill operation, and control improvements are sought. Sufficient coal drying is achieved when the mill temperature is kept around 100 Celsius degrees. The most common strategy for controlling the temperature and the mill pressure at the same time (primary air flow) is to construct a feedback loop which controls the cold air flow damper based on the differential pressure, and the hot air flow damper based on the temperature measurements. Such strategy introduces problems since there is a coupling between the control loops, and due to very

large time constant of the drying process. To prevent such problems Lu et al. [2002] propose a decoupling controller. Our approach is to treated differently.

Thanks to the heat balance equation obtained in the modeling chapter it is possible to extend the PID-type control strategy described above with a second degree of freedom, that is a feedforward term, which provides set-points for the actuators. The PID feedback loop acts to correct the set-points. The time response of the system is significantly improved, allowing to compensate for larger mass flow of the raw coal as it enters the mill.

A simulation study is performed to verify whether such controller structure outperforms the simple PID-type approach. Two cases have been analyzed: one with constant and known coal moisture content, the other with varying and unknown amount of water in the raw coal. The fuel flow has been controlled by the previously described PID-type controller with the same reference signal as before. In case of constant and changing coal conditions, the water content is set to $\rho_m = 6.8$ [%] as found in the modeling chapter. In the second scenario, the water content is changing sinusoidally in range between 5 and 15 [%] and with frequency 0.001 [rad/s]. The reference temperature for the coal mill is to be 100 degrees Celsius.

As can be seen from the plots presented in Figures 4.10 and 4.11 the temperature variations from the desired 100 [^oC] are significantly lowered with the 2DOF controller. Once again a more advanced control method, which is based on the mill model is desirable.

4.7   Chapter summary

In this chapter we have utilized the model derived previously to study the problem of coal mill control. We have investigated theoretical aspects, such as stability and optimality for system without and with actuator dynamics. The method of local coordinate transformation and feedback linearization was found to be difficult to apply. Finally, optimal control for the system with actuators has been studied with the use of Pontryagin's Maximum Principle.

Practical matters associated with the applicability of the control law have been analyzed through simulations. It has been found that it can be beneficial to implement a more sophisticated control law, which utilizes the
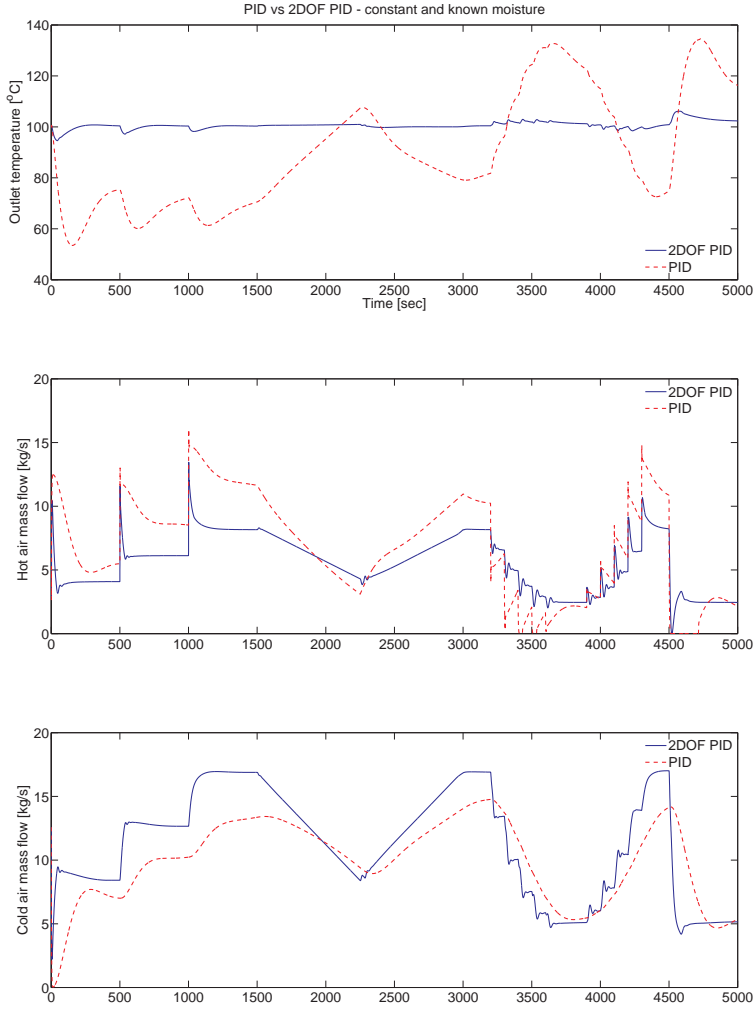
Figure 4.10: Comparison between PID-type controller and 2DOF PID-type controller in the mill temperature control. In this case water content in the raw coal is known and constant.
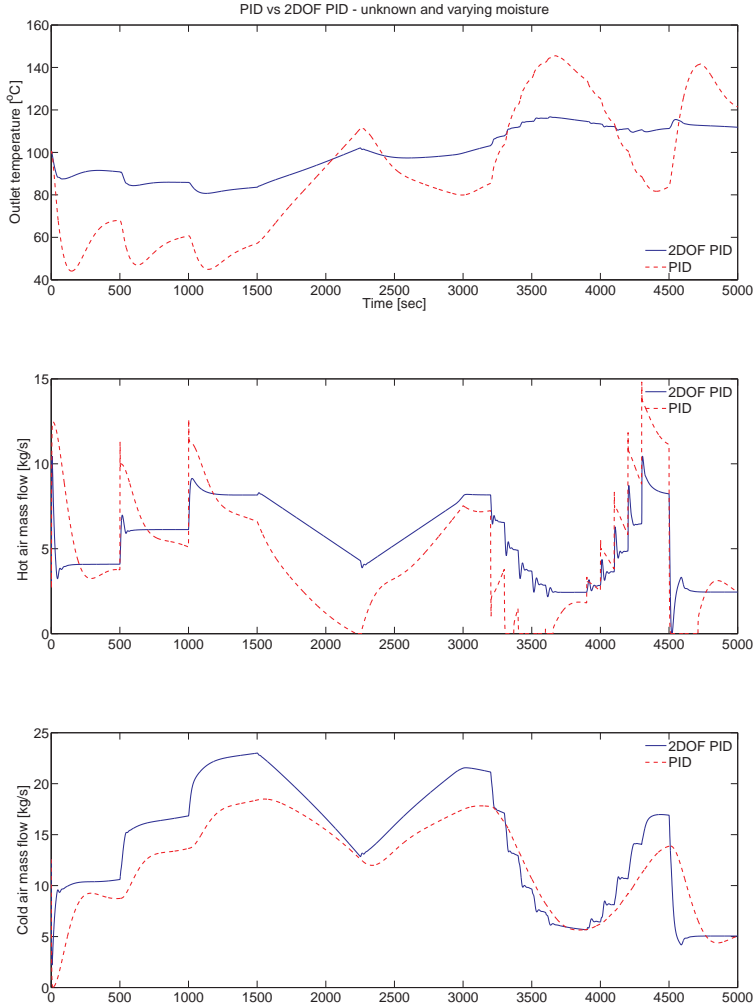
Figure 4.11: Comparison between PID-type controller and 2DOF PID-type controller in the mill temperature control. In this case water content in the raw coal is unknown and it is varying in range between 5 and 15 % .

knowledge of the plant obtained form the model. In particular the control of angular velocity of the classifier, and the use of feed-forward term in the temperature control, seem to be very effective.

5 Optimal load distribution

Contents

The problem of finding an optimal switching sequence for continuous producers that has to satisfy a bounded horizon production schedule is known to be computationally hard. In this paper we experiment with two techniques: Quantitative Model Checking (QMC) and a traditional approach, Mixed Integer Linear Programming (MILP). Both algorithms are found to be insensitive to the characteristics of individual production units, but very sensitive to the shape of the profile which characterizes the desired production. Two series of experiments with the two methods on carefully selected profiles for varying number of producers are considered. The results show that overall MILP performs better for larger sets of producers and longer horizons independent of the profiles. This corresponds well with the local versus global approach of the two methods. When suboptimal results are acceptable, for instance when computation time is limited, QMC shows promising performance.

5.1   Problem definition
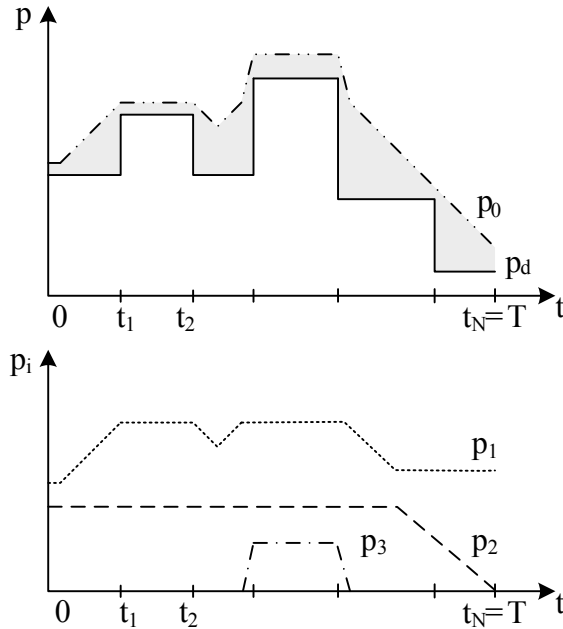
The production demands requested by *consumers*, p_d, is given by a piecewise constant function. The producers need to satisfy the demands at all times. The objective is to find the optimal schedule, i.e. the times at which to start-up or shut-down producers, as well as when to adjust the production levels where they are operating. The colored area represents overproduction, which should be minimized subject to costs and constraints.

Figure 5.1: A demand profile with example production profiles.

We consider a situation where a number of *consumers* requires a certain production rate, $p_d(t)$, within a bounded horizon $t \in [0, T] \subseteq \mathbb{N}$. The required production is provided by a number of *producers*, labeled by index $i = 1, \ldots, N$. The producers have various constraints, such as particular start-up and shut-down behavior, ramp constraints on the production, topology constraints for distributed consumers, etc.

We consider this general class of optimization problems with the following assumptions:

- The demand function is approximated by a piecewise constant func-

tion.

- The production demand must be satisfied at all times; overproduction is allowed, but costly.

- The costs of operations are known and constant.

- There is a maximum increase and decrease of production for each producer (gradient constraints).

- Each producer has bounded operating region.

The production rate of each producer is controlled by *events* ε_k. The event set Σ is a finite set of labels, as in (5.1), which may be sent to the producers, unless restricted by the constraints.

$$\Sigma = \{\varepsilon_k\} = \{\text{'Start', 'Stop', 'Increase', \ldots, 'Decrease'}\} \tag{5.1}$$

The optimization problem is defined as follows:

$$\min_{p_i, \varepsilon_k} J = \int_0^T p_0(\varepsilon_k, t) + \sum_{i=1}^N \phi_i(p_i(t)) + \sum_{i=1}^N \psi_i(\varepsilon_k) \; dt \tag{5.2}$$

s.t.

$$p_d(t) \leq p_0(\varepsilon_i, t) \tag{5.3}$$

$$\underline{p_i} \leq p_i(t) \leq \overline{p_i} \tag{5.4}$$

$$\underline{r_i} \leq \frac{d}{dt} p_i(t) \leq \overline{r_i} \tag{5.5}$$

for all $t \leq T$, $i = 1, 2, .., N$, where $\phi_i : \overline{\mathbb{R}}_+ \to \overline{\mathbb{R}}_+$ is the operation cost the of i-th producer[1]; $\psi_i : \Sigma \to \overline{\mathbb{R}}_+$ is the cost of control actions; $p_0(\varepsilon_i, t) = p_1(\varepsilon_i, t) + p_2(\varepsilon_i, t) + ... + p_N(\varepsilon_i, t)$ is the aggregated production; $\underline{r_i} \; (\overline{r_i})$ is the minimum (maximum) rate of production for the i-th producer.

The production trajectories that satisfy the constraints are called feasible solutions. A feasible solution that minimizes J is called an optimal solution. Due to the nature of the problem, there might exist more than one optimal solution for the provided demand profile.

As pointed out in Guan et al. [2003], the problem belongs to the class of $\mathcal{NP}$-complete problems, implying that we can expect an execution time that is exponential in both N and T from known algorithms.

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[1] The notation $\overline{\mathbb{R}}_+$ refers to the set $\{x \in \mathbb{R} \mid x \geq 0\}$

5.2 MILP formulation

The desired production profile is a piecewise constant function described by time points at which it assumes a new value, and the corresponding production rate in the intervals between these time points.

$$t_0 = 0, t_1 = t_0 + n_0, \ \ldots, \ t_N = t_{N-1} + n_{N-1} = T, \ n_i > 0 \qquad (5.6)$$

For simplicity we assume that all the mills have the same dynamics. The scheduling problem can be formulated as follows. For each producer we define a binary state for all time instances in the optimization horizon $n = 0, 1, \ldots, T$.

$$s_i(n) = \begin{cases} 1 & \text{if mill } i \text{ is ON} \\ 0 & \text{if mill } i \text{ is OFF} \end{cases} \qquad (5.7)$$

This state represents whether the producer is operating or not. The supply from producer i at time n depends on its state and the number of control actions (adjustments)

$$p_i(n) = s_i(n)\underline{p_i} + \sum_{m=n_0}^{n-1} \alpha_i(m) r_a \qquad (5.8)$$

where $\underline{p_i}$ is the minimum production rate when machine i is running, r_a is the adjustment rate per time unit, $\alpha_i(n)$ is the control adjustment in n-th time unit; it can take real values between -1 and 1. Notice that the maximum (minimum) change in the production rate of an operating unit is $\overline{r_i} = r_a \ (\underline{r_i} = -r_a)$. We define $\alpha_i = \sum_{n=0}^{T} \alpha_i(n)$.

The objective is to minimize the following function:

$$\min_{\substack{s_i \in \{0,1\} \\ \alpha_i \in [-1,1]}} J = \sum_n e(s_i, \alpha_i, n) + \sum_i \phi_i(s_i) + \sum_i \psi_i(s_i, \alpha_i) \qquad (5.9)$$

The terms of the function are determined by the excess of the production over demand, by the time of machine operation and by the number of on/off switches and control actions. To keep the description simple and the number of decision variables low, it is assumed that the cost of switching a producer on and off is the same for all units.

overproduction is

$$e(s_i, \alpha_i, n) = p_0(s_i, \alpha_i, n) - p_d(n) \qquad (5.10)$$

cost of operation is

$$\phi_i = \sum_{n=n_0}^{T} c_o s_i(n) \tag{5.11}$$

cost of control is

$$\psi_i = \sum_{n=n_0}^{T-1} |s_i(n+1) - s_i(n)| \, c_s + \sum_{n=n_0}^{T} |\alpha_i(n)| \, c_a \tag{5.12}$$

where c_o is the cost of operation, c_s cost of start up and shut down, and c_a is the cost of the production adjustment.

Moreover the following constraints must hold for all $n \in \{1, \ldots, T\}$:

- The control actions can be performed only if the machine is running

$$-s_i(n) \le \alpha_i(n) \le s_i(n) \tag{5.13}$$

- *Start* and *Stop* operations require n_u and n_d time units respectively. At this time the producer cannot be controlled. Therefore the minimum idle time between machine stop and start is $n_u + n_d$, which can be described by

$$s_i(n) - s_i(n-1) = 1 \Rightarrow \sum_{m=1}^{n_u+n_d} s_i(n-m) = 0 \tag{5.14}$$

$$s_i(n-1) - s_i(n) = 1 \Rightarrow \sum_{m=1}^{n_u+n_d} s_i(n-1+m) = 0 \tag{5.15}$$

  Note that in case a machine has been idle for $n_{i,init}$ prior to initialization, the duration of the idle period should be subtracted from the sum in (5.15).

- *Stop* operations can be performed only if the mill is producing at the minimum rate ($\underline{p_i}$)

$$s_i(n-1) - s_i(n) = 1 \Rightarrow \sum_{m=n_0}^{n} \alpha_i(m) = 0 \tag{5.16}$$

- *Start* operations can be performed only if the mill is idle

$$s_i(n) - s_i(n-1) = 1 \Rightarrow p_i(n-1) = 0 \tag{5.17}$$

- The production from each operating machine must be in the range $[\underline{p_i}, \overline{p_i}]$. Combined with the assumption that the production is $\underline{p_i}$ when the producer is shut down, means that the sum of control adjustments cannot exceed $[0, \overline{p_i} - \underline{p_i}]$

$$0 \leq \sum_{n=1}^{t} r_a \alpha_i(n) \leq \overline{p_i} - \underline{p_i} \qquad (5.18)$$

- It is assumed that there is a spinning reserve available at all times, i.e. the aggregated production is equal to or exceeds the demand

$$\forall_n \ p_0(s_i, \alpha_i, n) - p_d(n) \geq 0 \qquad (5.19)$$

- The initial conditions must be fulfilled.

The proposed formulation is based on a *ticking* model of the system. This approach is very common and probably the most intuitive description of the problem. Although the problem was originally in continuous time, in the solution strategy it is sampled and the operations can be performed only at the specified time instants. Often, in UC problems, the sampling time is set to one hour and the optimization horizon would be 24 hours. For the mill switching problem, we choose a sampling time of one minute.

The formulation has been implemented in YALMIP [Löfberg, 2004], which is an optimization toolbox for MATLAB that allows flexible problem formulations for many classes of problems. The solution has been found using the GLPK solver[2], which is a free solver available for download at the official website. We are aware that there exist other MILP solvers which are more efficient, for example the state-of-the-art IBM ILOG CPLEX Optimizer, however, it is a matter of decreasing the computation demands by a factor rather than changing the solver characteristics. For the purpose of this work, which concentrates on qualitative analysis, the GLPK solver is sufficient.

In general the procedure for finding optimal solutions to a Mixed-Integer Linear Program, $J^{\#}$, starts with solving a relaxed Linear Program, where decision and auxiliary variables need not be integral. An optimal solution to the relaxed problem, J^{*}, gives a lower bound, which is the best possible result that can be achieved with an integer formulation ($J^{*} \leq J^{\#}$). If the LP relaxed solution happens to yield integer values as required, the

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[2]GNU Linear Programming Kit, Version 4.39, http://www.gnu.org/software/glpk/

procedure is stopped. However, if this is not the case, a search procedure is performed to find integer values that give a best possible result. There are various methods for determining the integer values, among which are the *cutting-plane*, *branch-and-bound*, *branch-and-cut* and *branch-and-price* methods. Commercial MILP solvers provide more efficient methods for performing integer search than freely distributed solvers, decreasing the computation burden and enabling larger problems to be handled.

5.3   QMC formulation

Quantitative Model Checking has its roots in the theory of Timed Automata well known in the Computer Science and Hybrid Systems communities. Before we proceed with the proposed solution for the optimization problem, let us recall some definitions to ease the understanding of the solutions. Fuller descriptions of timed automata can found in Alur and Dill [1994]; Bengtsson and Yi [2004]; Behrmann et al. [2004].

Definition 1. (Behrmann et al. [2004])
A Timed Automaton is a tuple $(L, l_0, \mathcal{C}, A, E, I)$, where L is a set of locations, $l_0 \in L$ is an initial location, $\mathcal{C}$ is a set of clocks, A is a set of actions, co-actions and the internal τ-action, $E \subseteq L \times A \times B(\mathcal{C}) \times 2^{\mathcal{C}} \times L$ is a set of directed edges that denote transitions between locations. Transitions are ornamented with an action, a guard and a set of clocks to be reset, and $I : L \to B(\mathcal{C})$ assigns invariants to locations.

Intuitively, a Timed Automaton is a finite state machine with a set of clocks that is used to model constraints on the time spent in locations. The interesting part about timed automata is that key properties are *decidable*, i.e. can be checked with a terminating algorithm [Alur and Dill, 1994]. For example we can detect whether certain states are reachable or whether there are any *deadlocks* in the system, i.e. situations where the automaton *blocks*. An example situation where blocking may occur is when two processes wait for each other to access a resource. The verification of such properties is called model checking.

For the purpose of optimal scheduling we use an extension of model checking where we take into account certain additional quantities. In this case we assign costs to actions and to staying in locations (cost += 0 and cost' == 0 is default for non-decorated locations and transitions), resulting

in a Priced Timed Automata (PTA). We can now verify properties of the system taking into account the cost. More precisely we wish to find a path or *trace* that leads us to a goal state (end of the optimization horizon) with the lowest accumulated cost. For this purpose we use an extension of the model checker UPPAAL [Behrmann et al., 2004], called UPPAAL CORA, developed for the purpose of analyzing Priced Timed Automata.

The problem formulation as PTA provides interesting modeling possibilities for many systems. The models described as state machines are often more readable for users than the mathematical formulations of the constraints used in the MILP approach. Due to the possibility of automata compositions, bottom-up modeling - construct simple subsystems and combine them to express large and complicated systems - is feasible.

For the problem considered here, we create a template model of *Producer* and *Consumer* automata. By assigning concrete values to the parameters, we get concrete models of all the producers. The models are then composed with the *Consumer* model to create the overall system model.

An example template of a producer with distinct start and stop phases is shown in the automaton of Figure 5.2; the graph defines the state transition relation A as well. It is a timed automaton, where each state s has a maximal dwell time, denoted $D[s]_i$, and each transition $a = (s, s') \in A$ has a minimal enabling time $d[s, s']_i$. Note that the dwell times and other parameters may vary between producers.
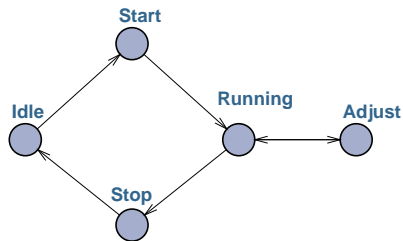
Figure 5.2: A producer automaton.

In the analysis performed in this thesis we consider a simplified model (Figure 5.3), which corresponds better to the MILP formulation. The locations of the example in Figure 5.2 are combined into one state *running*. The transitions are synchronized with the Consumer template, and they may be taken only if the guards are satisfied. For example, start up (sSTART) may be taken only if the producer is idle (lpr=0) and the time required

for starting the producer has elapsed (c>=DSTART+DSTOP). Similarly the other events are modeled.
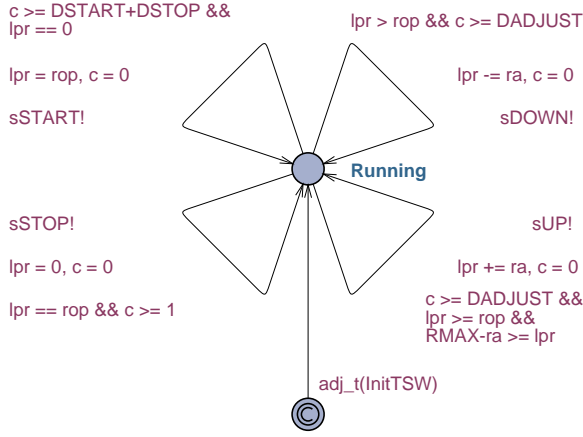
Figure 5.3: A simplified producer automaton used in the analysis.
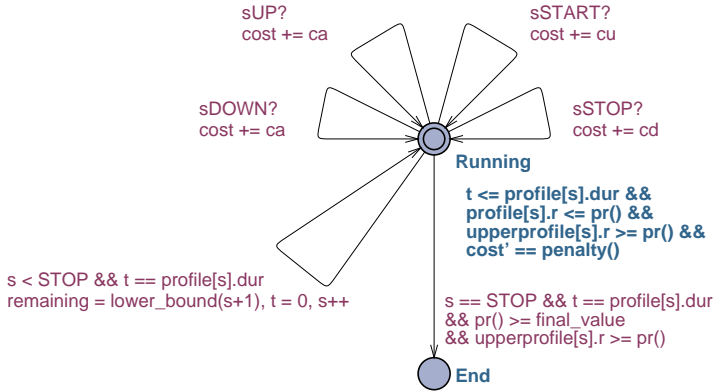
Figure 5.4: The Consumer template.

When the producer is operating, it can non-deterministically adjust the current production rate up or down, and even turn itself off or on. All of the operations are restricted by the time required to perform the operation (dynamics) and by the bounds on the allowed production region.

In each state s, a Producer i has a constant current production rate $p_i^s(t)$ corresponding to some set point. We allow $p_i^{OFF}(t) = 0$ for all i and t, and $p_i^{ON}(t)$ vary depending on the sequence of adjustments, that have

taken place.

A run of the system is recorded in a time stamped sequence of states for the producers. An element in such a sequence has the form, (i, s, t), where, as before, i is a Producer, s is a state, and t is a time stamp within the given horizon. A well-formed run $\sigma = \langle (i_0, s_0, t_0), ... (i_n, s_n, t_n) \rangle$ has weakly increasing time stamps, $t_k \leq t_{k+1}$ for $k = 0, \ldots, n-1$. For a specific producer j, the projected sequence is $\sigma \downarrow j = \langle (s'_0, t'_0), \ldots (s'_{n'}, t_{n'}), (s'_{n'}, T) \rangle$, where, for convenience, we have added a stuttering element at the end to mark the end of the horizon. The projected sequence has to satisfy the transition relation, $(s'_k, s'_{k+1}) \in A$, and the enabling and dwell time constraints, $d[s'_k, s'_{k+1}]_j \leq t'_{k+1} - t'_k \leq D[s'_k]_j$, for $k = 0, \ldots, n'$. It must also be initialized, $t'_0 = 0$. For specific producers one may constrain the initial state s'_0.

The objective is to find a run that minimizes the switching and running costs while satisfying the required production rate as tightly as possible. The switching cost is determined by giving each state transition a an associated cost c_i^a. The switching cost of a run σ is then the accumulated costs of the individual producers, $Js(\sigma) = \sum_{i=1}^{N} Js_i(\sigma \downarrow i)$; for the individual producers, the cost is the sum of the transition costs $Js_i(\sigma') = \sum_{m=0}^{\#\sigma'-1} c_i^{s'_m, s'_{m+1}}$, where we by convention assume a zero cost for the stuttering transition.

For a run, the state of producer i projected on time is $s_i[\sigma](t)$, which is uniquely determined by $\sigma \downarrow i$ containing a subsequence $(s_i, t_b)(s'_i, t_e)$ with $t_b \leq t < t_e$. A run will satisfy the production just when the error function $e[\sigma](t) = \sum_{i=1}^{N} p_i^{s_i[\sigma](t)} - p_d(t)$ is non-negative for all $t \in [0, T)$.

Since we want the run to be as close to the rate as possible, but never smaller than demands, we define a penalty function:

$$c[\sigma](t) = \begin{cases} e[\sigma](t) & (e[\sigma](t) \geq 0) \\ \infty & (e[\sigma](t) < 0) \end{cases} \tag{5.20}$$

Finally, we consider the cost of running the individual producers. Producer k is running when its production rate is different from zero. Assuming a flat cost rate of c_o, this is given at a point of time by

$$cp_i[\sigma](t) = \begin{cases} c_o & (s_i[\sigma](t) = 1) \\ 0 & (s_i[\sigma](t) = 0) \end{cases} \tag{5.21}$$

And a combined cost function is now

$$J(\sigma) = Js(\sigma) + \int_0^T (c[\sigma](t) + \sum_{k=1}^N cp_i(t))dt \qquad (5.22)$$

The objective is now to minimize this.

The penalty function and the profile is modelled by the Consumer automaton shown in Figure 5.4. The objective is to find whether the final state in the model, corresponding to the end of the time horizon, is reachable or not. If the state is not reachable it means that the considered production profile cannot be realized. This itself can often be a very useful indication for many applications as it represents the safety of the system with constraints. On the other hand, if the state is reachable, meaning that we can find a path (trace) consisting of states, transitions, clock valuations and prices, we wish to find the minimal total cost of this path (as defined earlier). Details on the solution methods may be found in an extensive literature, e.g. see Larsen et al. [2001]; Behrmann et al. [2005]; Bengtsson and Yi [2004]; Burch et al. [1992]; here we would like to make a few notes on this topic.

The common problem of all the model checkers such as UppAal is state space explosion. Moreover in case of the continuous time systems modeled by (priced) timed automata, there is an infinite number of possible trajectories that can be generated by such systems. In order to deal with the infinity problem and to reduce the state space special symbolic techniques are used. The symbolic states take form of (priced) zones described by a convex set of clock valuations. In case of the priced timed automata, the exploration of the state space can be guided by the optimality criterion while parts of the search tree are pruned by for example branch-and-bound techniques Larsen et al. [2001].

Contrary to the Mixed Integer Linear Program formulation, where the relaxed linear problem is solved first, the Quantitative Model Checking does not provide a *natural* lower bound for the cost J. Such a bound is very useful in order to cut many useless branches and thereby limit the computational burden and state explosion. UPPAAL CORA gives the option to define a lower bound on the *remaining* cost. A carefully chosen bound may significantly reduce the time required for obtaining the solution. In this work, where all producers have the same maximum production rate $\bar{p}$

and cost of operating c_o, we can define lower bound as follows:

$$J^* = \sum_{\mathcal{S}} \left\lfloor \frac{p_d(\mathcal{S})}{\overline{p}} \right\rfloor d(\mathcal{S}) \; c_o \qquad (5.23)$$

where $\mathcal{S}$ is remaining segments of the production demand function, $d(\mathcal{S})$ is the duration of the segment and the number of necessary producers is rounded down to the nearest integer value.

5.4   Simulation experiments

As mentioned, the problem belongs to the class of NP - complete problems, and we can thus expect an execution time that is exponential in both N and T.

Since the number of feasible solutions for the problem with lower bound production demand (constraint) is very large, the solver time required to finding an optimal solution is very high. At the same time some of the feasible solutions could be pruned from the beginning, as their cost is very large. We should therefore restrict some of the possibilities by either introducing the maximum cost bound or by limiting the production by an upper profile. The second approach seems to be more reasonable for our considerations, since we have rather different solution approaches, but we wish to have common constraints for both cases. Moreover it may sometimes be difficult to judge the approximate cost for certain production profiles.

An upper bound constraint reduces the required solver time significantly and in real applications it is very crucial to design it properly to achieve better results. In our work we generally do not apply very strict upper bounds on the profiles, as we want to show the complexity of the problem as well. Yet, we have observed that the optimization burden may be reduced significantly if tighter upper bounds are used.

5.4.1   Consumer

For the consumer, the time horizon should allow a reasonable amount of freedom for switching the producers. For many applications it is very good if we find the optimal schedule in time that is much shorter than the optimization horizon, especially if we consider a receding horizon strategy for the application. For the purpose of the paper we have chosen 3 schedul-

ing horizons, i.e. 20, 25 and 30 minutes. Therefore we use the scheduling horizon as an upper bound on the solver time as well.

Production profiles

The demanded production profiles are essentially very application specific, but for the experiment, we have selected the following exemplary ones which will occur as segments of most real profiles:

zero

    A profile of zero production for the whole time horizon.

constant

    Similarly to *zero*, but with constant, mid-range, production.

run up

    A profile that rises moderately steep. In general there are many possibilities to fulfill the profile.

run down

    The converse profile which falls moderately to zero.

sinusoid

    A gentle sinusoidal waveform that requires precise switching to get an optimal run. This scenario is very much like the characteristics of real profiles.

ramp (step)

    A nightmare for any branch and bound algorithm. It is 0 for most of the horizon and then rises steeply to a maximum. It would not be realistic in any unbuffered system, because it requires the producers to step up production ahead of time in order to reach the top of the ramp. However, it may show the limitations of brute force approaches and the need for clever approximations.

5.4.2   Producers

In order to use model checking, we have to quantize the production rate. We have selected a range of $[0, 100]$ with 8 steps – minimal production rate of 34 and then every 11 units until the maximum production rate. It fits

well with the mill switching problem, and allows ample room for adjusting the production. This has a direct impact on the required rate, it can at most be $100N$. In the MILP formulation, the production rate is modeled similarly. The most important difference is that the production can be a real value in the suitable region.

Delays

Delays determine the minimal switching times in case of QMC and the maximum ramp up in MILP. We consider a case with homogeneous producers, and one with a mix of two kinds - "Old" and "New", where the Old ones have longer delays for start up, shut down and adjustment. The constants are given in Table 5.1.
The numbers have been chosen to be coprime such that periodic behaviors are excluded. We shall conduct one experiment with N New producers and one with $N/2$ Old and the remaining ones New producers.

Cost

The costs of start up and shut down have been selected to be equal, keeping the MILP description simple and with lower number of decision variables. The running cost, c_o, is assigned a value such that it pays to stop a producer. We have not experimented with different costs for different producers, nor for New and Old producers.

	D_{Start}	D_{Adjust}	D_{Stop}	c_s	c_a	c_o
New	10	3	10	17	1	1
Old	11	4	13	17	1	1

Table 5.1: Constants used in the simulations.

The selection of parameters above is based on some experiments with the solvers. We have fixed most of the parameters to a small number of configurations, such that we can vary N more freely. The experimental setup has 3 time horizons, 6 considered scenarios (profiles), homogeneous and heterogeneous configurations for some interesting profiles, thus there is a total of 162 optimizations to be done. Each optimization has been run 5 times on a server with reserved resources. Significant differences in time required to solve particular scenario could be an indication of errors

	hetero	N		4			6			8	
		T	20	25	30	20	25	30	20	25	30
trivial	no	MILP	2	3	4	3	5	6	5	7	9
	yes		2	3	4	3	5	6	5	7	9
	no	QMC	0	0	0	0	0	0	0	0	0
	yes		0	0	0	0	0	0	0	0	0
constant	no	MILP	2	3	29	3	29	$\propto$	4	456	$\propto$
	no	QMC	0	0	0	0	0	0	0	0	0
run up	no	MILP	184	559	$\propto$	$\propto$	$\propto$	$\propto$	$\propto$	$\propto$	$\propto$
	no	QMC	258	$\propto$	$\propto$	$\propto$	$\propto$	$\propto$	$\propto$	$\propto$	$\propto$
run down	no	MILP	2	3	3	3	9	6	6	58	119
	no	QMC	21	413	$\propto$	$\propto$	$\propto$	$\propto$	$\propto$	$\propto$	$\propto$
ramp	no	MILP	2	3	4	3	5	6	5	7	9
	yes		3	3	4	22	5	6	13	7	9
	no	QMC	$\propto$	$\propto$	$\propto$	$\propto$	$\propto$	$\propto$	$\propto$	$\propto$	$\propto$
	yes		$\propto$	$\propto$	$\propto$	$\propto$	$\propto$	$\propto$	$\propto$	$\propto$	$\propto$
sinusoid	no	MILP	4	29	178	70	676	$\propto$	875	$\propto$	$\propto$
	yes		4	15	102	58	441	$\propto$	685	$\propto$	$\propto$
	no	QMC	171	1152	$\propto$	$\propto$	$\propto$	$\propto$	$\propto$	$\propto$	$\propto$
	yes		5	91	$\propto$	$\propto$	$\propto$	$\propto$	$\propto$	$\propto$	$\propto$

Table 5.2: The average time (in seconds) of optimization runs for the tested scenarios. Cases which could not be finished within the required time are marked with $\propto$. The computation time is essentially an initialization time and an execution time. The initialization time is significant (2 seconds) for MILP. Since we are interested in trends, we give the time in whole seconds.

or problems; but this has not been the case in the reported results. The average times in seconds from all the runs are listed in Table 5.2.

The simulations were performed on a designated server, to provide uniform conditions for executing each job. The server type and specification is Dell PowerEdge 2950, 2x2.5 GHz CPU (Quad Core Intel Xeon), 32 GB RAM with approximately of 12.5% CPU and 8 GB RAM available. The amount of memory assigned to the process was not a limiting factor for obtaining solution faster.

5.4.3   Discussion of the results

From the results presented in Table 5.2 it can be noticed that the constant profiles, where the demand is constant throughout the whole optimization horizon, are instantaneously solved with the QMC. Such scenarios with large number of producers or longer optimization horizons may pose troubles for MILP, with some cases where feasible solution cannot be found within the considered time.

The run up profile, where the production demands were increasing every 5 minutes from 0 at $t = 0$ to $\overline{p}\frac{N}{2}$ at $t = 25$ minutes poses difficulties for both methods. For the QMC it is clear because it will strive to minimize the cost locally. This will turn out to be too optimistic after some further steps, and that results in backtracking. The run down, although faster than run up, poses problems for QMC, especially when the number of producers is medium or large, but is solved quickly by MILP solver.

The ramp profile is easily solved using MILP while it is extremely difficult for model checking. The reason for this is that the optimal solution is obtained by enabling all producers at proper time and choosing maximum values of productions in each step. The relaxed version of the problem yields results such that there is no need to perform extensive branching. QMC on the other hand is guided by *random optimal first* strategy. In this strategy the low cost strategies are explored first, but they fail at the very end, when the final condition is violated.

Sinusoidal profiles, where it is very important to choose switching precisely are demanding. It should be noticed that introducing heterogeneous producers, that is breaking problem's symmetry, significantly reduces the computational complexity.

The simulations help to quantify the qualitative performance of both solution methods. It can be seen clearly that the shape of a profile determines the computation time no matter which method is used. QMC performs better when there are long sections of equal production values and the differences between the sections are not very large. Since MILP estimates the solution by solving the linear version of the global problem, it is more suited for profiles where there are larger variance of levels. In some cases, such as ramp profiles, where the branching search does not need to be extensive, solving MILP problems is easy.

An important consequence of using the model checking tools for the problems is the presence of quantization. This inevitably leads to quantization errors and suboptimal solutions. Ideally the error could be reduced

by modeling the problem with higher density of production levels or in a post-processing procedure. However, in some applications, such as the considered coal pulverization, the exact production levels might be unknown due to the technological limitations and thus they are approximated. Moreover, modest over-approximation of the required production can be used to advantage. It naturally increases the available reserves, therefore, large production fluctuations might be handled. Hence, the quantization may not necessarily pose significant problems in practice.
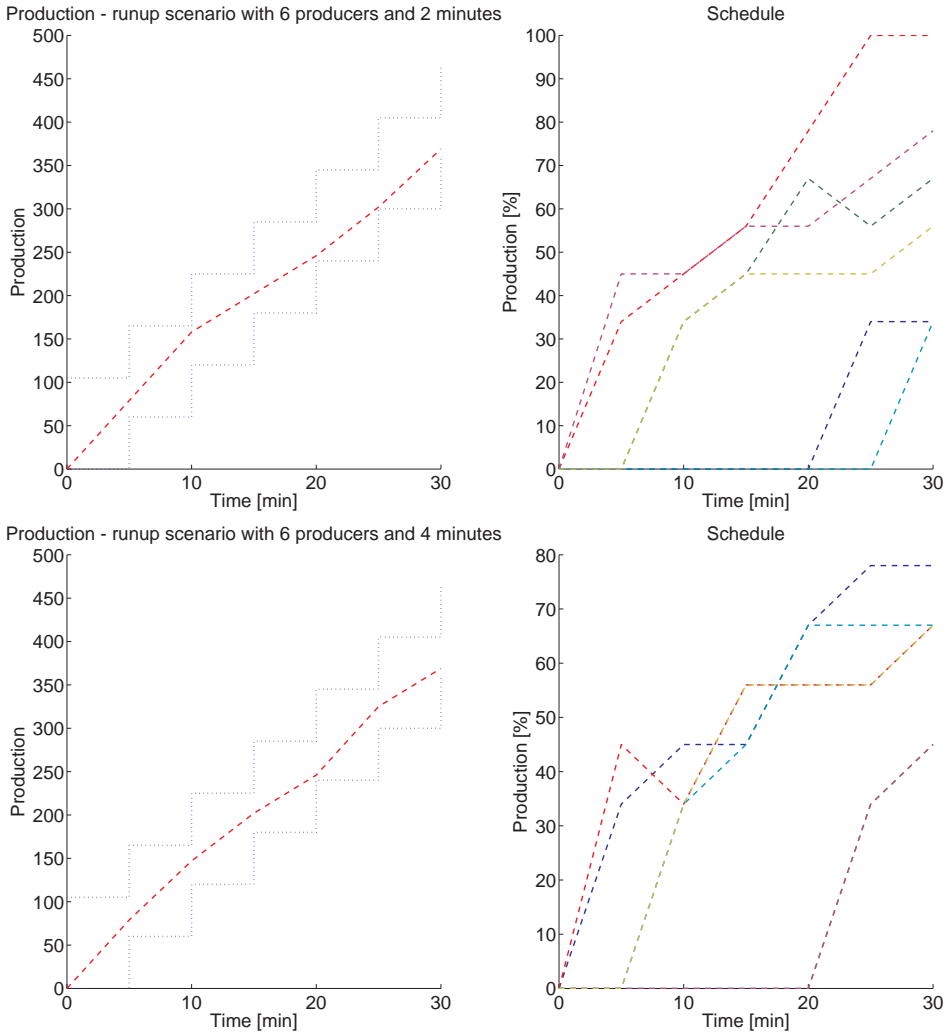

Figure 5.5: Suboptimal results with solution time 2 and 4 minutes - run up profile.
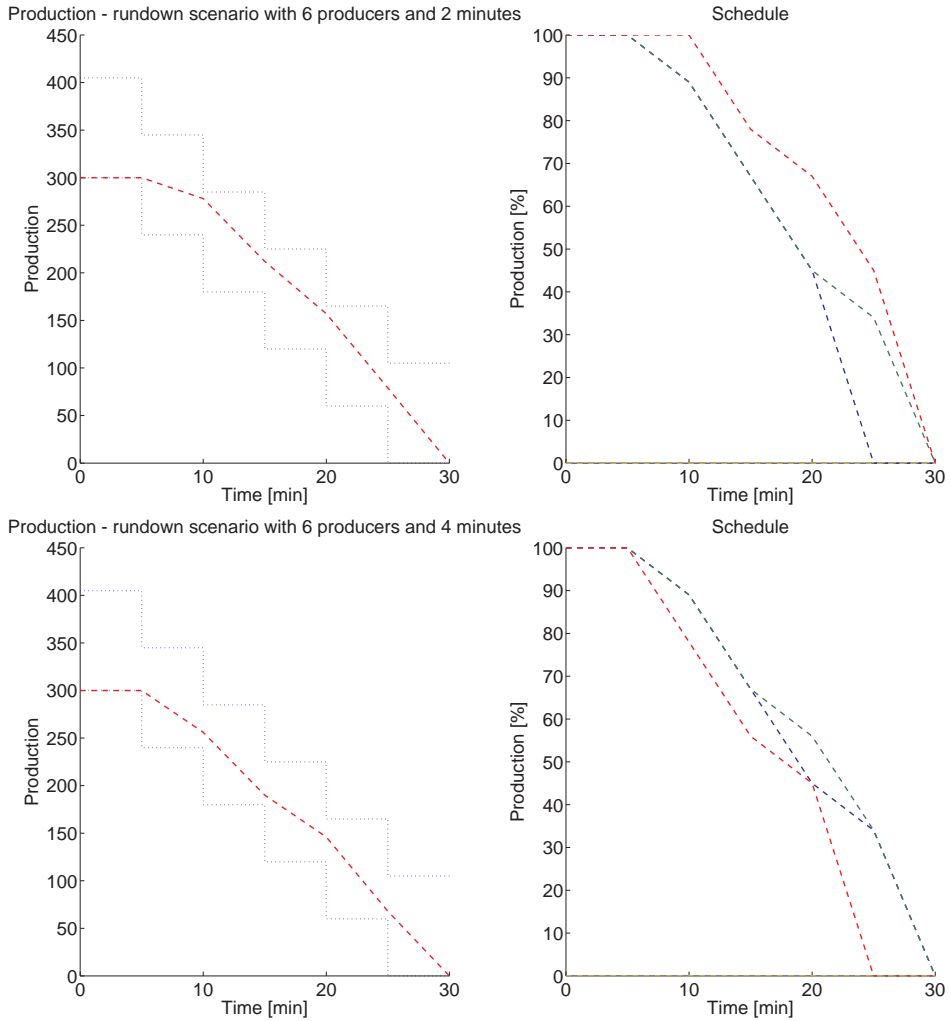
Figure 5.6: Suboptimal results with solution time 2 and 4 minutes
- run down profile.

5.4.4 Suboptimal results

Both solvers rely on exhaustive branching of the solution space and thus
the optimization time depends on those algorithms. In case of the MILP
solvers the lower bound for the performance index is known which makes
it possible to evaluate the quality of solution. Additionally a number of
solutions are excluded in the branching procedure, thus the solver performs
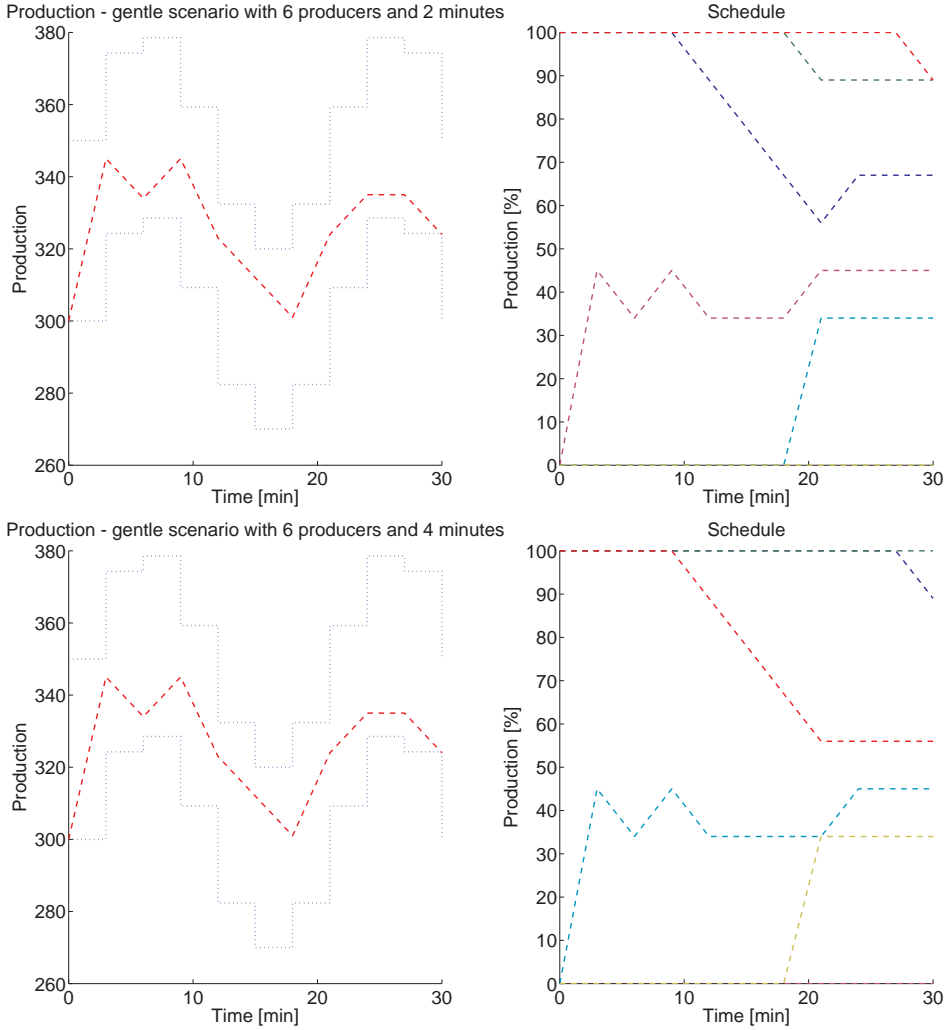less computations.

Figure 5.7: Suboptimal results with solution time 2 and 4 minutes
- sinusoidal profile.

There is a possibility to include the lower bound for branching in the model checking, however, it is still an experimental feature in UPPAAL CORA that could not be fully used in our tests. The bound is not calculated from a relaxed problem as in MILP solvers, but should be specified during modeling. For example the lower bound on the minimum number of machines running for a given profile can be specified as in equation (5.23). Other heuristic rules can be provided in order to speed up the computa-

tions. Ideally a well posed relaxed problem formulation should be solved first in an analogous manner to the MILP solvers.

Lack of lower bound significantly affects the QMC termination; many branches, including the infeasible one, i.e. below the minimum cost must be explored to prove that the result is optimal. This makes the branching procedure overly extensive. On the other hand it is quite likely that a very good candidate schedule is obtained much earlier and significant amount of the time is spent only to find small improvements.

To verify the convergence of QMC we perform another set of experiments. The quality of results are compared when only short time is given for solving the problem. We test the three most interesting profiles, run up, run down, and sinusoidal. The producers are homogeneous and the additional constraints are that only 2 or 4 minutes are available for obtaining solutions. Since the best result is not known for those cases it is not possible to provide the optimality slack. The results of optimization within 2 and 4 minutes are presented in figures 5.5 to 5.7.
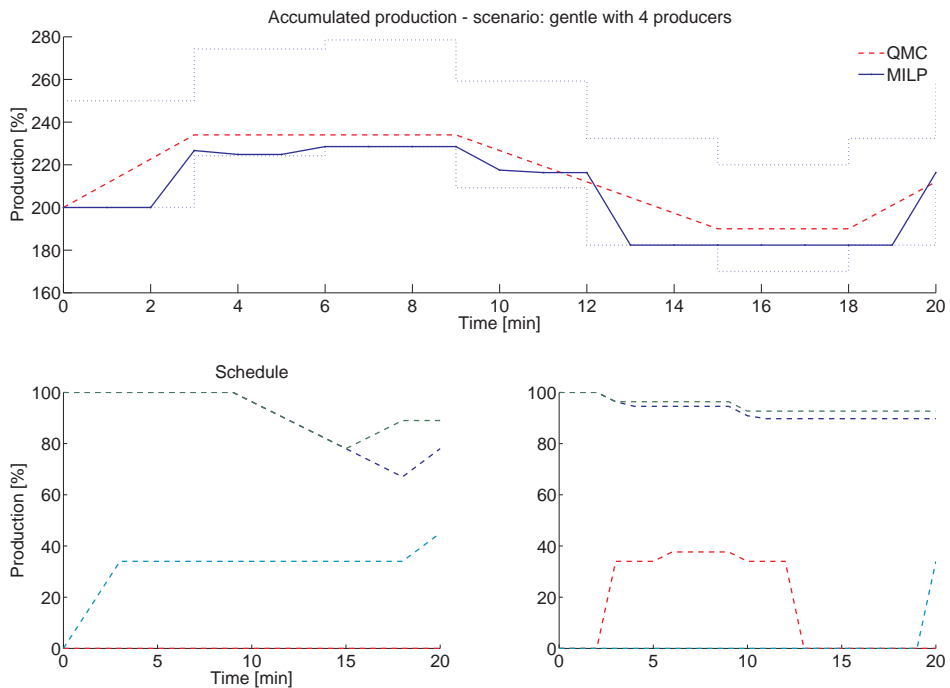

Figure 5.8: Comparison of optimal schedules: QMC and MILP.

5.4.5 Schedule comparison

Both obtained schedules for sinusoidal profile with 4 homogeneous producers and 20 minute time horizon are depicted in Figures 5.8. It can be noticed that the production levels are distributed differently among the producers. This shows that small differences in problem formulations may result in various schedules. In this case the most significant difference is the quantization of production levels in case of QMC.

5.5 Chapter summary

In this chapter we have studied two problem formulations and solution strategies for the scheduling problem, which yield the optimal results. We have studied various production profiles in order to make a qualitative analysis of the methods. It seems that a combination of both approaches could be beneficial. For example, the optimization with QMC can be quickened if adequate lower bound is provided, similarly to the lower bound obtained from the relaxed MILP problem.

Because the problem complexity is very high, we have analyzed the suboptimal results obtained by stopping the solver earlier. The quality of solutions were very good indicating that, in fact, it takes long time to explore the whole search space rather than to find a good schedule candidate.

6 Supervisory controller

Contents

In this chapter we describe a concept for a supervisory control of fuel supply in thermal power plants where multiple fuels can be used. The controller governs the fuel system of a power plant, namely the oil and the pulverized coal distribution to burners and is based on receding horizon strategy. An optimal schedule for each fuel unit can be obtained by employing one of the previously investigated methods, adapted to the considered scenario. The proposed strategy could be utilized for fully automatic fuel control in thermal power plants or in a knowledge based operator support/control system (KBOSS).

From a control point of view, power plants are highly complex systems that include many interacting chemical and mechanical processes. Some of the processes are not fully automated, such as the mill start up and shut down. Getting an overview of all the running processes is not an easy task; it requires a high level of knowledge obtained through experience. Due to the complexity it is often difficult to catch deviation from normal operation at an early stage, therefore knowledge base operator support system (KBOSS) have been proposed [Fan and Rees, 1997]. The goal of having such a system is intuitively clear, namely to lower the number of alarms triggered in a plant and to optimize the overall operation by assisting

the plant operators with additional information besides the measurement readings. Such system helps to detect a problem and understand the cause.

Fan and Rees describe the development of such a system with the purpose of improving operation of coal mills in a power plant. The system is based on a mill model and features man/machine interfaces with underlying sensors. From the collected data mill parameters are estimated and the implemented fault detection mechanisms are evaluated; various levels of alarms are displayed and optimal solutions are proposed to the crew.

It is proposed that the system is adjusted systematically during the operation as the advisory system, and after a test period it would allow fully automatic control, which acts directly on the coal mills. It is mentioned that it is possible to reduce the grinding power by controlling coal mills such that the amount of coal on the table is kept within a certain region, and it is the responsibility of KBOSS to control the mills such that the level is maintained whenever possible. It may be noted that the controller with state observer proposed in Chapter 4 is well suited for such supervisory control; the mass of coal on the table is estimated and a proper state reference can be provided.

In the paper on KBOSS, so-called automatic mill load-sharing control is mentioned, where instead of dividing load equally among all the mills, individual set points are provided for each machine based on the machine wear and maintenance requirements. It is observed that using such strategy lowers the number of mill runbacks that are very costly. A runback situation is a safety feature that occurs when differential pressure across the mill exceeds a threshold, which may indicate mill choking. The feeder belt speed and the primary air flow are lowered to the minimum level at that point.

The actual algorithm that distributes loads among the mills is not described in the paper probably due to confidentiality issues. It is clear that if the algorithm determines the number of operating mills, it is based on the desired grinding capability and required reserves. Most likely the problem is solved as a static optimization problem or based on heuristic rules, which is a simplification of the problem considered in this thesis. Therefore our work can be seen as a natural extension to KBOSS that gives additional information to the plant crew or in case of fully automatic control gives higher safety guarantees. The schedule calculated taking into account the grinding dynamics guarantees feasibility, which is not always the case with static optimization or heuristic approaches.

In the following sections of this chapter we consider a fuel system in

a power plant that besides coal mills consists of oil injectors which allow burning oil in the furnace. Such injectors are used during power plant start up when it is necessary to preheat the boiler and furnace before coal is used. In general oil is more expensive than coal, but it is easier to control its flow, hence more accurate control is possible. Various fuels can be used to improve the efficiency and flexibility of a plant. Most likely oil will be used when high load changes need to be handled, and for steady state operation or low production gradients it is replaced (partly) with pulverized coal.

The topic of propagating business objectives to individual processes and optimal fuel mixing in power plants is well studied in [Kragelund et al., 2008, 2009, 2010b,c,a], and summarized in [Kragelund, 2009]. In that work many aspects associated with power plant efficiency optimization obtained by changing fuels are discussed. For that purpose, Kragelund et al. assume that a mixture of coal, oil and gas can be used to heat up the boiler. An important problem studied in [Kragelund et al., 2008] which is neglected in our work is the relation between business and process objectives. Three different approaches have been used there: input space search, static optimization and Pontryagin's Maximum Principle. The first two approaches do not include dynamic properties of various fuels, which are included and treated using the Maximum Principle. Those studies are taking into account historical data of fuel costs and energy prices from Scandinavian electricity market NordPol.

In our study we simplify the problem to a situation when all the costs of fuels and various operations, such as mill start up, are known. We look at the problem from a different perspective: instead of modeling the fuel flows as smooth functions, we pay close attention to the discrete behavior observed in the system. Various phases of operations and the corresponding timing constraints are distinguished in our work, making the system discrete and event based.

6.1   Control strategy

There are two potential strategies for designing the supervisory controller. In the first strategy the problem is formulated as a game between the controller and the environment. The controller wishes to minimize the overall cost of the production, however, there are uncertainties caused by

forecast errors and modeling errors that need to be taken into account. In this case the controller strategy is to:

1. obtain the optimal schedule for the whole forecasted production horizon

2. generate suitable feasible counteractions (alternative schedules) for all possible changes in the forecasted production schedule.

Should the environment change due to various reasons, the supervisor updates its schedule and the system works without interruption. Production plans are stored in a lookup table and they are activated if needed.

Even though the schedules can be precomputed offline before the production starts, the number of possibilities may be very large. Moreover it is difficult to ascertain all the potential environment changes that result in schedule alterations. Those facts make the applicability of the strategy to the considered problem limited.

It should be noted that a conceptually similar strategy is used in case where a supervisor controls various subsystems according to a specification. The systems and the specification are modeled using formal languages and the goal is to synthesize a supervisor that ensures safe operation of the overall system, by blocking certain events such that the specification is met. The controller can be synthesized using the Ramadge-Wonham framework [Ramadge and Wonham, 1984]. In this case, however, the events of all the subsystems and the specification are known, while in our case it is difficult or even impossible to model all the possible events of the environment.

The alternative approach utilizes a receding strategy. An optimization window moves forwards and the optimal schedule is calculated taking into account system changes obtained from various measurements. The strategy is related to model predictive control (MPC) [Camacho and Bordons, 1999; Maciejowski, 2002] applied to time sampled systems. The knowledge of a system model is used to calculate the control inputs in the considered window (horizon), but only the first sample is applied; the optimization is then repeated. At each optimization the state of the system, which can deviate from the predicted behavior, and the up-to-date predictions are updated.

Two main parameters are relevant for the receding horizon strategy, namely the length of the optimization window called the optimization horizon, and the time required for solving the optimization problem, referred to as the control step. While the optimal solution is sought, the system is

controlled according to the previously specified strategy, but the result of the control actions is typically different from the predicted. Therefore it is desirable to specify a short control step, such that deviation between real and predicted response is not too large. However, this means that there is a limited time to perform the optimization in order to find the future schedule, which leads to restrictions on the optimization horizon. Clearly the limitations on the optimization horizon lead to suboptimal results. The optimal result may only be achieved if the horizon spans over the remaining prediction horizon. This is typically not possible in practice.

It is important to choose the control step and optimization horizon correctly to achieve good results. They depend on the system dynamics; *slow* systems are more suitable for that purpose than fast varying ones. Obviously the parameters are related due to the fact that the complexity of the optimization problem grows with the length of the optimization window. Solving difficult problems requires a long control step, which is undesirable due to modeling errors and changes in the reference signal.

This control approach is widely used in the industry, as it does not require sophisticated tuning, and thus is easy to maintain.

6.1.1 Receding horizon

Consider a general nonlinear discrete time system

$$x(k + 1) = f(x(k), u(k)) \tag{6.1}$$

where x is the system state and u is the control input.

The receding horizon control strategy follows the procedure (Figure 6.1)

Step 1: Apply the predicted (optimal) control sequence u^* during the control step $[t_0, t_{ctrl}]$.

Step 2: At the same time solve the optimization problem to obtain control signals, for the period $[t_{ctrl}, t_{ctrl} + t_{hor}]$.

Step 3: At time t_{ctrl} measure the state of the system and load updated reference signal; t_{ctrl} becomes t_0 and the procedure is repeated starting at step 1.

The system is essentially controlled in an open-loop fashion during the control step and the feedback is provided as the initial conditions for the
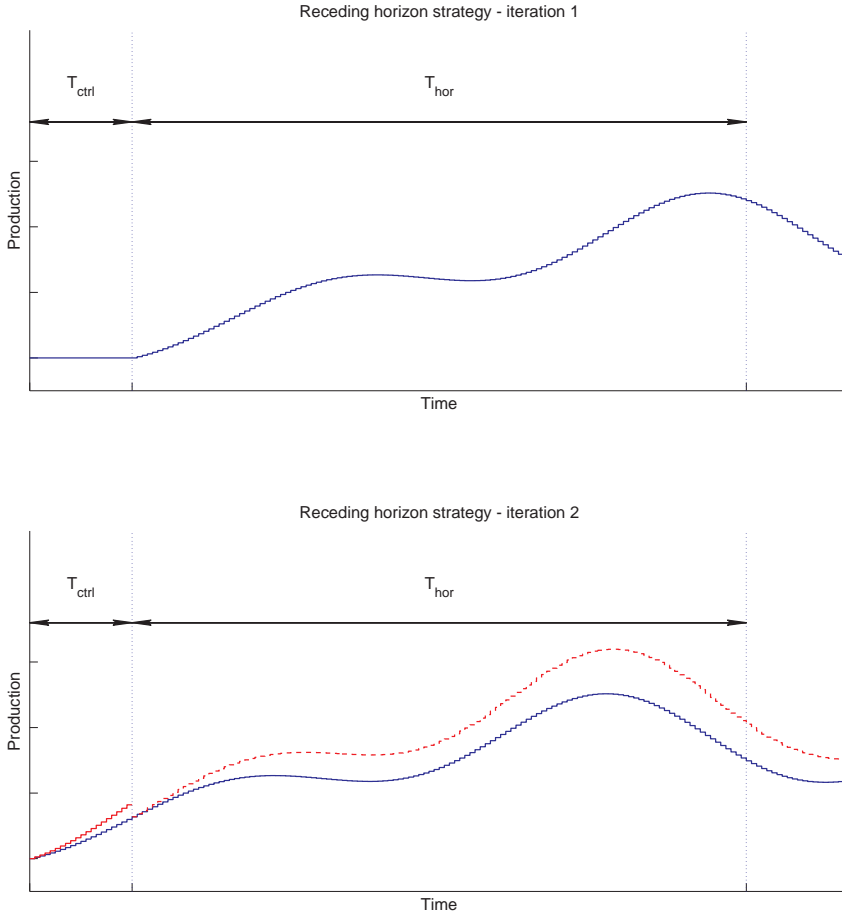
Receding horizon strategy - iteration 1

Receding horizon strategy - iteration 2

Figure 6.1: Receding horizon strategy. The system response during the control step is typically different than predicted. The reference signal may also be updated.

optimization problem. This may give robustness issues especially when a good model of the process is not available.

The sequence of control inputs is obtained by solving an optimization problem (6.2). The performance index $J(x, u)$ should be minimized, subject to the imposed constraints $g(x, u)$, which for example are the state bounds or gradient constraints on the inputs, and assuming that the model accurately reflects the controlled process.

$$u^* = \arg \min_{u \in [\underline{u}, \overline{u}]} J(x, u) = \sum_{i=1}^{T} h(x(i), u(i)) \tag{6.2}$$

subject to

$$g_1(x, u) < 0 \tag{6.3}$$

The system response during the control step is typically different than predicted (plotted with the solid red line in Fig. 6.1). This must be taken into account when calculating a new control sequence. This means that the period when system is controlled in an open loop should be as short as possible.

To reduce the control step, problem formulations and solvers that yield suboptimal results could be used. For example local search methods, greedy algorithms or other meta-heuristics are used. In this case it is trusted that a feasible and relatively good solution can be achieved quickly.

6.1.2 Local search methods

The considered problem has combinatorial nature. We wish to find a suitable order of machines from a given set that satisfy the production constraints. Many such problems belong to the complexity class $\mathcal{NP}$-hard or $\mathcal{NP}$-complete [Hoos and Stützle, 2005]. Hoos and Stützle present how they can be solved via local search, and compare when it is more beneficial to use systematic search or local search techniques. The methods we have used before in Chapter 5 rely on branching algorithms that guarantee finding optimal solution and they are classified as systematic search methods.

The drawback of the systematic search lies in the computational time required for obtaining solution. For that reason local search methods are employed. Very often they can provide a good candidate solution in a short time. Such ability is certainly valued when using receding horizon strategies. Especially in situations where the number of producers and the optimization horizon are large, it may be beneficial to use such meta-heuristics.

An important feature of the studied problem are the time constraints which need to be treated properly by the algorithm in order to model the distinct phases of operation. The local search methods do not yield optimal result and the optimality gap is unknown, but its potential strong advantage is the ability to acquire a close to optimal results within short time.

However, applying such methods to the problem of supervisory controller for the fuel system with the constraints specified in the previous chapter is not straightforward.

Stochastic local search

Basic local search algorithms, which are implemented to minimize the cost function at each iteration taking into account only information about neighboring points, suffer from convergence to local minimum points. To lower this problem randomized choices are introduced. In some iterations, instead of choosing candidate solution that lowers the cost, a random change is performed. The aim is to provide greater exploration of the solution space and hence lower the chance of algorithm getting stuck in local minimum. Another mechanism to escape from local optima is to restart the algorithm with new initial conditions. This does not give the guarantee to escape the local optima, nevertheless, Hoos and Stützle summarize these algorithms in the following way:

> *These stochastic local search (SLS) algorithms are one of the most successful and widely used approaches for solving hard combinatorial problems.*

The ability to acquire relatively good solution candidates is highly desired in the case of supervisory control with receding horizon strategy. However, while designing a suitable search algorithm for the problem we encounter issues with solution feasibility. The problems come from the fact that local change in the schedule affects the rest of the production plan, due to timing and production rate constraints. This can be easily seen in the following example.

Example of an optimization run

Lets consider situation depicted in Fig. 6.2 in which 2 machines are operating with the production rates 100 and 95 at t_0. A feasible production schedule is presented on the left.

In one of the iterations, the local search algorithm chooses to adjust the production of the second machine at $t = 40$ according to the optimality criterion. This change affects the production schedule from this time instance. In fact it causes the profile to become infeasible at $t = 60$ because the total production rate is lower than the demands.
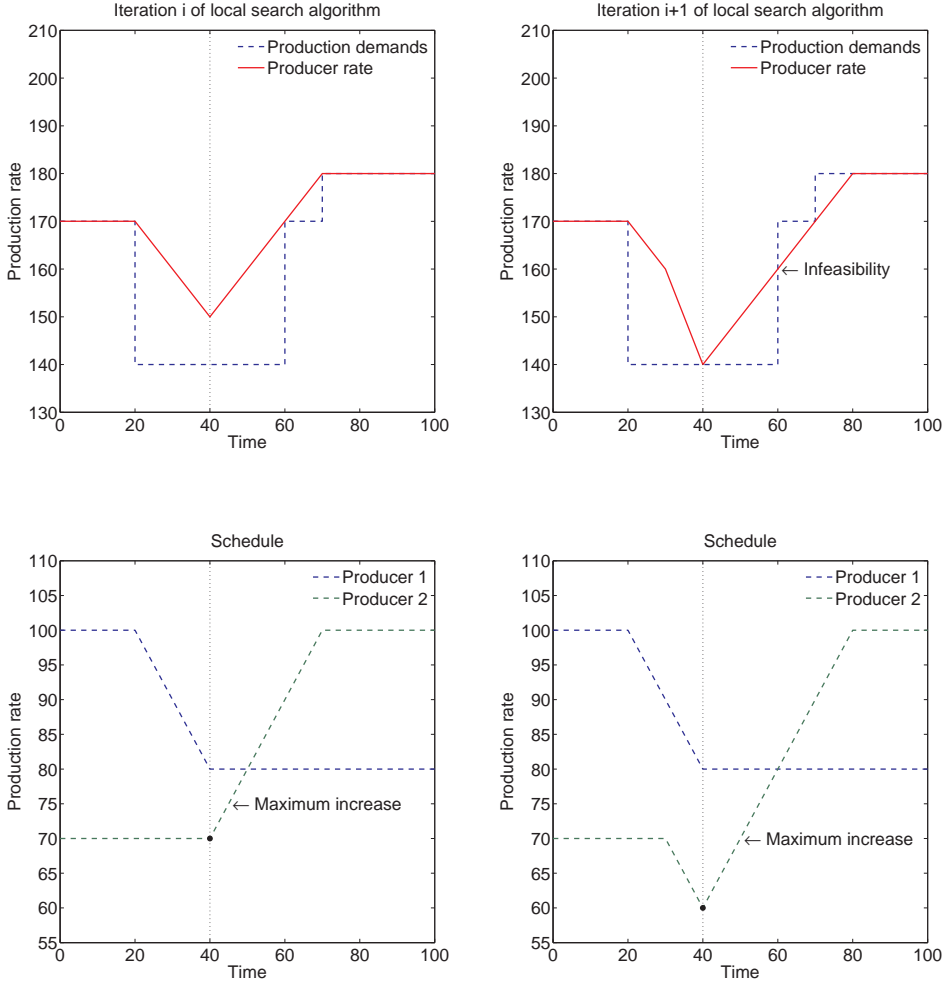
Figure 6.2: Local production adjustments have consequences in the remaining part of the schedule.

The problem becomes even more severe when machine start-up and shut-down are considered. Machine shut-down decreases the production by p_{min}, which needs to be compensated by other producers. This means that prior to the shut-down other machines increase the production rate, which is counter-optimal (the cost of overproduction increases). Moreover, the timing constraints of start-up and shut-down phases need to be satisfied. Increasing production rate of a machine may cause delay in the shut-down, since it is required that the machine is turned off when producing with the minimum rate.
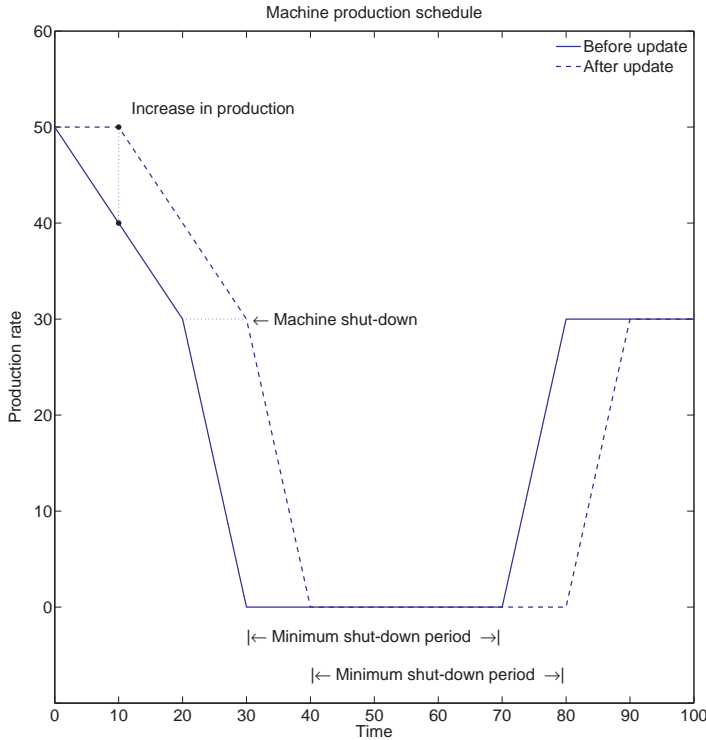
Figure 6.3: A machine can be switched off only when producing with minimum rate (in this case $p_{min} = 30$). Increase of the production rate ($p = 40 \rightarrow p = 50$ at $t = 10$) may result in shut-down delay ($t_{off} = 20 \rightarrow t_{off} = 30$) and consequently the next start-up ($t_{off} = 70 \rightarrow t_{off} = 80$).

This situation is illustrated in Fig. 6.3. In this case the production rate increase at $t = 10$ from $p = 40$ to $p = 50$ affects the remaining part of the schedule. The minimum rate is reached with a delay, hence, the shut-down cannot occur at $t = 20$ due to the constraint. Consequently, the start-up time is delayed because the machine must fully stop and be prepared for operation again.

From the presented examples it is clear that many local adjustments may result in non-feasible production schedules. Therefore many of the iterations of local search algorithms do not contribute to acquiring an improved candidate solution. This reduces the effectiveness of obtaining a good production profile through local search algorithms within a short time.

Therefore, there are two major problems encountered with the local

search methods applied to the considered problem.

1. Local change of schedule affects future production plan. They lead to violations of the time constraints, delays of the upcoming events, or they block certain events.

2. Local optimality does not relate to the overall optimality. Often it is necessary to perform counter-optimal steps to allow for other events, for example machine shut-down. Moreover optimal local adjustments may yield infeasible profiles.

Those characteristics must be taken into account when designing local search algorithm. If the algorithms cannot be used directly, a combination with systematic methods might be fruitful [Hoos and Stützle, 2005].

6.2 Supervisory control of a fuel system

The considered supervisory controller is realized in a receding horizon strategy, where the optimization problem can be solved by one of the methods discussed in the previous chapter. The schedule is passed to the units, that is coal mills and oil injectors. Pulverized coal and oil flow are controlled by individual controllers. Different dynamic properties associated with the use of various fuels are beneficial and can be exploited in the optimization problem. The supervisor is essentially responsible for realizing schedules properly, collecting data from the units and distributing the production profile updates among them. It is important to include additional constraints in the optimization problem which guarantee that there are necessary production reserves available. Such constraints are labeled here as *safety constraints* and they are described in the later part of this section.

A 24 hour production forecast is known in advance. The forecast is distributed to power plants by solving the *Unit Commitment* problem. Each plant has to follow its reference production, which we have previously called a *production profile*. Even though the forecast is fairly accurate, as the consumption patterns are well known and repeatable, there are frequent updates that adjust the profile. Those updates need to be handled by balance control systems, hence, the supervisory controller for the fuel system must handle the updates safely. An example of forecast and actual production

from one of Danish power plants is depicted in Fig. 6.4. The plot represents the power generation, however, this relates to the fuel flow demands.
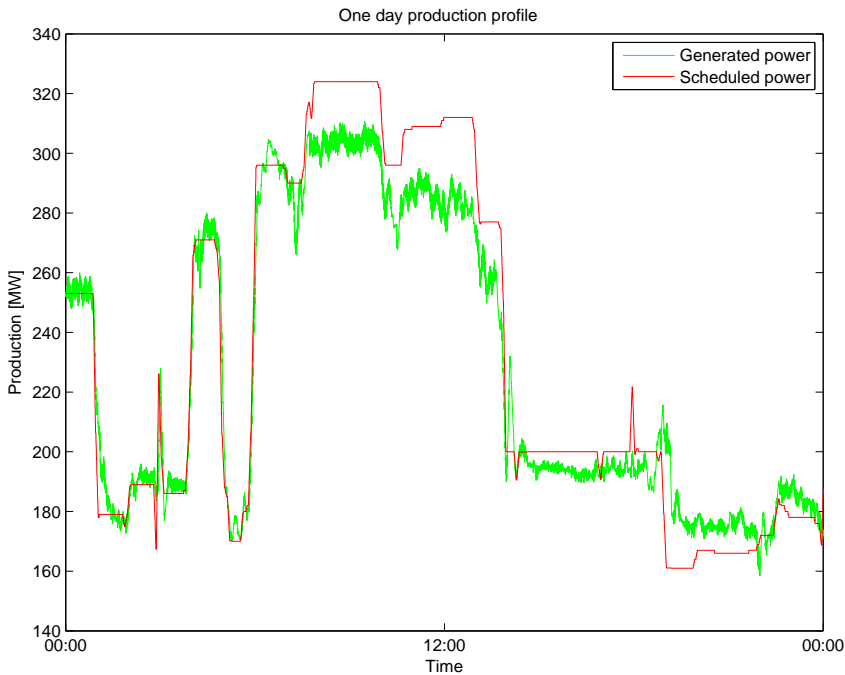

Figure 6.4: One day forecast and actual power production from a Danish power plant.

There are two kinds of production changes announced to the supervisor, which result in production *updates*. First there is the forecast update. Such information is passed to the optimization problem as initial parameter. An open-loop control sequence is obtained by solving the problem. Those kinds of updates correspond to significant changes in the forecasted production and they can be estimated in advance.

The second type of updates is related to smaller but fast varying adjustments which occur in the closed-loop control of the fuel. They may be caused by varying fuel quality or when fast production reserves are activated for balancing purposes. Those two types of updates are handled by separate control loops which form a cascaded structure.

Updates of the production profile need to be accommodated; the additional load needs to be distributed among available units immediately. When the demands are decreased below a certain threshold, the adequate set points are reduced. Such procedures are implemented in the *Addi-*

tional load distribution block in Figure 6.5. In order to distribute the loads correctly it is important to know the full schedule to avoid out of range production setpoints. The actual implementation of this block may vary depending on the particular application, structure of the plant or operating conditions. The simplest strategy is to iteratively increase the setpoints of the lowest fuel source until the whole demand is distributed.
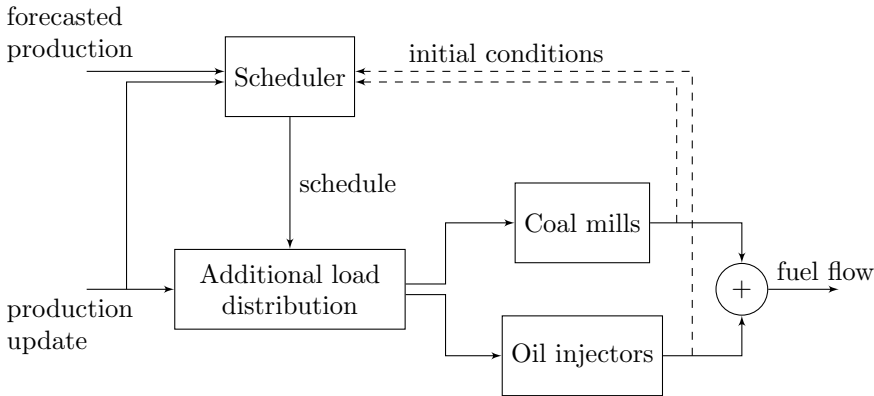
The production levels from each coal mill and oil injector are found by solving optimal schedule problem with e.g. UPPAAL CORA or GLPK solver. Each individually controlled coal mill and oil pump receives a reference signal from the supervisor. Due to the variations between the forecasted and the actual production demand, the changes in the load must be accommodated and distributed over the running units. This is done in the *Additional load distribution* block.

Figure 6.5: Structure of the automatic fuel controller in a power plant where coal and oil are used.

6.3 Applied optimization

From the simulation results presented in Chapter 5 it cannot be fully evaluated how both methods would perform in the considered application. Both appear to be feasible, and thanks to the analysis we have an indication which profiles should be avoided when solving such problems. For example, it seems rational to introduce intermediate steps, when solving ramp-like

problems with QMC. In this section a discussion of practical aspects of such implementation is presented. The goal is to adapt the general study presented before with the real application of fuel flow supervisory control which yields optimal production schedule.

QMC seems promising for applications where number of producers is moderate, while large-scale problems with long optimization horizons are better handled by MILP solvers. The statement is based on the assumption that further advances in the area of quantitative model checking, especially software development are possible. One should also keep in mind that additional constraints, such as topological or priority constraints, and proper selection of the upper profile or cost bounds will most likely lead to reduction of the computation time required to obtaining a solution. Such constraints are discussed in this section. The values presented in Table 5.2 are used purely for comparison purposes and tend to represent the worst case scenarios. They confirm the complexity of the considered problem which has combinatorial nature, and they motivate detailed study of the optimization problem.

6.3.1 Additional constraints

The general problem which was studied in the previous chapter was used as a benchmark to show the complexity of the problem. The differences in the problem formulations and solution methods allow to model the systems differently, nevertheless the problem remains very difficult to solve for both cases, as expected. In order to lower the required time for finding optimal solution it is beneficial to include additional constraints. Many application-related constraints were removed previously to allow more general and straightforward comparison, but they should be included in the final implementation. We can mention a few relevant constraints that are present in power plants, but have not been included so far.

Priority Machine priority might be very crucial. It breaks the symmetry in of the problem that causes multiple schedules to be equally optimal. This is particularly important for the model checking approach. In order to guarantee that the solution is optimal it needs to validate all equally good solution, only to find out that none of them is any better. The priority could be expressed directly through special definitions in UPPAAL CORA, or it could be a result of varying operation costs. The costs or machine order could vary periodically for example based on

the total running time which leads to machine wear, thus the *newest* machine should have the highest priority (lowest operating cost).

Topology Topological constraints, that is the relations between certain burners and mills or oil pumps limit the available number of choices to be made at each time sample. Such constraints, which are strongly dependent on the plant layout, help reducing the growth of the search tree in the optimization (branching). An example of plant layout where four burners are fed by six coal mills or alternatively by oil pumps is depicted in Figure 6.6.
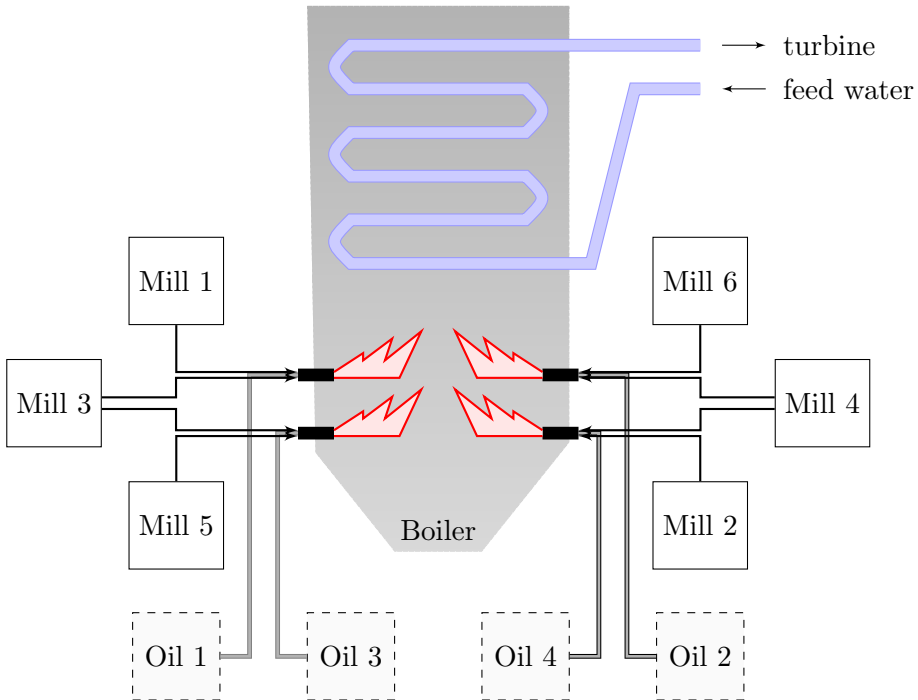
Figure 6.6: Example of power plant layout with four burners, six coal mills and available oil feed (topological constraints).

In order to guarantee uniform heating of the boiler, the requirement is to balance the use of burners on both sides of the boiler and on both levels.

Safety Safe and reliable operation of the plant is crucial posing additional constraints to the problem. For example it could be prohibited to start two mills at the same time, or within a short time. Moreover, it

might be important that at least two mills are running at all times, and that large rises of production capacity is available quickly.

Another important aspect is the problem of runback discussed previously. When a mill's differential pressure exceeds a certain threshold, which is an indication of possible mill choking (overfilling), the feeder belt and consequently primary air flow are driven to the minimum values. Hence, information about differential pressure of all the mills should be included in the optimization problem. If the risk of overfilling one of the machines becomes high, its production level should be lowered or at least kept at constant level such that it reaches steady state operation with an appropriate amount of coal on the grinding table.

Thermal stress Fast and large changes in the fuel flow lead to significant thermal stress of the boiler, thus the production gradient is often limited. This constraint translates to reduction of adjustment events.

Maintenance The number of available machines is sometimes limited, for example due to planned maintenance schedules or failures.

Heuristics Various constraints related to practical operation of the fuel system can be imposed. For example, the minimum operation time of a machine could be specified to ensure that it is not turned on/off to often. Such a constraint has a very good impact on the model checking search, as it lowers the number of possible start and stop events significantly.

6.3.2 Schedule post-processing

Post-processing methods can significantly reduce the computational burden and improve the quality of solutions. There are two immediate areas for improvement that can benefit from such strategy. One of them is associated to the problem of quantization error; the second relates to local improvements of the schedule.

Quantization error can be reduced to some extent by decreasing the production levels of each machine as long as the production bound is not violated. The amount of adjustment is easy to calculate. For each time sample compute the difference between the aggregated fuel flow and the lower bound. Find the minimum value and using heuristic methods distribute the amount among the available machines taking into account the
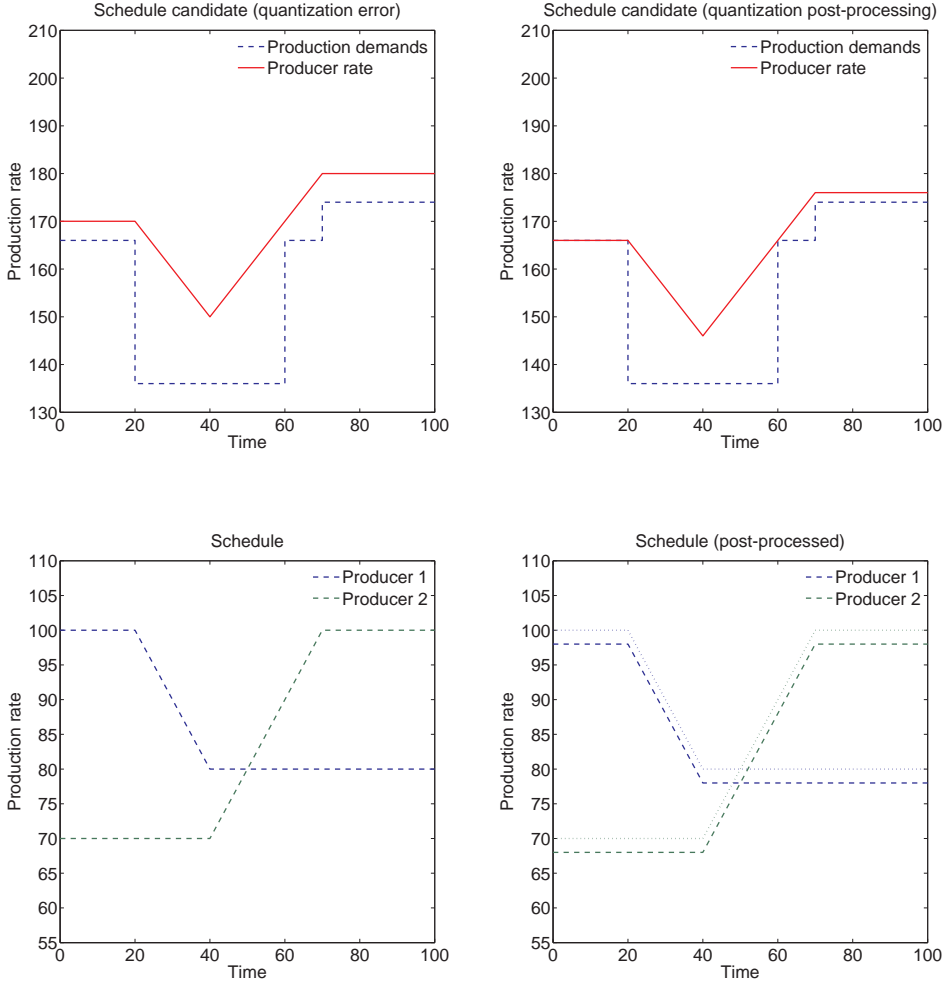
Figure 6.7: Post-processing of a schedule candidate can reduce the quantization error and thus lower the overproduction cost.

operating ranges of each machine. The distribution needs to be stored and recalled later as additional information to the optimization problem. Such post-processing strategy is illustrated in Fig. 6.7, where the overproduction resulting from quantization error is distributed equally among the two producers.

Another mechanism that can be employed is based on the local search strategy discussed before. Such adjustments, as long as they do not violate constraints, can improve the quality of solution to some extent. The easiest way of implementing it in practice is to discard the start-up and shut-down
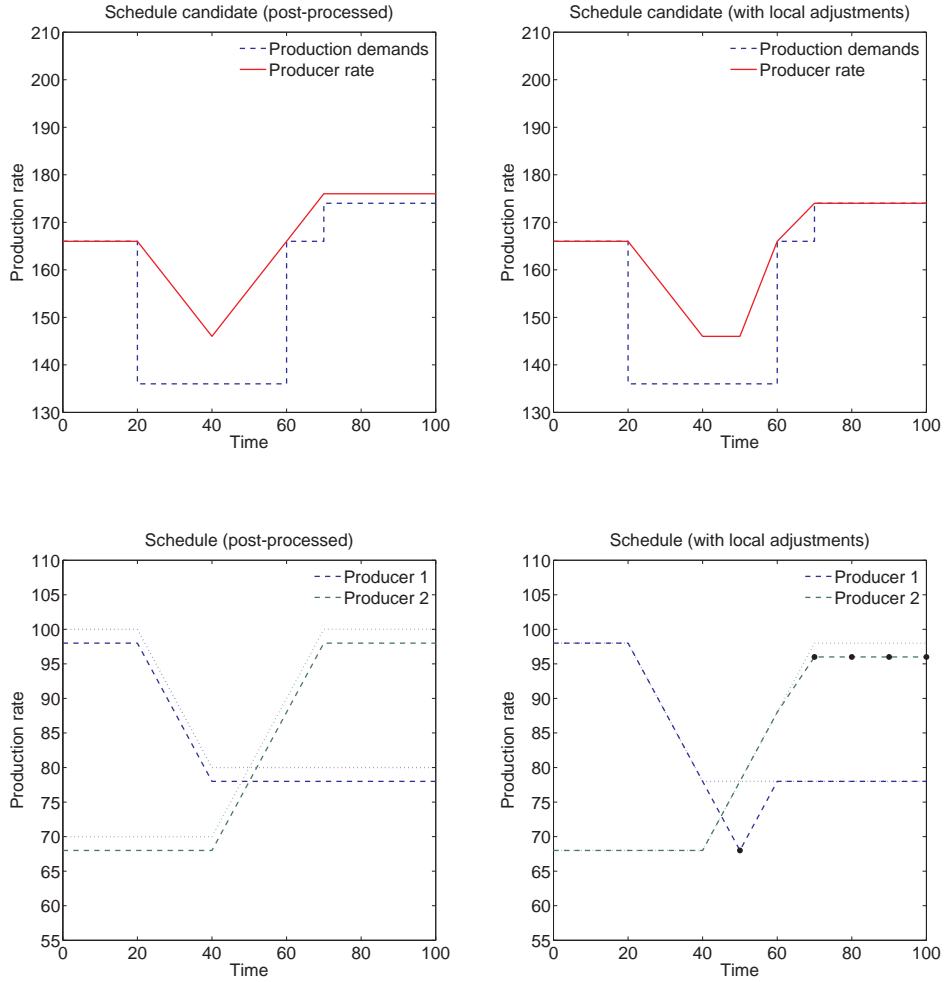
Figure 6.8: Local search and adjustments in a schedule candidate can reduce the the overproduction cost.

events, and consider only control adjustments. For each time sample it is possible to calculate the maximum production decrease and increase such that it does not change production in the neighboring points. A few iterations of such adjustments may yield locally optimal solution. The post-processed schedule candidate adjusted by the local search is plotted in Figure 6.8.

Such post-processing strategies can be done efficiently and does not take much computational time.

6.4   Chapter summary

The chapter has described practical aspects of supervisory controller design for a fuel system in a power plant. An example of a local search approach shows that such methods cannot be used directly to solve the problem. It seems that the timing constraints are most difficult to handle. On the other hand a combination of systematic search method, such as quantitative model checking with local search could be beneficial. For example a schedule candidate obtained from UPPAAL CORA can be postprocessed with the local search method. This way the candidate is improved and the cost upper bound decreases faster, which should lead to improved branching.

Implementation of the strategies discussed in the chapter lead to near-optimal production schedules for the fuel systems. Naturally, the longer optimization window and shorter control steps can be used, the better solution is acquired. It is clear that the complexity of the problem is quite high and that ad-hoc production schedules generated by plant operators are very likely to be far from optimal. Thus the optimal scheduler extension of the KBOSS, that assists the operators or controls the fuel system automatically, improves the efficiency of the plant. The method for more rigorous coal mill commissioning gives greater certainty on how the production is handled. This in turn leads to improved flexibility of the system because the production limits are well known.

7 Thesis summary

Contents

The flow of pulverized coal from mills to burners has always been difficult to control. For that reason, the performance of coal fired power plants is much lower than the oil fired plants, even though the overall design is very similar. The problem has remained unsolved, mostly due to the lack of good sensors, which can be used for closed loop control of pulverized coal flow. Control methodologies, which utilize such knowledge, have been proposed, however, they assume that the fuel flow can estimated from available measurements, for example oxygen concentration in the flue gas. Nevertheless, the lack of accurate knowledge about the fuel flow has complicated the development, or rather verification of coal mill models, which could be used to design model-based control strategies.

Recent advancements in the fuel flow measurement technology allow for improved coal mill control. PID-type controllers, which employ the fuel flow sensors, have already been tested in Danish power plants, showing promising results. The motivation for our research was to further analyze possibilities for improvements, obtained by employing more sophisticated control and optimization strategies.

The thesis presents development of a suitable control oriented mill model. The model is validated with two different types of mills and under various operating conditions. It is shown that it performs well despite its low complexity and number of parameters, which is very advantageous.

Even though the machine wear in case of coal mills is typically large, it is found, that most of the parameters remain unchanged for extended periods of mill operation. The Differential Evolution algorithm simplifies and automates the procedure of parameter identification of the model with respect to collected plant data. The algorithm is quite straightforward to implement, requires only three control parameters, and is very efficient where other optimization methods fail.

With the use of the model, it is possible to design, analyze theoretical aspects, and test coal mill control strategies. At first a simplified problem for system without actuators is considered. The system has bilinear structure, which is well studied in the literature. There exist suitable state observers and controller design methodologies, developed previously by other researchers. We survey some of the relevant results, in particular the stabilizing control law that minimizes generalized performance index, similarly to the quadratic cost function for linear systems.

A strategy, based on optimal control theory for bilinear systems, is applied and tested via simulations along with a well-tuned PID-type control. The study indicates that there are potential benefits to be obtained from more advanced control. The proposed control strategy minimizes the grinding power consumption while ensuring accurate fuel reference tracking. On the other hand, the performance of the PID-type controller is very consistent even when parameters of the plant change. The robust performance of the PID controller is an important advantage when it comes to the implementation in a plant, as it does not requires frequent maintenance nor tuning.

In addition to the practical investigations, which reveal potential usability and advantages of control, a more theoretical study of the system with actuators is conducted. The stability, local coordinate transformation, and optimal control with the use of Pontryagin's Maximum Principle are analyzed.

Overall, good knowledge about mill's internal dynamics, combined with improved control strategy based on the available sensors, leads to better overall power plant flexibility. This is highly desirable considering the liberalized European power markets and the environmental regulations. More accurate control of the fuel to air ratio, that can be improved especially in transient operation, should result in cleaner coal combustion.

Significant efficiency improvements are achieved from the supervisory control level that is responsible for choosing the production set-points for each machine. It is shown, that due to the problem complexity, achieving

optimal production schedules is difficult. Dependable comparison between the calculated and the human schedule is not possible at this moment, as it requires very precise modeling of all the constraints and production costs, which are often a matter of confidential information for companies. On the other hand, the supervisory control strategy based on receding horizon may yield near optimal schedules, which is typically difficult to be achieved by manual operations.

The problem of optimal supervisory control for the group of mills is investigated in this thesis. In order to guarantee proper operation, a number of practical matters, as described in Chapter 6, must be taken into account. For example it has been shown that adaptation of local optimality algorithms is not straightforward, while solvers that provide optimal results, such as MILP solvers or model checking for PTA, are computationally expensive. Hence restricting time allowed for computations, and post-processing the schedule with local search methods, seems to be the best strategy, which may yield near optimal solutions. It is also shown that the complexity depends on the production profile, differently for both methods. A combination of the two discussed approaches, for example calculating a lower bound in the PTA, as it is done in MILP, can be beneficial.

Besides the optimality criterion of the proposed scheduling methodology, which affects the efficiency of a power plant, an important aspect of such control is the reliability. The schedules are obtained for the approaching production with respect to the cost function and the constraints, which means that the resulting scenario is feasible to be realized. Therefore, it is known in advance that certain production profiles cannot be fulfilled by the plant. Possible counteractions, for example activation of production reserves, can be used at this point. Consequently, greater reliability affects the flexibility of the overall system; greater production gradients can be handled safely.

7.1   Verification of the hypothesis

Let us recall the scientific hypothesis stated in the beginning of this thesis

The coal pulverization process, that affects the load following capabilities and efficiency of the considered class of power plants can be significantly improved by

> *a) applying more sophisticated control methodologies based on a suitable coal mill system model*
>
> *b) introducing automated supervisory control of production rates and mill commissioning*

The verification criteria were specified along with the hypothesis. They are discussed below.

a) A simulation study that compares the more sophisticated control strategy to the state-of-the-art PID-type control used in the industry. The performance of both controllers is measured with respect to

- *Fuel control performance* - measure of the integrated fuel error
- *Efficiency* - measure of the energy consumption used for grinding
- *Risk of choking* - measure of the amount of coal in the mill
- *Robustness* - evaluation of the other performance criteria for perturbed system parameters

for a representative reference test signal.

In order to verify this part of the hypothesis a control-oriented coal mill model has been derived and validated. Good correspondence of the model with respect to the plant, analyzed using available data, and its simplicity with low number of parameters, are the strong advantages. Having such model allowed further theoretical and practical investigations of suitable control laws. As an outcome of this study we know, that significant improvements are to be achieved by: using fuel flow measurements over feeder belt speed; state feedback control law with integral action and classifier control over PID-type controller with fuel flow feedback and constant classifier speed, with respect to the above criteria; improvements in the temperature control with the used of two degree of freedom PID-type controller, utilizing the plant model, over classical PID-type controller.

The performance indexes were used in Chapter 4, where control strategies are analyzed, in the comparison of state feedback observer and PID-type controller. It has been shown that improved fuel flow performance can be achieved with improved efficiency and lowered risk of mill chocking. Monte Carlo simulations show that the model-based controller performs well when parameter uncertainties are present, but its performance may degrade.

b) This part of the hypothesis is validated by developing an algorithm that finds an optimal switching sequence for a number of mills and reasonable optimization horizon.

Two algorithms are developed for that purpose, one based on mixed integer linear programming, the other based on priced timed automata solved with model checking tool. Appropriate models of the system are derived for both problem formulations. This allows us to study the influence of various production profiles on the complexity of the problem, and thus identify characteristics of the methods. Good knowledge of the lower bound in case of MILP, obtained by solving the relaxed problem, is beneficial and provides *global* information about the solution, while lack of such lower bound in case o PTA results in having only *local* information when pruning the search tree. A combination of both methods can be beneficial, and they can be implemented in a power plant by utilizing the receding horizon strategy discussed in Chapter 6.

Therefore, we can conclude that the second point of the hypothesis is also verified to be true.

7.2   Summary of contributions

The list of contributions is recalled below concluding the results of the study.

(1) Derivation of a coal mill model suited for control application as an extension of previous developments. The model includes heat balance and coal particle circulation in a mill, and has a reasonable number of model parameters. The varying angular velocity of the rotating particle classifier is included in the model, which affects the fuel flow and coal circulation. Differential Evolution (DE) algorithm is validated as parameter identification method for the model [Niemczyk et al., 2009].

(2) The model is validated using two types of coal mills. It is observed that the model captures the dynamics of both types well, in spite of being of low complexity, making it a good control-oriented model. The parameters found with the DE algorithm for the different pulverizers are similar, which is a good indication that the model and the identi-

fication method are suitable for the problem at hand [Niemczyk et al., 2011].

(3) State estimation and control methods for bilinear systems are applied to the investigated problem. Simulations of the proposed controller show that it is possible to achieve a more accurate and energy-efficient operation of the process, in comparison to a well-tuned PID-type control. A simulation-based parameter sensitivity analysis of both controllers is performed, showing that the performance advantages may be lost in case of poorly identified system parameters. On the other hand, the PID-type controller is very robust to parameter uncertainties [Niemczyk and Bendtsen, 2011].

(4) Stability of an augmented system composed of a bilinear and linear systems is investigated. Such structure corresponds to the coal mill controlled through actuators with linear dynamics. It is found that a local coordinate transformation is nontrivial, however, it is proved that the control law for bilinear systems globally asymptotically stabilizes the augmented system provided certain requirements are satisfied.

(5) Optimal control problem based on Pontryagin's Maximum Principle is studied. The controller for the system with actuators is calculated, such that desired cost function, which corresponds to the verification criteria of the hypothesis, is minimized.

(6) Two formulations for optimal scheduling of continuous producers, such as coal mills, are discussed. The classical and well-known mixed integer linear programming (MILP) problem formulation is presented. Priced timed automata (PTA) model of the scheduling problem is developed, and used with a model checking tool, to find optimal results. Qualitative comparison study of both approaches is performed based on quantitative data obtained from solving the problem, for various production scenarios.

(7) A supervisory controller strategy, which generates schedules for the fuel system of a thermal power plant fired by pulverized coal and oil, is discussed as an extension of a knowledge base operator support system (KBOSS). The strategy is realized in a receding horizon fashion. Application related constraints are discussed. Suboptimal strategies for solving the problem are analyzed. Post-processing methods for improving the obtained schedules are described.

7.3 Future Work

The results obtained throughout the project show the benefits of improved fuel control, which affects the steam production in the boiler and leads to better control of the turbine-generator system. In this section the steps necessary to achieve the final results are discussed.

7.3.1 Coal mill control

In our work, the same model is used for the controller design and the validation. Even though parametric uncertainties are analyzed, and the model describes the milling process relatively well, such validation is not complete. Before the controller is implemented and tested in a plant, it would be beneficial to consider testing it with a more complex, simulation-oriented coal mill model.

In addition, it would be interesting to compare both controllers in a scenario where fuel flow measurements are not available. In that situation they would utilize the feeder belt speed instead, which is commonly done in the industry. Alternatively, the fuel flow estimate could be obtained based on sensor fusion and the developed model. In such case, the identification of model parameters could be performed using a mobile measurement equipment of the fuel flow, which is installed in a plant temporarily.

Once the controller is satisfactory validated with proper simulation model, it could be implemented in a plant. A phase of tests is necessary to tune its performance, such that the quality, and the efficiency of control are high. Especially, tuning the use of rotating classifier seems to be very important, as on one hand it lowers the grinding consumption while providing immediate *burst* of fuel, when the angular velocity is lowered, but at the same time there might be problems with combustion efficiency and extensive formation of ash.

In case the implemented nominal controller performs satisfactory, the next step would be to propose an on-line estimation method to determine parameters of the system. Especially the coal moisture and hardness (HGI) may have strong influence on the quality of control. Estimation of the water content has been presented in [Odgaard and Mataji, 2006, 2008]. Knowledge of the coal moisture has significant impact on the performance of temperature controller, that is the coal drying process.

Appropriate adaptation rules should be implemented as well. On the other hand it has been observed, in the model verification, that after six

months of operation most of the parameters remained unchanged, and the model was accurate. Only the parameters of differential pressure equation, and the water content have changed significantly. Since neither the controller nor the observer use the differential pressure relation, only the coal moisture parameter becomes significant.

Mill wear could be estimated based on the identified system parameters. Fault detection mechanisms could be of a great use [Odgaard et al., 2008] lowering the risks of mill damages or fires could be lowered.

7.3.2 Supervisory controller

In order to implement the supervisory control strategy discussed in the thesis a few necessary steps need to be completed. Firstly, all the costs of mill operations, such as fuel waste during the star-up and shut-down procedures, difficulties of such procedures expressed in terms of the cost, or cost of operating mill at various production levels, need to be determined. Should other fuels be used as well, the same needs to be done.

All the business objectives and system constraints need to be identified and properly modeled along with the system dynamics and ranges of operation. This way a more precise model with adequate costs can be obtained. Information about faults, planned maintenance and repair routines should be incorporated. Scheduling with the use of such model and problem formulation can then be compared with the decisions made by operators, in order to ascertain the potential advantages.

At first the scheduler should implemented as an advisory system, such as KBOSS, to verify its usability, find potential implementation flows, and tune its performance. After extended validation confirmed by correct operation as operators' assistance system, the automatic supervisory controller could be implemented. One of the issues, which could be encountered while using the supervisory control, is associated with the incomplete mill start-up, where due to some problems, the machine does not run the full pre-initialization routine, hence, it cannot be use. Such technical complications need to be taken into account.

7.4   Perspectives

Many interesting aspects of the problems discussed previously could not be investigated due to time limitations of this study. In this concluding

section, we would like to discuss the perspectives for further research, based on problems which we could not pursued.

Quasi-LPV control

The system with actuators could be studied described as

$$\dot{\xi} = (\mathcal{A}_0 + \mathcal{A}(\xi))\xi + \mathcal{B}w \tag{7.1}$$

with $\xi = \begin{bmatrix} x^T & z^T \end{bmatrix}^T$, x are the coal mill states, and z are the states of the actuators.

Matrix $\mathcal{A}(\xi)$ is non-unique; for the considered system it can be written to contain the actuator states

$$\mathcal{A}(\xi) = \mathcal{A}_1(z) = \begin{bmatrix} 0 & 0 & 0 & \\ 0 & -k_5 z_2 & 0 & 0 \\ 0 & k_5 z_2 & \frac{k_4}{k_6} z_3 & \\ & 0 & & 0 \end{bmatrix} \tag{7.2}$$

or to contain non of the actuator states

$$\mathcal{A}(\xi) = \mathcal{A}_2(x) = \begin{bmatrix} & 0 & 0 & 0 \\ 0 & 0 & -k_5 x_2 & 0 \\ & 0 & k_5 x_2 & \frac{k_4}{k_6} x_3 \\ & 0 & 0 & \end{bmatrix} \tag{7.3}$$

In fact there is an infinite number of possible formulations obtained from the property that $\mathcal{A}(x) = \alpha \mathcal{A}_1(z) + [1-\alpha]\mathcal{A}_2(x)$. From the application point of view $\mathcal{A}_1(z)$ differs significantly from $\mathcal{A}_2(x)$, due to the fact that the former one contains only measurable states (actuator states), while the later is dependent on the unknown plant states that need to be estimated. Hence, $\mathcal{A}_1(z)$ is known quite precisely, contrary to $\mathcal{A}_2(x)$.

Writing system (7.1) as

$$\dot{\xi} = (\mathcal{A}_0 + \mathcal{A}(\delta))\xi + \mathcal{B}w \tag{7.4}$$

where δ is a time varying parameter. Such system is called linear parameter varying (LPV). Because δ depends on the state, we call it quasi-LPV.

There exist suitable control design methodologies for such system [Bianchi et al., 2007], including multichannel performance indexes, and this area of research attracts considerable attention, especially with the application to wind turbine control [Bianchi et al., 2007; Østergaard, 2008; Sloth et al., 2010, 2011].

Model checking

One challenge for QMC is to find sharp lower bounds on remaining costs which helps early pruning and thus reduces backtracking. Here it may be useful to apply MILP methods on remaining parts of the profile.

Another challenge is to avoid exploration of symmetrical solutions. We would have liked to use the priority mechanism of Uppaal for that purpose, but unfortunately it is not supported in Cora. Another idea which has not been pursued yet, is to stagger the start time of the producers such that they at least initially avoid getting into phase.

Integral Hybrid Automata

As mentioned in the introductory chapter, an interesting approach for optimization of event-driven hybrid systems with integral dynamics presented in Di Cairano et al. [2009]. The methods is proposed for a class of systems called integral continuous-time hybrid automata (icHA).

The obtained result is highly relevant and well suited to be applied to our problem, and the mathematical formulation is elegant. The profiles could be modeled with first order approximations instead of piecewise-constant functions, which could reduce the problem complexity, especially in the case of ramp profiles.

It would be interesting to make Uppaal model with such profiles, compare it with the icHA approach and combine both methods to exploit all the benefits.

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A Differential Evolution

This appendix presents the fundamental principles of Differential Evolution (DE) algorithm [Storn and Price, 1995; Price et al., 2005; Feoktistov, 2006], which is a type of Evolutionary Algorithm [Ahn, 2006; Rothlauf, 2006]. We have applied this method to the model parameter identification procedure described in Chapter 3. The DE algorithm combines benefits of population-based algorithms (Evolutionary Algorithms) and gradient-based optimization methods. One of the advantages of the algorithm is that it requires only three tunning parameters: population size $\mathsf{P_S} \in \mathbb{Z}_+$, scaling factor $\mathsf{F} \in (0,1]$ and crossover constant $\mathsf{C} \in (0,1)$, and is quite robust to the choice of these parameters, whereas classical EA are more sensitive with regard to the tunning parameters.

Let us begin by defining the optimization problem. Having a set of optimization variables $K = \{K_1, \ldots, K_n\} \in \mathcal{K} \subset \mathbb{R}^n$ we wish to find variables $K^\star$ such that a cost function, also called fitness function $Q(K) : K \in \mathcal{K} \to \mathbb{R}^+$ is minimized, that is $Q^\star = Q(K^\star) \leq Q(K)$.

The population $\mathsf{P} = \{K^i\}_{i=1}^{\mathsf{P_S}}$ is a collection of vectors K. Elements of K are the optimization variables. For each individual in the the population, its *fitness* value, $Q(K)$, is calculated. Then the *evolution* strategy, which consists of gradient calculations between individuals and crossing over strategy, is applied in order to explore the parameter space, and hopefully find a set of optimal variables, $K^\star$.

The core part of the algorithm is the way the elements of the population are generated in each iteration. Although several variants for the procedure have been proposed [Storn and Price, 1995; Feoktistov, 2006], the new elements are generally constructed by creating a trial candidate.

In one of the basic strategies, for each element in the population, K^i, a set of three random and different elements $\pi = \{K^\alpha, K^\beta, K^\gamma\}$ is selected. A gradient is calculated between the element with the highest and the

---

Algorithm 1 Basic Differential Evolution

Generate $g \leftarrow 0$

Initialize population P^g, constants $\mathsf{P_S}$, C, F

Evaluate fitness $Q(\mathsf{P}^g)$

while (stopping condition not met) **do** // evolutionary cycle //

    $g \leftarrow g + 1$

    for all $i \in \{1, \ldots, \mathsf{P_s}\}$ // calculate gradients //

        Select K', K'', $K''' \in \mathsf{P}^g$
        Evaluate $Q(K')$, $Q(K'')$, $Q(K''')$
        Sort $Q(K^\alpha) \leq Q(K^\beta) \leq Q(K^\gamma)$,
                   $\{K^\alpha, K^\beta, K^\gamma\} = \{K', K'', K'''\}$
        Evaluate gradient $\nabla K \leftarrow K^\beta - K^\gamma$
        Evaluate candidate $c^t \leftarrow \mathsf{F}\, \nabla K + K^\alpha$
        Evaluate $c \leftarrow \text{crossover}(K^i, c^t)$
        Evaluate $\mathsf{P}^{g+1} \ni K^i \leftarrow \text{selection}(c, K^i \in \mathsf{P}^g)$

    end for

end while

---

intermediate cost. The vector is then scaled by a user-defined factor F and is translated to the best element. This way a trial candidate c^t for the new iteration is found (equation (A.1)).

$$c^t = \ K^\alpha + \mathsf{F}(K^\beta - K^\gamma) \quad \text{for} \quad Q(K^\alpha) \leq Q(K^\beta) \leq Q(K^\gamma) \qquad \text{(A.1)}$$

Next a crossover is performed between the trial candidate and the investigated set of parameters K. The crossover operation defines a final candidate

$$K_i = \begin{cases} c_i^t & rand_i \geq CR \\ K_i & \text{otherwise} \end{cases} \qquad \text{(A.2)}$$

where K_i is the i-th model parameter and $rand$ is a random operator with uniform distribution over $[0, 1]$. The crossover operation replaces K_i with the candidate c_i^t randomly depending on the parameter C. The procedure of gradient calculation in Differential Evolution is illustrated in Figure A.1.

In a slightly different strategy, the gradient between the investigated element K^i and the best element in the population, $Q(K^{best}) = \min Q(\mathsf{P})$,
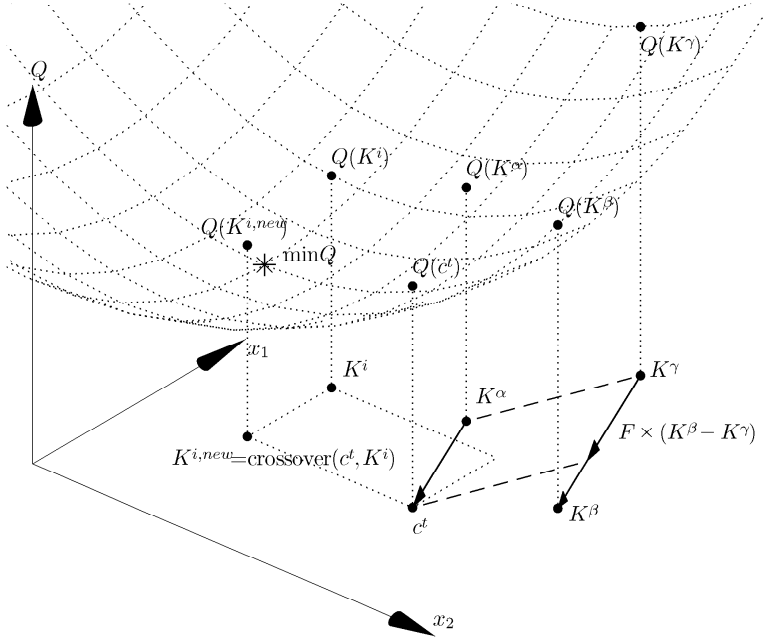

Figure A.1: An example of a candidate evaluation in a two dimensional optimization problem using Differential Evolution. K^i is the i-th element of the population; K^α, K^β, K^γ are the three randomly chosen elements of the population which are used for gradient calculation; c^t is the trial candidate. The crossover operation of c^t and K^i may yield element $K^{i,new}$. The procedure is repeated for all element of the population at each iteration.

is calculated and used for generating the intermediate candidate (A.3).

$$c^t = K^\alpha + \lambda(K^{best} - K^\alpha) + \mathsf{F}(K^\beta - K^\gamma) \text{ for } Q(K^\alpha) \leq Q(K^\beta) \leq Q(K^\gamma) \tag{A.3}$$

Algorithm 1 presents an easy to follow pseudo-code routine. A more detailed description of Differential Evolution can be found in [Storn and Price, 1995], [Price et al., 2005] or [Feoktistov, 2006].

B Coordinate transformation

We follow the coordinate transformation procedure described in [Isidori, 1995] and apply it to our problem. The simplest case is developed for square systems, i.e. have the same numbers of inputs and outputs, $w \in \mathbb{R}^m$, $y \in \mathbb{R}^m$, of the following form

$$
\begin{aligned}
\dot{\xi} &= f(\xi) + \sum_{i=1}^{m} g_i(\xi) w_i \\
y &= \begin{bmatrix} h_1(\xi) \\ \dots \\ h_m(\xi) \end{bmatrix}
\end{aligned}
\tag{B.1}
$$

where $\xi \in \mathbb{R}^n$.

Based on the entries in (B.1) and Lie derivatives, the method produces a local coordinate transformation $\Phi : \xi \mapsto (\zeta, \eta)$ around ξ° where

$$
\zeta^i = \begin{bmatrix} \zeta_1^i \\ \zeta_2^i \\ \dots \\ \zeta_{r_i}^i \end{bmatrix} = \begin{bmatrix} \phi_1^i(\xi) \\ \phi_2^i(\xi) \\ \dots \\ \phi_{r_i}^i(\xi) \end{bmatrix} = \begin{bmatrix} h^i(\xi) \\ L_f h_i(\xi) \\ \dots \\ L_f^{r_i-1} h_i(\xi) \end{bmatrix} \qquad 1 \le i \le m \tag{B.2}
$$

$$
\zeta = \begin{bmatrix} \zeta^1, & \zeta^2, & \dots, & \zeta^m \end{bmatrix} \tag{B.3}
$$

$$
\eta = \begin{bmatrix} \eta_1 \\ \eta_2 \\ \dots \\ \eta_{n-r} \end{bmatrix} = \begin{bmatrix} \phi_{r+1}(\xi) \\ \phi_{r+2}(\xi) \\ \dots \\ \phi_n(\xi) \end{bmatrix} \qquad r = \sum_{i=1}^{m} r_i \tag{B.4}
$$

where $L_f^k h$ is the k'th iterated Lie derivative of h along f, $\{r_1, ..., r_m\}$ the vector relative degree which will be explained later, and η the zero dynamics

as explained in Isidori [1995]. Using Φ the system (B.1) becomes

$$\dot{\zeta}_1^i = \zeta_2^i \tag{B.5}$$

$$\ldots$$

$$\dot{\zeta}_{r_i-1}^i = \zeta_{r_i}^i \tag{B.6}$$

$$\dot{\zeta}_{r_i}^i = \mathsf{b}_i(\zeta, \eta) + \sum_{j=1}^m \mathsf{a}_{ij}(\zeta, \eta) w_j \tag{B.7}$$

$$y_i = \zeta_1^i \tag{B.8}$$

$$\dot{\eta} = q(\zeta, \eta) + p(\zeta, \eta) w \tag{B.9}$$

where $i, j \in \{1, \ldots, m\}$. The maps $p(\zeta, \eta)$ and $q(\zeta, \eta)$ are discussed in Isidori [1995], and

$$\mathsf{a}_{ij}(\zeta, \eta) = L_{g_j} L_f^{r_i-1} h_i(\Phi^{-1}(\zeta, \eta)) \tag{B.10}$$

$$\mathsf{b}_i(\zeta, \eta) = L_f^{r_i} h_i(\Phi^{-1}(\zeta, \eta)) \tag{B.11}$$

Choosing the control law

$$w = \mathsf{A}^{-1}(\zeta, \eta)[-\mathsf{b}(\zeta, \eta) + \mathsf{u}] \tag{B.12}$$

$$\mathsf{A}(\zeta, \eta) = [\mathsf{a}_{ij}(\zeta, \eta)], \quad \mathsf{b}(\zeta, \eta) = [\mathsf{b}_1(\zeta, \eta), \ldots, \mathsf{b}_m(\zeta, \eta)]^T \tag{B.13}$$

feedback linearization is performed. The linearized system is controlled through u, which is designed using linear control methods.

The first step of the procedure is to determine the vector relative degree. This is a generalized of relative degree to be used with MIMO systems. The system (B.1) has relative degree, $\{r_1, \ldots, r_m\}$, at ξ°, if [Isidori, 1995]

(i) for all $i, j \in \{1, \ldots, m\}$, and for all $k < r_i - 1$, and for all ξ in a neighborhood of ξ_0

$$L_{g_j} L_f^k h_i(\xi) = 0 \tag{B.14}$$

(ii) the matrix $\mathsf{A}(\xi)$ in (B.15) is nonsingular at ξ°.

$$\mathsf{A}(\xi^\circ) = \begin{bmatrix} L_{g_1} L_f^{r_1-1} h_1(\xi^\circ) & \ldots & L_{g_m} L_f^{r_1-1} h_1(\xi^\circ) \\ L_{g_1} L_f^{r_2-1} h_2(\xi^\circ) & \ldots & L_{g_m} L_f^{r_2-1} h_2(\xi^\circ) \\ \ldots & \ldots & \ldots \\ L_{g_1} L_f^{r_m-1} h_m(\xi^\circ) & \ldots & L_{g_m} L_f^{r_1-1} h_m(\xi^\circ) \end{bmatrix} \tag{B.15}$$

The procedure applies for square systems, hence, we choose to analyze two possible cases:

Case 1: system with 2 inputs: raw coal flow, w_{in}, primary air flow, w_{air}; and 2 outputs: mass of coal in the mill $h_1 = \xi_1 + \xi_2 + \xi_3$, power consumption $h_2 = k_3\xi_1 + k_2\xi_2$.

In this case we consider the system to have constant angular velocity of the classifier equal nominal value $\bar{u}_3$, and the amount of coal in the mill and the power consumption can be measured. We disregard the air flow equation in the coal mill model as it is already linear and does not need to be transformed. Thus, the states, in the notation established throughout Chapters 3 and 4 are $\xi = \begin{bmatrix} x_1 & x_2 & x_3 & z_1 & z_2 \end{bmatrix}^T$, and the system equations are

$$
f(\xi) = \begin{bmatrix}
-k_1 & 0 & k_9 & 1 & 0 \\
k_1 & -k_5(\xi_5+\bar{u}_2) & 0 & 0 & 0 \\
0 & k_5(\xi_5+\bar{u}_2) & -k_4(1-\frac{\bar{u}_3}{k_6})-k_9 & 0 & 0 \\
0 & 0 & 0 & -\tau_1 & 0 \\
0 & 0 & 0 & 0 & -\tau_2
\end{bmatrix} \xi \tag{B.16}
$$

$$
g = \begin{bmatrix}
0 & 0 \\
0 & 0 \\
0 & 0 \\
\tau_1 & 0 \\
0 & \tau_2
\end{bmatrix} \tag{B.17}
$$

and the calculation of the Lie derivatives yields the following matrix

$$
\mathsf{A}(\xi^\circ) = \begin{bmatrix}
L_{g_1} L_f h_1(\xi^\circ) & L_{g_2} L_f h_1(\xi^\circ) \\
L_{g_1} L_f h_2(\xi^\circ) & L_{g_2} L_f h_2(\xi^\circ)
\end{bmatrix} = \begin{bmatrix}
\tau_1 & 0 \\
k_3\tau_1 & -k_2 k_5 \tau_2 \xi_2^\circ
\end{bmatrix} \tag{B.18}
$$

The above matrix is nonsingular for $\xi_2^\circ \neq 0$, hence, the transformation is viable except in neighborhoods containing the point $\xi^\circ = \{\xi_1^\circ, 0, \xi_3^\circ, \xi_4^\circ, \xi_5^\circ\}$ and the relative degree is $\{1,1\}$. Moreover

$$
\mathsf{b}(\xi^\circ) = \begin{bmatrix}
\xi_4^\circ - k_4(1-\frac{\bar{u}_3}{k_6})\xi_3^\circ \\
-k_2 k_5 \xi_2^\circ (\xi_5^\circ + \bar{u}_2) + k_3(\xi_4^\circ + k_9\xi_3^\circ) + k_1(k_2 - k_3)\xi_1^\circ
\end{bmatrix} \tag{B.19}
$$

thus, all the quantities of (B.12) are known.

Case 2: system with 3 inputs: raw coal flow, w_{in}, primary air flow, w_{air}, angular velocity of the classifier ω; and 3 outputs: mass of coal in the

mill $h_1 = \xi_1 + \xi_2 + \xi_3$, power consumption $h_2 = k_3\xi_1 + k_2\xi_2$, fuel flow $h_3 = k_4(1 - \frac{\xi_6 + \bar{u}_3}{k_6})\xi_3$.

In this case the angular velocity of the classifier can be controlled, and the additional measurement is the fuel flow out of the mill. Again, we disregard the air flow equation, the states are $\xi = \begin{bmatrix} x_1 & x_2 & x_3 & z_1 & z_2 & z_3 \end{bmatrix}^T$, and the system equations are

$$f(\xi) = \begin{bmatrix} -k_1 & 0 & k_9 & 1 & 0 & 0 \\ k_1 & -k_5(\xi_5+\bar{u}_2) & 0 & 0 & 0 & 0 \\ 0 & k_5(\xi_5+\bar{u}_2) & -k_4(1-\frac{\xi_6+\bar{u}_3}{k_6})-k_9 & 0 & 0 & 0 \\ 0 & 0 & 0 & -\tau_1 & 0 & 0 \\ 0 & 0 & 0 & 0 & -\tau_2 & 0 \\ 0 & 0 & 0 & 0 & 0 & -\tau_3 \end{bmatrix} \xi \quad \text{(B.20)}$$

$$\text{(B.21)}$$

$$g = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ \tau_1 & 0 & 0 \\ 0 & \tau_2 & 0 \\ 0 & 0 & \tau_3 \end{bmatrix} \quad \text{(B.22)}$$

and the calculation of the Lie derivatives yields the following matrix

$$A(\xi^\circ) = \begin{bmatrix} L_{g_1}L_f h_1(\xi^\circ) & L_{g_2}L_f h_1(\xi^\circ) & L_{g_3}L_f h_1(\xi^\circ) \\ L_{g_1}L_f h_2(\xi^\circ) & L_{g_2}L_f h_2(\xi^\circ) & L_{g_3}L_f h_2(\xi^\circ) \\ L_{g_1}h_3(\xi^\circ) & L_{g_2}h_3(\xi^\circ) & L_{g_3}h_3(\xi^\circ) \end{bmatrix} \quad \text{(B.23)}$$

$$= \begin{bmatrix} \tau_1 & 0 & \frac{k_4}{k_6}\tau_3\xi_3^\circ \\ k_3\tau_1 & -k_2k_5\tau_2\xi_2^\circ & 0 \\ 0 & 0 & -\frac{k_4}{k_6}\tau_3\xi_3^\circ \end{bmatrix} \quad \text{(B.24)}$$

$$\text{(B.25)}$$

The determinant of the above matrix is $det(A(\xi^\circ)) = -\frac{k_2k_4k_5\tau_1\tau_2\tau_3\xi_2^\circ\xi_3^\circ}{k_6}$, hence, $A(\xi^\circ)$ is singular if $\xi_2^\circ = 0$ or $\xi_3^\circ = 0$. Otherwise the relative degree is $\{1,1,0\}$. Additionally

$$b(\xi^\circ) = \begin{bmatrix} \xi_4^\circ - k_4(1 - \frac{\xi_6^\circ + \bar{u}_3}{k_6})\xi_3^\circ \\ -k_2k_5\xi_2^\circ(\xi_5^\circ + \bar{u}_2) + k_3(\xi_4^\circ + k_9\xi_3^\circ) + k_1(k_2 - k_3)\xi_1^\circ \\ k_4(1 - \frac{\xi_6^\circ + \bar{u}_3}{k_6})\xi_3^\circ \end{bmatrix} \quad \text{(B.26)}$$