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Simple Model Representation of Underbalanced Drilling Hydraulics and Control

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MSC THESIS DESCRIPTION SHEET

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Background

In drilling operations performed in the oil and gas industry it is important to control pressure in the open section of the hole by adjusting drilling mud flow and annular back pressure. Drilling mud is used primarily for removing cuttings from the well. It is injected at high pressure at the top of the drill string. At the end of the drill string, called the drilling bit, the drilling mud gets into the annulus and then rises together with cuttings up to the surface. At the surface, the cuttings are separated from the mud and the cleaned mud is reinjected into the drill string for further circulation. Apart from removing cuttings from the well, drilling mud is also needed for pressurizing the well. If the pressure in the well is too low, the pressure of the surrounding rock formation can make the well collapse, trapping the drill string. At the same time, if the pressure exceeds a certain threshold, it may fracture the well leading to costly consequences.

In underbalanced drilling, the target pressure is slightly below the reservoir pore pressure, allowing for influx of gas from the reservoir while drilling. The drawback of drilling underbalanced is the need for equipment on the rig to handle the gas, while the advantage is that the method avoids clogging reservoir pores with drilling mud and cuttings. The result is a well that produces at higher rates than if drilled conventionally (over-balanced). The objective of this work is to develop automatic control algorithms for pressure/influx control during underbalanced drilling. The following points should be addressed by the student:

Tasks:

1) Review literature on underbalanced drilling, and particularly on any available automated systems.
2) Set up a simulation framework for simulating an underbalanced drilling operation. Consider methods for obtaining simple models that can be used for control design.
3) Based on the modelling work, design control algorithms that can be used while drilling ahead and during pipe connections.
4) Use the simulation framework to test your control algorithms and demonstrate their performance.
5) Write a report.

Supervisor: Professor Ole Morten Aamo

Abstract

Oil reservoirs can be sensitive to unfamiliar fluids such as drilling fluids. In order to prevent fluids to enter the formations surrounding the well, the well pressure can be lowered below the reservoir pressure, called underbalanced drilling. This technique calls for injecting of gas into the mud to lower the pressure, with additional inflow of oil and gas to the well as a result. This thesis evaluates current modelling of two-phase flow related to underbalanced drilling, and possible simplifications. Through investigation of simulation data, the current modelling based on first principles, is considered too complex compared to data of the key dynamics. To simplify the modelling, a black box system identification approach is used. By identifying solely from simulation data, low order models with good fit to validation data are obtained. Through testing, the models' validity are tested, and it is concluded that a number of simple models will be needed to represent the whole system given by the simulator. Models with specific orders are tested at different set points, and one model order produces good accuracy at all the operating points tested. This model is likely to be able to accurately represent the whole system with updated parameters.

The accuracy of the simple models identified reveals simple system dynamics, and a PI controller is considered to be sufficient. The models are being used to tune the controller, and the controller perform great on set point changes. In addition, the controller is tested with an emulated connection, with satisfactory performance.

Sammendrag

Oljereservoarer kan være sensitive for fremmede væsker som for eksempel borevæsker. For å hindre at væsker trenger inn i formasjonene rundt brønnen må trykket i brønnen senkes under trykket i reservoaret, kalt underbalansert boring. For å muliggjøre denne teknikken kan gass bli injesert i borevæska for å senke trykket, med innflyt av ytterligere gass og olje fra reservoaret som resultat. Denne oppgaven vurderer nåværende modellering av to-fase strømning relatert til underbalansert boring og mulige forenklinger. Studering av simuleringsdata avslører at modelleringen basert på fysiske prinsipper kan være unødvendig kompleks, i forhold til den viktigste dynamikken i systemet. For å forenkle modelleringen blir en ”svart boks” identifikasjonstilnærming valgt. Ved å utelukkende bruke simuleringsdata blir enkle og presise modeller identifisert. Modellenes gyldighet blir testet og det blir konkludert med at et antall enkle modeller trengs for å representere hele systemet gitt av simulatoren. Modeller med gitt orden blir testet på forskjellige arbeidspunkt og en enkelt modellorden viser seg å være nøyaktig på alle punktene med oppdaterte parametere. Denne modellordenen kan sannsynligvis bli brukt til å representere hele systemet med oppdaterte parametere. Nøyaktigheten til de enkle modellene som er identifisert avslører enkel systemdynamikk, og en PI regulator er vurdert til å være god nok. Modellene blir brukt til å stille inn regulatorparameterne før den suksessfullt blir testet på forandringer i arbeidspunkt. I tillegg blir regulatoren testet på en emulert forlengelse av drillstrengen, med brukbart resultat.

Preface

This thesis is the final project of the M.Sc. in Engineering Cybernetics at the Norwegian University of Science and Technology. It is written during the spring of 2014 and counts for 30.0 credits through the course TTK4900. The work has been inspiring as the results show that large industrial processes still have potential for improvements with the knowledge and tools obtained through five years of education.

I would like to express my appreciation to Professor Ole Morten Aamo for valuable guidance through the whole project. I would also like to thank Ulf Jacob Flø Aarsnes for simulator framework and guidance through parts of the project. Thanks to my fellow students for valuable feedback through discussions in the office: Siri Garli Dragset, Johan Fredrik Holm Totland, Pirashanna Nanthakumaran and Thomas Hasfjord. Finally I would like to thank my family and friends, especially Katrine, for being supportive through my whole education.

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Abbreviations

UBD	**U**nder **B**alanced **D**rilling
BHCP	**B**ottom **H**ole **C**irculating **P**ressure
WHP	**W**ell **H**ead **P**ressure
MPD	**M**anaged **P**ressure **D**rilling
PE	**P**ersistent **E**xcitation
NRMSE	**N**ormalized **R**oot **M**ean **S**quare **E**rror
PID	**P**roportional **I**ntegral **D**erivative (controller)
ROP	**R**ate **O**f **P**enetration
RCH	**R**otating **C**ontrol **H**ead

Symbols

α_l	Liquid fraction
α_g	Gas fraction
ρ_l	Liquid density
ρ_g	Gas density
v_l	Liquid velocity
v_g	Gas velocity
a_l	Speed of sound through liquid
a_g	Speed of sound through gas
s	Water saturation
μ_l	Liquid viscosity
μ_g	Gas viscosity
A	Cross sectional flow area
k_l	Liquid production rate
k_g	Gas production rate
z	Choke opening
u	Input to system identification

Chapter 1

Introduction

1.1 Motivation

Conventional drilling is today considered to be drilling with higher pressure in the well than the reservoir. This overbalanced pressure can lead to a loss of drilling fluids to the surrounding formations. Large losses of mud will fill up the formations close the the well, and significant resources have to be used to clean up the well before production can start. What once were easy accessible oil and gas, can get inaccessible with this technique.

A solution to this problem is to drill with lower pressure than surrounding formations. This is called underbalanced drilling (UBD) and leads to an inflow from the surrounding formations, rather than an outflow of mud. This inflow of oil and gas is considered a "kick" during overbalanced drilling, and can cause a "blowout" if not kept under control. A solution to this problem is currently to dimension the equipment on the rig to handle whatever comes up from the well, rather than using control tools actively to prevent flow and pressure to escalate. Due to this approach, underbalanced drilling is often considered unsophisticated. This thesis aims to identify simple models of the drilling process. With the knowledge of structure and complexity of the system, suitable control methods can be developed making the drilling process more sophisticated.

1.2 Scope

Current modelling of two-phase flow is advanced and too complex to use as a base when developing control methods. Simplifying current models such as the drift flux model or identifying new models from scratch, enables for simple control methods to be developed. This thesis will mainly focus on the system identification part, with some additional testing of simple controllers.

1.3 Problem Description

1. Review literature on underbalanced drilling, and particularly on any available automated systems.

2. Set up a simulation framework for simulating an underbalanced drilling operation. Consider methods for obtaining simple models that can be used for control design.

3. Based on the modelling work, design control algorithms that can be used while drilling ahead and during pipe connections.

4. Use the simulation framework to test your control algorithms and demonstrate their performance.

5. Write a report.

1.4 Outline

This thesis is divided into six chapters. Following this introduction with motivation and problem description, chapter 2 comes, which is about drilling. The chapter aims to give necessary background information about different drilling techniques and main challenges related to this work. Chapter 3 summarizes the popular drift-flux model used to model two-phase flow systems, such as an underbalanced well. A simplified model is also mentioned, before further modelling options are discussed. Chapter 4 starts with a brief introduction to system identification techniques, relevant data from the drilling process and Matlab tools, before the systems are identified and tested. Chapter 5 gives a short introduction to PID controllers, before a controller is tested at the system. Following is the concluding discussions and suggestions for further work in chapter 6. Appendix A lists the attached Matlab files and data sets together with their purpose.

Chapter 2

Underbalanced Drilling

2.1 Conventional Drilling

Conventional drilling is today considered to be drilling with higher pressure in the well than the surrounding formations (overbalanced). The well pressure is obtained by sending mud with a certain density and volume flow down the pipe to clean out cuttings and stabilizing the walls. By making sure this mud pressure is higher than the pressure from the surrounding formations, the risk of inflow into the well is reduced. In overbalanced drilling, sudden inflow from the formations is called "kicks" and can lead to a dramatic increase in well pressure, which is the beginning of "blowouts" if not handled properly. The simplicity and safety are the main reasons this technique today is widely used both onshore and offshore. There are however some related issues.

2.1.1 Mud Loss

When drilling with higher well than formation pressure, some of the mud will flow into the formation rather than up the annulus to be reused. This is called mud loss, and will cause a drop in the well pressure if not handled correctly by the operators. Some reservoirs seem to absorb endless amounts of drilling fluid, and the drilling has to stop until well circulation resumes. To avoid abandoning the well, the solution is often to pump down large amounts of mud until a ”mud-cake” is formed which blocks further leakage. [1]

2.1.2 Formation Damage

With low formation pressure the mud can start to make new ways through the formations and react with certain substances. For instance, sand with high content of mud will react with fresh water based drilling fluids and cause swelling up to 500%. In addition to expansion of the sands, the different reactions can reduce the permeability of the formations, which make the oil and gas harder to extract.

The damage caused by both the mud loss and the formation damages, makes it difficult to access the oil and gas, and a ”clean up” is required before the production can start. Both the mud loss and the clean up cause production delays and reduce the profit of the operation. [1]

2.1.3 Differential Sticking

Since the formation pressure is lower than the well pressure, there is a risk that the drill string will get stuck in contact with the wall of the well. This makes it impossible to rotate or move the string and is considered to be the greatest drilling problem in terms of time and cost. Millions of pounds of force may be needed to remove the pipe by brute force, and it often proves impossible. Another solution is to lower the mud density, thus lower the well pressure. The reduced pressure will cause less outflow of mud to the surrounding formations, which will help release the pipe. If none of the mentioned solutions work, a ”fishing” company, which is specialized in retrieving stuck/lost equipment, will apply more advanced methods to solve the problem. [1]

2.2 Managed Pressure Drilling

In a normal drilling well, the mud flow or density has to be adjusted in order to control the well pressure. Both adjustments are often too slow and limited if a sudden rise of pressure (kick) should occur. Instead, there is a principle called managed pressure drilling (MPD) which main control tool is a choke at the outlet of annulus. By controlling the outflow, the choke can close if the pressure drop, and vice versa. There are two main MPD techniques:

- Reactive MPD
- Proactive MPD

The reactive MPD reacts on measured kicks in the well and will try to stabilize the pressure. It is the easiest method and can be applied at drilling operations not intentionally designed for MPD. The proactive MPD will use measurements to predict potential kicks and eliminate them before any damage can occur. This method is more sophisticated and requires good planning ahead of the drilling operation in addition to accurate measurements and estimations, but will provide better control of the well pressure. [2]

2.3 Underbalanced Drilling

A remedy for many of the problems related to conventional drilling is to use MPD techniques together with a lower well pressure. Instead of pressurising the well like conventional overbalanced drilling, the pressure is maintained under formation pore pressure. This can be achieved by using a lower density drilling fluid, often with gas injected, such that the weight of the mud decrease. The lower pressure will cause inflow of reservoir fluids and gas to the well during the drilling process.

2.4 Benefits

Both the reservoir and the drilling process itself benefits from maintaining a lower well pressure than formation pore pressure.

2.4.1 Reduced Mudloss and Formation Damage

By maintaining underbalanced well pressure, the drilling fluids will rather flow in the annulus than into the formations. The better control of the drilling fluids will also prevent penetration of the formations. The lack of mud cakes and fluid loss decrease the need for time consuming "clean-up" of the well. By avoiding foreign fluids into the formations, the permeability will be kept at the natural level, which will result in greater utilization of the well.

In operations, it is proven that applying underbalanced drilling increases the utilization of the reservoir up to eight times. [3]

2.4.2 No Differential Sticking

With a continuous inflow to the well, the drill string will be pushed away from the well wall. The pipe will drift away from the areas with highest inflow, but never get stuck in the same way as with conventional drilling. Differential sticking is considered to be a major problem in drilling, and great cost savings can be obtained by reducing down-time. [1]

2.4.3 Increased Rate of Penetration

The drill bit is mounted at the end of the drill string and is responsible for the actual drilling at the bottom of the well. When the bit becomes worn, the whole drill string have to be pulled out in order to change it. By lowering the pressure in the well, the bit will meet less resistance and the rate of penetration (ROP) will increase in addition to reduce wear and tear. Both the increased ROP and the longer time between change of drill bits contribute to make the drilling process more efficient. [1]

2.4.4 Location of Productive Zones

A variety of tools can be used to measure both flow and pressure in different parts of the drilling process. By interpreting when the inflow is greatest, it is possible to locate the productive zones and retrieve helpful information to the production stage. If it is a horizontal directional drilling (HDD) process, these measurements can also be used as guidance and lead to a more productive well.

2.5 Challenges

The inflow of oil and gas into the well poses some challenges to both equipment and control methods.

In conventional overbalanced drilling, inflow to the well from the formations is considered to be a kick and may in the worst case lead to a blowout. Underbalanced drilling will operate with kicks and unpredictable well pressure continuously. The solution to this problem is often to dimension the equipment on the rig to withstand greater pressure than the potential pressure in the reservoir. This approach can work fine with predictable low pressure reservoirs, but that is not always the reality. The current equipment are getting stronger each year, but guaranteeing it to be strong enough to handle the reservoirs is a big challenge.

Another challenge is offshore rigs with limited space. Equipment that is developed to handle great pressure, often gets large and heavy. This is no problem in land-based operations with unlimited space, but on an offshore rig, the equipment has to be scaled down in order to fit. This clearly restricts which reservoirs to drill underbalanced offshore. A solution to this problem is to apply control methods that limits the well pressure within certain limits.

2.6 Control

The main focus in underbalanced drilling is to keep the well pressure lower than formation pore pressure. This limit has to be kept strictly since even short periods of time over this limit can affect the reservoir dramatically.

When it comes to a lower well pressure limit, there are several factors that need to be considered. The most important is the functionality of the mud itself. A certain flow is needed in order to clean out the cuttings from the drill bit. This flow corresponds to a certain pressure which is a strict lower limit. Another concern is the reservoir collapse pressure, which is the lower pressure needed to keep the well wall stable. Both the pressure needed to clean out the well and the collapse pressure, pose as strict lower pressure limits.

2.6.1 Control Target

Upper and lower boundaries are clearly defined, but there are different strategies for a control set point between these limits.

One approach can be to set the target right in between them in order to maximize the buffer in case of fluctuations while drilling. This approach is the safest when it comes to not breaking the boundaries, but simultaneously is the well likely to produce significant amounts of oil and gas. The returnings from the well have to be separated in order for the mud to be reused. To avoid environmental pollution, the resulting oil and gas have to stay within the capacity of what the drilling rig can handle.

A way to reduce this production is to set the target pressure closer to the reservoir pressure, without breaking the limit. This approach will, however, leave a smaller buffer for fluctuations in the well pressure. As a result, the capacity of the topside equipment has to be taken into consideration when controlling the well. The pressure target has to be set as far away from the strict boundaries as possible, while still manage to set corresponding production below the handling limit of the equipment.

2.6.2 Tools

Underbalanced drilling use the same basic tools as MPD and conventional drilling. In addition, there are some equipment needed to handle the production and two-phase flow.

Mud

The mud has to be adapted to the characteristics of the reservoir and the current depth of the well. In order to decrease the well pressure, the mud has to be lightened. This can be done by injecting gas into the original mud, or using foam or soap mixtures. If the need for higher bottom hole pressure arises, it is possible to reduce the amount of gas, or using a single phase liquid mud. Typical mud density range is from near zero to 700 $\frac{kg}{m^3}$. In addition to mud density, rate of flow can also be adjusted to alter the pressure and cleaning properties down hole. [1]

Choke

The choke is introduced in section 2.2. In UBD, the pressure will fluctuate and choke is used actively as the main control tool to keep the pressure within the limits.

Rotating Control Head and Separator

The mud, including produced fluids and gas, needs to be separated from the rig floor on the return up to the surface. A rotating control head (RCH) acts as a seal on the surface, while still letting the drill string rotate. When the fluids pass the rotating head, they will flow into a separator which will remove cuttings, and separate the different fluids and gas. When separated, the mud will be recycled and sent down the drill string again.

2.6.3 Non-Intuitive Response

A well drilled with overbalanced pressure and single phase mud, can be controlled with relative simple MPD techniques. With no inflow from the formations and negligible compressibility, the well pressure will behave in a straightforward way when applying a control move.

However, with underbalanced well pressure and two-phase liquids, the response from a control move can be more complex. The bottomhole pressure is given by:

$$BHCP = WHP + F + G \tag{2.1}$$

where $BHCP$ is bottom hole circulating pressure, WHP is well head platform, F is fluid friction and G is the hydrostatic pressure which depends linearly on the fluid density ρ.

With gas inflow to the well, the fluid density ρ will decrease. In the same way the fluid friction F will increase, but not with the same rate as the fluid density. The friction will increase depending on the amount of gas already in the system, and it can both over and under compensate for the decrease in fluid density. Depending on the state of the well, a specific change of the choke opening can cause both a pressure rise or fall. More specifically, the well will move into the non-intuitive regime when approaching overbalanced pressure and the BHCP is greater than the WHP.

As a result, the control algorithm needs to take into account the state of the system before making a control move. Trying to control the system without this knowledge can cause instability. [4]

2.7 Instrumentation

Good control methods need accurate measurements to perform properly. The instrumentation technology is in rapid development and new data get available for control methods.

2.7.1 Topside Measurements

The rig handles both the fluids that go down the drillstring, and what comes in return. Even though it is a tough environment and good instrumentation can be a challenge, it is assumed that good measurements can be obtained from all processes topside. The most relevant data for control purposes are listed below.

- Pump rate
- Choke opening
- Well Head Pressure
- Choke outlet pressure
- Choke flow
- Fraction of gas and liquid through choke

2.7.2 Downhole Measurements

New technology are being tested and well measurements are starting to become available for control purposes. The most commonly used measurement technology is mud-pulse telemetry which send the measurements binary as pulses in the mud in the drill string. This technique is relatively accurate, but the delay makes it too slow for control purposes.

A newer and faster technology is a principle called wireline. The downhole information is sent up to the surface through wires built in all the equipment and drill pipes, which offer high bandwith and fast response. Due to some reliability issues however, control systems have not yet been able to solely be supported by measurements from this technique. For simplicity and despite the fact that the instrumentation technology is not functioning properly yet, we assume that the following downhole measurements are available.

- BHCP
- Flow in annulus

2.8 Applications

Most of the easy accessible reservoirs today are drilled with overbalanced drilling techniques. As these reservoirs are being emptied, new and more difficult reservoirs have to be opened in order to maintain a steady production. Many of these reservoirs are filled with tight gas, where the gas is trapped in rock pores with low permeability. Overbalanced drilling will in these reservoirs isolate the gas further with mud, and decrease the potential production. Underbalanced drilling will on the other hand maintain the permeability and locate the areas with greatest potential for successful production.

Another key element is the development of tougher equipment. Reservoirs otherwise well suited for underbalanced pressure, often have to be drilled overbalanced due to reservoir pressure greater than what current equipment can handle. Rotating heads with working pressure over 14 000 kPa opens up a wider range of depths and formations [5].

The need for new reservoirs, tighter economical margins and the development of tougher equipment have all led to an increasing share of underbalanced drilled wells. In North America, 25% of the new wells drilled use elements from this technique and great results have been reported [5]. Wells in Mexico, Texas and Libya states that circulation loss and formation damage were reduced, differential sticking was prevented, a decreased number of drilling bits were used and increased rate of penetration [1]. In addition, Shell states that the production have improved up to 800% compared to overbalanced drilled wells [3].

Offshore drilling meets the same basic challenges as landbased underbalanced drilling operations, but with added complexity due to the often deeper wells and limited rig area. Despite the added complexity, hundreds of wells have been drilled offshore with the same tools and elements as onshore underbalanced drilling [6].

Chapter 3

Modelling

In order to lower pressure sufficiently to obtain underbalanced pressure, the mud can be mixed with gas. In addition, the lower pressure can cause inflow of gas to annulus. These effects both cause dynamic two-phase flow properties which are difficult to model accurately. To make suitable control algorithms, good knowledge of the structure of the system is needed. Evje [7] and Aarsnes [8] have used the popular, already simplified Drift-Flux model as a base, and made some further simplifications. The following sections will summarize their work.

3.1 Original Two-Phase Flow Modelling

Modelling of compressible gas-liquid wellbore and porous media two-phase flow are used as a basis to a simplified model.

3.1.1 Drift-Flux Model

The drift flux model simplify the modelling of two-phase flow by considering the mixture as one, rather than the phases separately. The assumptions made in the simplifications cause some key characteristics of two-phased flow to be lost, but years of testing have proved it accurate enough for many applications. The model is best suited for mixtures where the fluid and gas are closely coupled, relative to the dimensions of the system. Large dimension systems, such as oil wells, will increase the components interaction times, and therefore justify weaker coupled mixtures. The result of the simplification is a system consisting of energy equations, mixture continuity, momentum and gas continuity. [9]

Evje [7] states a one-dimensional transient drift flux model the following way

$$\frac{\partial \alpha_g \rho_g}{\partial t} + \frac{\partial \alpha_g \rho_g v_g}{\partial x} = 0 \tag{3.1}$$

$$\frac{\partial \alpha_l \rho_l}{\partial t} + \frac{\partial \alpha_l \rho_l v_l}{\partial x} = 0 \tag{3.2}$$

$$\frac{\partial \alpha_g \rho_g v_g + \alpha_l \rho_l v_l}{\partial t} + \frac{\partial \alpha_g \rho_g v_g^2 + \alpha_l \rho_l v_l^2 + P}{\partial x} = q \tag{3.3}$$

where ρ_l, ρ_g and v_l, v_g are density and velocity respectively for the liquid and gas components. The volume fractions α_l and α_g are given in the same way and satisfies $\alpha_l + \alpha_g = 1$. P is the common pressure for liquid and gas and q represents external forces.

The relations between density and pressure are stated as

$$\rho_l = \rho_{l,0} + \frac{P - p_0}{a_l^2} \tag{3.4}$$

$$\rho_q = \frac{P}{a_g^2} \tag{3.5}$$

where a_l and a_g represent the speed of sound through the liquid and gas, while $\rho_{l,0}$ and p_0 are characteristic values for the liquid.

Finally, a simple slip relation can be given as

$$u_g = c_0 v_M + c_1 \tag{3.6}$$

where c_0 is the distribution parameter and c_1 is the drift velocity.

Due to strong nonlinearities and some challenges related to transitions to single phase regions, this model is difficult to solve and implement. By analysing the mechanisms of the model, it is possible to make further simplifications.

3.1.2 Two-Phase Porous Media Flow

The Buckley-Leverett method successfully find the analytical solution for one-dimensional porous two-phase flow, such as water and oil. It is well suited for describing forced injection of one fluid to displace another immiscible and incompressible fluid. The Buckley-Leverett equation is given

$$s_t + f(s)_x = 0 \tag{3.7}$$

where $f(s)$ is the fractional flow function and s is water saturation. When a strongly wetting fluid displaces a nonwetting fluid spontaneously under influence of capillary forces, the flow can be described by the nonlinear diffusion equation

$$s_t = \Big(a(s)J(s)_x\Big)_x \tag{3.8}$$

where $J(s)$ is related to the capillary pressure and $a(s)$ is nonlinear function depending on the fluid and rock properties of the porous formations. [7]

3.2 Reduced Drift-Flux Model

The reduced drift flux model aims to bring together the functionality of the original drift flux model in equations 3.1 - 3.3 and the simplicity of the Buckley-Leverett model in equation 3.7 and 3.8. This section will summarize the final modelling as stated by Aarsnes [8].

The drift flux model is now given by

$$\frac{\partial \alpha_g \rho_g}{\partial t} + \frac{\partial \alpha_g \rho_g v_g}{\partial s} = 0 \tag{3.9}$$

$$\frac{\partial \alpha_l \rho_l}{\partial t} + \frac{\partial \alpha_l \rho_l v_l}{\partial s} = 0 \tag{3.10}$$

$$\frac{\partial P}{\partial s} = -\alpha_l \rho_l g \sin(\phi(s)) - F v_m \tag{3.11}$$

which can be rewritten with the mass variables $m = \alpha_l \rho_l$ and $n = \alpha_g \rho_g$ as

$$\frac{\partial n}{\partial t} + \frac{\partial n v_g}{\partial s} = 0 \tag{3.12}$$

$$\frac{\partial m}{\partial t} + \frac{\partial m v_l}{\partial s} = 0 \tag{3.13}$$

$$\frac{\partial P}{\partial s} = -mg \sin(\phi(s)) - F v_m. \tag{3.14}$$

The closure relations are given as

$$F = f(\alpha_g \mu_g + \alpha_l \mu_l) \tag{3.15}$$

$$v_m = \alpha_g v_g + \alpha_l v_l \tag{3.16}$$

$$v_g = c_0 v_m + v_\infty \tag{3.17}$$

where μ_g and μ_l are viscosity for the gas and liquid respectively. The slip parameters c_0 and v_∞ must be state dependent to allow for transitions to one phase flow

$$c_0(\alpha_g) = \begin{cases} 1 + \frac{K-(K-1)\alpha_g^r - 1}{\alpha_g^*}\alpha_g & \text{if } 0 \leq \alpha_g \leq \alpha_g^* \\ K - (K-1)\alpha_g^r & \text{if } \alpha_g^* \leq \alpha_g \leq 1 \end{cases} \tag{3.18}$$

$$v_\infty(\alpha_g) = (1 - \alpha_g)s = \alpha_l s \tag{3.19}$$

while the liquid and gas phase are compressible

$$\rho_l = \rho_{l,0} + \frac{P - p_0}{a_l^2} \tag{3.20}$$

$$\rho_g = \frac{P}{a_g^2} \tag{3.21}$$

such that the pressure law becomes

$$P(n, m) = \frac{a_l^2}{2}\left(-B(m, n) + \sqrt{B(m, n)^2 + 4\frac{a_g^2}{a_l^2}C(n)}\right) \tag{3.22}$$

$$B(m, n) = \left(\rho_{l,0} - \frac{p_0}{a_l^2}\right) - \frac{a_g^2}{a_l^2}n - m \tag{3.23}$$

$$C(n) = n\left(\rho_{l,0} - \frac{p_0}{a_l^2}\right) \tag{3.24}$$

where $\rho_{l,0}$, p_0,a_l and a_g depend on the compressibility and density of the gas and fluid.

3.2.1 Boundaries

In addition, the downhole boundary conditions are depending on the mud and produced fluids/gas

$$Amv_l|_{x=0} = k_l \max\left(P_{res} - P(0), 0\right) + Wl, inj \tag{3.25}$$

$$Amv_g|_{x=0} = k_g \max\left(P_{res} - P(0), 0\right) + Wg, inj \tag{3.26}$$

where A is the cross sectional flow area, k_l and k_g are production rates for liquid and gas respectively, and P_{res} is reservoir pressure. A choke equation relating topside pressure to mass flow rates represents the topside boundary condition

$$A\left[mv_l + nv_g\right]|_{x=l} = C_v(z)\frac{\sqrt{P(l) - P_s}}{\frac{m}{\sqrt{\rho_l}} + \frac{n}{Y\sqrt{\rho_g}}} \tag{3.27}$$

where $C_v(z)$ is the choke opening and Y is correction factor for gas flow.

3.3 Further Modelling

The already simplified drift-flux model has now been further simplified to the reduced drift flux model in section 3.2. However, the model is still complex and does not give any clear signals about the response from possible control moves to well properties. As further mathematical reduction is likely to impact the accuracy and create limitations, it is decided to look into alternative modelling options.

Chapter 4

System identification

Despite the fact that the modelling of two-phase flow is complex and difficult to simplify enough for control purposes, the modelling can be implemented as a simulator. Instead of trying to simplify the modelling in chapter 3 further, there are methods that utilize the fact that good simulation data can be obtained. This chapter will look into methods used for identifying systems partially or solely from simulation data.

4.1 Simulator

In order to produce rich data sets, a simulator has to be developed. Frameworks such as Olga [1] and WeMod [2] are based on advanced modelling and will produce the most accurate results if correctly implemented. They are however advanced programs, and require good knowledge of the properties of wells with certain dimensions.

Another approach is to use current modelling, such as the reduced drift flux model in chapter 3. Aarsnes [8] has implemented the model in section 3.2 with boundary conditions corresponding to an underbalanced drilling process and specifications

[1]Drilling simulator framework owned by Schlumberger Information Solutions(SPT)
[2]Drilling simulator developed by the International Research Institute of Stavanger (IRIS)

Property	Parameter name	Value z
Length	p.L	2530 [m]
Casing diameter	p.Dc	0.1548 [m]
Pipe outer diameter	p.Dp	0.0889 [m]
Gravitational constant	p.g	9.81 $[\frac{m}{s^2}]$

TABLE 4.1: The key specifications of the well used in the simulator.

as shown in table 4.1. Although not tested thoroughly for every scenario, it works satisfactory for normal operating modes and is used as a base when producing data.

4.2 Identification Technique

The identification process can use existing modelling as a base together with the simulation data, or identify new models from scratch.

4.2.1 White Box

White box modelling is based on physical laws and principles. These principles are known as "first principles", and can for instance be given as energy equations. Physical systems identified with this method often get complex and not well suited for getting an overview of the system dynamics. The modelling in chapter 3 is trying to simplify a model based on first principles, but the result is still too complex.

4.2.2 Grey Box

Grey box modelling is based partly or completely on first principles from white box modelling. There are however a set of free parameters or some structure that need to be identified from system data.

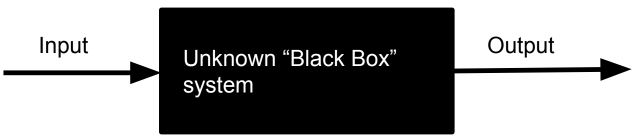

FIGURE 4.1: The basic "black box" system identification principle.

4.2.3 Black Box

Black box system identification, shown in figure 4.1, utilizes the fact that good process data can be obtained from a simulator. By selecting a model structure likely to fit the system, all parameters are identified solely from process data. The models are optimized by choosing a basic model structure and preferred input/output data from the simulator, and with the help from basic system identification tools, minimize the deviation between the new model and the data.

It is expected that the underbalanced drilling process is a slow system. Further investigations, see figure 4.11, also reveal a relative simple response from possible control moves to well properties. First principles are likely to result in more advanced models than necessary, thus it is decided to use a black box approach in the further work.

4.3 Model Data

All data will be generated by the simulator in section 4.1. Since the theoretical model in the simulator can provide all possible data, some real life restrictions apply as stated in section 2.7. In addition, a selection of data have to be selected in order to only include the key dynamics of the system. Since the identified model will be made for control purposes, a correlation between well properties and possible control moves will be investigated.

4.3.1 Output

The target for the controller is to keep the well pressure within the limits described in section 2.6.1. Section 2.7 states two possible downhole measurements, but BHCP will be chosen since the control target is pressure.

4.3.2 Input

The input signal needs to clearly affect the output signal and be able to be persistent excitated(PE). A PE signal has to be rich enough to make sure the identified model is unique and represent the actual physical system. Lack of PE can cause the identified system to come up with a correct response for some inputs, but give incorrect response when other inputs are being applied.

Both the properties of the mud flow and the choke are considered as control tools in section 2.6. Density and rate of mud is a slow control tool, and is not used actively to control the well under normal operating modes. If the well pressure becomes overbalanced however, decreasing the mud density can be the only way to get it back to an underbalanced state. By avoiding increasing the pressure to overbalanced state [3], the mud properties are not needed as control tools in this case.

The choke is able to react rapidly to pressure alterations with great impact, and is therefore considered to be the only control tool. Note that other inputs and outputs could be selected by using a multiple input/multiple output (MIMO) approach. This approach is more relevant for more advanced control methods with a bigger demand for model data, and will hence not be used in this work.

Two-phase flow through a choke is given by equation 3.27 and shows that there are nonlinearities between the choke opening and well behaviour. This behaviour is caused by the fact that a certain increase in choke opening will have greater effect

[3]The simulator case becomes overbalanced with a pressure greater than about $293 * 10^5$Pa, corresponding to the steady state obtained by a choke opening under 6.5%

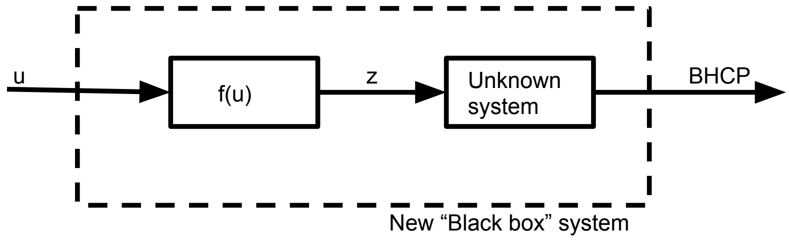

FIGURE 4.2: New ”black box” system with variable change

with small initial choke opening, than with a big initial opening. Using choke opening as input to the system identification will therefore introduce unnecessary complexity to the system and should be avoided. Using choke pressure (WHP) as input will remove the nonlinearity, but also introduce new complexity. By setting a certain WHP, a controller is needed to set the corresponding choke opening. When trying to control the well, this WHP controller has to be used actively to set choke openings and is likely to increase run time and introduce error to the system.

A remedy for this problem is to introduce a new linear input u which will produce linear steady states of BHCP. The choke opening z will then be given as a nonlinear function of u

$$z = f(u) \tag{4.1}$$

such that the system identification will have the form shown in figure 4.2. The input u will then function as choke opening z, just corrected for the nonlinearity.

Figure 4.3 and 4.4 show how linear steps on the choke opening z cause nonlinearties at the output BHCP. The selected steady state values of the BHCP can be used to produce simple polynomials by using the Matlab command ”polyfit”. Both the selected values and the resulting models are shown in figure 4.4 which indicate both a reasonable order and form of the function f needed to make the response linear. A physical interpretation makes it clear that the function needs to produce small steps at small initial choke opening, and then increase the steps as the choke opening gets larger.

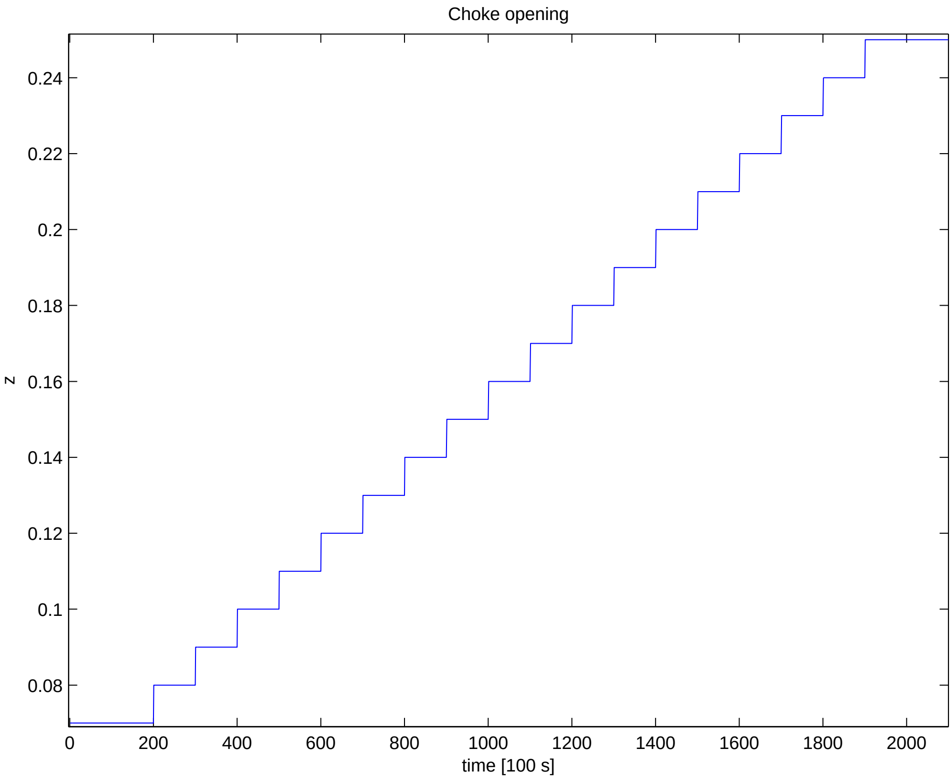

FIGURE 4.3: Shows 1% increase in choke opening every 10000 second. Note that the starting value is greater than 6.5% in order to avoid overbalanced well pressure.

Both 2nd and 3rd order polynomials are satisfactory, but since the resulting models are likely to be working within narrower areas in pressure than the simulation in figure 4.4, a 2nd degree polynomial is selected.

With the knowledge of form and degree of the nonlinearity, a set of choke openings likely to give a linear BHCP response was chosen. The data were tuned through several simulations to give the most linear response. The function f in equation 4.2 was then found by using a simple polynomial fit to the choke data, with result shown in figure 4.5 and 4.6.

$$z = f(u) = 1.75 * 10^{-7}u^2 + 1.75 * 10^{-5}u + 0.0665 \tag{4.2}$$

As mentioned in this section, the choke opening has to be greater than 6.5% in order to keep the well underbalanced. Once underbalanced, the well will not

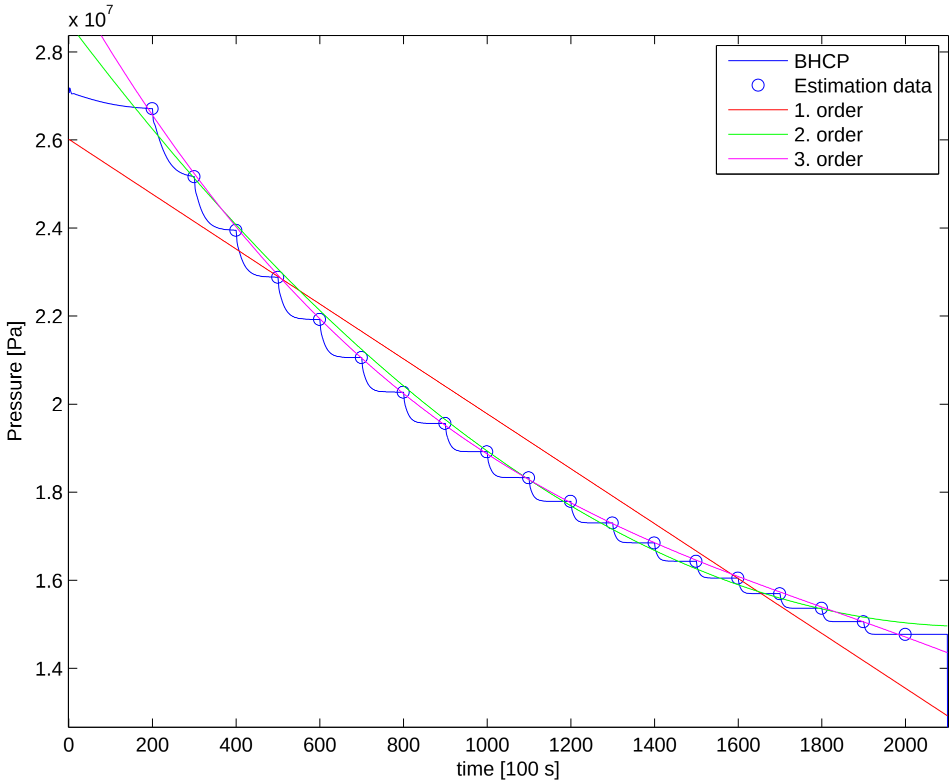

FIGURE 4.4: The nonlinear response on BHCP from the linear input in figure 4.3

become underbalanced again by opening the choke, but rather adjusting the pump rate. To simplify the modelling, the simulations will mainly focus on data from choke openings from 6.5% to about 30%. The new input u is scaled to fit within this scope easily as shown i table 4.2.

For validation of the improved performance, the models in table 4.5 is used as reference. The properties of the models and the methods used are not important at this stage, but rather the comparison of fit to validation data shown in table 4.3. The results clearly show an improvement of the accuracy of the models obtained, especially for the higher order models.

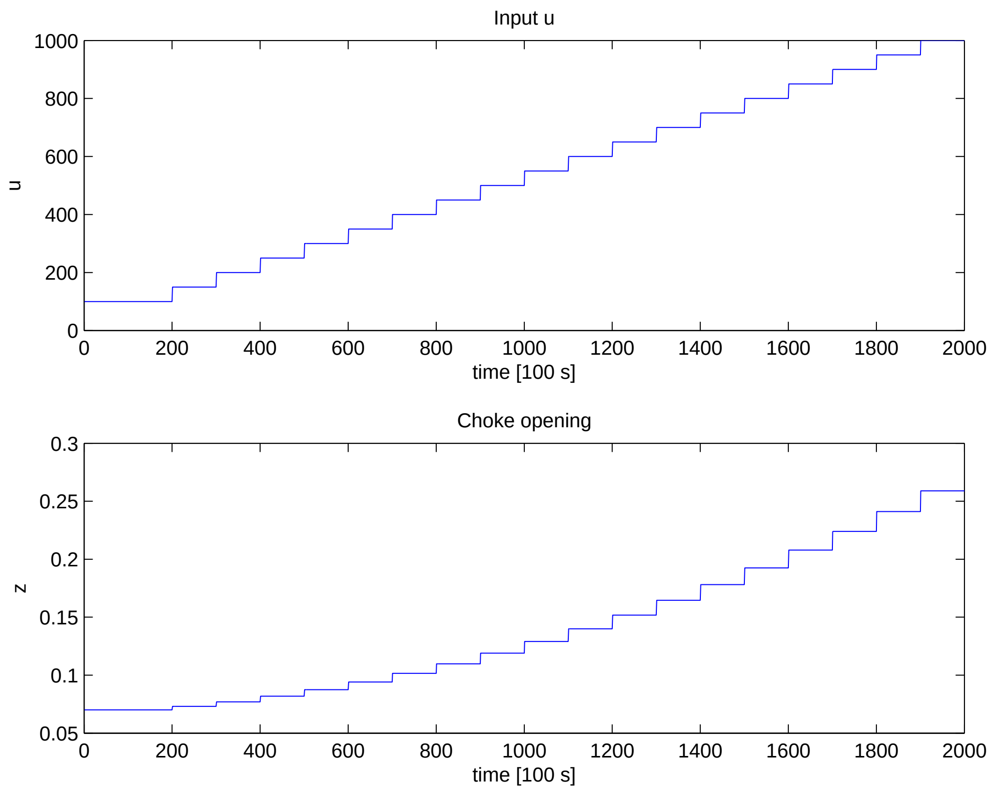

FIGURE 4.5: The linear input values u and the corresponding nonlinear values of the choke opening z.

Input value u	Choke opening z	Note
0	0.0665	Lower limit for underbalanced state
200	0.0770	
400	0.1015	Set point in the further work
600	0.1400	
800	0.1925	
1000	0.2590	

TABLE 4.2: The new input u and corresponding choke openings z.

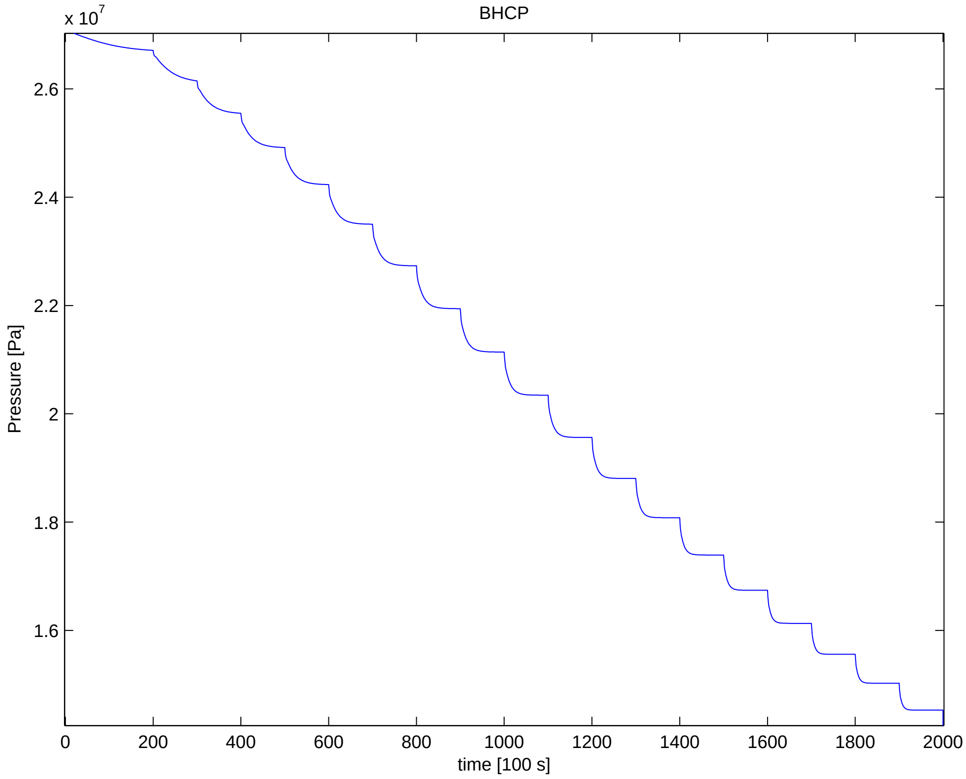

FIGURE 4.6: The linearized output due to the variable change at the input shown in figure 4.5.

Name	Input: z	Input: u
tf1	90.56	92.34
tf5	93.67	96.32
tf10	93.80	96.22
tf18	-0.5531	97.11
tf23	91.79	97.20
ss5	92.62	96.89

TABLE 4.3: The fit to validation data [%] of the same models estimated with both the choke opening z and the new input u as input.

4.4 Matlab System Identification Toolbox

Matlab contains a toolbox called "sysid" with various methods to construct mathematical models from data. By defining the input and output data as an object using the "iddata" command, it is possible to use a wide selection of techniques to identify a model. The command "ident" opens up an application which allows you to upload data, pre-process the data, try out different estimation methods and compare the different properties of the resulting systems easily. The methods can in addition be used with direct Matlab commands in scripts if desirable. Following are two methods considered to be the simplest and a more advanced method suitable for complex systems.

4.4.1 Transfer Function Model

"tfest" estimates a transfer function from input/output data with a given number of poles and zeroes, in addition to optional transport delay and initial parametrization. By default, the initialization method is set to instrument variable(IV) approach, but other methods such as state variable filters(SFV) approach can be selected. Once well defined, the search method for the optimization problem is selected automatically from (adaptive) Gauss-Newton, Levenberg-Marquardt, trust region reflective Newton and Gradient search. Any of these methods can also be selected manually in addition to iteration parameters such as number of iterations and output weighting.

The estimated model is stored as a "idtf" object with parameters and fit compared to the estimation data.[10]

4.4.2 State Space Model

"n4sid" is used to estimate state space models. The model structure is given in equations 4.3 and the parameters are being estimated from input/output data with a given order, and some additional options including initial conditions, weighting, prediction horizon and focus.

$$
\begin{aligned}
\frac{dx}{dt} &= Ax(t) + Bu(t) + Ke(t) \\
y(t) &= Cx(t) + Du(t) + e(t)
\end{aligned}
\tag{4.3}
$$

The weighting option specify weighting scheme used by the singular value decomposition used in the estimation. The most important option related to this system identification is however the focus. The focus option defines how the error between outputs are being weighed during the minimization. Default setting is "prediction" where the weighting function minimize one-step ahead prediction. This setting is favourable for small time intervals, but can lead to unstable models. For longer intervals the "simulation" option is more suited as the weighting is more refined and provides a stable model. In addition, there are options enabling manually weighting and weighting with the help of filters.

The resulting model is stored as a "idss" object with parameters given in matrices A, B, C, D and K from system 4.3 with dimensions given by the selected order, and fit compared to the estimation data.[11]

4.4.3 Nonlinear Model

A nonlinear model is more complex than the other model structures. There are two model types to choose between, Hammerstein-Wiener ("idnlhw") and Nonlinear ARX ("idnlarx"). Both model types can be adapted with a great number of options which enables for great fit even to complex systems. Unlike the previous methods, the resulting identified model does not have a certain structure and given parameters. It appears as a "black box" and does not necessarily simplify the initial system. Details about the methods can be found in [12] and [13].

4.4.4 Fit

The "compare" function compares the prediction of the estimated model with validation data. The fit is calculated using the normalized root mean square error (NRMSE) which is able to gather the magnitude of error from many samples into one measure of fit. The function is given as

$$fit = 100\left(1 - \frac{\|y - \hat{y}\|}{\|y - mean(y)\|}\right) \tag{4.4}$$

where $\hat{y}$ is the output BHCP of the estimated system and y is the validation data. [14]

4.5 Identification Data

As the amount of gas in the system varies with the state, the system is dynamic and some testing is required before settling for data sets used in the final identification. With increasing amounts of gas in annulus, the system changes properties and it is therefore assumed that the identified model looses accuracy when operating far from the original set point. It is therefore decided to use a low initial set point of 400 on input (about 10% choke opening), as a basis for the identification.

All data sets used for estimation come from simulations of 300,000s and is considered to be PE due to the random fluctuations.

4.5.1 Integral Effect

Because the transfer function models in section 4.4.1 identify prediction models rather than simulation models, some unwanted effects might occur. A model is estimated from data shown in 4.7 using the "tfest" function. Figure 4.8 clearly shows how the prediction gives the correct response, while the simulation obtains an integral effect. The reason for the difference is the fact that the predicted response uses previous validation data when computing the next step, while the

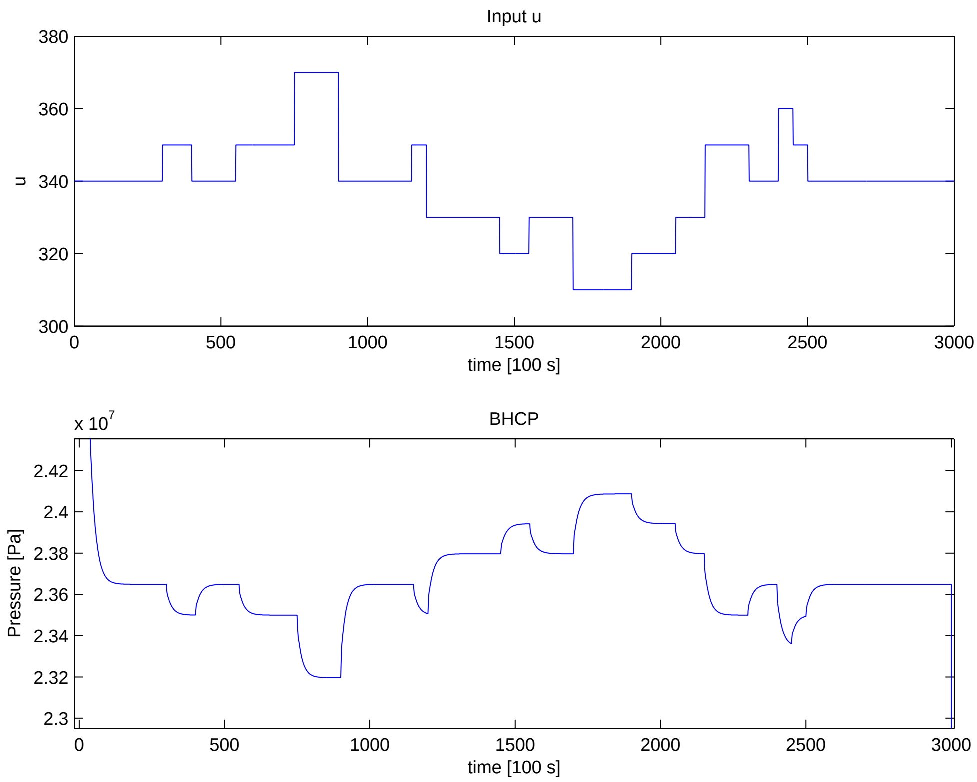

FIGURE 4.7: The simulation of the estimation data with integral effect.

simulation is independent of validation data. Since the "compare" function only uses the predicted response when validating and calculates a fit value, this effect does not occur before actually using the model. A remedy for this problem is to correct both the estimation and validation data such that the set point is zero. This can be obtained by simply subtracting the set point on the input and output.

Beside eliminating the integral effect, adjusting the set point to zero also simplify the control problems in chapter 5.

4.5.2 Data Testing

The range of the identified models are investigated through a series of estimation and validation data sets. The estimation script, see appendix A.2, is used for the estimations and produce 38 transfer functions and state space models. The nonlinear model estimations are not being used due to the potential complexity

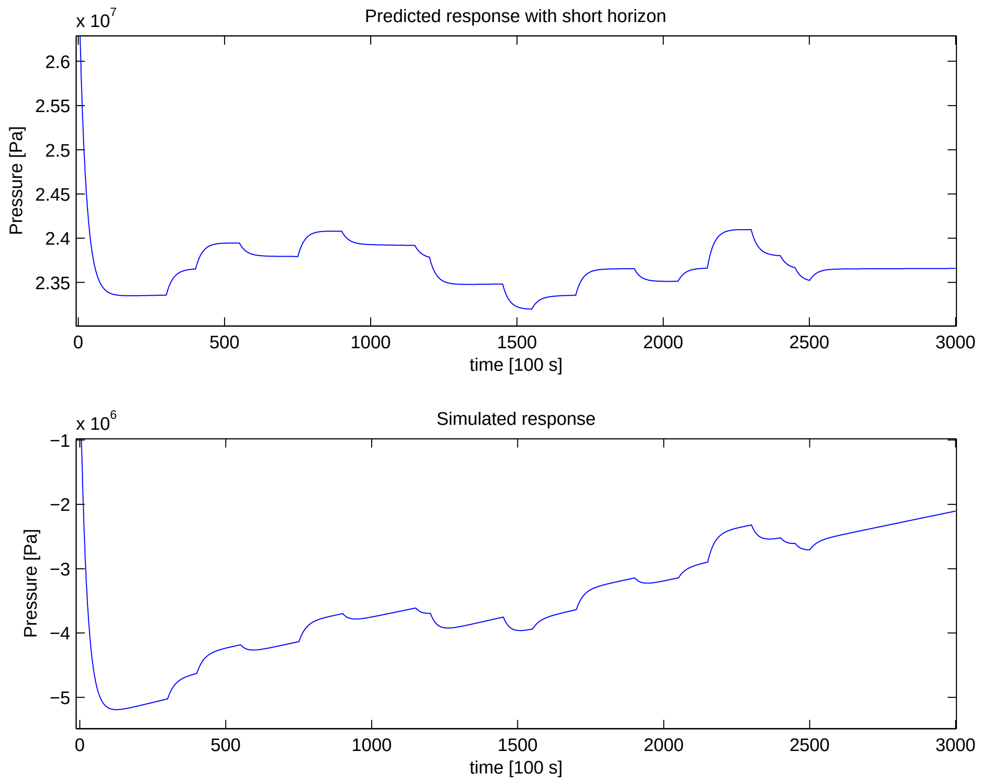

FIGURE 4.8: The prediction use validation data when predicting the next step, thus avoiding integral effect.

of the models. Note that the set point (400 on input) has been subtracted from all data due to the effects discussed in 4.5.1.

To find well suited estimation data, models are identified from data set 1-5 with increasing amplitude on the fluctuations shown in figure 4.9. Each set of estimated models is then tested with validation data 1-5 shown in figure 4.10, also with increasing amplitude on the fluctuations. Note that the data sets with the same number (Estimation 1 and Validation 1 etc.) have the same amplitude on the fluctuations, but different behaviour.

Since some models can produce a good fit for one set of validation data and other models produce good fit for other validation data, one model is selected from each estimation data set. The model selected is the model with the best overall fit when compared to all the validation data. The fit values of the model from each estimation data set compared to all the validation data are shown in table 4.4.

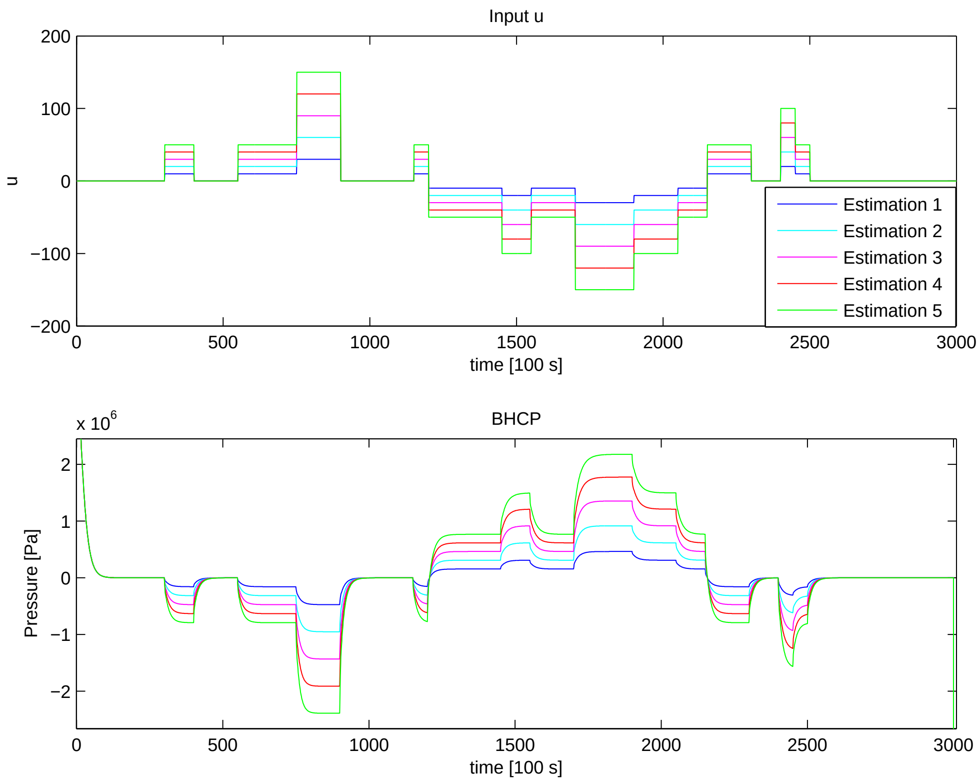

FIGURE 4.9: The estimation data sets with increasing amplitude on the fluctuations. [Input set point: 400]

	Validation1	Validation2	Validation3	Validation4	Validation5
Estimation1	99.02	98.06	96.98	95.78	94.45
Estimation2	98.97	98.10	97.09	95.94	94.65
Estimation3	97.73	97.64	97.20	96.50	95.57
Estimation4	98.43	97.84	97.16	96.26	95.15
Estimation5	95.14	96.04	96.28	96.10	95.58

TABLE 4.4: The fit [%] of the best model from each estimation data set compared to each validation data set.

Table 4.4 shows how small fluctuations leave less room for error and the best fit values often are obtained for the first validation data sets. The best model from the estimation data with greatest amplitude (Estimation 5), does not seem to obtain high accuracy for any of the validation data tested, but is likely not to deteriorate as fast as the other models when moving away from the set point.

Models from Estimation data 1 to 4 are all accurate enough compared to validation data with small amplitude, but estimation data 1 and 2 are considered to have

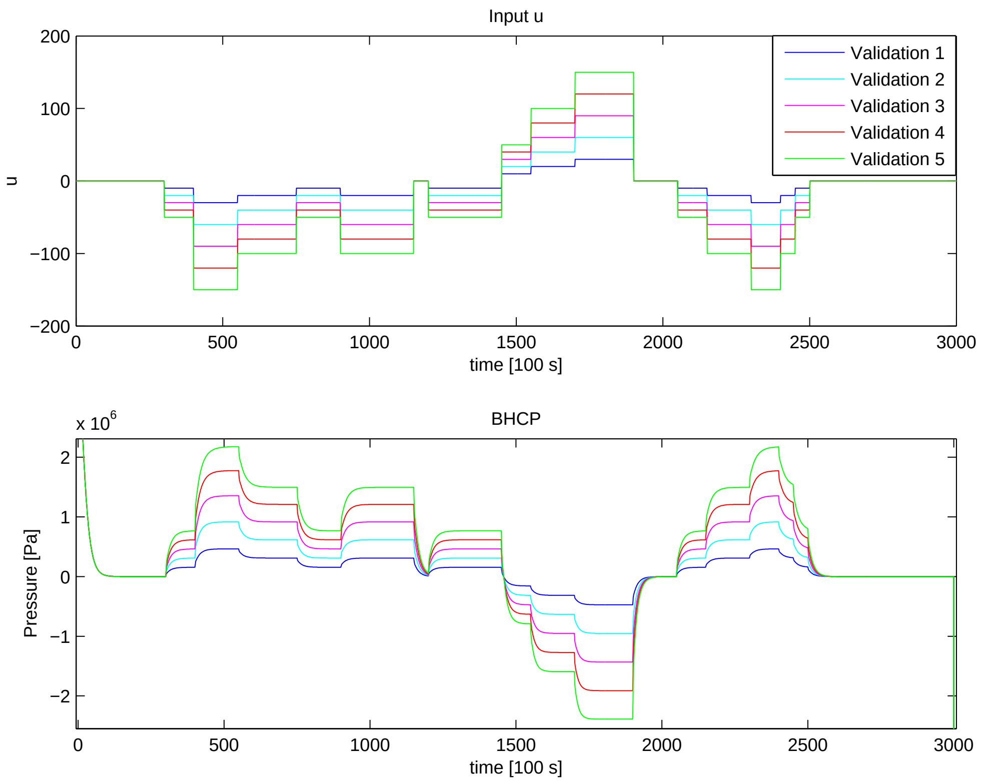

FIGURE 4.10: The validation data sets with increasing amplitude on the fluctuations. [Input set point: 400]

too poor range. Although not the most accurate for Validation 1, the model from Estimation 3 seems to have consistent and good accuracy over the whole range tested. Further investigations also reveal a selection of low order models with good accuracy for the whole range. It is therefore decided to use estimation data 3, shown if figure 4.11, as the estimation data when identifying the final models. To validate the final models, validation data 3 shown in figure 4.12, will be used.

4.6 Identified Systems

The estimation script, see appendix A.2, is used to produce the models with estimation data in figure 4.11 and validation data in figure 4.12. When selecting the best estimations, models of lower order are preferred as long as they produce what is considered to be "accurate enough" results. Besides the fit values, the

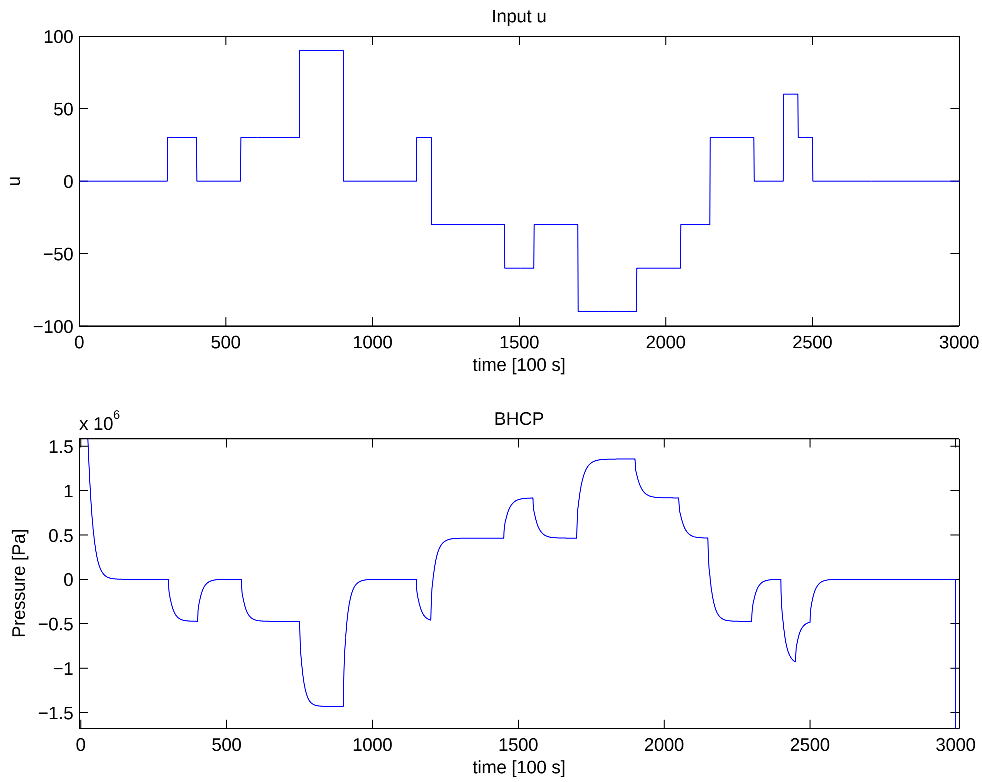

FIGURE 4.11: The input and output of Estimation 3 in table 4.4 and figure 4.9, that will be used for final identifications. [Input set point: 400]

response has to be studied to determine if the error is caused by minor deviations over time or sudden transients.

An overview of the best models are shown in table 4.5, while figure 4.13 and 4.14 show the typical error in steps and stationary error respectively.

All models produce accurate responses compared to validation data in figure 4.10. For control purposes however, the models have some different properties to be discussed in next section.

4.6.1 Stability and Properties

The transfer functions in table 4.5 represents continuous-time LTI systems. Since all the poles and zeroes are placed in the left half plane, the models are stable and minimum phase. The state space model is discrete, and the pole-zero plot is

Name	Type	Parameters	Poles	Zeroes	Fit
tf1	Transfer function	$\frac{-884.6}{s+0.0571}$	-0.0571	-	92.34%
tf5	Transfer function	$\frac{-3419s-407.1}{s^2+0.5555s+0.02629}$	-0.5033, -0.0522	-0.1191	96.32%
tf10	Transfer function	$\frac{-2223s^2-3150s-408.4}{s^2+0.5329s+0.02636}$	-0.4777, -0.0552	-1.2730, -0.1444	96.22%
tf18	Transfer function	$\frac{-48880s^3-12120s^2-833.3s-16.8}{s^5+11.58s^4+10.64s^3+1.375s^2+0.06693s+0.001088}$	-10.591, -0.8484, -0.0549±0.0234i, -0.0340	-0.1490, -0.0613, -0.0376	97.11%
tf23	Transfer function	$\frac{-8794s^4-1802s^3-176.5s^2-10.74s-8.682*10^{-5}}{s^5+1.615s^4+0.2054s^3+0.02004s^2+0.0006932s+1.258*10^{-10}}$	-1.4861, -0.0508, -0.0393±0.0874i, -1.8*10^{-7}	-0.1225,-8*10^{-6}, -0.0412±0.0910i	97.20%
ss5	State space model	5. order	0.2226, 0.9346, 0.5068±0.3086i, 0.9469	0.7440, 0.9475, 0.5452±0.2548i	96.89%

TABLE 4.5: The estimated models with parameter values, poles, zeroes and fit to validation data. The state space model ss5 has the form of equations 4.3.

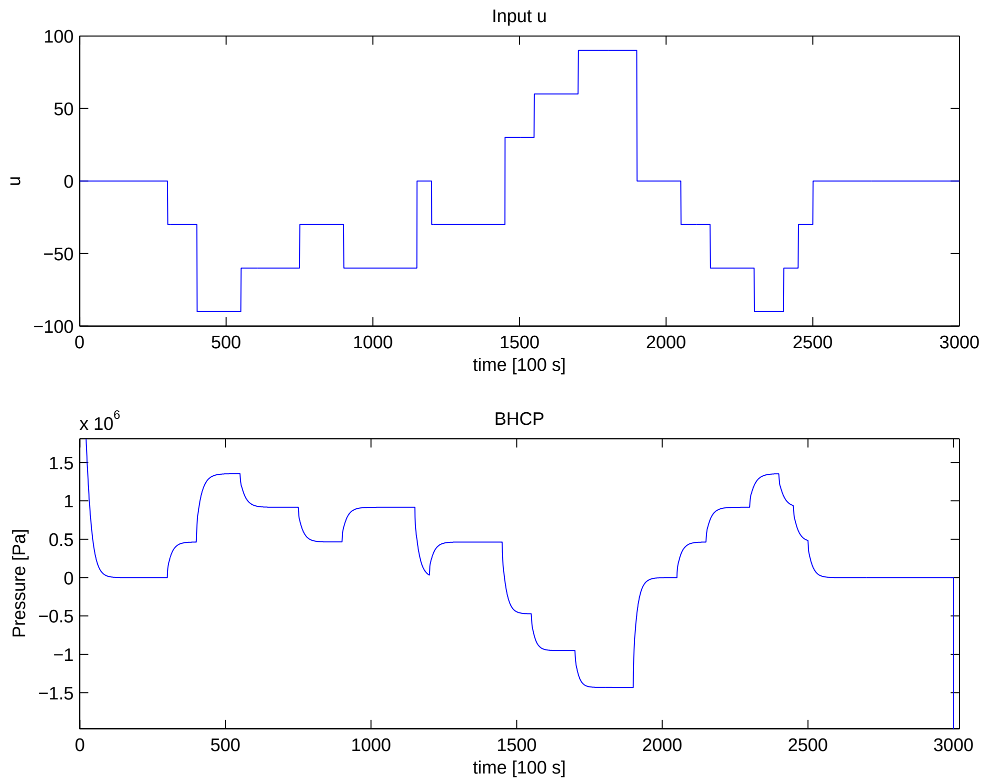

FIGURE 4.12: The input and output of Validation 3 in table 4.4 and figure 4.10, that will be used to validate the final models. [Input set point: 400]

shown in figure 4.15. Since the poles and zeroes are placed within the unit circle, the model is stable and minimum phase. All models seem to match the stable steady state behaviour of the simulation data.

The relative degree for the transfer function models are listed in 4.6. Functions with positive degree are proper, while degree greater or equal one are strictly proper. The strictly proper transfer functions will trend towards zero as s approaches infinity and will therefore also be physically realisable [15].

All of the models in table 4.5 are likely to function properly as a base for control purposes. There are however some features that are preferred in order to maintain simplicity in the further work:

- Strictly proper functions as they are more applicable on a general basis.
- Lower order models if they deliver satisfactory accuracy.

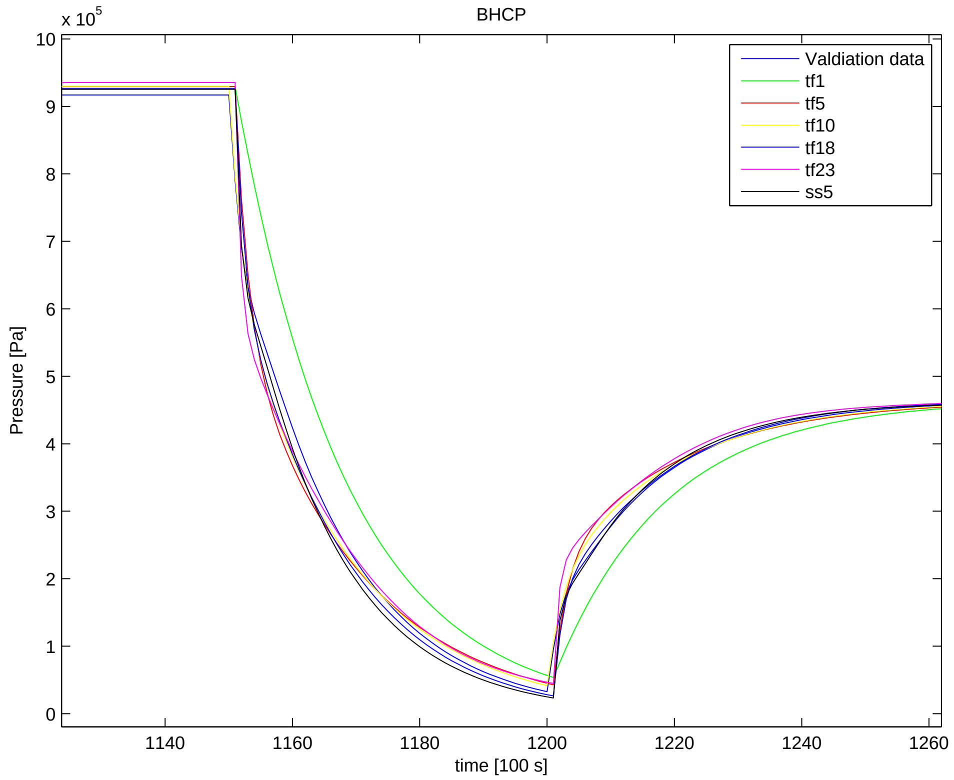

FIGURE 4.13: The typical error when applying steps on estimated models in table 4.5.

Model	Poles/zeroes	Relative degree	Property
tf1	1/0	1	Strictly proper
tf5	2/1	1	Strictly proper
tf10	2/2	0	Biproper
tf18	5/3	2	Strictly proper
tf23	5/4	1	Strictly proper

TABLE 4.6: The relative degree of the transfer functions and corresponding property.

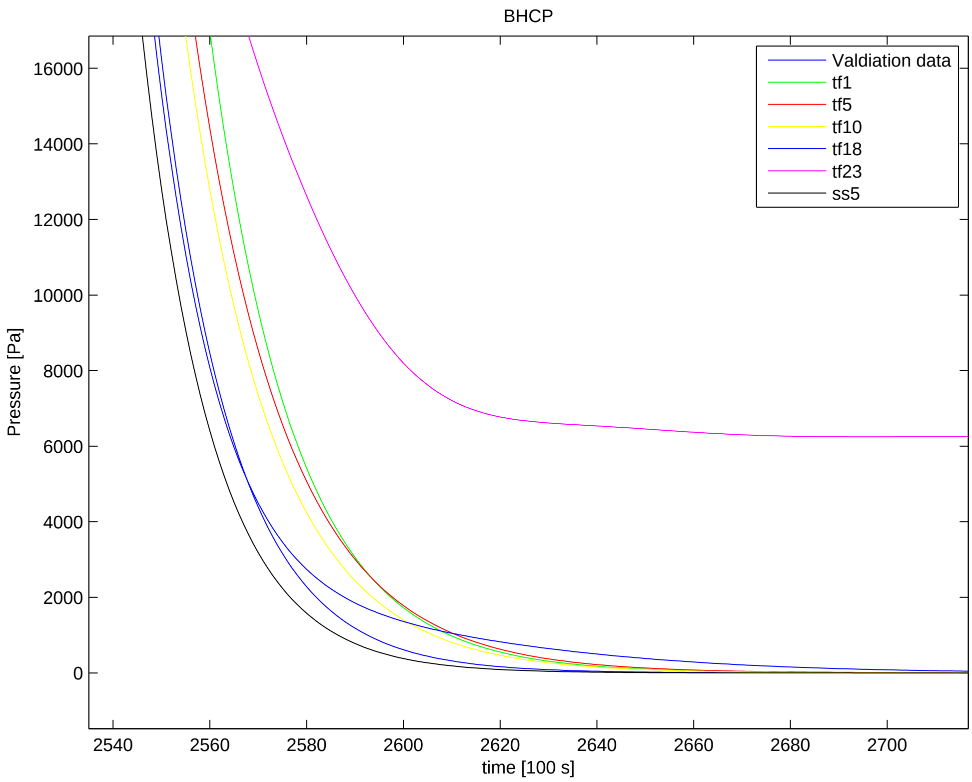

FIGURE 4.14: The stationary error for the estimated models in table 4.5.

tf5 satisfies these requirements together with a good accuracy within a wide pressure window, and will therefore be used as base for the control problem.

4.6.2 Range of Identified Model

Due to underlying non-linearities, the simple models identified are expected to become inaccurate when moving away from the initial set point used for estimation. To investigate the range of the selected model tf5, the model is validated with data given in figure 4.16. The resulting output of the model is shown in figure 4.17. When the input value increases to 500 of the set point (equivalent to a choke opening of about 22% from a set point of 10%) the modelled pressure is $8 * 10^5$ Pa higher than the validation data. The fact that the validation data do not obtain this steady state pressure before an input value of about 1000 (equivalent to a choke opening of about 26%) emphasizes the magnitude of this error.

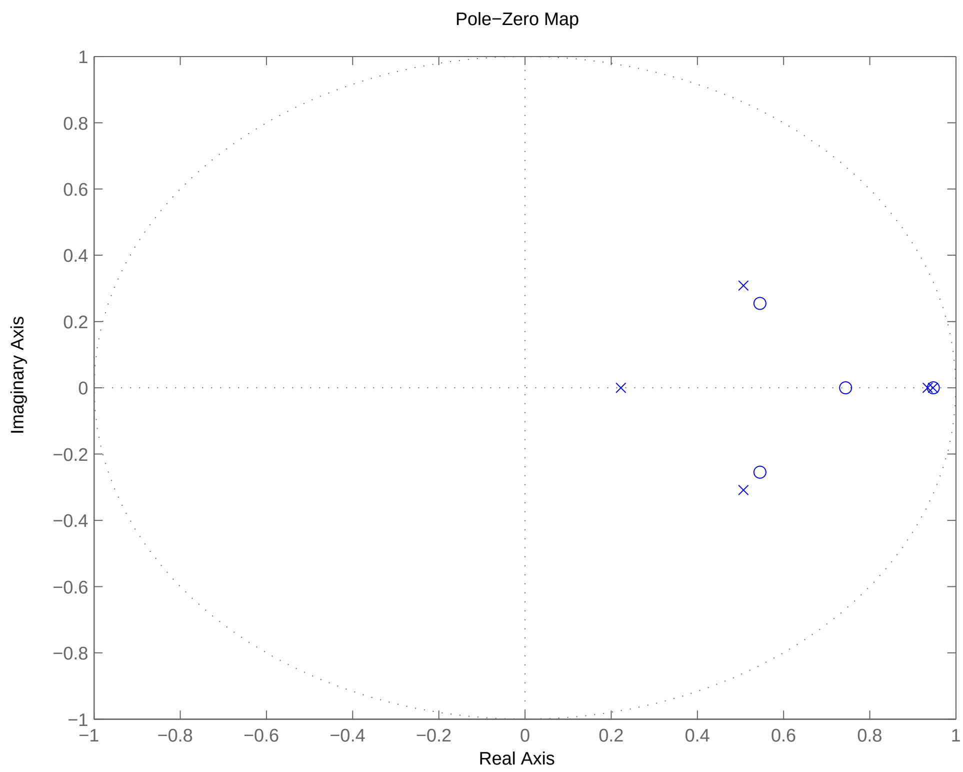

FIGURE 4.15: The position of the poles and zeroes of the state space model ss5 in table 4.5. The poles are indicated by a X, while the zeroes are indicated by a circle.

Input values less than 400 however (equivalent to a choke opening of about 19%), seem to produce accurate response with error less than $2 * 10^5$ Pa. The model is then proved to have a valid response from 8% (lower limit in the test) to about 19%.

4.7 General Model

Section 4.6.2 confirms that the model identified from data fluctuating around a certain set point has a limited range due to underlying non linearities. By changing the set point it can be clarified whether the same models with updated parameters are able to become accurate at other set points, or if a new model order is needed.

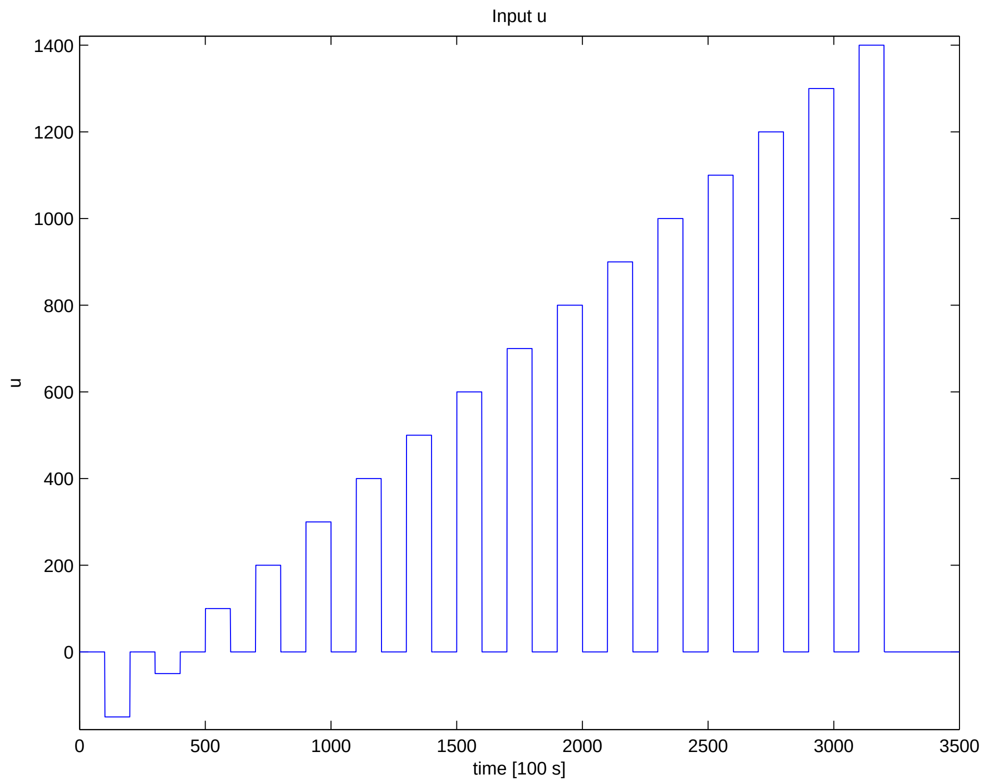

FIGURE 4.16: The input of the validation data used to investigate the range of the selected model. The set point is the same as used when estimating the model. [Input set point: 400]

4.7.1 Increased Set Point

To investigate if the previous models can be used as a general basis, new estimation and validation data are created with the same fluctuations as the previous estimations, see figure 4.11 and 4.12, but with set points increased to 1500 and 2000 (choke opening of about 49% and 81% respectively).

Since the fluctuations on the data are the same as the previous identification in section 4.6, the results can be compared to table 4.5.

The results are shown in table 4.7 and the new models perform in general poorer than the original. In addition, it seems to be random which models are able to maintain good accuracy with new parameters and which deteriorates. The model order with the best overall performance is tf5, which is used in the final identification used for control purposes in chapter 5.

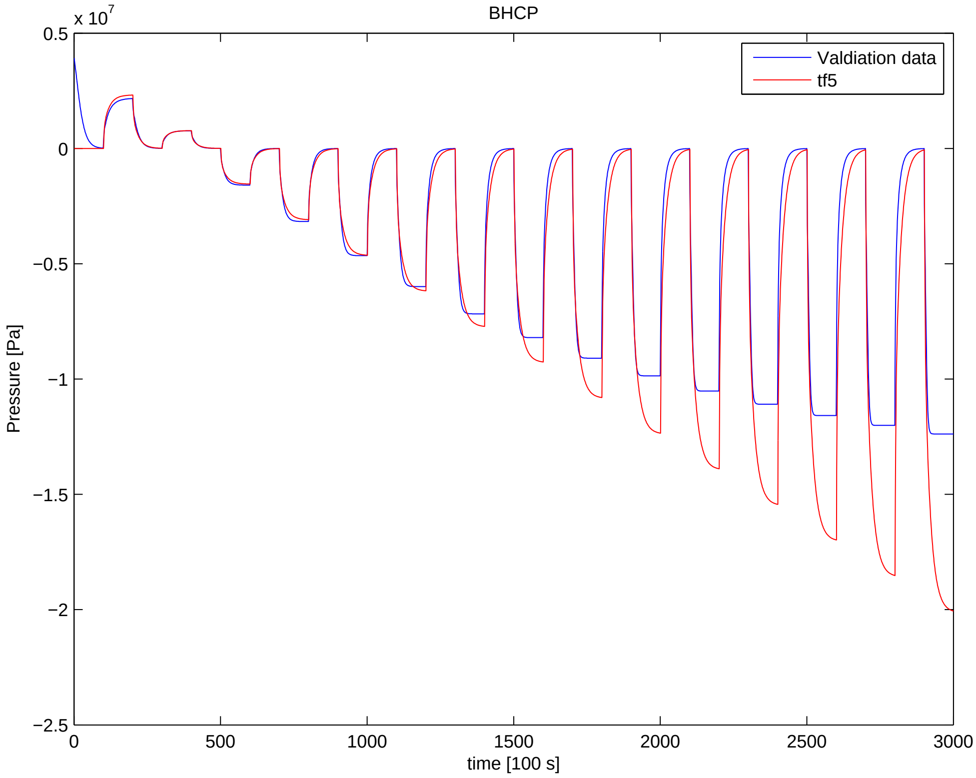

FIGURE 4.17: The response of model tf5 compared to the validation data. Input of the data is shown in figure 4.16. [Input set point: 400]

Model	Set point: 400	Set point: 1500	Set point: 2000
tf1	92.34	83.53	81.69
tf5	96.32	86.53	90.78
tf10	96.22	68.09	76.84
tf18	97.11	96.06	53.43
tf23	97.20	58.64	47.03
ss5	96.89	76.16	67.05

TABLE 4.7: The fit values of the models originally identified in table 4.5 compared to models of the same order identified from similar data with greater set point.

Model	Poles/zeroes	Fit
tf1	1/0	87.18
tf5	2/1	88.40
tf10	2/2	89.07
tf18	5/3	84.03
tf23	5/4	87.58
ss5	5/4	88.33

Table 4.8: The fit values of the best models identified from estimation data near overbalanced state in figure 4.18 compared to validation data in figure 4.19.

4.7.2 Operational Limit

When operating near the limit to overbalanced drilling, the fraction of gas in the system can change rapidly and cause effects discussed in section 2.6.3. To test if simple models are able to behave accurately when approaching overbalanced state, data sets shown in figure 4.18 and 4.19 with a set point at 95 (choke opening of about 7%) are created (the behaviour of the fluctuations remains the same as previous data). The settings on the current simulator made it difficult to obtain non-intuitive response, but the figures clearly show how the system becomes dramatically slower when decreasing the choke opening and the well pressure increases. The results are shown in table 4.8 and reveals that the models accuracy still are satisfactory[4].

Since the performance of tf5 is satisfying both at other set points and near overbalanced state, the model order has the potential to become a general basis for models to cover the whole pressure range. This can however not be confirmed before further testing is performed. The results do, however, confirm that underbalanced drilling, as stated in the simulator, can be modelled by simple transfer functions under normal operating modes. This knowledge of the simple system dynamics is helpful for creating a suitable controller.

[4]Note that the decreased amplitude in the data might impact the fit value.

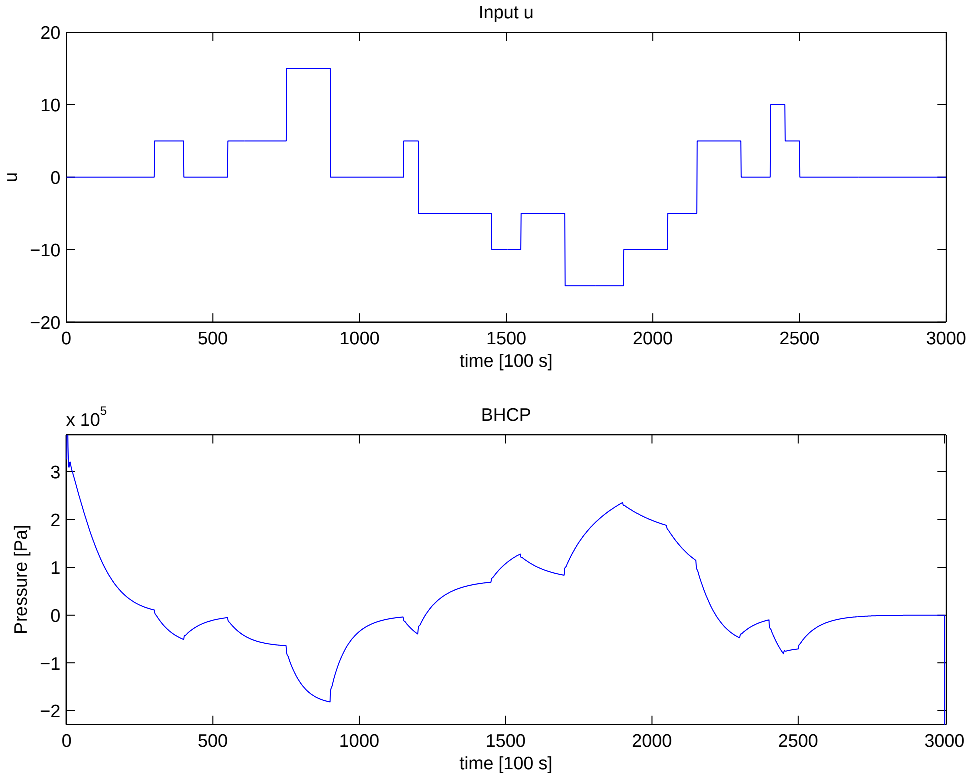

FIGURE 4.18: The estimation data used to explore model properties when operating close to overbalanced pressure. [Input set point: 95]

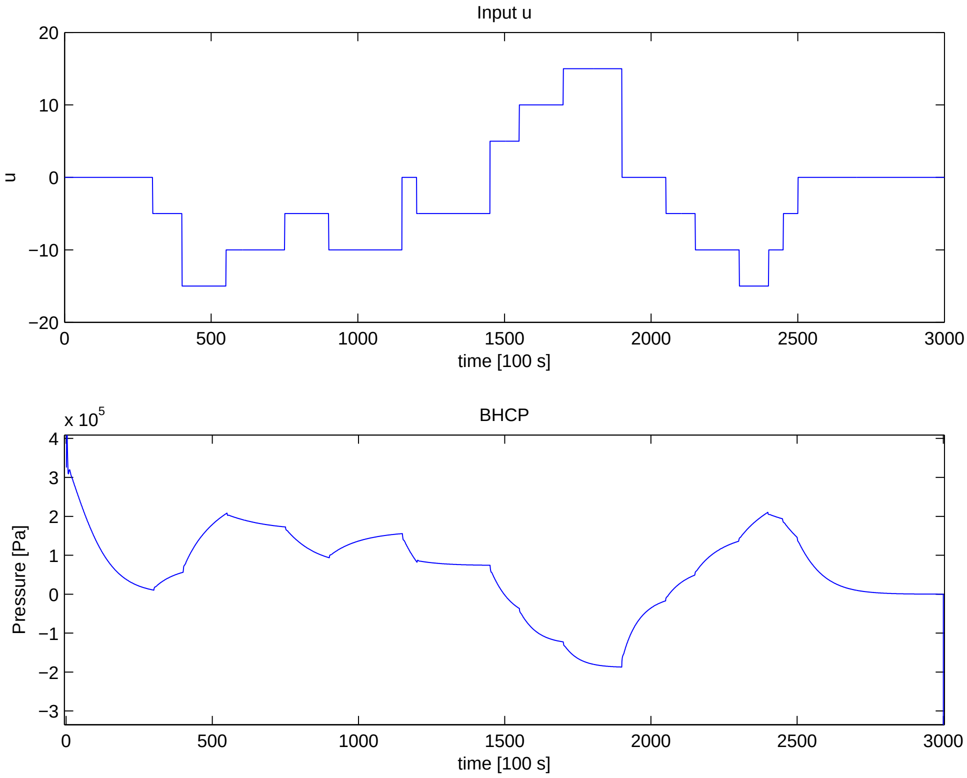

FIGURE 4.19: The validation data used to explore model properties when operating close to overbalanced pressure. [Input set point: 95]

Chapter 5

Control

5.1 Theory

Simple control methods such as proportional integral derivative controllers (PID) have been applied since the beginning of the 20. century. Even though the design and principles are simple, the controllers often perform good. The PID controllers' main focus is to minimize the error between a process variable and desired set point. The error is processed by three separate terms which focus on different parts of the minimizing problem. Since the control target is to keep the pressure within certain limits, see section 2.6.1, the controller set point is given as pressure. The simple control sections are based on [16] and [17].

5.1.1 Proportional

The proportional term u_p is given as

$$u_p = K_p(P_{sp} - BHCP) \tag{5.1}$$

where K_p is the proportional gain, P_{sp} is the pressure set point and $BHCP$ is the actual bottom hole pressure. This part of the controller corrects the present error in the system.

5.1.2 Integral

The integral term u_i is given as

$$u_i = K_i \int_0^t (P_{sp} - BHCP) d\tau \tag{5.2}$$

where K_i is the integral gain. The integral term uses the sum of error over time to correct the offset not corrected earlier. The gain depends on both the magnitude and duration of the error, and is therefore well suited to remove stationary offset not corrected by the other terms.

5.1.3 Derivative

The derivative term u_d is given as

$$u_d = K_d \frac{d}{dt}(P_{sp} - BHCP) \tag{5.3}$$

where K_d is the derivative gain. The derivative term uses the derivative of the error to predict the behaviour of the system, thus improving the controllers performance. Systems conflicted with noise however, will have a very variable contribution from this term. These effects can impact the stability of the system, and the term is therefore often omitted in real applications.

5.1.4 PID

The final output of the PID controller, called the manipulated variable (MV), is the sum of the three terms. Due to the fact that the identified system has a simple and slow response, the derivative term can be removed. The PI controller is then considered to be a suitable control method.

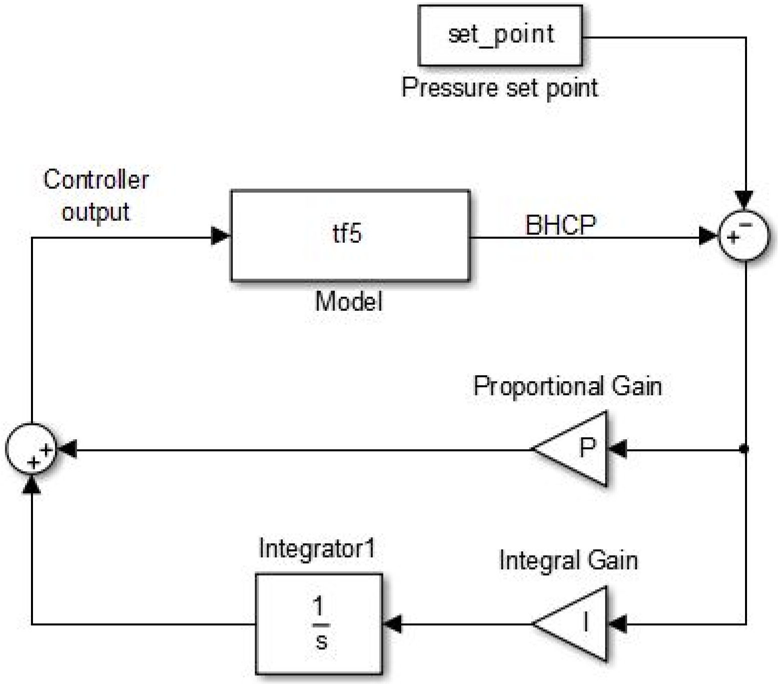

FIGURE 5.1: The model tf5 with a PI control loop.

5.2 Set Point Control

The system identified in chapter 4 is imported to Simulink and the controller is constructed as feedback control loop according to equation 5.1 and 5.2. The system is shown in figure 5.1, and the parameters K_p and K_i are tuned by trial and error. With confirmation of the controllers performance on the identified model in Simulink, it is also implemented as part of the simulator.

5.2.1 Performance

To test the controllers performance, the validation data in figure 4.12 were again put to use. By setting the validation output BHCP as the controller reference, the controlled input should match the validation input. The resulting model output compared to the reference, and the controlled input compared to the validation input can be found in figure 5.2 and 5.3 respectively.

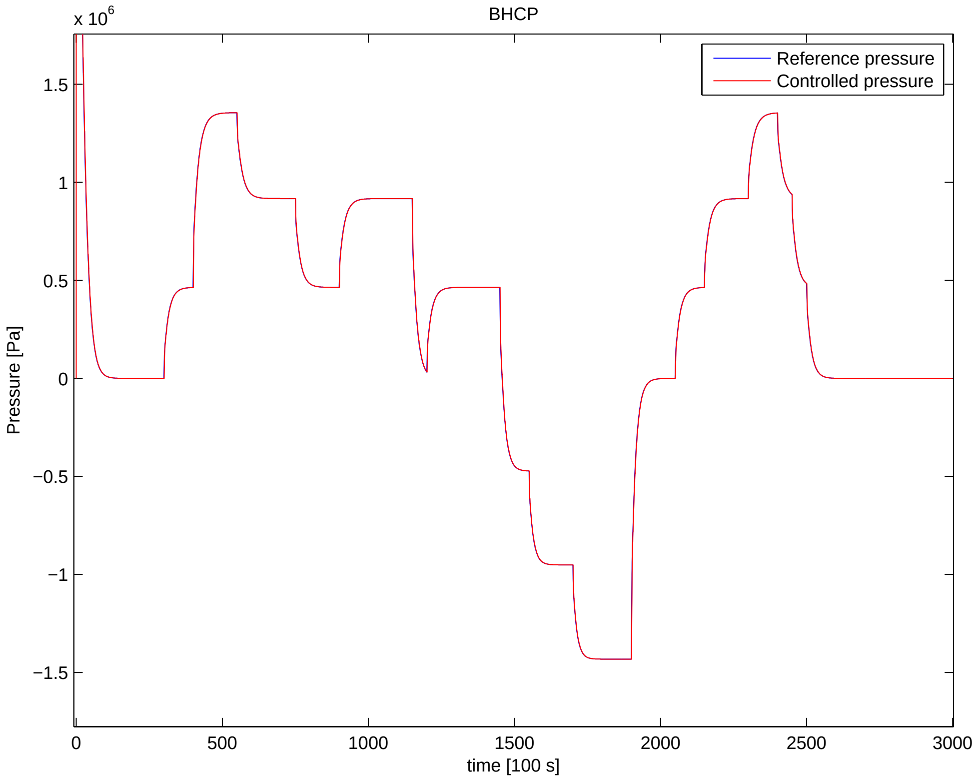

FIGURE 5.2: The controlled output compared to the reference pressure.

The results show that a PI controller with simple tuning are able to control set point changes accurately. This is expected due to the simplicity and slow nature of the response from choke opening to BHCP generated by the simulator.

5.3 Connection

Connections are an important part of the drilling process as they have to be done often when drilling effectively. When performing a connection, the drilling drive and mud flow are stopped in order to connect a new drill pipe to the string. The process can be emulated in the simulator by ramping down the mud flow to zero, and then ramping it up again to normal after a period of time. The system properties when varying the flow are unfamiliar since all the system identifications have been done with constant flow. The target for the controller is to keep the BHCP at a given value through the connection without any major oscillations.

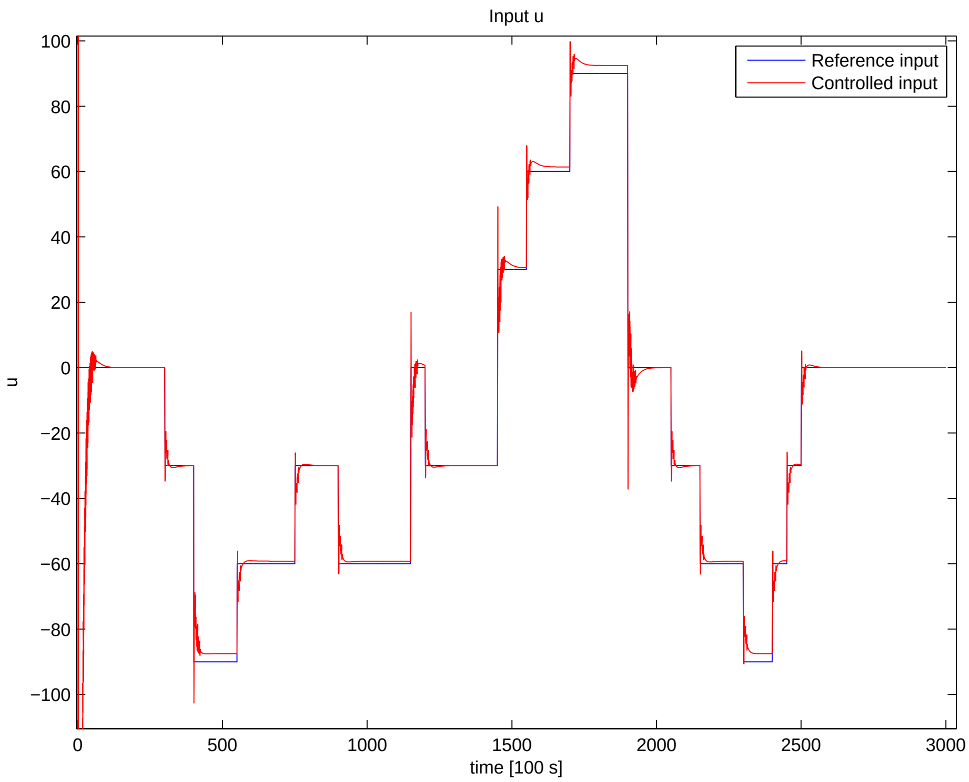

FIGURE 5.3: The controlled input compared to the validation input.

The flow, see figure 5.4, is initially set to the same value as previous estimations, then ramped down to zero during 2 minutes, stay stationary at zero for 21 minutes and then ramped up again to the initial flow during 3 minutes. The pressure set point for the controller is set to match the stationary value of a given constant choke opening for comparison. The result of the controlled process compared to the constant choke opening is given in figure 5.5. Note that the time horizon is significantly shorter than the previous data sets.

When ramping down the pump rate, the system will gradually be drained for fluids and the BHCP will drop, see figure 5.5. As the BHCP drop, gas inflow from the formations increases together with the WHP. With the constant choke opening this will lead to a blowout. The controller avoid this by quickly closing the choke and maintaining a steady BHCP.

Despite oscillations with amplitude up to $10 * 10^5$ Pa on the BHCP, the controller seems to be performing satisfactory. In addition to control the pressure during the

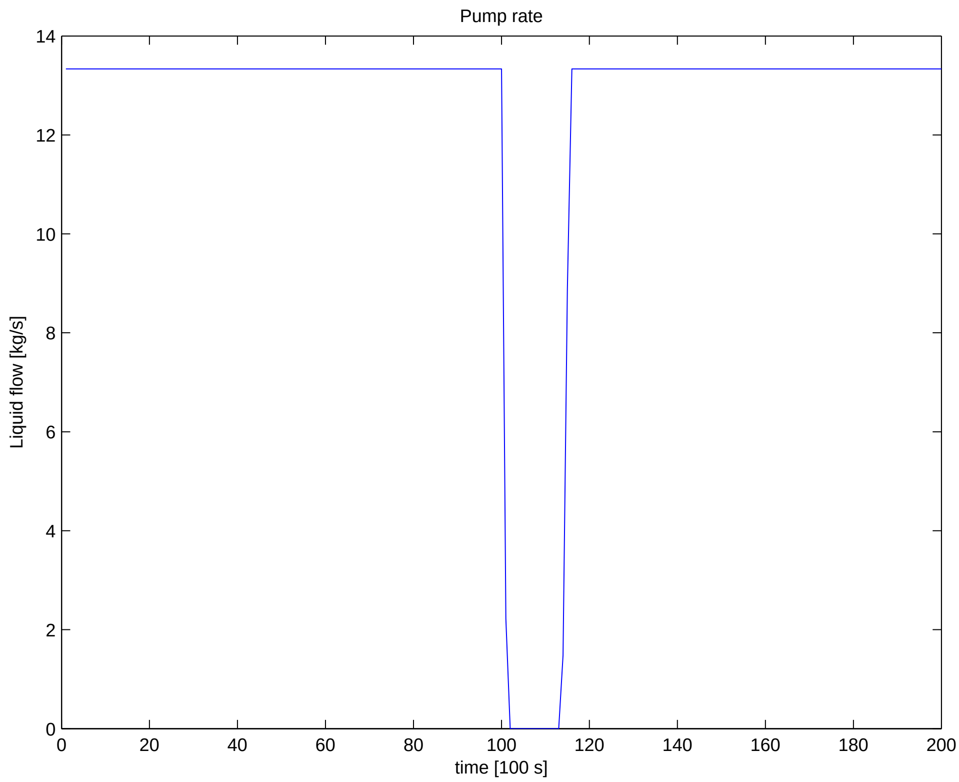

FIGURE 5.4: The pump rate during an emulated connection.

connection, the controller also manage to reach the initial set point quicker than the constant choke opening. When running longer connections, the controller maintain the same performance, while the simulator is having trouble with the constant choke opening as it develops to a blowout.

These results emphasize that the controller perform satisfactory, and that it is needed during connections to avoid disasters.

5.4 Gain Scheduling

The tuning of the PI controller is optimized for the chosen model and the performance is likely to decrease when changing to a slightly different model at another set point. If all the models representing the complete underbalanced drilling system are known, a principle called gain scheduling can be used.

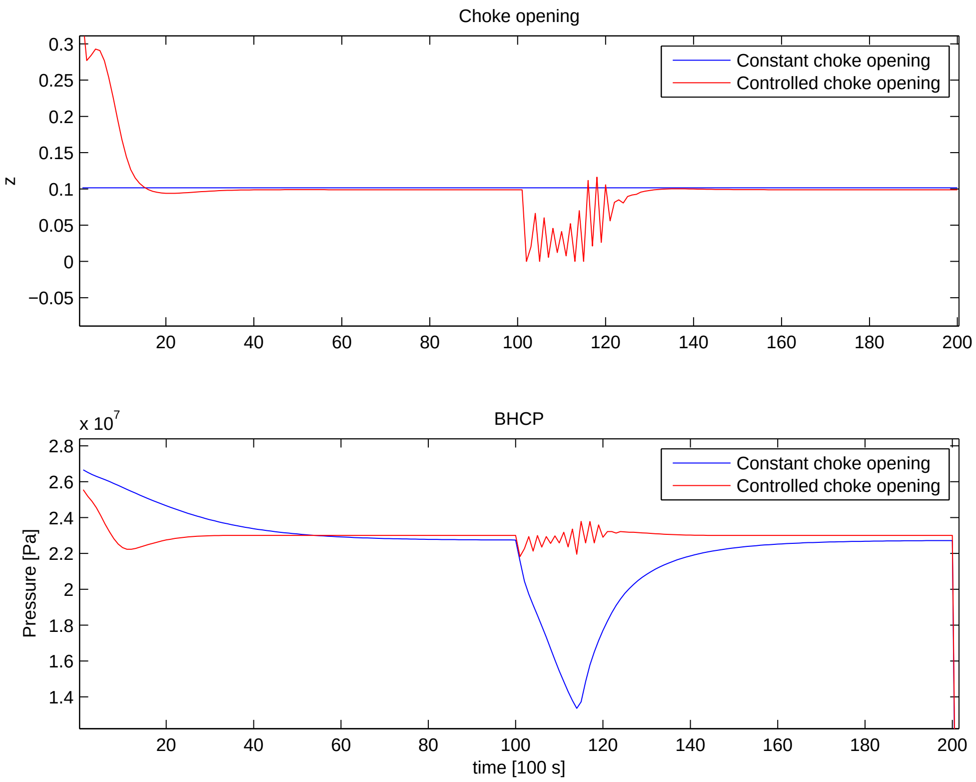

FIGURE 5.5: The controlled input and responding BHCP compared to the response of a constant choke opening.

The principle behind gain scheduling is to find the optimal controller parameters for each operating point (i.e. each identified model), and then make the final controller switch between the parameters depending on the state of the system. Even though unpredictable changes in the well can lead the controller to fail, gain scheduling is known for good performance and is a popular choice for dynamic systems. [15]

Chapter 6

Concluding Discussion and Future Work

This chapter will summarize the discovered results, in addition to suggest future improvements and expansion of the modelling and control methods.

6.1 System Identification

It was expected that the response from possible control moves to BHCP would be slow moving, but the testing also revealed that it was fairly simple. As the first principles of two-phase flow processes are likely to cause more complexity than necessary, the black box system identification method is the best choice. To remove unnecessary non-linearities not caused by the well itself, the input was changed from choke opening z to a new input u. Due to some problems with the calculations and run time in Matlab, this function was found and tuned by trial and error. The resulting function improved performance of the models and is satisfactory for the purposes of this work, but for improved accuracy of the models the function can be further tuned or the order can be increased.

The data sets used for estimating the models are considered PE and increasing the length or change the behaviour of the fluctuations does not seem to impact the models noticeably. Choosing higher order models than the transfer function tf5 with 2 poles and 1 zero used for main parts of this work, have some potential for increased accuracy as seen in table 4.5. However, studying the response in figure 4.13 and 4.14 does reveal that the increased accuracy is caused by minor changes in the step response and will most likely be negligible in rough environment such as drilling processes in addition to cause increased computational time. The tested steady states of the system all proved to be stable, the models identified from this data are thus also stable and minimum phase.

The final range of the models are tested in section 4.6.2. It is concluded that the model perform satisfactory with choke openings from 8% to 19 %. If this trend is general for all the models identified at different set points, in addition to the case close to overbalanced state discussed in section 4.7.2, the whole spectrum of choke openings in the underbalanced drilling process can be modelled by 8-10 models. Section 4.7 investigates the performance of the identified models of different order at other set points. As far as the investigation goes, the model order corresponding to tf5 seems to perform satisfactory at the set points tested, and can be an alternative for a general model order. By having a specific order, only a simple parameter update is needed at a new set point, instead of a full system identification process. This will simplify the process and enable for increased number models to be used, each with a smaller pressure area to cover, such that the overall accuracy increases.

As mentioned in section 2.6.3, the response can in some cases be more complex than the data obtained from the simulator in this work. These effects did not occur when testing the behaviour of the simulator at different set points, but should nonetheless be investigated if attempting to create a complete model of the process. Aarsnes [4] has done some investigation of these effects and discovered both the non-intuitive regime and even an unstable regime when testing steady states. His work suggests that there are strict limits where the system becomes non-minimum phase and his control methods based on WHP will become unstable. While not being able to test these effects, it is hard to predict the modelling needed to represent them accurately. Should the low order transfer function and state space models not be able to perform when approaching these regimes, the nonlinear models mentioned in section 4.4.3 can be an alternative.

However, for the simulator case investigated, the identified models are able to represent the underbalanced drilling dynamics with great accuracy.

6.2 Control

The slow nature of the oil well investigated was not expected to demand an advanced high performance controller. As the response was identified with low order models it turned out that a simple PI controller will suffice. Implementing the controller in Simulink together with the identified model in section 5.2, revealed that set point changes are performed with great accuracy even with simple tuning. Testing the controllers performance during an emulated connection in the simulator was unfamiliar territory as the pump rate is constant throughout the work. Despite the uncertainty the controller performed satisfactory also in this case, and simulations made it clear that the controller is needed to avoid blowouts.

When setting a new set point far away from the initial set point, a new model becomes active and the controllers performance is likely to decrease. To update the controller with new parameters, gain scheduling discussed in section 5.4 can be used. A suggestion for future work is to implement a parameter update algorithm such that the controller will perform satisfactory for the whole process.

If the non-intuitive effects are modelled, the control methods can become more advanced depending on the complexity of the models obtained. This will complicate the controller as a simple parameter update will no longer suffice to maintain good performance through the whole drilling process. A remedy for this problem can be an adaptive algorithm that is able to change the structure of the controller depending on the state of the system.

6.3 Selecting Set Point

The set point has to be selected within the limits discussed in section 2.6.1. There are however different strategies of how to select this value with knowledge of the systems current limits. To be able to maximize the effectiveness and safety of the operation, an optimization is needed. The algorithm needs to use current measurements and knowledge of the well to estimate the lower and upper pressure limits, and optimize the set point within the handling limits of the rig.

In addition, merging this optimization with the controller can be used as a base when developing a model predictive controller (MPC).

Appendix A

Simulation and Identification Software

Some of the Matlab code attached are based partly or solely on Aarsnes [8] and Evje [7]. In addition to code used to simulate and identify models, some key data sets are included as these are time consuming to generate. All the work have been performed with Matlab 2013a.

A.1 Simulation

The simulation code is taken solely from Aarsnes [7] and Evje [8], except some minor parameter changes. The files with their purpose are given in table A.1.

A.2 Identification and Control

The identification script and PI controller are listed in table A.2.

File	Properties
main.m	The main base for the simulations. Enables for choke openings, control parameters and pump rate to be set before the simulation is run.
redDFMFun.m	The reduced drift flux model from section 3.2, implemented by Aarsnes [7].
redDFMparams	The parameters of the well, the fluids involved and the discretization, in addition to the duration and time-steps of the simulation. There are two different cases implemented, the "Rune2013" case is used throughout this work.
ssInt	Used the given parameters to initialize the system.
pressure_2p	Calculates some parameters used in the initialization and the plotting.

Table A.1: List of the different files used to simulate.

File	Properties
Identify.m	Script that takes in simulation data, defines it as input/output data objects and runs 38 system identifications with models of different structure and order. The models are being compared to data by a plot and corresponding fit values.
PIcontroller.m	Function that takes in the controller parameters and pressure set value defined in Main.m and returns a new choke value.
Simulink_controller.slx	A Simulink diagram used to test and tune controllers on the identified models.

Table A.2: List of the different files used to identify and control new models.

A.3 Data Sets

Due to long run time, the key data sets used during this work are included. The sets are listed in table A.3 together with their purpose, and include all data generated by the simulator.

Name	Purpose
Data_estimation1	Data used for estimation in section 4.5.2
Data_estimation2	Data used for estimation in section 4.5.2
Data_estimation3	Data used for estimation in section 4.5.2
Data_estimation4	Data used for estimation in section 4.5.2
Data_estimation5	Data used for estimation in section 4.5.2
Data_Estimation_nearoverbalanced	Data used for estimation in section 4.7.2
Data_Estimation_set1500	Data used for estimation in section 4.7
Data_Estimation_set2000	Data used for estimation in section 4.7
Data_Validation1	Data used for validation in section 4.5.2
Data_Validation2	Data used for validation in section 4.5.2
Data_Validation3	Data used for validation in section 4.5.2
Data_Validation4	Data used for validation in section 4.5.2
Data_Validation5	Data used for validation in section 4.5.2
Data_Validation_nearoverbalanced	Data used for validation in section 4.7.2
Data_Validation_set1500	Data used for validation in section 4.7
Data_Validation_set2000	Data used for validation in section 4.7
Data_Validation_rangetest	Data used for validation in section 4.6.2
Data_Connection	Data of connection without controller in section 5.3
Data_Connection_controlled	Data of connection with controller in section 5.3
Data_Overbalanced	Data of a simulation which become overbalanced
Data_Inputfunction_testing	Data from the validation of the choke function f in section 4.3.2

TABLE A.3: List of the data sets included.

A.4 How To:

A.4.1 Run Simulation

- The choke openings have to be set or the PI controller has to be activated
- The mud flow can either be set as constant, or the interpolation function can be activated to vary the pump rate
- The simulation time parameters can be set in redDFMparams.m

When these parameters are set, the simulation is started by running main.m. Note that the simulation is sensitive for increased calculations, which will increase run time dramatically. Thus several of the calculations are performed before the simulation process. If the simulator crash, it will enter a debug mode.

A.4.2 Identify Models

New models can be identified by setting desired estimation and validation data before running Identify.m.

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