EXAMENSARBETE

Pressure and Flow Control of a Pulverized Coal Injection Vessel

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Abstract

This Master's Thesis deals with a model-based pressure and flow control of a fine coal injection vessel for use in the blast furnace injection process. Through a transportation pipe, pulverized coal is conveyed from the coal injection vessel to the blast furnace where it is injected through the tuyeres. Irregularities in the coal mass flow to the blast furnace might cause significant variations in the raw iron quality. Therefore, a control system should be in place to maintain a constant pressure in the injection vessel and a constant coal mass flow from the injection vessel to the blast furnace.

By means of system modeling and identification, the structure and behavior of the coal injection vessel have been analyzed. It has been shown that by use of model-based design, the control goals can be achieved and the control performance can be sufficiently improved compared to the conventional PI-controllers. Several dynamic models of the plant have been developed. A number of control strategies are presented and compared by means of simulation studies. The LQG design method is used to design the controllers. All the controllers have been validated through experiments on the coal injection plant at SSAB Tunnplåt in Luleå, Sweden.

Preface

This report constitutes my master of science thesis, carried out at SSAB Tunnpååt Luleå and the Control Engineering Group at the Luleå University of Technology, Sweden in co-operation with the department of *Systemtheorie der Elektrotechnik* at the University of Saarland in Saarbrücken.

During this project, I gained new knowledge in automatic control and improved my knowledge of the Swedish language. I got in contact with many pleasant people, especially the people at SSAB's research department and the Control Engineering Group.

I want to thank my academic advisor, Dr. Alexander Medvedev, who invited me to this project and supported me during the work; my advisor, Robert Johansson, and the reference group for this project at SSAB, especially Ingemar Lundström who helped me with the practical tests. I also want to thank Andreas Johansson and Annika Bäckström, for the hours we spent together at SSAB, during our master's thesis. Information and assistance provided during the project by Andreas Weber, BMH are also gratefully acknowledged. Finally I want to thank Prof. Hilmar Jaschek, from my home university in Saarbrücken who took the responsibility for my master's thesis in Germany.

Contents

1	Introduction	5
2	The coal injection plant	7
2.1	Structure	7
2.2	Injection process	9
2.3	Existing control unit	12
2.3.1	Sensors	12
2.3.2	Actuators	13
2.3.3	The pressure control	14
2.3.4	The mass flow control	16
3	Nonlinear physical model	19
3.1	Aspects on pneumatic conveying of solids	19
3.2	The model	20
4	Identification	22
4.1	Measurement data	22
4.2	Validation of the existing model	24
4.3	Model for the mass	25
4.4	MIMO model	28
4.5	State space model and model order reduction	31
5	State Observer	34
5.1	Steady-state Kalman filter	34
5.2	Coal mass flow estimation	35
5.3	Validation of coal mass flow estimation	38
5.3.1	Preprocessing	39

5.3.2	Comparison	40
6	Control strategies	42
6.1	Analysis	42
6.2	Design	43
6.2.1	Two separate control loops	43
6.2.2	MIMO controller	45
6.2.3	Feed forward design	47
6.3	Simulations	49
7	Practical Tests	54
8	Recommendations	59
9	Conclusions and Outlook	60
A	Table of Symbols	64
A.1	Indices and Abbreviations	64
A.2	Variables	65
A.3	Constants	66
B	Flow chart of the injection process	67
C	Validation with statistical tests	71

Chapter 1

Introduction

Already in the early middle ages, the Chinese discovered how to reduce iron ore to iron, see [1]. Ever since the process has become more and more sophisticated. Nowadays, iron is a mass product, produced in blast furnaces and later refined to steel. All this could lead to the conclusion that the process is efficient and optimized, which is not completely true. It has become more usual to bring down the cost factors in the iron production, by reducing the share of undesired by-products or the costs of energy supply.

Although coke is one of the most expensive energy carriers, it is common to use it in the iron production. In Luleå, SSAB Tunnplåt tries to reduce the production costs by partly substituting coke and using pulverized coal instead. Pulverized coal is about 40% cheaper than coke. Assuming an injection level of $150\text{kg}/\text{thm}$, this results in a reduction of total costs of fuel by 16% and of hot metal by 5%, according to [16], and this makes pulverized coal injection very attractive.

Since pulverized coal, in its pure form, is highly inflammable even under normal conditions, it is difficult to supply it to the process. Therefore, it is important to keep the pulverized coal isolated from the air, which can be done by using a pneumatic conveying device, where the transportation gas is nitrogen or at least has a higher rate of nitrogen compared to that of the air. The used coal injection plant is planned, designed and constructed by BMH (Babcock Materials Handling in Hamburg, Germany), where two injection vessels are used alternatively to maintain a continuous injection. While one injection vessel is sending the coal, the other is ventilated, filled with coal powder and finally pressurized again. During the injection phase, the sending vessel is held at a constant high pressure level.

Injecting coal powder in the blast furnace at a high rate of about $190\text{kg}/\text{thm}$ makes the blast furnace process very sensitive. According to [11], the process outage becomes critical, due to the fact that large amounts of coal are not delivered to the furnace. The prime concern in fine coal injection is therefore a constant coal mass flow to the blast furnace.

Since the injection vessels operate under high pressure, pressure stabilization during the injection phase is also a control concern, but somewhat of lesser importance than mass flow control. In the experiments, it appears that a constant pressure in the injection vessel makes flow stabilization easier.

Chapter 2

The coal injection plant

The coal injection plant is a highly automated plant, where incoming raw coal is stored, grinded, dried and finally injected into the blast furnace. During operation, human interaction is only needed for set point adjustments.

2.1 Structure

Figure 2.1 shows the structure of the plant, where the different sections are marked and referred to by the capital letters in the marked area. The sections A, B, C are common for the two fine coal silos. Sections D, E and F, G belong to Blast Furnace 1 and Blast Furnace 2, respectively. This master's thesis deals only with the coal injection of Blast Furnace 2. Therefore, the emphasize is placed on section E . The analysis of the structure is based on [14].

The raw coal handling is done in section A , where the receiving hopper is filled by trucks, delivering the raw coal from the stock. A grating on the top of the receiving hopper prevents feeding large lumps of material in a size larger than $150mm$. The incoming raw coal is then transported by a horizontal and vertical belt conveyor system to the top of the raw coal storage bin. This storage bin has a volume of $250m^3$ and works like a buffer silo in order to equalize the raw coal feeding cycles and make coal continuously available to the mill.

The next section is the grinding plant. The mill performs several operations in one unit : grinding, drying and classifying. The mill works at a normal temperature between 250 and $300^{\circ}C$. The working temperature is reached by blowing hot gas produced by the hot gas generator. The original corn size of the raw coal is reduced

Figure 2.1: Coal injection plant

down to $100\mu m$, and the humidity of the raw coal, which normally varies around 7%, is reduced to about 1%. The grinding capacity of the mill is controlled by the storage level in the fine coal silos.

In section *C*, the hot gas is blown through the mill in order to transport the classified final grinding product to the filter separator, which is placed on the top of the coal injection plant. The receiving filter separates the coal dust from the transport gas and collects the coal dust in the storage hopper from which it is discharged by a screw conveyor and a rotary airlock feeder into the fine coal silos.

There are two fine coal silos, one for each blast furnace. To each fine coal silo, two injection vessels are attached. Each one of them is built in the same way and has the same functionality. Then, only Sections *D* and *E* are described below.

The fine coal silo collects the injectable coal powder and has a capacity of $130m^3$. It is operating under inert gas conditions which means that there is a slight overpressure of nitrogen in the silo. Since the silo is not pressure tight, a gas flow from the inside to the outside occurs, which guarantees that no air enters the fine coal silo. This gas flow is about $0.5 \frac{Nm^3}{min}$. To guarantee the continuous discharge of the coal powder into the injection vessels, two outlet cones of the fine coal silo are equipped with fluidization nozzles. The two injection vessels feed the coal powder into the injection pipe where a coal distributor distributes the coal/gas flow to 24 tuyeres, injecting the coal into the blast furnace. The injection vessels operate alternatively in order to avoid switch over stops.

2.2 Injection process

Principally, the injection process can be divided into two separate phases : a high-pressure and a low-pressure phase, where, as the names already imply, the pressure in the injection vessel is high or low, respectively. In figure 2.2, characteristic curves of vessel pressure and mass changes during a process working cycle are shown.

As already mentioned, one vessel is depressurized, charged and pressurized while the other vessel is injecting coal powder. To facilitate process identification and control, the high pressure and low pressure phases can be sub-divided into more specific phases.

Figure 2.3 shows one process cycle of injection vessel S21. *A* represents the low pressure phase and *B* to *E* belong to the high pressure phase. In Table 2.1, the

Figure 2.2: Characteristic curve for the injection process. Injection vessel S21 (solid), Injection vessel S22 (dashed)

Figure 2.3: Process cycle of injection vessel S21

Phase	Name	Description
A	Charging	The pressureless vessel is filled with coal powder
B	Pressurizing	The injection vessel is set under pressure
C	Pressure holding	Standby until the other vessel has finished injection
D	Injection	The coal powder is injected into the blast furnace
E	Ventilation	Depressurizing and ventilation of the vessel

Table 2.1: Process phases

Phase	Pressure [kPa]	Mass [kg]
A	~ 0	rising to ~ 5000
B	rising to ~ 950	slight rise to ~ 5100
C	~ 950	~ 5100
D	~ 950	falling down to ~ 650
E	falling down to ~ 0	slight fall to ~ 550

Table 2.2: Typical pressure and mass values for all phases

nomenclature used in the sequel to refer to process phases is summarize. In Table 2.2, typical values for each process phase are given.

After the injection vessel is filled with coal powder, the inlet valve and the ventilation valve at the top of the injection vessel are closed. At this time, the vessel has a weight of about $5000kg$. When the two valves have closed, the injection vessel is pressure tight. The pressure control valve and the corresponding shut-off valve, closed during the low pressure phase, are now open. The pressure increases until it reaches the set point and the valves are shut again. As there exist leakages in the vessel body and the valves themselves are not completely tight, the pressure changes notwithstanding all valves are closed. Consequently the pressure controller is activated and maintains the pressure around the set point value. When the other vessel has finished the injection, the vessel switches from pressure holding to injection. Then, the flow control valve opens and injection starts. Meanwhile, the other vessel flow control valve closes. During the injection phase both control valves, the pressure and the flow control valve, are active. The weight of the vessel is ramping down to a minimum value while the pressure remains constant. Reaching the minimum weight, the injection vessel flow control valve closes. In the meantime, the other vessel has been charged, pressurized

and stands by. If the pressure control valve and the flow control valve have closed, the ventilation valve opens and depressurizes the injection vessel. Once the pressure has dropped down to normal, the inlet valve opens and coal powder is filled in again. In Appendix B the flow charts of the injection process are given.

2.3 Existing control unit

The control unit of the fine coal injection plant consists of two independent loops. One loop is for injection vessel pressure stabilization, and the other is for controlling the coal mass flow to the blast furnace. The process working cycle duration depends on the actual coal mass flow set point. Logically, a higher set point shortens the cycle time. Normally, the cycle time is about 40 minutes, which means that the injection phase takes 20 minutes, approximately.

2.3.1 Sensors

Since the whole plant has many processes running separate from each other, partly without knowledge of the other processes, they are disturbing each other. Furthermore many parts of the plant are mechanically coupled, for example the two injection vessels are coupled over the injection pipe. This results in errors in the measurement, which may not be neglected.

Therefore it has to be discussed, what signals are usable for process identification and how they are acquired. Mainly the process has four input signals. They are :

- pressure in the vessel
- pressure in the nitrogen net
- weight of the injection vessel
- pressure in the injection pipe.

All pressure sensors are difference pressure meters. They are calibrated on a pressure range from 0 to 1600 kPa , and have an accuracy of $\pm 0.5\%$. Zero is calibrated on normal outside pressure. The pressure signal is linearly converted into a current signal. Table 2.3 shows how the signal is converted.

Pressure signal	Current signal
0 kPa	4 mA
1600 kPa	20 mA

Table 2.3: Pressure signal conversion

Mass signal	Current signal
0 kg	0 mA
6000 kg	20 mA

Table 2.4: Mass signal conversion

The weight sensor is metering the mass of the injection vessels. As the injection vessels are coupled with each other over the injection pipe, the metered weight is disturbed by the weight of the other vessel. The weight sensor is calibrated on the empty injection vessel to be zero. The mass signal is linearly converted into a current signal, too. Table 2.4 shows how the signal is converted. Obviously this conversion is different and the signal from the sensor has a different range.

All current signals are amplified before sampling by a buffer amplifier, with gain one. This is done because of safety reasons, in order to separate the circuits galvanically. The used buffer amplifiers have an error less than 0.2%.

2.3.2 Actuators

The pressure and flow control of the injection vessels involves two actuators. The pressure control valve (PCV) and the flow control valve (FCV). The PCV is a standard valve, while the FCV is a special design from BMH, [15]. Both valves have a position control which is not discussed closer. It can be assumed that the position control has a sufficient fast and accurate behavior. Later the behavior of these inner loops is assumed to be proportional.

Since characteristic curves are not available for the PCV, only a principle characteristics can be given. Parameters can be obtained from experiments and identification as shown in [8]. Figure 3.1 shows a principle characteristic. Obviously the PCV has a dead-zone and an exponential characteristic, as it is an equal percentage valve. It should be possible to linearize this characteristic around a working point.

A look at the principle structure of the valve, figure 2.5, shows why the valve has

Figure 2.4: Principle characteristic curve of the PCV

a dead-zone. The flexible ring seal will prevent nitrogen passing through the valve, although the valve is open. This is valid for openings between zero and 5%.

As the FCV is a special design by BMH, no characteristic curve is available. Only a principle structure of the FCV can be given in figure 2.6. It becomes clear, that there is a non-linear coherence between the valve opening and the resulting mass flow through the valve. It will be shown later that a linear model works sufficiently good for this valve. The FCV has also a dead-zone, this results from the slide movement. In order to tighten, the valve has to pass over the opening completely and for safety reason a bit more. The calibrated valve will open physically for control signals between 21 and 100%. The resulting non-linearity can not be neglected.

2.3.3 The pressure control

The pressure controller is placed in SattCon, close to the coal injection vessels. The cycle time for the pressure loop is 0.3s. The input from the pressure sensor is sampled with the cycle time and acquired by an A/D Card which converts the analogue current signal into a digital signal. Filtering is probably applied but not mentioned or described in the control units description. The used controller is a quasi continuous PI controller

Figure 2.5: Principle structure of the PCV (sideview)

Figure 2.6: Principle structure of the FCV (topview)

Figure 2.7: Block diagram of the pressure control

with an integration time of 5s and a gain of 5. The gain had been increased as a result of the recommendations from the pre-studies done by the CEG. It was shown that a higher gain, in former times 3, increases the performance of the controller.

The controller output is limited between 0 and 75%, during pressurization. The reason for this limitation is that the capacity of the nitrogen net is too low. If the PCV is opened too much during the pressurizing phase, the pressure in the nitrogen net drops. This causes pressure oscillations during the injection phase of the other vessel.

Since the controller is already active during the pressurizing phase, it has to follow a ramp. This is realized by ramping the set point value from zero up to set point value during the injection phase. Using a fixed opening value for the PCV would have the same result. An opening value resulting in the same time, needed to pressurize the vessel, could be computed easily and would reduce valve wear-off, as the controller is oscillating a lot in the beginning.

Figure 2.7 shows the block diagram of the actual used pressure control and figure 2.8 shows how the pressure controller performs. It is clear that the controller has a long correction time.

2.3.4 The mass flow control

As the mass flow cannot be measured, the control unit uses the mass loss of the injection vessel during the injection phase as input signal. The mass loss is then derivated. A first order difference is used to approximate the derivative. The resulting signal is then low pass filtered and limited to a maximum deviation from the set point, in order to reduce noise that has been amplified because of the differentiation. This mass flow is computed every fourth second. The controller itself is a quasi continuous PI controller with integration time of 3 minutes and a gain of 0.75. The controller for injection vessel

Figure 2.8: Performance of the pressure controller

Figure 2.9: Block diagram of the mass flow control

S22 is tuned differently, the integration time is set to 2.5 minutes. Furthermore the control unit contains a compensation of the set point value, in order to compensate errors in the computed mass flow. The mass loss of the injection vessel is compared with the ideal mass loss. From this difference a compensation factor is computed.

Figure 2.9 shows a block diagram of the actual used mass flow control, and figure 2.10 shows how the mass flow controller performs. A look at the deviation of the mass flow shows that the actual controller is not able to drive the control error to zero. This is also sustained, looking at the deviation of the mass loss from the ideal mass loss of the injection vessel, which is displayed in figure 2.11.

Figure 2.10: Performance of the mass flow controller

Figure 2.11: Mass loss deviation from the ideal mass loss

Chapter 3

Nonlinear physical model

In order to design and simulate a new controller for the injection vessel it is necessary to have a model of the process. In this chapter important terms on pneumatic conveying of solids are explained and a non-linear physical model of the process is presented.

3.1 Aspects on pneumatic conveying of solids

Pneumatic conveying of solids is the process of moving dry material through an enclosed pipe by motion of air, according to [2]. The first question that arises here is, how does the dry material, in this case coal powder, behave in contact with a gas, in this study nitrogen. As the coal powder is said to be *fluidized* in the injection vessel, the first impression is that nitrogen and coal powder can be treated like a fluid. Unfortunately, this is probably one of the most misunderstood expressions.

The term *fluidization* describes the fact that the angle of repose of material on material is reduced, and material will freely flow by gravity. In the case of the injection vessel, this means that the coal powder is not becoming a compact mass in the vessel and it will not stick to the walls of the vessel during injection. Reported in [2] the angle of repose of a material is changing from 90° to about 0.5° . In order to realize fluidization in the injection vessel, a constant flow of nitrogen into the vessel has to be guaranteed. Fluidization also strongly depends on the construction of the injection vessel on the inside. As these factors are either measurable nor analysable, it is assumed that the coal powder is optimally fluidized. For the development of a physical model, it is assumed that the coal powder and the nitrogen are ideally separated. This means that the nitrogen is placed in the top of the vessel while the coal powder is placed in

Figure 3.1: Schematic drawing of an injection vessel

the bottom.

The material flow through the transportation pipe is not the main concern in this master thesis, because a measurement of the coal mass flow through the pipe is not available. Furthermore, the behavior of the two-phase flow in the pipe is very complex.

3.2 The model

The basis for the physical model is the common pressurized tank process, [4]. Figure 3.1 shows a schematic drawing of the injection vessel.

Input signals in the model are u_N and u_C . Outputs are the mass of the vessel m and the pressure in the vessel p . It is assumed that the temperature changes are small, so that the temperature T is constant.

In general, the mass flow through both control valves can be written as

$$\dot{m}_N = k_N \cdot g_{PCVP}(p_N, p) \cdot g_{PCVu}(u_N) \quad (3.1)$$

$$\dot{m}_C = k_C \cdot g_{FCVP}(p_T, p) \cdot g_{FCVu}(u_C) \quad (3.2)$$

where $g_{PCVP}(p_N, p)$, $g_{PCVu}(u_N)$ and $g_{FCVP}(p_T, p)$, $g_{FCVu}(u_C)$ are non-linear functions. These functions depend on the design of the valves. As not only coal powder is passing the FCV, also nitrogen will leave the vessel, a second nitrogen flow should be defined. This flow is assumed to be zero. Furthermore, the coal mass flow resulting from the weight of the coal powder is neglected.

The mass balance and its derivative then result in

$$m = m_N + m_C \quad (3.3)$$

$$\dot{m} = \dot{m}_N + \dot{m}_C \quad (3.4)$$

According to [3], for an ideal gas holds

$$p \cdot V_N = m_N \cdot R_N \cdot T \quad (3.5)$$

Assuming $\dot{T} = 0$, the derivative of (3.5) results in

$$\dot{p} \cdot V_N + p \cdot \dot{V}_N = \dot{m}_N \cdot R_N \cdot T \quad (3.6)$$

Introducing the volume balance and its derivative

$$V_N = V - V_C \quad (3.7a)$$

$$= V - \frac{m_C}{\rho_C} \quad (3.7b)$$

$$\dot{V}_N = -\frac{\dot{m}_C}{\rho_C} \quad (3.8)$$

equation (3.6) can be rewritten

$$\dot{p} = \frac{R_N \cdot T \cdot k_N \cdot g_{PCVp}(p_N, p) \cdot g_{PCVu}(u_N) + p \cdot \frac{k_C}{\rho_C} \cdot g_{FCVp}(p_T, p) \cdot g_{FCVu}(u_C)}{V - \frac{m_C}{\rho_C}} \quad (3.9)$$

Choosing $\mathbf{x} = [p, m]^T$ as state vector, $\mathbf{y} = [p, m]^T$ as output vector and $\mathbf{u} = [u_N, u_C]^T$ as input vector, a non-linear state space model for the injection process is defined. As the valve functions g_{PCVp} , g_{PCVu} and g_{FCVp} , g_{FCVu} are unknown and cannot be derived from existing data sheets, these functions has to be identified from process data. Furthermore the factors k_C , k_N have to be determined from process data.

As described in [8], it is possible to linearize the state space model by using non-linear input and output transformations. In addition, the valve functions and factors are derived there.

Since the valves operate around a quiescent point during the injection phase, it should be possible to linearize the model or gain a model from a direct identification.

Chapter 4

Identification

Because of the hard non-linearities in the physical model a direct identification of a linear model, that approximates the non-linear model, is employed. In this section, it is shown that a linear model derived from input/output data works sufficiently good for the injection phase. An already existing model for the plant is validated using new data.

For identification the Identification Toolbox for Matlab[®] is used.

4.1 Measurement data

In order to identify the plant, input/output data is needed. At SSAB Tunnplåt two different possibilities exist to log data. SSAB has a data-base, called MÖSS, at its disposal. The data-base is placed on a server which is connected to all control units at SSAB. All measurement data is transferred to this server and stored there. The data is used for statistics and analysis. The local network allows the downloading of measurement data to every PC at SSAB.

The data itself on the server is divided into two groups : minute mean values and diverse time based values. The minute mean values are not suitable for identification, because the sample rate is too slow and the values are mean values. Therefore, a new time base for the needed values from the coal injection plant has been implemented in MÖSS. These values are logged at a sample rate of 5s, the maximum rate allowed by the control unit AlCont. As AlCont has no priority on logging data and transferring it to MÖSS, the sample rate is varying. This results in sample rates varying between 3 and 10s, which makes identification difficult. Data sets have to be interpolated and

Figure 4.1: Plant input and output signals during injection phase. PCV and FCV are inputs, pressure and mass are outputs

may be re-sampled. Furthermore, there is no information about the filtering of the data. Because of these reasons, the data from MÖSS is not used for the identification.

Since a re-designed controller should be tested in real-time on the plant, all important signals should be accessible for a PC with A/D-Board. It appeared to be possible to get access to the signals from/to the valves, and to the sensors for mass and pressure of the injection vessel. By use of signal converters the current signals are translated into voltage signals for the A/D-Board. The low pass filtering by the signal converters has been suppressed. For identification purposes four signals are logged :

- pressure in the vessel
- mass of the vessel
- actual value of the PCV
- actual value of the FCV

Figure 4.1 displays the signals.

Because of the non-linearity of the FCV that has been described above, the input signals are transformed. In this way, the non-linearity becomes part of the plant. This

Quantity	logged with PC	logged with MÖSS
Valve opening	1V	10%
Pressure	1V	161kPa
Mass	1V	614.25kg
Mass flow	1 $\frac{V}{s}$	2211.3 $\frac{t}{h}$

Table 4.1: Conversion of signals in volts to physical units

is the reason why all output signals to the FCV have to be transformed with the inverse transformation. The transformation is a scaling of the signal from the FCV. As the dead-zone of the valve is between 0 and 21%, the signal range from 0 to 100% is scaled into the range 21 to 100%. This leads to the following transformation

$$u_{C,FCV} = h(u_C) = 2.1 + 0.79u_C \quad (4.1)$$

where u_C has a range from 0 to 100% and $u_{C,FCV}$ a range from 21 to 100%. This means that $u_{C,FCV}$ is the actual position value of the FCV, that can be measured. The inverse transformation results in

$$u_C = h^{-1}(u_{C,FCV}) = \frac{u_{C,FCV} - 2.1}{0.79} \quad (4.2)$$

To be able to compare the logged data from the PC with the data logged by MÖSS, the voltage value need to be converted into physical units. The conversion factors can be obtained from a comparison of data logged at the same time instance. Table 4.1 shows how the voltage signals can be converted into physical units.

The mass flow is a composite quantity and can not be logged as a signal. But it is needed later for the controller, as a set point value. This value must be given in $\left[\frac{V}{s}\right]$.

4.2 Validation of the existing model

Until the summer 1996 the two injection vessels were physically connected to the nitrogen net with only one PCV. Naturally, only one controller was used for both vessels. Using several shut-off valves, the PCV was connected to the vessel needed to be controlled. During the pressure holding phase, a limit switch and one separate shut-off valve were used to hold the pressure in a certain range. The CEG recommended the

use of two controllers and PCV's. Based on the results of the pre-study SSAB reconstructed the pressure control and implemented two controllers and PCV's. Now each vessel is controlled completely separate.

Since the existing model was developed before these changes had been made, it is necessary to validate this model. If it is valid, the pressure controller, developed during the pre-study, can still be used.

To validate the single input/single output model for the pressure as output and the PCV opening as input two tests are applied, as proposed in [7, chapter 11] :

- Compare measured and simulated output. Use common sense to validate.

A data set different from the identification data set is used. The measured and simulated output are plotted in the same figure. The behavior of the simulated and the measured output are compared. Common sense is used to make a decision on whether the model is accepted or rejected, see figure 4.2.

- Use of a statistical test on the prediction error.

From the measured and the simulated output the prediction error is derived. If the model fits and the noise is white, the prediction error is white noise with zero mean. The autocorrelation of the prediction error should then be zero for all lags $\tau \neq 0$. Furthermore, the prediction error can be cross correlated with the input signal, they should be uncorrelated. This test is normally not successful in closed loop, as the input is a result of the output. Whether to reject or accept a model is determined by a confidence level, as the correlation functions are not zero in reality. [7, page 424] describes how this confidence level is computed. Figure 4.3 shows the result of the statistical test for the model validation.

Figures 4.2 and 4.3 show that the existing model is still valid, although the structure of the plant has been changed. However these changes did not have any influence in the plant behavior. The existing model has the following model equation :

$$p(t) = -0.0106 \cdot \frac{1 - 1.0566q^{-1}}{1 - 0.8858q^{-1} - 0.1114q^{-2}} \cdot u_N(t) \quad (4.3)$$

4.3 Model for the mass

For the design of two separate single input/single output systems, one controlling the pressure and the other controlling the mass flow, a model for the mass is derived. As

Figure 4.2: Comparison of measured output (dashed-dotted) and simulated model output (solid)

Figure 4.3: Result of the statistical test. Correlation values (solid), confidence level (dotted)

Figure 4.4: Comparison of measured mass (dashed-dotted) and simulated mass (solid)

input the FCV and as output the mass of the vessel are chosen. Using a least square method for the identification gives the best result. The resulting ARX-model has the following equation :

$$m(t) = \frac{-0.00101q^{-1}}{1 - 0.99994q^{-1}} \cdot u_C(t) \quad (4.4)$$

Obviously the model is of first order and has a pole close to the stability border. This seems to be logically correct as from the knowledge of the plant the mass of the vessel is an integral of the mass flow out of the injection vessel. This leads to the result that the FCV together with its position controller can be assumed to have a proportional behavior. Assuming the structure of the model being more complex, does not give a better identification result.

The model from equation (4.4) is now validated in a way similar to that for the model in the previous section. The result of the common sense test is displayed in figure 4.4 and 4.5. From the results of the statistical test one might reject the model. But as described in [7, chapter 11] the statistical tests deliver no absolute degree, that decides whether a model has to be rejected or accepted. In the sequel, the identified model is accepted.

Figure 4.5: Result of the statistical test. Correlation values (solid) and confidence level (dotted)

4.4 MIMO model

In order to do a parametric estimation of the model, a model structure and its order has to be chosen. Since the sought model has two inputs and outputs and a least square method is used at first, the model structure for the MIMO case is now presented. The input, output and equation error vectors are defined as

$$\mathbf{u}(t) = \begin{bmatrix} u_N(t) \\ u_C(t) \end{bmatrix} \quad (4.5a)$$

$$\mathbf{y}(t) = \begin{bmatrix} p(t) \\ m(t) \end{bmatrix} \quad (4.5b)$$

$$\boldsymbol{\varepsilon}(t) = \begin{bmatrix} \varepsilon_1(t) \\ \varepsilon_2(t) \end{bmatrix} \quad (4.5c)$$

and according to [5], the ARX-process results in

$$\mathbf{A}(q^{-1}) \cdot \mathbf{y}(t) = \mathbf{B}(q^{-1}) \cdot \mathbf{u}(t) + \boldsymbol{\varepsilon}(t) \quad (4.6)$$

where q^{-1} is the back-shift operator and

$$\mathbf{A}(q^{-1}) = \begin{bmatrix} 1 + a_{111}q^{-1} + \dots + a_{11na}q^{-na} & a_{121}q^{-1} + \dots + a_{12na}q^{-na} \\ a_{211}q^{-1} + \dots + a_{21na}q^{-na} & 1 + a_{221}q^{-1} + \dots + a_{22na}q^{-na} \end{bmatrix} \quad (4.7a)$$

$$\mathbf{B}(q^{-1}) = \begin{bmatrix} b_{111}q^{-1} + \dots + b_{11nb}q^{-nb} & b_{121}q^{-1} + \dots + b_{12nb}q^{-nb} \\ b_{211}q^{-1} + \dots + b_{21nb}q^{-nb} & b_{221}q^{-1} + \dots + b_{22nb}q^{-nb} \end{bmatrix} \quad (4.7b)$$

The order of the model is defined by the parameters na and nb , which have to be determined in advance. This means that eight polynomials have to be estimated. These eight polynomials describe six independent ARX-processes.

The disadvantage of this model structure for the MIMO case is that all polynomials in $\mathbf{A}(q^{-1})$ and those in $\mathbf{B}(q^{-1})$ have the same order. This means that all six ARX-processes are assumed to be of the same order. If pole-zero cancellations in the identified ARX-model appear, the order of this process is chosen to high. A model order reduction is then possible.

In [7, chapter 7] the least-squares method is applied to the problem of parameter estimation of SISO ARX-process. The equations can be rewritten for the MIMO case. Equation (4.6) becomes

$$\mathbf{y}(t) = \boldsymbol{\varphi}(t)^T \boldsymbol{\Theta} + \boldsymbol{\varepsilon}(t), \quad (4.8)$$

by introducing the measurement data vector $\boldsymbol{\varphi}(t)$ and the parameter matrix $\boldsymbol{\Theta}$ as

$$\boldsymbol{\varphi}(t)^T = [-\mathbf{y}^T(t-1) \dots -\mathbf{y}^T(t-na) \quad \mathbf{u}^T(t-1) \dots \mathbf{u}^T(t-nb)] \quad (4.9a)$$

$$\boldsymbol{\Theta} = \begin{bmatrix} (a_{11}, a_{12})_1 \dots (a_{11}, a_{12})_{na} & (b_{11}, b_{12})_1 \dots (b_{11}, b_{12})_{nb} \\ (a_{21}, a_{22})_1 \dots (a_{21}, a_{22})_{na} & (b_{21}, b_{22})_1 \dots (b_{21}, b_{22})_{nb} \end{bmatrix} \quad (4.9b)$$

The estimated parameter matrix $\hat{\boldsymbol{\Theta}}$ that minimizes $\frac{1}{N} \sum_{t=1}^N \boldsymbol{\varepsilon}^2(t)$ can be computed from

$$\hat{\boldsymbol{\Theta}} = \left[\frac{1}{N} \sum_{t=1}^N \boldsymbol{\varphi}(t) \boldsymbol{\varphi}(t)^T \right]^{-1} \left[\frac{1}{N} \sum_{t=1}^N \boldsymbol{\varphi}(t) \mathbf{y}(t) \right] \quad (4.10)$$

An algorithm to solve this problem is already implemented in the Identification Toolbox. The measured data is imported into Matlab[®]. Separate identification and validation sets are used. As the model order has to be defined for the algorithm, a

Figure 4.6: Measured pressure (dashed-dotted) and simulated pressure (solid)

choice of $na = 2$, $nb = 2$ seems to be appropriate for the first trial. This choice is based on the order of the existing model. Several identification runs have been made, varying the parameters na and nb . The validation of each model proves, that the first choice with $na = 2$, $nb = 2$ performs best.

The validation consists of the two tests described in the previous section. The number of plots increases extremely compared to the SISO case, therefore only the common sense test is displayed here. The plots from statistical test can be found in Appendix C. Figure 4.6 and 4.7 show the results of the common sense test. It is easy to see that the model is performing well.

The resulting model parameters are

$$\mathbf{A}(q^{-1}) = \begin{bmatrix} 1 - 0.3821q^{-1} - 0.5823q^{-2} & 0.0060q^{-1} - 0.0064q^{-2} \\ -0.0146q^{-1} + 0.0178q^{-2} & 1 - 0.4366q^{-1} - 0.5633q^{-2} \end{bmatrix} \quad (4.11a)$$

$$\mathbf{B}(q^{-1}) = \begin{bmatrix} 0.0030q^{-1} + 0.0001q^{-2} & -0.0004q^{-1} - 0.0016q^{-2} \\ -0.0009q^{-1} + 0.0010q^{-2} & 0.0030q^{-1} - 0.0047q^{-2} \end{bmatrix}. \quad (4.11b)$$

The equation error $\varepsilon(t)$ is neglected. This means that the estimated model is assumed to match reality. As the state space representation has advantages for observer and

Figure 4.7: Measured mass (dashed-dotted) and simulated mass (solid)

controller design, the ARX representation is converted to a state space representation. Furthermore, the model contains several pole-zero cancellation, this means that the model structure is partly too complex. A model order reduction seems to be necessary.

4.5 State space model and model order reduction

The identified model from the direct identification with the model parameters in (4.11a,b) is now converted into a state space representation by use of the Matlab[®] function *th2ss*. The resulting model seems to have a rather high order, 8th order. As mentioned before several pole-zero cancellations exist in the model.

A look at the pole loci shows that a pole of 4th order is in zero. These modes are very fast compared to the other modes, given by the poles at :

$$\begin{aligned}
 p_1 &= 0.9999 \\
 p_2 &= 0.9778 \\
 p_3 &= -0.5919 \\
 p_4 &= -0.5670
 \end{aligned}
 \tag{4.12}$$

Furthermore, it seems to be convenient to remove the modes with the poles p_3 and

p_4 . The resulting reduced order model would then be of second order. There are two ways to remove the modes :

- Transforming the state space model into the modal form.

The eigenvalues are then placed on the diagonal of the Φ matrix. To remove modes, the rows and columns containing the eigenvalue of the mode are discarded from the Φ matrix. The corresponding rows in the Γ matrix and columns in the C matrix are discarded, too. The resulting model is now of reduced order.

- Using the Matlab[®] function *dmodred* of the Control Toolbox.

Reduces the order of a model, while preserving the steady-state input-output relationships. This is done by making the modes, that should be removed, infinitely fast. [9, on page 2-117,2-118] describes how the new state equations are formed.

The resulting reduced order model has the following state equations

$$\mathbf{x}(k+1) = \Phi_r \mathbf{x}(k) + \Gamma_r \mathbf{u}(k) \quad (4.13a)$$

$$\mathbf{y}(k) = C_r \mathbf{x}(k) + D_r \mathbf{u}(k) \quad (4.13b)$$

with

$$\Phi_r = \begin{bmatrix} 0.99991 & 0.00003 \\ 0.00011 & 0.97775 \end{bmatrix} \quad (4.14a)$$

$$\Gamma_r = \begin{bmatrix} -0.00313 & -0.03092 \\ -0.04030 & 0.02563 \end{bmatrix} \quad (4.14b)$$

$$C_r = \begin{bmatrix} 0.00058 & -0.04753 \\ 0.03107 & -0.00473 \end{bmatrix} \quad (4.14c)$$

$$D_r = \mathbf{0} \quad (4.14d)$$

as model parameters. This model performs well in the validation. The validation plots are not presented here.

In the next step the states are transformed. This is done by applying a similarity transformation on the state equations. The resulting model equations have the pressure

in the vessel and the mass of the vessel, as state variables. This is important for the design of the flow estimator, which is presented later. An advantage of this description of the model is, that the states have a physical meaning. The similarity transformation is defined as

$$\mathbf{x}_t(k+1) = \mathbf{T}\Phi\mathbf{T}^{-1}\mathbf{x}_t(k) + \mathbf{T}\Gamma\mathbf{u}(k) \quad (4.15a)$$

$$\mathbf{y}(k) = \mathbf{C}\mathbf{T}^{-1}\mathbf{x}_t(k) + \mathbf{D}\mathbf{u}(k) \quad (4.15b)$$

where $\mathbf{x}_t = \mathbf{T} \cdot \mathbf{x}$ and $\mathbf{T} = \mathbf{C}$. The resulting model parameters have in addition the index t.

$$\Phi_{rt} = \begin{bmatrix} 0.97772 & 0.00023 \\ -0.00223 & 0.99994 \end{bmatrix} \quad (4.16a)$$

$$\Gamma_{rt} = \begin{bmatrix} 0.00191 & -0.00124 \\ 0.00009 & -0.00108 \end{bmatrix} \quad (4.16b)$$

$$\mathbf{C}_{rt} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \quad (4.16c)$$

$$\mathbf{D}_{rt} = \mathbf{0} \quad (4.16d)$$

As this model is easy to handle, it will be used in the design of observers and controllers.

Chapter 5

State Observer

Since state estimation also represents a possibility of filtering signals, a steady-state Kalman filter is designed in this chapter. Furthermore, an estimator for a not measurable signal, the coal mass flow, is designed. It is also shown how this estimation can be validated by means of image processing.

5.1 Steady-state Kalman filter

Solving the one-step-ahead prediction problem as shown in [6, chapter 11.3], leads to the Kalman filter. It is shown that the feedback gain is not used to give the system desired eigenvalues, instead the variance of the estimation error is minimized. The optimal feedback gain is not constant. It is varying, but approaches a steady-state value.

The design of an optimal Kalman filter requires initial conditions for the state vector and the noise covariances. Since these properties are not available, the initial conditions for noise covariances are set to infinity and the initial condition of the state vector is set to zero. Then, the resulting optimal Kalman filter gain is constant and equal to the steady-state value.

During the design, the weighting matrices are not set to the values given by the noise variances from the process. This has two reasons :

1. The noise properties are hard to determine. This makes it hard to compute the covariances of the noise.
2. The derived models contain model errors. The sensitivity to the modeling error

Figure 5.1: Autocorrelation of the estimation errors

can be decreased by introducing artificial noise, as described in [6, page 359]. The noise covariances used in the design are chosen larger than the true values.

The weighting matrices are chosen as

$$\mathbf{Q}_e = \begin{bmatrix} 5000 & 0 \\ 0 & 5000 \end{bmatrix}, \quad \mathbf{R}_e = \begin{bmatrix} 0.02 & 0 \\ 0 & 0.02 \end{bmatrix} \quad (5.17)$$

where $\mathbf{Q}_e$ is the covariance matrix of the process noise and $\mathbf{R}_e$ the covariance matrix of the sensor. By use of the Matlab[®] Control Toolbox the steady state Kalman filter is designed. The functions *dlqe* and *destim* are used. A look at the autocorrelation of the estimation error in figure 5.1 shows that the estimation error has almost a white noise characteristic.

5.2 Coal mass flow estimation

Since the coal mass flow is not measurable, an estimation of the mass flow is necessary. The resulting estimator should be run in real-time, therefore a discrete design is also here used. In order to validate the estimation the resulting coal mass flow is integrated.

The integrated signal is then compared with the measured mass signal. If the estimation is accurate, the error should be zero.

The coal mass flow is approximated as

$$\dot{m}_C(k+1) \approx \frac{m_C(k+1) - m_C(k)}{\Delta t} \quad (5.18)$$

where Δt is the sample time.

A look at the model equation resulting from (4.16a-d) shows that the state x_2 is equal to the mass of the vessel. Because of the high coal density compared to that of the nitrogen, the coal mass m_C is assumed to be equal to mass of the vessel. The second model equation is

$$x_2(k+1) = -0.00223x_1(k) + 0.99994x_2(k) + 0.00009u_1(k) - 0.00108u_2(k) \quad (5.19)$$

Subtracting $x_2(k)$ results in

$$x_2(k+1) - x_2(k) = -0.00223x_1(k) - 0.00006x_2(k) + 0.00009u_1(k) - 0.00108u_2(k). \quad (5.20)$$

Introducing a third state by

$$x_3(k+1) = x_2(k+1) - x_2(k) \quad (5.21)$$

augments the state space model in (4.16a-d) to

$$\Phi_{rtf} = \begin{bmatrix} 0.97772 & 0.00023 & 0 \\ -0.00223 & 0.99994 & 0 \\ -0.00223 & -0.00006 & 0 \end{bmatrix} \quad (5.22a)$$

$$\Gamma_{rtf} = \begin{bmatrix} 0.00191 & -0.00124 \\ 0.00009 & -0.00108 \\ 0.00009 & -0.00108 \end{bmatrix} \quad (5.22b)$$

$$\mathbf{C}_{rtf} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \quad (5.22c)$$

$$\mathbf{D}_{rtf} = \mathbf{0} \quad (5.22d)$$

where $\mathbf{C}_{rtf}$ does not map the state x_3 to an output, as this state is not measurable and cannot be used in the design of the Kalman filter as a so-called sensor output.

A Kalman filter is designed for the state estimation, where the estimation error in the mass flow can not be derived from the comparison with measurement data. Therefore the estimation errors in the pressure (x_1) and the mass (x_2) are observed. To validate estimated mass flow, the estimate is integrated and then compared with the measured mass. As said before the artificial noise method is used to correct modeling errors.

Using the functions *dlqe* and *destim*, a numerical problem occurs. To use *dlqe* the matrix Φ_{rtf} has to be non-singular and this condition is obviously not fulfilled. By introducing an element Φ_{rtf33} not equal to zero, this condition is fulfilled, but the approximation of the coal mass flow becomes more inaccurate. Choosing this element very small, less than 10^{-6} , the error during an injection phase is less than 0.1%. This accuracy is sufficient and the conditions for *dlqe* are still fulfilled.

The resulting coal mass flow estimator produces an estimate for the coal mass flow that still contains a lot of noise, but less than the derivative of the mass signal. It is necessary to filter the estimate with a low pass filter. Using a 3rd order Chebyshev filter with the transfer function

$$H_{cheb}(q^{-1}) = \frac{0.00696 + 0.00284q^{-1} + 0.00284q^{-2} + 0.00696q^{-3}}{1 - 2.41515q^{-1} + 1.98968q^{-2} - 0.55493q^{-3}} \quad (5.23)$$

the estimate is low pass filtered. The pass frequency is set to $0.1Hz$ and the stop frequency to $0.2Hz$. The resulting filter estimate is then integrated and validated with several sets of validation data. The integrated estimated mass flow follows the mass signal accurately.

Figure 5.2 shows the estimated flow and the error in its integral during the whole injection phase. Obviously, the error is not equal to zero, but less than 0.2%. This is sufficiently accurate, compared with the rate of noise on the sensor signals and the accuracy of the sensors.

Figure 5.2: Estimated coal mass flow and error of the integrated estimated.

5.3 Validation of coal mass flow estimation

Since no measurement of the coal mass flow exist, it is hard to validate the estimated coal mass flow. Although integration of the flow estimate delivers the right result, it does not prove that the estimation is a good estimate for the real flow.

Between the injection vessel and the blast furnace, there exists no point to observe the coal mass flow or any effects caused by the mass flow. Only the injection of the pulverized coal into the tuyeres can be observed through a watch hole. What can be seen is the raceway of blast furnace and the not yet burning coal particles. Figure 5.3 shows what this looks like. The fine coal particles build a dark cloud. A viable idea is to film the changes in this cloud. The first guess is, that the size of the cloud changes when the coal mass flow is changes. It seems reasonable to assume that the size of the cloud will increase if the coal mass flow is increasing. To analyze this thoroughly, a model of the behavior of the cloud and particularly its size is needed. Because of the difficulty involved in the development of such a model, good knowledge in fluid mechanics is needed, a far more simple strategy is used to gain first results.

As the particle cloud is dark and its background, the raceway, very light, a change in the size of the raceway results in a change in the light intensity of the picture. Sure,

Figure 5.3: View into a tuyere

many disturbances have to be taken into consideration, as for example the light intensity of the flame in the blast furnace varies. Since the light intensity of the particle cloud is not changing, a comparison of light intensity histograms for several pictures of the raceway gives information on which light intensities belong to the particle cloud. From this comparison a light intensity threshold is determined, that separate the picture into black (particle cloud and fixtures) and white (raceway).

Several steps are necessary :

1. The particle cloud is filmed with a video camera. An adequate lens with the right zoom has to be chosen, to enhance the relevant parts of the picture.
2. The logged data from the process is synchronized with filming
3. The film is sampled using a frame grabber card. The sample rate is determined. As the sampling of pictures is a very memory demanding procedure, this has to be done with care.
4. The acquired frames have to be filtered, analyzed and finally compared with the estimated coal mass flow.

Using a lens with variable zoom, the best zoom position is easily obtained. The filming has been synchronized with the data logging by a clock. As the process has a long cycle time and large changes in the coal mass flow are slowly, the synchronization by use of a clock is sufficiently accurate. The sample rate is chosen to 5s.

5.3.1 Preprocessing

The acquired frames from the frame grabber have a color resolution of 256 gray shades, or light intensities, where 255 is white or highest intensity and zero is black or lowest

Figure 5.4: The four steps of the image pre-processing. (a) shows the grabbed frame in 256 grayshades. (b) shows the resulting histogram with 1 equal to 255. (c) shows the converted b/w frame. (d) shows the final filtered frame

intensity. The frame has to be converted into a black and white picture, where the raceway in the blast furnace is white and all fixtures and the particle cloud are black. In order to determine a light intensities threshold for the conversion, histograms of several frames have been analyzed. Figure (5.4b) shows a typical histogram.

From the comparison a light intensity threshold of 50 is chosen. By use of this threshold the frames are now converted to a black and white frames. Values of 50 and higher are interpreted as white and values less than 50 are interpreted as black. The converted frames are then filtered by the filter functions *dilate* and *erode*. These functions remove the areas in the frame that are probably a result of disturbances and aliasing effects. Figure 5.4 shows the four steps.

Finally the number of white pixels in the picture is evaluated. The resulting value describes the size of the particle cloud.

5.3.2 Comparison

The resulting sequence has to be scaled and the mean value has to be removed to make the curves comparable. A direct comparison of the estimated mass flow and

Figure 5.5: Comparison of mass deviation and light intensity. Light intensity (dashed), mass deviation (solid).

the sequence does not lead to a validation, but a comparison with the mass deviation during an injection phase shows similarities, figure 5.5.

The cross-correlation between the sequence and the mass deviation shows a peak at a lag of 14 samples. Since the data set of the mass deviation is shorter than the film sequence, the data set of the mass deviation has been augmented at the beginning with 139 elements. The film sequence is chosen to be longer, because of the unknown dead time of the transportation process. The total lag for the peak is therefore at $139 + 14 = 153$. This would lead to an estimate of the dead time of 765s for the transportation of the coal powder to the blast furnace.

It remains to prove the correlation of the coal mass flow and the size of the coal particle cloud. A physical model for the size of the coal particle cloud would be helpful in finding this correlation.

Chapter 6

Control strategies

Since several different strategies exist to control the injection vessels these strategies are discussed. For the chosen strategies, controllers will be designed and their behavior tested by means of simulation studies. The resulting best controllers will then be tested on the plant in practical tests.

6.1 Analysis

As mentioned before, the control objectives are to maintain a constant pressure in the injection vessel and to guarantee a constant coal mass flow from the injection vessel to the blast furnace. Though, a steady coal mass flow has a higher priority than pressure stabilization. This can be achieved by pursuing different strategies. Here are three of them:

1. Two separate control loops for the pressure and the mass.

One unit controls the vessel pressure and the other controls the coal powder mass, where the mass has to follow a pre-defined ramp. The slope of the ramp is the coal mass flow set point. For the controllers design, two SISO models for the plant are used.

2. Two separate control loops using the pressure and the estimated coal mass flow.
3. A MIMO design controlling the pressure and mass.

Since the estimated coal mass flow could not be checked against a corresponding measurement, it is questionable to use this quantity for control purposes. Therefore,

Strategy 2 is excluded. Nevertheless, the estimated coal mass flow can still be used for evaluation and comparison of control performances.

Strategy 1 and Strategy 3 both have their own advantages and disadvantages.

Strategy 1 is based on SISO models which makes the controller design and implementation easy to handle. The main disadvantage is that the couplings in the process are not taken in account. To achieve a better control performance, the effects of the coupling between the injection vessel pressure and the fine coal flow have to be modeled as disturbances.

Strategy 3 takes the couplings into consideration. Furthermore, this strategy has one more degree of freedom, as the two actuators are used together to achieve the control goals. Another advantage is that the controller can eventually be tuned so that the two loops work separately. In this case, a controller similar to that of Strategy 1 is obtained, and yet the couplings in the plant are accounted for through the model. A relative disadvantage is that the design process appears to be more complicated.

6.2 Design

An optimal design method is used to design the controllers. The separate loops and the MIMO design are based on the so-called linear quadratic gaussian (LQG) theory, as described in [6]. It is also a major design tool for multivariable linear systems.

6.2.1 Two separate control loops

Since a pressure controller already has been developed in [12], only a controller for the mass needs to be designed. In order to design a LQG controller the model in (4.4) is used. Furthermore the control law has to be defined. Normally, assuming state feedback, a proportional-integral control law is chosen to eliminate the steady-state error. However, controlling the fine coal mass, one of the closed-loop system outputs has to follow a ramp. Then, the use of a single integrator leads to a constant steady-state response error. Thus, a double integration is used to drive the error in reference signal following to zero. In order to recast this control law into the framework of LQG design, the process models have to be augmented with a double integrator, see also [10, on pages 522ff].

In the first design step the model equations are transformed into a state space rep-

resentation. Equation (4.4) leads to

$$x_m(k+1) = \Phi_m x_m(k) + \Gamma_m u_C(k) \quad (6.1a)$$

$$y_m(k) = C_m x_m(k) + D_m u_C(k) \quad (6.1b)$$

where

$$\Phi_m = 0.99994 \quad (6.2a)$$

$$\Gamma_m = -0.00101 \quad (6.2b)$$

$$C_m = 1 \quad (6.2c)$$

$$D_m = -0.00101 \quad (6.2d)$$

The state space model is augmented with a double integrator, where Γ_m and D_m are augmented with zeros and C_m with an identity matrix. The resulting parameters have the additional index a.

$$\Phi_{ma} = \begin{bmatrix} 0.99994 & 0 & 0 \\ 1 & 1 & 0 \\ 0 & 1 & 1 \end{bmatrix} \quad (6.3a)$$

$$\Gamma_{ma} = \begin{bmatrix} -0.00108 \\ 0 \\ 0 \end{bmatrix} \quad (6.3b)$$

$$C_{ma} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad (6.3c)$$

$$D_{ma} = \begin{bmatrix} -0.00101 \\ 0 \\ 0 \end{bmatrix} \quad (6.3d)$$

Because of the new structure the steady-state Kalman filter has to be re-designed. The states of the integrators have to be taken into consideration. For the weighting matrices values in the same range are chosen. Hence, the covariance matrix for the

sensor noise has to be augmented and the covariance matrix for the process noise is reduced to a scalar, because only the FCV is an input for the model and not the PCV. The matrices have the following form :

$$\mathbf{Q}_{me} = [5000] \text{ , } \mathbf{R}_{me} = \begin{bmatrix} 0.002 & 0 & 0 \\ 0 & 0.002 & 0 \\ 0 & 0 & 0.002 \end{bmatrix} \quad (6.4)$$

Since $\mathbf{D}_{ma}$ is not equal to zero, see (6.3d), this matrix has to be considered during the Kalman gain design, therefore the function *dlqew* has to be used. It is also possible to substitute the matrix $\mathbf{D}_{ma}$ by a zero-matrix. In this case the model has to be validated again. Here the function *dlqew* is used.

To design the LQG gain matrix, the matrices $\mathbf{Q}_{mc}$ and $\mathbf{R}_{mc}$ have to be determined. Some conditions of the closed loop system have to be fulfilled. At first the Kalman filter should be faster than the LQG, and second the poles of the open loop system should not be moved too much, as this results in strong movements of the actuator. They should not go into saturation.

For a choice of

$$\mathbf{Q}_{mc} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \text{ , } \mathbf{R}_{mc} = [10000] \quad (6.5)$$

these conditions are fulfilled. The function *dlqr* can compute the LQG gain. Using the existing pressure controller the closed loop system can be put together. Figure 6.1 shows the block diagram for the simulation.

6.2.2 MIMO controller

The Kalman filter designed in Section *Steady-state Kalman filter* can be directly used for the controller design. Since integrators are introduced here too, the weighting matrix for the sensor noise has to be augmented. The states of the integrators get the same weight as the other states. Therefore the weighting becomes

$$\mathbf{Q}_{rte} = \begin{bmatrix} 5000 & 0 \\ 0 & 5000 \end{bmatrix} \text{ , } \mathbf{R}_{rte} = 0.02 \cdot \mathbf{I} \quad (6.6)$$

Figure 6.1: Block diagram of the two separate control loops

where $\mathbf{I}$ is a 6×6 identity matrix.

The optimal LQG gain depends on the weighting matrices, as they weight the costs for actuator usage and errors in the states. This means that high values in the $\mathbf{R}_{rtc}$ matrix result in high costs for the usage of the actuator. As a result the controller does not try to use this actuator or at least as little as possible. On the other hand too high values in $\mathbf{Q}_{rtc}$ cause high costs if errors in a state occur. The controller tries to minimize this error as fast as possible.

Hence, the MIMO-LQG controller is very flexible. It is possible to set priority, which quantity has to be controlled fast and which slow, and which actuator that should be used the most. This is the reason why a MIMO-LQG controller can be tuned very flexible. Naturally this also causes problems, since the controller can be badly tuned easily. Therefore the following tuning rules have been set up :

1. Priority has to be set on the mass. Errors in the mass have to be driven fast to zero.
2. The pressure can be used to control the mass. Errors in the pressure are allowed to remain for a while.
3. The FCV should not be used to control errors in the pressure and the valve movement has to be minimal, as these movement directly propagate into the behavior of the coal mass flow.

draw the logic conclusion that the FCV has to be open a certain amount all the time in order to achieve a certain coal mass flow. In steady-state without any disturbances the FCV and the PCV should have a fixed steady-state value.

In [10, section 6.2] it is described how these values can be determined. Since all assumptions are given for continuous time models, the model described by (4.16a-d) is transformed to continuous time. The resulting model equations are

$$\dot{\mathbf{x}}(t) = \mathbf{A}_{cont}\mathbf{x}(t) + \mathbf{B}_{cont}\mathbf{u}(t) \quad (6.8a)$$

$$\mathbf{y}(t) = \mathbf{C}_{cont}\mathbf{x}(t) + \mathbf{D}_{cont}\mathbf{u}(t) \quad (6.8b)$$

where

$$\mathbf{A}_{cont} = \begin{bmatrix} -0.02253 & 0.00024 \\ -0.00225 & -0.00006 \end{bmatrix} \quad (6.9a)$$

$$\mathbf{B}_{cont} = \begin{bmatrix} 0.00194 & -0.00125 \\ 0.00010 & -0.00108 \end{bmatrix} \quad (6.9b)$$

$$\mathbf{C}_{cont} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \quad (6.9c)$$

$$\mathbf{D}_{cont} = \mathbf{0} \quad (6.9d)$$

This model equation can be rewritten

$$\begin{bmatrix} \dot{\mathbf{x}}(t) \\ \mathbf{y}(t) \end{bmatrix} = \begin{bmatrix} \mathbf{A}_{cont} & \mathbf{B}_{cont} \\ \mathbf{C}_{cont} & \mathbf{D}_{cont} \end{bmatrix} \cdot \begin{bmatrix} \mathbf{x}(t) \\ \mathbf{u}(t) \end{bmatrix} \quad (6.10)$$

The sought result is a feed forward from the steady-state coal mass flow, which is assumed to be the coal mass flow set point. In steady-state the equation (6.10) becomes

$$\begin{bmatrix} \dot{\mathbf{x}}^*(t) \\ \mathbf{y}^*(t) \end{bmatrix} = \underbrace{\begin{bmatrix} \mathbf{A}_{cont} & \mathbf{B}_{cont} \\ \mathbf{C}_{cont} & \mathbf{D}_{cont} \end{bmatrix}}_{\mathbf{F}} \cdot \begin{bmatrix} \mathbf{x}^*(t) \\ \mathbf{u}^*(t) \end{bmatrix} \quad (6.11)$$

Solving this equation, $\mathbf{u}^*(t)$ can be expressed by means of $\dot{x}_2^*(t)$, the steady-state coal mass flow. The matrix $\mathbf{F}^{-1}$ represents the inverse process model. If the matrix $\mathbf{F}$ is not invertible, because $\det(\mathbf{F}) = 0$, [10, on pages 510ff] present several ways to solve this problem. In this case the matrix $\mathbf{F}$ is invertible and the feed forward results in

Figure 6.3: Block diagram of the two separate control loops with implemented feed forward

Figure 6.4: Block diagram of the MIMO controller with implemented feed forward

$$\mathbf{u}^*(t) = \begin{bmatrix} -632.16 \\ -978.57 \end{bmatrix} \dot{x}_2^*(t) \quad (6.12)$$

Figures 6.3, 6.4 show both controllers with the feedforward.

6.3 Simulations

In this section, the following four cases are compared to each other by means of computer simulation:

1. Two separate controller loops without feedforward
2. Two separate controller loops with feedforward

Figure 6.5: Simulation result of the two separate controller loops without feed forward. Pressure deviation (dashed), mass deviation (solid).

3. MIMO controller without feedforward
4. MIMO controller with feedforward

For the simulations, a rather high but realistic coal mass flow set point is chosen ($15 \frac{t}{h}$), and a step in the pressure reference of about $16kPa$. In order to examine the controllers ability to work around a different working point, the parameters have been changed. In addition, process noise and sensor noise are simulated.

figure 6.5 and figure 6.6 show the simulation results for two separate controller loops. In these simulations, the MIMO process model is used, because it is closer to reality and captures the couplings in the plant dynamics. As expected, according to simulations with the SISO process models, the steady-state error is zero. Unfortunately, this performance is not confirmed during the practical tests. Therefore, it is necessary to re-design the pressure controller and also to implement a second integrator.

Naturally, introducing a second integrator increases the controller complexity. In fact, the resulting structure has the same complexity as the MIMO controller which fact hints to the conclusion that the latter is to be preferred.

Figure 6.6: Simulation result of the two separate controller loops with feed forward. Pressure deviation (dashed), mass deviation (solid).

Simulating the MIMO controller shows that the steady-state error is driven to zero, (figure 6.7). Comparing this simulation with the one of the MIMO controller with feedforward, (figure 6.8), indicates that the feedforward has a similar beneficial effect on the performance of the MIMO controller. The settling time for the mass control is very small, while the settling time for the pressure control is longer. This is a result from the tuning rules.

A look at the control signals, figure 6.9, shows that the FCV position changes smoothly and, logically, the coal mass flow is expected to be similarly smooth. Besides, the valve opening signal lies far from the saturation limits. Several simulation tests with different parameters suggest that it takes a pressure reference step of about $50kPa$ to drive the PCV into saturation. According to the logged data, such a step is unlikely to occur in practice.

As a summary it can be said, that the MIMO controller is working well, and is fulfilling all the tuning rules. Furthermore the MIMO controller has advantages, that the two separate controller loops do not have. The MIMO controller will be chosen for the practical tests.

Figure 6.7: Simulation result of the MIMO controller without feed forward. Pressure deviation (dashed), mass deviation (solid).

Figure 6.8: Simulation result of the MIMO controller with feed forward. Pressure deviation (dashed), mass deviation (solid).

Figure 6.9: Control signals of the MIMO controller with feed forward. PCV (dashed), FCV (solid).

Chapter 7

Practical Tests

The developed controllers are implemented and tested in REGSIM, according to [13]. A PC has been connected to the control system SattCon. Using several signal transformers, all needed input signals for the control are logged and the output signals are sent to the control valve. For safety reasons the controllers are connected via switches to the plant. By use of software commands, it is possible to choose which controller is used to control the plant. This has the advantage that tests can be run anytime. The computer is connected to the plant so that the control can be switched over to/from the computer. Figure 7.1 displays the principle structure.

A start signal from SattCon initializes the controller in the PC. Therefore the controller is run in a standby mode. The set point values are entered manually, but as they represent parameters in the controller, it is easy to acquire them as an input signal. The needed conversion can be easily implemented.

In this section, two different tests are described. Firstly, the MIMO controller is tested and, secondly, a pressure control is run, with the existing controller for the mass flow. The latter test is important, as it demonstrates that a better pressure control leads to less variations in the mass flow, although the controller for the mass flow has not been changed. Furthermore, the couplings in the plant dynamics can be illustrated by this test too, since there would be no change in the control of the mass flow otherwise.

In the following four controllers are compared to each other :

1. Existing controller (PI). This controller is referred to as *old PI controller*.
2. Existing controller (PI, better tuned). In the course of project, the tuning of

Figure 7.1: Principle diagram of the set up for the practical tests

the PI controller has been improved. Naturally, this one is denoted as *new PI controller* in the comparative study.

3. Combined controller (LQG-design). The model-based controller from the preliminary study [12] is used to control the vessel pressure and the existing controller for the mass flow is used. All curves of this control solution are entitled *combined controller*.
4. MIMO controller (LQG-design). As this controller is completely model-based the curves are entitled *model-based controller*

figure 7.2 depicts performance for each controller. As expected, the MIMO controller yields the best result. This can also be seen by comparing the pressure deviation, (figure 7.3). Examining the estimated coal mass flow in figure 7.4 leads, in principal, to the same conclusion. Though, comparing the combined controller (only the pressure controller is changed) with the MIMO controller reveals an interesting effect. The coal mass flow in case of either controller is almost equally good. The only difference is that the MIMO controller seems to be somewhat faster than the combined one.

From the experiments on the plant, it becomes clear that in the process there exist strong dynamic couplings that can not be neglected in the controller design. Although

Figure 7.2: Comparison of the mass deviation of the four controllers.

	old PI	new PI	Combined	MIMO
mass $[kg]$	51.8	11.3	6.8	1.5
pressure $[kPa]$	5.1	5.1	1.0	1.0
mass flow $[\frac{t}{h}]$	1.8	1.6	0.9	1.0

Table 7.1: Standard deviations of all control results

the mass flow control has not been changed, the overall controller performance becomes better because of a tighter pressure control loop.

Table 7.1 shows the standard deviations achieved by the corresponding controllers. Once again, it can be seen that the MIMO controller produces the best results.

Performance improvements achieved by the MIMO controller compared to the new PI controller are given in Table 7.2.

Figure 7.3: Comparison of the pressure deviation of the four controller.

Figure 7.4: Comparison of the estimated mass flow of the four controllers

	Improvement
mass	79%
pressure	86%
mass flow	35%

Table 7.2: Control performance improvements

Chapter 8

Recommendations

1. Implementation of the designed MIMO controller

2. Introduction of video monitoring

Since the coal mass flow distribution and the injection of the pulverized coal in the blast furnace are not observable, video monitoring presents a tool to ensure process safety.

3. Purchase of coal mass flow meters

Controller design based on a coal mass flow measurement can additionally increase the control performance improvements.

Chapter 9

Conclusions and Outlook

The coal injection plant at SSAB Tunnplåt, Luleå is analyzed, and the used control strategies studied. Identification and control of the coal injection process are discussed. By means of modern identification tools, models for the plant are developed. The LQG design method is applied for the controller design.

It is shown that by use of model-based designs, the flow and pressure control of the coal injection vessel could be significantly improved. With the new control, the coal mass flow can be used as a control parameter for the blast furnace. High injection rates can be used and more coke substituted.

Since neither SattCon nor AlCont provides a possibility to implement a model based MIMO controller, a separate industrial controller is needed. In a future work, it could be analyzed what structure is needed and how the controller can be incorporated into the existing control system. Furthermore, the models have to be validated on injection vessel S22.

Concerning the validation of the estimated mass flow, it is necessary to investigate the behavior of the coal particle cloud in the blast furnace raceway more accurate. In a future work, a model for the behavior of the particle cloud is to be developed and the results should be compared with the already found results. As video monitoring of the particle cloud is involved, the implementation of the video signal in the controller structure as an additional sensor signal has to be discussed.

The existing and measurable disturbances like pressure in the nitrogen net and the pressure in the nitrogen net have to be modelled. These disturbances are neglected in the presented solution.

In a separate Master's Thesis, [8], Andreas Johansson and Annika Bäckström have

developed a gas leakage detection system. They have proved it's usefulness. How this detection system is influenced by the MIMO controller has to be analyzed. It is also important to discuss the possibility of implementing fault detection algorithms in the existing controller structure. The result would be a fault tolerant control unit.

Robustness of the designed controller has to be analyzed, too, since parameter changes in the model can significantly effect the control performance. The parameters changes in the plant have to be analyzed and effects on the controller have to be determined. A more robust controller has to be designed.

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Appendix A

Table of Symbols

A.1 Indices and Abbreviations

a	: augmented system
BMH	: Babcock international Materials Handling Division
c	: controller related
C	: coal
e	: estimator related
f	: flow
FCV	: flow control valve
LQG	: linear quadratic gaussian
m	: mass
MIMO	: multiple input, multiple output
N	: nitrogen
p	: pressure related
PCI	: pulverized coal injection
PCV	: pressure control valve
r	: reduced order
SISO	: single input, single output
t	: transformed
T	: transportation pipe
u	: input related

A.2 Variables

a_{ijk}	: coefficients of the polynomial matrix $\mathbf{A}$
$\mathbf{A}$	: polynomial matrix of the ARX model
$\mathbf{A}_{cont}$	: continuous-time system matrix
b_{ijk}	: coefficients of the polynomial matrix $\mathbf{B}$
$\mathbf{B}$	: polynomial matrix of the ARX model
$\mathbf{B}_{cont}$	: continuous-time system matrix
$\mathbf{C}$	: discrete-time system matrix
$\mathbf{C}_{cont}$	: continuous-time system matrix
$\mathbf{\Gamma}$	: discrete-time system matrix
$\mathbf{D}$	: discrete-time system matrix
$\mathbf{D}_{cont}$	: continuous-time system matrix
Δt	: sampling time
$\boldsymbol{\varepsilon}$	: modelling error vector
$\mathbf{F}$	: process model matrix
$g_{FCV,u}, g_{FCV,p}$	: valve functions of the flow control valve
$g_{PCV,u}, g_{PCV,p}$	: valve functions of the pressure control valve
h	: input transformation
h^{-1}	: inverse input transformation
H_{cheb}	: transfer function of the Chebyshev filter
k_N	: valve coefficient of the flow control valve
k_C	: valve coefficient of the pressure control valve
m	: mass of the injection vessel
m_N	: nitrogen mass
m_C	: coal mass
na	: order of the denominator polynomials

nb	: order of the nominator polynomials
N	: number of samples
p	: pressure in the injection vessel
p_i	: model poles
p_N	: pressure in the nitrogen net
p_T	: pressure in the transportation pipe
Φ	: discrete-time system matrix
φ	: measurement data vector
$\mathbf{Q}$	: weighting matrix
$\mathbf{R}$	: weighting matrix
T	: temperature in the injection vessel
$\mathbf{T}$	: transformation matrix
Θ	: parameter matrix
$\hat{\Theta}$	: estimated parameter matrix
$\mathbf{u}$	: input vector
u_C	: opening of the FCV (transformed)
$u_{C,FCV}$	: physical opening of the FCV
u_N	: opening of the PCV
$\mathbf{u}^*$	: steady-state input vector
V	: volume of the injection vessel
V_C	: coal volume
V_N	: nitrogen volume
$\mathbf{x}$	: state vector
$\mathbf{x}^*$	: steady-state state vector
$\mathbf{y}$	: output vector
$\mathbf{y}^*$	: steady-state output vector

A.3 Constants

R_N	: gas constant of nitrogen
ρ_C	: density of coal

Appendix B

Flow chart of the injection process

As not all process concern the injection process, only three flow charts are displayed. The first, figure B.1, describes the start-up procedure for the coal injection plant. The incoming signal B , is a result from the flow chart in figure B.2, describing the start-up conditions for the hydraulic system. If the hydraulic system is not starting up correctly then the injection process cannot start.

Finally figure B.3 shows, how the injection process is working. Unfortunately this flow chart does not describe the actual structure, as only one pressure control unit is mentioned in it. But this has no effect on the principle process flow.

Figure B.1: Flowchart of the start-up procedure for the coal injection plant

Figure B.2: Flow chart for the hydraulic start-up conditions

Figure B.3: Flow chart for the injection process

Appendix C

Validation with statistical tests

Since the model has two inputs and outputs, three additional correlation functions have to be computed. At first the output residuals are computed and autocorrelated; next the output residuals are cross correlated with the inputs. Although the cross correlation test is not that reliable in closed loop, the results are displayed here.

A Look at the autocorrelation functions might lead to the conclusion that the model should be rejected. But as seen in the common test, the simulated output follows the measured output well. Therefore the model is accepted.

Figure C.1: Autocorrelation of pressure residuals and cross correlation of pressure residuals with PCV. Confidence levels (dotted), correlations functions (solid).

Figure C.2: Autocorrelation of pressure residuals and cross correlation of pressure residuals with FCV. Confidence levels (dotted), correlations functions (solid).

Figure C.3: Autocorrelation of mass residuals and cross correlation of mass residuals with FCV. Confidence levels (dotted), correlations functions (solid).

Figure C.4: Autocorrelation of mass residuals and cross correlation of mass residuals with PCV. Confidence levels (dotted), correlations functions (solid).