Dynamic modelling of a Cheng Cycle

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Computational Mechanics

Dynamic Modelling of a Cheng Cycle

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Abstract

A Cheng Cycle cogeneration plant consists of a Steam Injected Gas Turbine (StIG) and a Heat Recovery Steam Generator (HRSG). Purpose of the installation is to supply a process with electricity and steam. Electricity is generated by the gasturbine, steam is produced in a drum-boiler system. The main feature of the power plant is that a part of the steam can be injected into the combustion chamber of the gasturbine in order to bring about an increase in electrical power. A Cheng Cycle allows for a flexible coupling between steam and electricity production.

The aim of the design project is to develop a model for the Cheng Cycle. The model describes the relations between the system variables by means of a differential equation. The model takes the interactions between the multiple inputs and multiple outputs into account and does not neglect nonlinear effects.

Measurement data have been collected at an industrial scale Cheng Cycle plant. The I/O data were obtained from normal operating records. Based on these data dynamic models for parts of the system have been derived. The approaches followed are known as black box system identification and first principles modelling.

Black box models describe the system dynamics through a linear, time-invariant vector difference equation of finite dimension. This equation is not based on physical grounds. The model parameters are estimated by minimizing a scalar function of the prediction errors, i.e. the difference between the observed output and the by the model predicted output.

First principles models are derived from conservation laws on mass, momentum and energy. In this case the model parameters are derived from construction drawings. From steam tables constitutive equations have been derived relating the properties of steam and water to the state variables.

For the gasturbine and the superheater/supplementary burner part of the Cheng Cycle black box system identification is used. These separately developed models have been combined into a single model. For the drum-boiler part of the Cheng Cycle the first principles approach is used. The grey model of the Cheng Cycle as a whole is composed of the model for the gasturbine/superheater/supplementary burner and the model for the drum-boiler.

With respect to the goals of the design project it may be concluded that the models developed take into account the interactions in the process. The black box models are linear models, only the drum-boiler model considers the nonlinear system behaviour.
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Chapter 1

Introduction

1.1 Incentive for Dynamic Modelling

In process industry plants and control rooms modern computer technology is used for monitoring and controlling the processes. However, when taking a closer look at how the plant’s processes are controlled, it is not seldom encountered that the algorithms are of the classical PID (proportional, integral and differential) type. The tuning of these controllers is performed on the basis of experience, trial-and-error methods or tuning techniques. Though embedded in state-of-the-art hardware, these control techniques date from the 40’s and 50’s, and by applying them we ignore several decades of progress in control theory.

It seems worthwhile to investigate whether modern control can match or even improve the performance of classical control. Modern control techniques can deal with interactions between the multiple in- and outputs, nonlinear and instationary system behaviour or model uncertainties. Classical control techniques require the system to be linear and assume to have only one input effect only one output. As most of the modern control techniques are model based, dynamic process models are required. The obvious choice for the class of models is given by state-space or to state-space transformable representations, since most of the modern available control theory regards these representations. Other kinds of models may excellently describe plant phenomena, but can be unsuitable for control purposes.

The system to be modelled is a steam and electricity generating power plant in a cardboard producing factory. Steam is needed for drying purposes, while electricity is needed to fulfill the power demand of the machinery. The steam demand can vary drastically: in case of a malfunction in the production process, for example a rupture of the cardboard sheet, and that happens on average a few times a day, the steam demand declines, while extra electrical energy is needed to restart the process.

In order to design a modern controller for the plant a dynamic model is required that can deal with the transient system behaviour described above. In the next section we will describe the way steam and electricity are produced and in the last section of this chapter we will outline how the development of a control model will be done.
CHAPTER 1. INTRODUCTION

1.2 System Description

In a cogeneration plant electricity (power) and steam (heat) are generated simultaneously in a single installation. In many cases, this is done by a gasturbine driving a generator. While the generator takes care of the electricity production, the heat of the exhaust gases from the gasturbine is used in a waste heat boiler where steam is generated. However, for a cogeneration plant of the type Cheng Cycle, the gasturbine is of a special kind. A variable part of the generated steam can be injected into the gasturbine's combustion chamber, by that increasing the mass flow through it, and as a result producing additional work. This is called a Steam Injected Gas Turbine (StIG). The main application of steam injection into gas turbines was, until recently, to reduce the NO\textsubscript{2}-emissions, but in the case of a StIG the injection of steam is meant to make the power plant flexible in offering process steam and electricity at a freely to be chosen ratio within the operating range of the plant.

A scheme depicting the process in a Cheng Cycle is shown in Fig. 1.1. Air is compressed in the compressor. In the combustion chamber the temperature of the air and the injected steam is raised by burning a gaseous fuel. Subsequently, the mixture of steam and combustion gases expands, and the power delivered by the expander is used to drive the compressor and the generator. The exhaust gases flow through the superheater and via the supplementary burner to the evaporator. During this course the exhaust gas' heat is transferred to the steam.
and water. In the supplementary burner the temperature of the combustion gases is raised again in order to increase the gas’ energy contents, and so the steam producing capability of the gas in the evaporator is maintained. The exhaust gases preheat the feedwater in the economizer and leave the system through the stack.

The feedwater enters the plant via the economizer and flows into a drum. From the drum the water heads to the evaporator where steam is generated. The steam-water mixture is led from the evaporator back into the drum and separated. From the drum the steam can either be directed towards the process, or it can be injected into the gasturbine. Before the steam is injected into the combustion chamber, it passes the superheater.

1.3 Modelling Techniques

A way to distinguish the techniques used when modelling dynamic processes is to picture them on a scale with at the ends two extremes: at the one side black box system identification, and at the other side theoretical modelling.

In black box system identification, a model class is posited, which does not reflect the internal structure of the process. The model parameters are estimated from the observed data using an optimisation technique for minimising a criterion of the misfit between the behaviour of the model and the behaviour of the process. In order to parameterize a black box model only the input-output behaviour is required; detailed knowledge about the internal behaviour is not necessary. Black box models usually have a linear structure, and because of this built-in linearity they have a limited validity range. Within this range black box models have shown to be effective for the purpose of prediction and controller design.

In theoretical modelling, or first principles modelling, basic laws from thermodynamics, together with empirical relations are used to construct a model. Then, detailed knowledge about the physical phenomena involved is required, and because of the model’s on physics based fundament the states and parameters have a direct interpretation. However, states might be hard to identify and parameters might be hard to identify without estimation procedure or adapting algorithm. Often the physics behind the process is complex, e.g. the dynamic behaviour is described by a partial differential equation. In that case simplifying assumptions are made in order to write down ordinary differential equations and avoid the area of control theory concerning systems described by partial differential equations.

1.4 Outline of this Report

Chapter 2 presents the so-called black box approach. It is used for modelling the dynamic behaviour of the gas turbine and the superheater/supplementary burner. In this approach parameters are identified in linear models with no physical interpretation, and prior knowledge is not used. We use this approach because we think that the system behaviour within the operating range of interest can be well captured by a linear model.
In Chapter 3 the modelling problem for the drum-boiler dynamics is tackled by using white box techniques. In this case model development is based on conservation laws of mass, momentum and energy. The system equations allow for a physical interpretation and the model parameters are obtained from construction data and steam tables. Here the white box approach is used because we think that the internal behaviour, more specifically the process of steam generation, has such a nonlinear nature that the black box approach will not suffice.

In Chapter 4 the separately developed models, black models for the gas turbine and superheater/supplementary burner and a white model for the drum-boiler, are combined into a grey model for the Cheng Cycle as a whole.

Finally, in Chapter 5 conclusions are drawn and recommendations for future investigations are given.
Chapter 2

Black Box System Identification

This chapter deals with the parametric identification of dynamic models for the Steam Injected Gas Turbine and the Superheater/Supplementary Burner according to the so-called black box approach. Black box models are not based on physical principles. They describe the system dynamics through a linear, time-invariant vector difference equation of finite dimension. The model parameters are estimated by minimizing a scalar function of the prediction errors, i.e. the difference between the observed output and the by the model predicted output. In this chapter we will show how based on (1) the observed data, (2) an adopted model set and (3) a loss function models are parametrized and validated. Before we come to the identification part we will give an overview of the Cheng Cycle as a system with the signals available from measurements, and motivate our choice for the division into subsystems.

2.1 Division of the Cheng Cycle into Subsystems

Figure 2.1 presents a scheme indicating which signals are accesible for measurement. This scheme is a major simplification of the original Process and Instrumentation Diagram. Simplification has been performed by omitting

- drawing numbers
- line diameters and specifications
- normally closed valves, safety relief valves and reducers
- supplier limits

Furthermore, the symbols used here are not according to DIN- or ISO-standards. This abuse of representation should not create any misinterpretation. The following letter codes are used:

- \( p \): pressure
- \( f \): flow
- \( T \): temperature
- \( l \): level
- \( P \): power
Let's consider the Cheng Cycle as a system built up from several subsystems in interaction. The choice of where to define the subsystem’s borders is quite arbitrary. For example, the compressor could be taken as a subsystem: the input signal is the pressure of the air at the compressor inlet, the output signal is the pressure of the air at the compressor outlet. One could also consider the gas turbine as a subsystem: an input signal is the fuel flow to the combustion chamber, an output signal is the electrical power provided by the generator. Aiming at a division of the Cheng Cycle into the smallest component levels is not preferred because the model complexity increases accordingly. In a division too coarse the required accuracy might be lost. In view of the signals measured at the power plant and the objective of the modelling, i.e. modelling for control, we consider the Cheng Cycle built up from

- Steam Injected Gas Turbine
- superheater/supplementary burner
- drum-boiler
- economizer
2.2 Prediction Error Method

A steady state first principles analysis of the gasturbine and the superheater/supplementary burner shows a nonlinear behaviour. Nonlinear dynamic modelling via the black box principle in the form of a neural network, or via first principles in the form of conservation laws is worth investigating. We, however, assume that a linear model is justified, because the plant mainly operates around a stationary working point. We have chosen for the black box approach because compared to first principles modelling it is less time-consuming and relatively simple. In the next chapter we will focus on the theoretical modelling of the drum-boiler. In the case of the drum-boiler the nonlinear system behaviour cannot be circumvented. Here we shall concentrate on the black box modelling of the gasturbine and the superheater/supplementary burner.

Predictor models provide a prediction of the output $y(k)$, given the data from the past. A linear predictor model is determined by

$$ y(k) = G(q^{-1}, \theta)u(k) + H(q^{-1}, \theta)\varepsilon(k) $$

where

- $k$: discrete time, $k = 1, \ldots, N$
- $\theta$: parameter vector, $\theta \in \mathbb{R}^p$
- $q^{-1}$: unit backward shift operator, $q^{-1}u(k) = u(k-1)$
- $u(k)$: measured input signal, $u(k) \in \mathbb{R}^n$
- $y(k)$: measured output signal, $y(k) \in \mathbb{R}^l$
- $\varepsilon(k)$: sequence of zero mean, independent and identically distributed random variables, $\varepsilon(k) \in \mathbb{R}^l$
- $G(q^{-1}, \theta)$: linear stable filter, $G(q^{-1}, \theta) \in \mathbb{R}^{l \times m}(q^{-1})$
- $H(q^{-1}, \theta)$: linear stable filter, $H(q^{-1}, \theta) \in \mathbb{R}^{l \times l}(q^{-1})$

With $A \in \mathbb{R}^{l \times c}(q^{-1})$ we mean to say that matrix $A$ has $r$ rows and $c$ columns and that each element of $A$ is a ratio of polynomials in $q^{-1}$.

The filters $G(q^{-1}, \theta)$ and $H(q^{-1}, \theta)$ are defined by

$$ G(q^{-1}, \theta) = \sum_{i=0}^{\infty} G_i q^{-i}, \quad H(q^{-1}, \theta) = \sum_{i=0}^{\infty} H_i q^{-i} $$

with $G_0 = 0$ and $H_0 = I$, i.e. $G$ is strictly proper, respectively $H$ monic.

It can be derived that the one-step-ahead prediction of $y(k)$, also denoted $\hat{y}(k | k - 1; \theta)$, is given by (see Appendix A)

$$ \hat{y}(k | k - 1; \theta) = H^{-1}(q^{-1}, \theta)G(q^{-1}, \theta)u(k) + \left[ I - H^{-1}(q^{-1}, \theta) \right] y(k) $$

$$ = W_u(q^{-1}, \theta)u(k) + W_y(q^{-1}, \theta)y(k) $$

where $W_u$ and $W_y$ are stable linear filters.
CHAPTER 2. BLACK BOX SYSTEM IDENTIFICATION

The notation \( \hat{y}(k \mid k-1; \theta) \) might be misleading. The left part of 2.2 states that the predicted output at a certain time \( k \) solely depends on the inputs and outputs at the preceding time instants, while the right part of 2.2 suggests that the in- and output at time instant \( k \) are required in order to compute the prediction \( \hat{y} \). It is easily shown that if \( H \) is monic, also \( H^{-1} \) is monic, and with \( G \) strictly proper, the right hand side of 2.3 will only contain filters depending on \( q^{-1}, q^{-2}, \ldots \), and thus \( \hat{y} \) will only depend on \( u(k-1), u(k-2), \ldots \), and \( y(k-1), y(k-2), \ldots \).

The error made by the predictor is defined as
\[
\varepsilon(k, \theta) = y(k) - \hat{y}(k \mid k-1; \theta) = H^{-1}(q^{-1}, \theta) \left[ y(k) - G(q^{-1}, \theta)u(k) \right]
\]
(2.4)
The model is accurate if it generates "small" prediction errors.

Estimation of the model parameters on the basis of these prediction errors is performed through minimization of a scalar-valued function of \( \varepsilon(k, \theta) \) over \( \theta \). This function \( V_N \) is defined by
\[
V_N(\theta, Z_N) = \frac{1}{N} \sum_{k=1}^{N} \varepsilon^T(k, \theta)W(k)\varepsilon(k, \theta)
\]
(2.5)
the estimated parameter vector \( \hat{\theta} \) is obtained through
\[
\hat{\theta} = \arg \min V_N(\theta, Z_N)
\]
(2.6)
where \( Z_N = \{u(n), y(n) \mid n = 1, \ldots, N\} \)
We see no reason for not weighting each element of \( \varepsilon \) equally in the criterion and constant in the time interval. Therefore, the symmetrical positive definite weighting matrix \( W \) is chosen equal to the identity matrix, i.e. \( W = I \).

A quantity to 'measure' the performance is the relative output error \( ROE \). For each element of the output vector it is defined as
\[
ROE = \frac{1}{N} \sum_{k=1}^{N} \left[ \frac{y(k) - G(q^{-1}, \hat{\theta})u(k)}{\frac{1}{N} \sum_{k=1}^{N} y^2(k)} \right]^2
\]
(2.7)

2.3 Identification Results for the StiG

For the StiG (see Fig. 2.2) the following I/O data were available and grouped into the input vector \( u \) with
\[
\begin{align*}
  u_1 &= m_{\text{fuel,cc}}: \quad &\text{fuel flow to the combustion chamber (see Fig. B.1)} \\
  u_2 &= m_{\text{steam, inj}}: \quad &\text{steam flow to the combustion chamber (see Fig. B.2)} \\
  u_3 &= T_{\text{steam, inj}}: \quad &\text{temperature injection steam (see Fig. B.3)}
\end{align*}
\]
and the output vector \( y \) with
\[
\begin{align*}
  y_1 &= P_d: \quad &\text{electrical power produced by the generator (see Fig. B.4)} \\
  y_2 &= T_{\text{turb, out}}: \quad &\text{turbine outlet temperature (see Fig. B.5)}
\end{align*}
\]
These I/O data were obtained from normal operating records and acquired with a time interval of 60 [s]. No use was made of particular inputs such as impulse functions, step functions or PRBS \(^1\). Persistence of excitation of the input signals is guaranteed. It can be shown that for each input a symmetric Toeplitz matrix can be constructed from the auto-correlaton sequence of that input, and that the Toeplitz matrix is nonsingular. We will not digress on this topic here. For a formal proof of the method we refer to [Ljung, 1987]. We conclude that the input signals are able to extract sufficient information from the plant concerning its dynamics.

Outliers and the linear trend have been removed from the sequence and the signals have been compensated for their mean. In order to identify a model, the set of observed data \(Z_N\) is divided into an estimation part and a validation part. The estimation part is used for the model building, the input data from the validation set are fed into the model and the simulated output is checked against the observed output.

There exists a number of model structures applied in black box system identification. Without further proof we follow the recommendations in [Zhu and Backx, 1993, Sect. 5.4.2] and [Rijnsdorp, 1994] and use a model with the so-called ARMAX structure. According to their experience ARMAX models are very suitable for controller design techniques. The ARMAX model is a special case of the general predictor model given in 2.1 and is described by

\[
A(q^{-1}, \theta) y(t) = B(q^{-1}, \theta) u(t) + C(q^{-1}, \theta) e(t)
\]  

(2.8)

The acronym ARMAX is explained as follows:

- **AR** refers to the AutoRegressive part \(A(q^{-1}, \theta) y(t), A(q^{-1}, \theta) \in \mathbb{R}^{l \times l}(q^{-1})\)
- **MA** refers to the Moving Average part \(C(q^{-1}, \theta) e(t), C(q^{-1}, \theta) \in \mathbb{R}^{l \times m}(q^{-1})\)
- **X** refers to the exogenous part \(B(q^{-1}, \theta) u(t), B(q^{-1}, \theta) \in \mathbb{R}^{l \times m}(q^{-1})\)

\(^1\)PRBS (Pseudo Random Binary Sequence): binary noise signal added to the input signal in order to increase the input signal's information content.
Note that $A(q^{-1}, \theta)$, $B(q^{-1}, \theta)$ and $C(q^{-1}, \theta)$ contain polynomials in $q^{-1}$ with degrees $n_a, n_b$ and $n_c$ and that the loss function $V_N$ decreases as the orders $n_{a,b,c}$ increase. To obtain a model as simple as possible, yet accurate enough for control purposes, the loss function $V_N$ is computed as a function of $n_{a,b,c}$ and those values for $n_{a,b,c}$ are selected for which $V_N$ stops decreasing significantly.

Figure 2.3 to 2.6 present the fit of the StIG model on the estimation and validation interval. The solid lines denote the observed output, the dashed line the simulated output. In Table 2.1 and Table 2.2 the modelling results for the electrical power $P_{el}$ and the turbine outlet temperature $T_{turb,out}$ are given. The relative output error is small indicating that the process dynamics can be well described by a linear model (at least within the operating range of 2 [MWe] for the electrical power and 100 [°C] for the turbine outlet temperature). In the experience of [Zhu and Backx, 1993, Sect. 4.2.3] a proper threshold for the relative error for purposes such as feedback control and simulation is between 10% and 20%; the output error is small enough to consider the model reliable for simulation and controller design. System identification has been done using MATLAB.


Table 2.1: modelling results $P_{el}$

<table>
<thead>
<tr>
<th></th>
<th>ARMAX</th>
<th>ROE</th>
</tr>
</thead>
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<tr>
<td>na</td>
<td>3</td>
<td>6</td>
</tr>
<tr>
<td>nb</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>nc</td>
<td>0.5%</td>
<td>0.6%</td>
</tr>
</tbody>
</table>

Table 2.2: modelling results $T_{turb, out}$

<table>
<thead>
<tr>
<th></th>
<th>ARMAX</th>
<th>ROE</th>
</tr>
</thead>
<tbody>
<tr>
<td>na</td>
<td>3</td>
<td>6</td>
</tr>
<tr>
<td>nb</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>nc</td>
<td>4.3%</td>
<td>4.4%</td>
</tr>
</tbody>
</table>
2.4 Identification Results for the Superheater/Supplementary Burner

For the superheater/supplementary burner the following I/O data were available and grouped into the input vector $u$ with

- $u_1 = T_{turb, out}$: turbine outlet temperature (see Fig. C.1)
- $u_2 = p_{drum}$: drum pressure (see Fig. C.2)
- $u_3 = m_{fuel, suppl}$: fuel flow to supplementary burner (see Fig. C.3)
- $u_4 = m_{steam, inj}$: steam flow to the combustion chamber (see Fig. C.4)

and the output vector $y$ with

- $y_1 = T_{steam, inj}$: temperature injection steam (see Fig. C.5)
- $y_2 = T_{exh, ev, in}$: temperature exhaust gas before evaporator (see Fig. C.6)

![Figure 2.7: Superheater/Supplementary Burner](image)

The identification procedure for the superheater/supplementary burner model is the same as for the StIG model. The model fit on the estimation and validation interval are shown in Fig. 2.8 to Fig. 2.11. The solid lines denote the observed output, the dashed lines denote the simulated output. The results concerning the relative output error for the injection steam temperature and exhaust gas temperature are given in the first row of Table 2.3 and Table 2.4. The value of the relative output error is also in this case within the range indicated in [Zhu and Backx, 1993, Sect. 4.2.3]; a linear model captures the process dynamics sufficiently well. For the model misfit at sample 800 in the validation interval of the exhaust gas temperature (Fig. 2.11) we do not have a proper explanation. It might be caused by the high absolute value of the amount of steam injection, or the sudden drop from maximum to minimum steam injection (see Fig. C.4). This should be further investigated.
The relative output error in case the by the StIG model calculated turbine outlet temperature is fed as input into the superheater-supplementary burner model is given in the second row of Table 2.3 and Table 2.4. The relative output errors are in the same order of magnitude. Apparently, the establishment of a coupling between the models via the turbine outlet temperature is allowed. We will focus on this coupling in the next section.
CHAPTER 2. BLACK BOX SYSTEM IDENTIFICATION

Figure 2.8: fit on estimation interval

Figure 2.9: fit on validation interval

Figure 2.10: fit on estimation interval

Figure 2.11: fit on validation interval

<table>
<thead>
<tr>
<th>temperature injection steam</th>
<th>temperature exhaust gas</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARMAX</td>
<td>ROE</td>
</tr>
<tr>
<td>na</td>
<td>nb</td>
</tr>
<tr>
<td>7</td>
<td>7</td>
</tr>
</tbody>
</table>

Table 2.3: modelling results $T_{steam,inj}$

Table 2.4: modelling results $T_{exh,ev,in}$
2.5 A Combined Black Box Model

In order to take into account the effects of variations in the turbine outlet temperature on the temperature of the injection steam the models proposed in Section 2.3 and 2.4 need to be combined. The coupling is accomplished by connecting the separate models for the StIG and superheater/supplementary burner according to the following scheme (see Fig. 2.12). The input vector \( u \) for the combined model consists of

\[
\begin{align*}
  u_1 &= \dot{m}_{\text{fuel,cc}}: & \text{fuel flow to the combustion chamber} \\
  u_2 &= \dot{m}_{\text{steam, inj}}: & \text{steam flow to the combustion chamber} \\
  u_3 &= p_{\text{drum}}: & \text{drum pressure} \\
  u_4 &= \dot{m}_{\text{fuel, supp}}: & \text{fuel flow to supplementary burner}
\end{align*}
\]

The output vector \( y \) consists of

\[
\begin{align*}
  y_1 &= P_{\text{el}}: & \text{electrical power generator} \\
  y_2 &= T_{\text{steam, inj}}: & \text{temperature injection steam} \\
  y_3 &= T_{\text{exh, ev, in}}: & \text{temperature exhaust gas before evaporator}
\end{align*}
\]

The validation results for the combined model are depicted in Fig. 2.13 to Fig. 2.16. The solid lines denote the observed output, the dashed lines denote the simulated output. Compared to the output errors obtained when neglecting the interactions between the systems, the coupling has had a benefit on the total result; the relative output error for the injection steam temperature has decreased significantly (see Table 2.5).
CHAPTER 2. BLACK BOX SYSTEM IDENTIFICATION

Figure 2.13: combined model: $P_{el}$

Figure 2.14: combined model: $T_{turb, out}$

Figure 2.15: combined model: $T_{steam, inj}$

Figure 2.16: combined model: $T_{exh, ev, in}$

<table>
<thead>
<tr>
<th>output</th>
<th>ROE - separate models</th>
<th>ROE - combined model</th>
</tr>
</thead>
<tbody>
<tr>
<td>electrical power generator</td>
<td>0.6%</td>
<td>0.6%</td>
</tr>
<tr>
<td>turbine outlet temperature</td>
<td>4.4%</td>
<td>3.6%</td>
</tr>
<tr>
<td>temperature injection steam</td>
<td>2.9%</td>
<td>0.8%</td>
</tr>
<tr>
<td>temperature exhaust gas</td>
<td>10.9%</td>
<td>7.6%</td>
</tr>
</tbody>
</table>

Table 2.5: results separate models and combined model
Case 1: An Increase in Electrical Power

The aim of this case is twofold. First, we would like to demonstrate the attractiveness of a Multi Input Multi Output (MIMO) approach by showing that there are interactions that would remain hidden in a Single Input Single Output (SISO) approach. Second, although black box models are not based on physics they might provide "white box" insight.

Suppose that a situation occurs where more electrical power is needed, e.g. a rise of 1 [MWe] is required. A possible solution is to increase the fuel flow to the combustion chamber and keeping the amount of injected steam at a constant level. In case there is a surplus of process steam another solution is possible. The same power incline can be realised by raising the amount of steam injected into the combustion chamber and keeping the fuel flow at a constant level. Responses are shown in Fig. 2.17 to Fig. 2.20. The solid lines represent the responses when the fuel flow to the combustion chamber is stepwisely raised with 330 [m³/hr]. The dashed lines show the responses when the amount of injection steam is stepwisely increased with 6 [ton/hr]. The dash-dotted lines depict the responses when a step of 100 [m³/hr] is applied in the fuel flow to the supplementary burner. In each 'experiment' the remaining inputs are kept constant. These step amplitudes have been obtained after some 'experiments'.

In the first two cases the required power level is reached with admissible overshoot. The responses for the turbine outlet temperature, however, indicate that it is worthwhile to look for control algorithms manipulating the inputs such that a more elegant response, i.e. with less overshoot/undershoot, is obtained. In a SISO approach with only the electrical power of the generator as output, the overshoot in the turbine outlet temperature would have remained unnoticed. We fail to reply why the system responds like an undercritically damped second order system or why the model is erroneous. The fundamental data were sampled at 60 [s] so it is unlikely that the 'fast' phenomena will be represented well by the model.

It is not likely that the outputs of the StIG or the injection steam temperature can be influenced by a change in the fuel flow to the supplementary burner. Simulations show (Fig. 2.20) that only in the exhaust gas temperature there is a significant effect, as expected.
CHAPTER 2. BLACK BOX SYSTEM IDENTIFICATION

Figure 2.17: step response: power generator

Figure 2.18: step response: turb outlet temp

Figure 2.19: step response: temp inj steam

Figure 2.20: step response: temp exhaust gas
CHAPTER 2. BLACK BOX SYSTEM IDENTIFICATION

2.6 Conclusions and Discussion

Our aim was to find a dynamic model for the gasturbine and superheater/supplementary burner. To develop these models we used the black box approach. The largest relative output error encountered when identifying the models separately is 11%. The establishment of a coupling between the models, and thus bringing the models more in accordance with the physical reality, has had a benefit on the total result. The relative output error for the temperature of the injection steam decreased significantly. The largest relative output error encountered when identifying the combined model is 8%. In the experience of [Zhu and Backx, 1993, Sect. 4.2.3] a proper threshold for the relative error for purposes such as feedback control and simulation is between 10% and 20%. We conclude that the combined model for the StIG/superheater/supplemental burner captures the system dynamics sufficiently accurate.

We have shown that the multi-input multi-output (MIMO) modelling approach renders more insight in the dynamics of the process than the classical single-input single-output (SISO) counterpart, for in the MIMO case the interactions within the system are taken into account. Further, we demonstrated that also the interactions between systems need to be considered. It was shown that taking in consideration the mutual influences between the gas-turbine and the superheater/supplementary burner resulted in a lower relative output error.

The model is linear, in practice this means that the model’s validity range is restricted to a limited area around a working point. It should be investigated whether the model performance is maintained in larger areas.
Chapter 3

First Principles Modelling

This chapter presents the theoretical modelling of the drum-boiler of the Cheng Cycle. In contrast to the black box models described in the previous chapter this model is nonlinear and is derived from first principles using construction data and steam tables. We owe this model to [Åström and Bell, 1988]. We report how the derivation of the state equation describing the drum-boiler dynamics is done, subsequently, we present the assumptions made and confront the model data with real life plant data. In the last section conclusions are drawn.

3.1 State Space Representation of the Drum Boiler

3.1.1 Energy Balance Drum-Boiler

The total steam volume in the drum-boiler $V_{st}$ consists of the steam volume in the drum $(V_{drum} - V_w)$ and the steam volume in the riser $a_m V_r$ (see Fig. 3.1), and is given by

$$V_{st} = V_{drum} - V_w + a_m V_r$$  \hspace{1cm} (3.1)

with

- $V_{drum}$: drum volume
- $V_w$: water volume in the drum
- $V_r$: riser volume
- $a_m$: ratio of the steam volume in the riser and $V_r$

The total water volume in the drum-boiler $V_{wt}$ consists of the water volume in the drum $V_w$, the water volume in the downcomer $V_{dc}$ and the water volume in the riser $(1 - a_m) V_r$ (see Fig. 3.1), and is given by

$$V_{wt} = V_w + V_{dc} + (1 - a_m) V_r$$ \hspace{1cm} (3.2)

with

- $V_{dc}$: volume of the downcomer
Applying the conservation principle to the energy in the drum-boiler gives

\[
\frac{d}{dt} \left( \rho_s h_s V_{st} + \rho_w h_w V_{wt} + m c T \right) = P + q_{fw} h_{fw} - q_s h_s \tag{3.3}
\]

with
- \( \rho \): density
- \( h \): enthalpy
- \( V \): volume
- \( m \): total mass metal
- \( c \): specific heat metal
- \( T \): average metal temperature
- \( q \): mass flow
- \( P \): input power

The subscripts \( s, w \) and \( fw \) denote respectively, steam, water and feedwater. An energy balance in state space format with state vector \( x^T = [p, V_w, x_r] \) and \( p, V_w, \) and \( x_r \) denoting respectively the drum pressure, the water volume in the drum and the steam quality at the riser outlet can be derived as follows. For simplicity, the drum pressure is considered uniform throughout the drum and all liquid resides at the bottom of the drum and gas at the top.

Assumption 1 \( a_m = a_m(x_r) \), saying that the average steam-water volume ratio in the riser \( a_m \) is related to the steam-water mass ratio at the riser outlet \( x_r \).

Assumption 2 \( [\rho_s, \rho_w, h_s, h_w, T = T_{sat}] = [\rho_s, \rho_w, h_s, h_w, T = T_{sat}] (p) \), in words rephrased, the system is in thermal equilibrium and only one variable is necessary and sufficient to define the water and steam properties. This variable is chosen to be the drum pressure \( p \). The temperature of the metal parts equals the steam saturation temperature.
CHAPTER 3. FIRST PRINCIPLES MODELLING

Using Ass. 1, Ass. 2 and substituting (3.1) and (3.2) in (3.3), the energy balance for the drum-boiler can be written into

\[ \frac{d}{dt} \left( e_{11} \frac{dp}{dt} + e_{12} \frac{dV_w}{dt} + e_{13} \frac{dx_r}{dt} \right) = b_1 \]  

(3.4)

with

\[ e_{11} = \frac{d}{dp} (h_s \rho_s) V_{st} + \frac{d}{dp} (h_w \rho_w) V_{wt} + mc \frac{dT}{dp} \]
\[ e_{12} = (\rho_w h_w - \rho_s h_s) \]
\[ e_{13} = (\rho_s h_s - \rho_w h_w) V_r \frac{da_m}{dx_r} \]
\[ b_1 = P + q_{fw} h_{fw} - q_s h_s \]

3.1.2 Mass Balance Drum-Boiler

Application of the conservation principle to the mass in the drum-boiler (see Fig. 3.1) yields

\[ \frac{d}{dt} \left[ \rho_s V_{st} + \rho_w V_{wt} \right] = q_{fw} - q_s \]  

(3.5)

By using Ass. 1, Ass. 2 and substituting (3.1) and (3.2) in (3.5), this mass balance can be written as

\[ \frac{d}{dt} \left( e_{21} \frac{dp}{dt} + e_{22} \frac{dV_w}{dt} + e_{23} \frac{dx_r}{dt} \right) = b_2 \]  

(3.6)

with

\[ e_{21} = \left( V_{st} \frac{dp_s}{dp} + V_{wt} \frac{dp_w}{dp} \right) \]
\[ e_{22} = (\rho_w - \rho_s) \]
\[ e_{23} = V_r (\rho_s - \rho_w) \frac{da_m}{dx_r} \]
\[ b_2 = (q_{fw} - q_s) \]

3.1.3 Mass and Energy Balance For the Riser

For the riser an energy equation can be derived by combining the mass and energy balance. The mass balance states that

\[ \frac{d}{dt} \left[ \rho_s a_m V_r + \rho_w (1 - a_m) V_r \right] = q_{dc} - q_r \]  

(3.7)

The energy balance yields

\[ \frac{d}{dt} \left[ \rho_s a_m V_r h_s + \rho_w (1 - a_m) V_r h_w \right] = P + q_{dc} h_w - x_r q_r h_s - (1 - x_r) q_r h_w \]  

(3.8)
Multiplying the mass balance (3.7) by \(- (h_w + x, h_c)\) and adding to the energy balance (3.8) yields after some straightforward formula manipulation an energy equation for the riser section in the form of

\[
e^{31} \frac{dp}{dt} + e^{32} \frac{dV_w}{dt} + e^{33} \frac{dx_r}{dt} = b_3
\]  

with \(h_c = h_s - h_w\) and

\[
e^{31} = \left[ (1 - x_r) h_c \frac{dp_s}{dp} + \rho_s \frac{d h_s}{dp} \right] a_m V_r + \left[ \rho_w \frac{dh_w}{dp} - x_h h_c \frac{dp_w}{dp} \right] (1 - a_m) V_r
\]

\[
e^{32} = 0
\]

\[
e^{33} = \left[ (1 - x_r) \rho_s + x_r \rho_w \right] \frac{d a_m}{dx_r}
\]

\[
b_3 = P - x_r h_c q_{dc}
\]

### 3.1.4 State Equation for The Drum-boiler

Summarizing the steps in the modelling of the drum-boiler, we have the following:

- variables denoting the effect of the surroundings on the process; these variables are grouped in the input vector \(u^T = [P \ q_{fw} \ q_s \ h_{fw}]\) with
  - the input power \(P\)
  - the incoming water flow \(q_{fw}\)
  - the outgoing steam flow \(q_s\)
  - the enthalpy of the incoming waterflow \(h_{fw}\)

- parameters characteristic for the drum-boiler system; they are grouped in the parameter vector \(\theta^T = [V_{dum} \ V_r \ V_{dc} \ m \ c \ k]\)

- variables completely defining the mass and energy within the drum-boiler system; these variables are called state variables and are grouped in the state vector \(x^T = [p \ V_w \ x_r].\)
  - drum pressure \(p\)
  - steam quality \(x_r\)
  - water volume in the drum \(V_w\)

The equation that relates the state variables to to the input variables and system parameters is called state equation and is given by

\[
E(x, u, \theta) \dot{x} = b(x, u, \theta)
\]  

with \(E\) and \(b\) defined by Eq. 3.4, Eq. 3.6 and Eq. 3.9.
Assuming \(E^{-1}(x, u, \theta)\) exists, this yields

\[
\dot{x} = f(x, u, \theta)
\]  

\((3.11)\)
3.2 Additional Relations

3.2.1 Steam Tables

From steam tables constitutive equations can be derived relating the properties of water and steam to the state variables.

Second order polynomials have shown to be accurate in order to describe the dependency of the enthalpy, density and saturation temperature of water and steam on the drum pressure in the interval \([10, \cdots, 16]\) [bar] (see App. E).

3.2.2 Steam Quality

We have assumed that \(a_m = a_m(x_r)\). In this section we will derive this relation under the assumption that the steam quality \(x\) varies linearly along the riser.

The steam quality \(x\) and equivalently, the volume ratio \(a\) are defined as

\[
x = \frac{m_s}{m_s + m_w} \quad a = \frac{V_s}{V_s + V_w}
\]

It is easily derived that

\[
a(x) = \frac{\rho_w x}{\rho_s + (\rho_w - \rho_s)x}
\]

The average volume ratio \(a_m\) is defined as

\[
a_m = \frac{1}{x_r} \int_0^{x_r} a(x) dx
\]

This yields

\[
a_m(x_r) = (1 + \alpha) \left[ 1 - \frac{\alpha}{x_r} \ln(1 + \frac{x_r}{\alpha}) \right], \quad \alpha = \frac{\rho_s}{(\rho_w - \rho_s)}
\]

3.2.3 Water Volume in the Drum

It can be derived from Fig. 3.2 that the water volume in the drum \(V_w\) is given by

\[
V_w = zr^2 (\pi - \arccos \chi + \chi \sqrt{1 - \chi^2})
\]

\[
\chi = \frac{l - z}{r}
\]

with

- \(z\): length of the drum
- \(r\): radius of the circular cross-section of the drum
- \(l\): distance between liquid level and reference plane
- \(y\): distance between reference plane and centerline
3.2.4 Downcomer Flow

The flow through the downcomers \( q_{dc} \) can be obtained from a momentum balance. In natural circulation boilers the flow is driven by the difference between the densities of water and steam. A momentum balance gives

\[
a_m V_r (\rho_w - \rho_s) = \frac{1}{2} k q_{dc}^2
\]

(3.16)

3.3 Simulation Results vs. Plant Data

Unfortunately, not all the variables wanted and required for validation can be derived from plant data. For example, a system parameter such as the friction factor \( k \) in Eq. 3.16 cannot be obtained from available construction data. It’s choice is derived from a steady-state analysis. The numerical values of the model parameters obtained from construction data and used in the simulations are given in App. E. Uncertainties in parameters, however, will not prevent the use of the model in a controller algorithm; modern control theory provides controllers that are robust with respect to parameter mismatch.

Our major difficulty is that a part of the input signal \( u^T = [P \ q_{fw} \ q_s \ h_{fw}] \) cannot be inferred from plant data. Our data set contains the temperature of the exhaust gas when it enters the evaporator, but lacks the outlet temperature and the exhaust gas mass flow. The missing outlet temperature could be set equal to the steam saturation temperature, the mass flow could be computed from a steady-state analysis. Anyhow, the necessary information to determine the input power is missing. As alternative we reconstructed the input power \( P \) by approximating it through its steady-state equivalent, i.e. assuming the input power \( P \) to be proportional to the steam mass flow \( q_s \). The proportionality factor is obtained from Eq. 3.10 by setting \( \frac{dh}{dt}(\cdot) = 0 \). Further we assumed the feedwater enthalpy \( h_{fw} \) to be constant. The following subsections present the confrontation of the plant data with the simulation data.

3.3.1 Drum Pressure

The measured drum pressure (solid) and the simulated drum pressure (dashed) are shown in Figure 3.3. The agreement between plant and model data is bad. The input power \( P \), being the amount of heat transferred per unit of time from the exhaust gas to the water, determines the amount of steam entering the drum, and thus the pressure in the drum. Obviously, our reconstruction of the input power \( P \) is not accurate enough to obtain a reliable simulation result for the drum pressure \( p \).

3.3.2 Water Volume in the Drum

The water volume in the drum (solid) (derived from the measured water level) and the simulated water volume (dashed) are shown in Figure 3.4. The agreement between model data and plant data is slightly better, in spite of the fact that the approximation of the input power was crude. It seems like the amount of water in the drum is less sensitive to inaccuracies regarding the input power than the drum pressure; the input power \( P \) does not play a direct role in the system’s mass balances.
3.3.3 Steam Quality at Riser Outlet

As measurements of the steam quality are not available, no conclusions can be drawn from this simulation, except that it varies within a realistic and acceptable range. The simulated steam quality at the riser outlet \( x_r \) is shown in Figure 3.5.

![Figure 3.3: drum pressure](image)

![Figure 3.4: water volume in the drum](image)

![Figure 3.5: steam quality riser outlet](image)
3.4 Conclusion and Discussion

In this chapter we reported our attempts to develop a dynamic model for the drum-boiler based on first principles. Difficulties encountered concern the quantification of poorly known parameters. The main reason for unsatisfactory model responses is that a part of the input signal could not be inferred from plant data. The input power $P$ is approximated by its steady state equivalent and the feedwater enthalpy is assumed constant.

The issue of parameter identification can be tackled by applying estimation techniques, although in nonlinear models identification becomes more complicated than in the case that the system equation is linear. Identification techniques can improve the simulation results, but that does not necessarily mean that the estimated parameter converges to its real physical value.

The issue of input reconstruction is a more severe obstacle in model validation. It seems desirable to not only measure the temperature of the exhaust gas when the gas enters the evaporator, but also to measure the mass flow and the temperature when the gas leaves the evaporator. Simulations show that assuming a constant exhaust gas mass flow and the exhaust gas temperature equal to the steam saturation temperature, does not improve the simulation result.

Simulations also show that the heat capacity of the metal parts in the drum-boiler model may be neglected. Supposing the metal temperature equal to the steam saturation temperature, and because the saturation temperature hardly fluctuates with varying drum pressure, the addition of the metal to the energy equation is negligible.
Chapter 4

A Grey Model for the Cheng Cycle

We have developed models for parts of the Cheng Cycle based on two different approaches. In the first approach hardly any a priori knowledge is assumed and parameters in a system equation without physical fundament are estimated from observed data. This is called black box modelling. Model development has also been done based on conservation laws and derivation of system parameters from construction data and steam tables. This is called white box modelling. In this chapter we propose a model for the Cheng Cycle based on both approaches. The black model for the gas turbine/superheater/supplementary burner is combined with the white model for the drum-boiler. This combination can be referred to as grey box modelling. In the first section of this chapter we explain how the coupling between black and white model is established. Next, we present simulation results and end with the conclusions.

4.1 A Grey Model for the Cheng Cycle

In the previous chapter we stated that our dataset lacks crucial information in order to properly validate the drum-boiler model. Still we would like to demonstrate the dynamics captured by the model. To do that the interconnection between the model for the gas turbine/superheater/supplementary burner and the model for the drum-boiler is established by assuming that the input power $P$ satisfies:

$$P = \dot{m}_{exh} c_{pg} (T_{exh, ev, in} - T_{exh, ev, out})$$

(4.1)

with

- $\dot{m}_{exh}$: exhaust gas flow
- $c_{pg}$: specific heat exhaust gas ($c_{pg} = 1200 \ [J/kgK]$)
- $T_{exh, ev, in}$: temperature exhaust gas before evaporator
- $T_{exh, ev, out}$: temperature exhaust gas after evaporator

The temperature of the exhaust gas before the evaporator is an output signal of the black box model, and is via Eq. 4.1 converted to an input signal for the white drum-boiler model. The temperature of the exhaust gas after the evaporator is considered equal to the steam saturation temperature. We will show how the open loop Cheng Cycle, as a plant consisting of several interacting units, would respond to changes in the manipulated variables if the exhaust gas flow is known. In section 3.3 we reconstructed the input power $P$ by assuming it to be proportional to the steam flow $q_s$. An indication for the gas flow is found by substituting this reconstructed input power in Eq. 4.1.
Case 2: An Increase in Electrical Power

The system is operating in steady-state. Suppose a situation occurs in which more electrical power is needed, while the demand for process steam remains the same. A way to establish the required power increase is to inject steam into the combustion chamber. The effects of the steam injection are represented by the solid lines in Fig. 4.1 to Fig. 4.5. Steam is stepwisely withdrawn from the drum (6 [ton/hr], see also case 1), and directed to the gasturbine. The result of this steam injection is an increase in electrical power (see Fig. 4.1). The incoming feedwater flow and outgoing steam flow are pressure independent, so the drum reacts as an integrator, and there is a linear falling off of the drum pressure (see Fig. 4.3). When steam is injected into the gasturbine there is also a drop in the exhaust gas temperature. As a result, the input power drops accordingly (see Fig. 4.2), less steam is produced (see Fig. 4.5) and an extra drop is imposed upon the drum pressure. Drum water is used to produce steam, and because the feedwater flow remains the same, the water volume in the drum decreases (see Fig. 4.4). It is essential that the drum pressure is maintained, for else, if the drum pressure falls off the steam flow to the process will diminish also.

In order to maintain the steam producing capability of the system, as soon as steam is withdrawn from the drum, the fuel flow to the supplementary burner is stepwisely raised with 700 [m$^3$/hr]. The effects are depicted by the dashed lines in Fig. 4.1 to Fig. 4.5. The exhaust gas temperature increases, the input power raises accordingly (see Fig. 4.2), and more steam is produced in the riser compensating for the loss of steam meant for injection purposes (see Fig. 4.5). Apparently, in order to fully retrieve the loss in drum pressure, and thus guarantee an unchanged process steam flow, a pressure controller seems appropriate (see Fig. 4.3). Water is consumed in order to fulfill the steam demand, so to maintain the water level also the feedwater flow should be increased (see Fig. 4.4). Burning more fuel in the supplemental firing has no consequences for the generation of electrical power (see Fig. 4.1).
In this chapter we reported how a model for the Cheng Cycle as a whole is made up from models of the composing subsystems. We illustrated by means of a case how the model can be used for gaining insight in the dynamics of the process. The case illustrates how the open loop Cheng Cycle responds when steam is withdrawn from the drum, injected in the gasturbine and at the same time the fuel flow to the supplementary burner is raised. This relatively simple case is merely one of many situations that can be encountered in practice. Still we hope we have shown how dynamic modelling can be used for simulation and can serve for control system design.
Chapter 5

Conclusions and Future Investigation

5.1 Conclusions

The design project aimed at finding a dynamic model for a Cheng Cycle. Thereto the Cheng Cycle is considered to be composed of a number of interacting units: the gasturbine, the superheater-supplementary burner, the drum-boiler and the economizer. Data were collected at an industrial scale Cheng Cycle plant. Based on these data dynamic models have been developed by using black box system identification and first principles modelling. The reason that no attention has been paid to the modelling of the economizer is that the temperature of the water entering the drum is practically constant, and only the temperature of the exhaust gas leaving the stack is available from measurement. Data concerning the feedwater are not on hand.

To model the gasturbine and the superheater-supplementary burner multi-input multi-output ARMAX models have been used. It can be concluded that within the range of the measured signals the dynamics are sufficiently captured. These separately developed models of the gasturbine and the superheater-supplementary burner have been combined into an integrated model not only describing the interactions within each plant, but also the mutual influencing between the plants. This combined model is accurate enough to serve for simulation and controller design purposes.

To model the drum-boiler system conservation laws on mass, momentum and energy have been used. Unfortunately, our dataset lacks crucial information, causing the simulation results to be poor and the model validation questionable. However, the system equations are funded in physical principles. It is therefore justified to illustrate the features captured by the model. The white drum-boiler model has been connected to the black model of the gasturbine/superheater-supplementary burner, missing data have been assumed to be known, and a model for the Cheng Cycle as a whole is obtained. It is illustrated how the model could be used to study the Cheng Cycle’s responds to changes in certain input variables.
5.2 Future Investigations

5.2.1 Investigations Regarding Modelling and Identification

We have used two different approaches for modelling the Cheng Cycle: black box system identification and first principles modelling. A first principles model gives fundamental insight in the process dynamics, provided that expert knowledge concerning the relevant aspects is incorporated in the model. Moreover, accurate data in the form of signals and system parameters must be available. In practice, the ideal situation of having all the data you want is seldom met. This also holds for our case. In order to properly validate the drum-boiler model the input power should be known more accurately. Therefore, attention should be focussed on determining the input power, either by measurement, or by computation. To identify system parameters modern control theory supplies algorithms, provided that the input signal is known.

Those parts of the installation that are now covered by black models, can also be modelled by using first principles techniques. In order to use a model for control purposes it is required that the model is represented in state space form or in a to state space transformable representation. Otherwise the link to modern control theory will be lost, since most of the theory regards these state space representations. A state space model for a single-shaft simple cycle gas turbine engine is derived in [Watts et al., 1992]. The gas turbine is split up in engine components and control volumes. For the control volumes conservation laws of mass and energy are applied and combined with an equation of motion for the shaft. To take into account the effects of steam injection the balance laws over the combustion chamber and expander need to be adjusted. In that way a dynamic model for the StIG could be derived. A state space model for a heat exchanger is derived in [Jonsson et al., 1992]. The heat exchanger is divided into sections and the temperature of each section is taken as a state. Empirical relations are used in order to account for the mass flow and temperature dependence of the heat transfer coefficient. Parameters are estimated using an extended Kalman filter. This approach could be used to model the dynamics of the superheater.

The models presented are models of open loop systems. In order to investigate whether modern control can match or improve the performance of classical control, comparison must be possible between systems closed by the conventional PID controller and a modern controller. Consequently, the first step is to model the PID controller as it is implemented as yet. Alternatives for modern controllers are given in the next section.

Strictly speaking, the identification technique used in the black box modelling is only allowed for open loop systems. We gathered data from the plant operating in closed loop, that means there is feedback present and active. We have applied an open loop identification technique while the process was operating under closed loop conditions, and discarded the presence of feedback. The issue of whether the performance of this so-called direct identification approach was allowed should be further investigated. An overview of methods to identify systems operating in closed loop is given in [Heij and Van den Hof, 1993].
5.2.2 Investigations Regarding Control

Preceding the actual controller design, one should carefully pay attention to how to design the structure of the controller, i.e. where, how many and what kind of actuators and sensors are to be used and how should the information streams between measured and manipulated variables by means of feedback or feedforward be established. A wrong choice for the controller structure may put limitations on the system to be controlled that cannot be overcome by advanced control law design. Moreover, the controller structure greatly affects the complexity of the system. In a complex control system there is a large number of inputs, outputs and control loops. Obviously, a more complex control system is more expensive, less reliable, and harder to maintain. A survey on Control Structure Design (CSD) is given in [van de Wal and de Jager, 1995].

For the design of controllers for linear systems the possibilities range from classical PID-, to modern LQG- and $H_{\infty}$-control and $\mu$-synthesis [Bosgra and Kwakernaak, 1994].

For multivariable process control problems the concept of Model Predictive Control (MPC) has shown to be most promising. In the MPC algorithm the dynamic model of the plant is used to predict the effect of future actions of the manipulated variables on the output. The future moves of the manipulated variables are determined by optimization with the objective of minimizing the predicted error subject to operating constraints. The optimization is repeated at each sampling time based on updated information from the plant. MPC has left the stage of infancy for linear systems and is becoming to be more widely used in process industry. A survey on Model Predictive Control (MPC) is given in [García et al., 1989].

For systems with a nonlinear structure the design of a controller is less obvious. Nonlinear versions of existing linear control concepts are still subject of current research. Fuzzy Logic Control (FLC) is still considered in its infancy, although it is already applied in consumer electronics [Schwartz et al., 1994].

Controller design based on Lyapunov's direct method has turned out to be most rewarding for mechanical systems. In this method first a Lyapunov function candidate is selected. Next, the candidate function is adapted such that it satisfies the requirements of a real Lyapunov function. The method has proven to be successful if the mechanical energy in the system is chosen as candidate Lyapunov function. In the first principles modelling of the drum-boiler we have used energy conservation in order to formulate the system equations. Why not exploit the energy conservation equation by selecting it as a candidate Lyapunov function and use it for controller design? Lyapunov’s direct method is illustrated in [Slotine and Li, 1991, Sect. 3.6].
Bibliography


Appendix A

One-Step-Ahead Predictor

Consider the process.

\[ v(k) = H(q^{-1}, \theta)e(k) = \sum_{i=0}^{\infty} H_i q^{-i} e(k) \]

\( H(q^{-1}, \theta) \) is monic \( \Rightarrow v(k) = e(k) + \sum_{i=1}^{\infty} H_i e(k - i) \)

Choose as predictor

\[ \hat{v}(k | k - 1) = E\{v(k) | v(s), s \leq (k - 1)\} \Rightarrow \]
\[ = E\{e(k) + \sum_{i=1}^{\infty} H_i e(k - i)\} \]

The noise sequence \( e(k) \) has zero mean, i.e. \( E\{e(k)\} = 0 \). This yields

\[ \hat{v}(k | k - 1) = \sum_{i=1}^{\infty} H_i e(k - i) \Rightarrow \]
\[ = \left[ H(q^{-1}, \theta) - I \right] e(k) \Rightarrow \]
\[ = \left[ H(q^{-1}, \theta) - I \right] H^{-1} v(k) \Rightarrow \]
\[ = \left[ I - H^{-1}(q^{-1}, \theta) \right] v(k) \]

Consider as process

\[ y(k) = G(q^{-1}, \theta)u(k) + H(q^{-1}, \theta)e(k) \]

\[ = G(q^{-1}, \theta)u(k) + v(k) \quad (A.1) \]

Choose as predictor

\[ \hat{y}(k | k - 1) = E\{y(k) | y(s), u(s), s \leq k - 1\} \Rightarrow \]
\[ = E\left\{ G(q^{-1}, \theta)u(k) + v(k) | u(s), v(s), s \leq k - 1 \right\} \Rightarrow \]
\[ = G(q^{-1}, \theta)u(k) + \hat{v}(k | k - 1) \Rightarrow \]
\[ G(q^{-1}, \theta)u(k) + \left[ I - H^{-1}(q^{-1}, \theta) \right] v(k) \Rightarrow \]
\[ G(q^{-1}, \theta)u(k) + \left[ I - H^{-1}(q^{-1}, \theta) \right] \left[ y(k) - G(q^{-1}, \theta)u(k) \right] \Rightarrow \]
\[ \left[ I - H^{-1}(q^{-1}, \theta) \right] y(k) + H^{-1}(q^{-1}, \theta)G(q^{-1}, \theta)u(k) \]
\[ \text{(A.2)} \]
Appendix B

Plant Data Steam Injected Gas Turbine

Figure B.1: fuel flow to comb. chamb.

Figure B.2: steam flow to comb. chamber
Figure B.3: temperature injection steam

Figure B.4: electrical power generator

Figure B.5: turbine outlet temperature
Appendix C

Plant Data
Superheater/Supplementary Burner

Figure C.1: turbine outlet temperature
Figure C.2: drum pressure
APPENDIX C. PLANT DATA SUPERHEATER/SUPPLEMENTARY BURNER

Figure C.3: fuel flow to suppl. burner

Figure C.4: steam flow to gas turbine

Figure C.5: temperature injection steam

Figure C.6: temperature exhaust gas
Appendix D

Plant Data Drum-Boiler

Figure D.1: feedwater flow

Figure D.2: process steam flow
Figure D.3: injection steam flow

Figure D.4: drum level

Figure D.5: drum pressure

Figure D.6: exhaust gas temperature
Appendix E

Polynomial Approximation of Steam Tables

Figure E.1: enthalpy steam

Figure E.2: enthalpy water
APPENDIX E. POLYNOMIAL APPROXIMATION OF STEAM TABLES

Figure E.3: density steam

Figure E.4: density water

Figure E.5: saturation temperature steam
### APPENDIX E. POLYNOMIAL APPROXIMATION OF STEAM TABLES

#### APPENDIX E. POLYNOMIAL APPROXIMATION OF STEAM TABLES

<table>
<thead>
<tr>
<th>parameter</th>
<th>symbol</th>
<th>value</th>
<th>unit</th>
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</thead>
<tbody>
<tr>
<td>drum diameter</td>
<td>( d )</td>
<td>1.482</td>
<td>[m]</td>
</tr>
<tr>
<td>drum height</td>
<td>( z )</td>
<td>3.1</td>
<td>[m]</td>
</tr>
<tr>
<td>riser volume</td>
<td>( V_r )</td>
<td>3.36</td>
<td>[m³]</td>
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<tr>
<td>downcomer volume</td>
<td>( V_{dc} )</td>
<td>0.295</td>
<td>[m³]</td>
</tr>
<tr>
<td>mass metal parts</td>
<td>( m )</td>
<td>10350</td>
<td>[kg]</td>
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<tr>
<td>heat capacity metal</td>
<td>( c )</td>
<td>0.540</td>
<td>[kJ/kgK]</td>
</tr>
<tr>
<td>friction coeff</td>
<td>( k )</td>
<td>1</td>
<td>[-]</td>
</tr>
<tr>
<td>distance</td>
<td>( x )</td>
<td>765</td>
<td>[mm]</td>
</tr>
<tr>
<td>enthalpy feedwater</td>
<td>( h_{fw} ) (15 [bar] 180 [°C])</td>
<td>763.1</td>
<td>[kJ/kg]</td>
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</tbody>
</table>

Figure E.6: drum-boiler parameters

<table>
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<th>parameter</th>
<th>symbol</th>
<th>value</th>
<th>unit</th>
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</thead>
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<tr>
<td>feedwater flow</td>
<td>( q_{fw} )</td>
<td>6.31</td>
<td>[ton/hr]</td>
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<tr>
<td>process steam flow</td>
<td>( q_{ps} )</td>
<td>3.15</td>
<td>[ton/hr]</td>
</tr>
<tr>
<td>injection steam flow</td>
<td>( q_{is} )</td>
<td>3.15</td>
<td>[ton/hr]</td>
</tr>
<tr>
<td>exhaust gas flow</td>
<td>( \dot{m}_{exh} )</td>
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<td>[kg/s]</td>
</tr>
<tr>
<td>specific heat exhaust gas</td>
<td>( c_{pg} )</td>
<td>1200</td>
<td>[J/kgK]</td>
</tr>
<tr>
<td>mean temp exhaust gas before evaporator</td>
<td>( T_{exh, ev, in} )</td>
<td>760</td>
<td>[°C]</td>
</tr>
<tr>
<td>initial value drum pressure</td>
<td>( p )</td>
<td>15</td>
<td>[bar]</td>
</tr>
<tr>
<td>initial value water volume in drum</td>
<td>( V_w )</td>
<td>2.09</td>
<td>[m³]</td>
</tr>
<tr>
<td>initial value steam quality</td>
<td>( x_r )</td>
<td>0.097</td>
<td>[-]</td>
</tr>
</tbody>
</table>

Figure E.7: parameters and initial values case 2