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Data-Driven MPC

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Industrial Cybernetics

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Preface

This thesis is submitted as the final part of the degree Master of Science in Industrial Cybernetics at the Norwegian University of Science and Technology (NTNU). It is the culmination of my work at NTNU, under the supervision of Lars Imsland, during the spring semester of 2021. The thesis summarizes findings and the methods used to apply a data-driven methodology in Equinor's in-house software for model predictive control (MPC), SEPTIC. The thesis is written in collaboration with Equinor, from where John-Morten Godhavn and Pål Kittilsen have been supervisors and collaborators. The thesis was inspired by recent research in the field of data-driven MPC and on the initiative of Equinor to explore the opportunity of implementing a data-driven MPC in SEPTIC. The main contribution of this thesis will be to implement a data-driven inspired methodology for MPC in SEPTIC, which will be tested on a single subsea well system. The data-driven methodology is based on using online data from simulations in SEPTIC and using the data for sustained and increased MPC performance through identifying and updating step response model gains.

It would benefit the reader to have some knowledge and understanding of control engineering, especially MPC. The thesis assumes the reader has prior knowledge of linear and nonlinear systems and some knowledge of optimization. However, the thesis is structured to give a reader with little or no knowledge on the topics both a theoretical understanding and understanding of the implementations in the thesis.

Acknowledgements

I would like to express my gratitude to the always helpful and inspiring supervisors from Equinor, John-Morten Godhavn and Pål Kittilsen. Throughout the writing of this thesis, they have helped and challenged me.

I would like to extend my thankfulness to my supervisor at NTNU, Lars Imsland, for important advice in our meetings throughout the semester.

Lastly, I would like to say thanks to Mandar Thombre from Equinor for our co-operative SEPTIC learning experience.

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Summary

The main objective of this thesis is to implement a data-driven methodology in Equinor's in-house software for MPC, SEPTIC. Data-driven control consists of directly utilizing online data from the process subject to control to design the controller. In this thesis, online data will be used for updating model gains for the step response models, which are used to predict how a controllable variable (CV) responds to a change of a manipulated variable (MV). The models in SEPTIC are built with experimental single-input single-output (SISO) step response models. Step response models assume linearity. However, the system on which the data-driven methodology is implemented is highly nonlinear. Therefore, the step response models will lose their accuracy if the process parameters move away from where the models were created. Since MPC is a model-based method of control, an MPC application depends on having an accurate mathematical model of the process it is controlling. If the step response models lose their accuracy, the predicted optimal inputs from the MPC will not be optimal. Updating the steady-state gains for the step response models yields sustained MPC performance despite the initial models losing their accuracy, as identified and updated model gains maintain model quality. Based on process parameters, an automatic gain identifier will excite the process to identify more precise steady-state gains. Correct steady-state gains will ensure good MPC performance despite the process parameters moving away from where the initial step response models were created.

The automatic gain identifier will be tested on a simulated subsea well system. In a subsea well system, safety is of utmost importance. Preventing constraint violation is a general objective for an MPC and is considered crucial in the subsea well system in this thesis. Constraints are added to the MPC application for safety reasons and are considered the highest priority in the controller. When the

process is excited, there is a risk of constraint violation. The automatic model gain identifier will excite the process while respecting the constraints by utilizing the online data to reduce the risk of constraint violation.

Sammendrag

Hovedmålet med denne oppgaven er å implementere en data-drevet metode i Equinors interne programvare for MPC, SEPTIC. Data-drevet kontroll består av direkte bruk av online data fra en prosess underlagt regulering, for å designe regulatoren. I denne oppgaven vil online data brukes til å oppdatere modellforsterkning for stegresponsmodeller, som brukes til å forutsi hvordan en kontrollerbar variabel reagerer på en endring av en manipulert variabel. Modellene i SEPTIC er bygget med ekspermintelle enkelt-pådrag enkel-måling stegresponsmodeller. Stegresponsmodeller antar linearitet. Systemet som den data-drevne metoden er implementert på er imidlertidig svært ulineært. Derfor vil stegresponsmodellene miste nøyaktighet hvis prosessparametrene beveger seg bort fra der modellene ble opprettet. Siden MPC er en modellbasert reguleringsmetode, er en MPC-applikasjon avhengig av å ha en nøyaktig matematisk modell av prosessen den regulerer. Hvis stegresponsmodellene mister nøyaktighet, vil ikke de forutsagte optimale pådragene fra MPCen være optimale. Oppdatering av likevektstilstandsforstekninger for stegresponsmodellene gir vedvarende MPC-ytelse til tross for at de initielle stegresponsmodellene mister nøyaktighet, da identifiserte og oppdaterte modellforsterkninger opprettholder modellkvaliteten. Basert på prosessparametre, vil en automatisk modellforsterkningsidentifikator eksitere prosessen for å identifisere mer presise likevektstilstandsforsterkninger. Korrekte likevektstilstandsforsterkninger vil sikre god MPC-ytelse til tross for at prosessparametrene beveger seg bort fra der de initielle stegresponsmodellene ble opprettet.

Den automatisk modellforsterkningsidentifikatoren vil bli testet på et simulert undervannsbrønnsystem. I et undervannsbrønnsystem er sikkerhet av høyeste betydning. Forhindring av brudd på sikkerhetsgrenser er et generelt mål for en MPC, og anses som avgjørende for undervannsbrønnssystemet i denne oppgaven.

Sikkerhetsgrenser legges til i MPC-applikasjonen av sikkerhetsmessige årsaker og anses å være av høyeste prioritet i regulatoren. Når prosessen eksiteres, er det en risiko for brudd av sikkerhetsgrensene. Den automatiske modellforsterkningsidentifikatoren vil eksitere prosessen mens sikkerhetsgrensene blir respektert ved å bruke online data for å redusere risikoen for brudd på sikkerhetsgrensene.

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Chapter 1

Introduction

1.1 Background and Motivation

Model predictive control (MPC) has been successfully applied for multiple decades in industrial processes. There are multiple reasons for the MPC's success, including its ability to handle multivariable control problems naturally and its ability to account for actuator limitations. MPC allows for operation closer to constraints and allows industrial processes to meet their specialized control needs while respecting constraints in the process. MPC, in general, are suitable for different operation modes with different operation behaviors, ranging from process start-ups to normal operation.

SEPTIC is Equinor's in-house software tool for MPC. The first installation of SEPTIC was done in 1997, and the status in 2019 is that there are about 100 SEPTIC MPC applications in Equinor. SEPTIC is used upstream and downstream for various processes, ranging from production well start-up to gasoline blending. Business cases are generally excellent – for example, the Mongstad Refinery reports an incentive of 500 MNOK/year, and offshore activities show similar numbers [1].

An MPC's performance is highly dependent upon having accurate models of the process being controlled. Practitioners usually spend up to 80% of the overall MPC design effort to obtain an adequate model for MPC [2]. A common approach for obtaining an adequate model of input-output behavior in industrial applications is the use of step responses. SEPTIC uses the same approach for describing input-output behavior. Step response models assume linearity, which is based upon the superposition principle. A real-life system, however, is inherently nonlinear. Previously the step response models have represented the process sufficiently to achieve good controller performance and are favored because of simplicity [3]. However, as higher product quality specifications and increasing productivity demands, tighter environmental regulations, and demanding economic considerations, it is required to operate systems over a broader range of operating conditions and often near the boundary of the admissible region. By operating over a broader range of operating conditions in a nonlinear process, the step response models may lose their accuracy, and they may not be sufficient to describe the process dynamics adequately [4]. If the linear step response models lose their accuracy, an MPC controller can not predict optimal inputs to the process, and the performance degrades. The models may also lose accuracy due to changing process parameters over time, as external conditions during model identification may change.

Models with less accuracy ultimately lead to performance degradation in the MPC, as calculated inputs may not be optimal. Practitioners are, for this reason, now focused on ease of commissioning and automation of maintenance [5], including continuous performance monitoring and automated model re-identification.

Data-driven control is a term that includes control theories and methods where the controller is designed directly using online or offline input-output data of the controlled system [6]. Due to more complex systems and high commissioning costs, a correctly implemented data-driven methodology might reduce the overall MPC design effort. A data-driven control methodology will also be an effective option for highly nonlinear processes and processes affected by process noise and disturbances.

Data-driven MPC uses data-driven control methods to design the MPC. [7] states that learning from data is now considered a prime issue in control engineering, and by applying a data-driven methodology for MPC, sustained MPC performance can be achieved using online data from the process being controlled.

By improving upon previous successful implementations of SEPTIC in industrial processes, performance degradation due to step response models losing their accuracy could be avoided. Sustained MPC performance in SEPTIC could be achieved by including elements from data-driven control. SEPTIC could potentially be used in more complex and nonlinear processes by including an automatic model gain identifier. In addition to sustained MPC performance, updated model gains allow SEPTIC to choose more optimal inputs for the manipulated variables. More optimal inputs include less wear and tear on equipment, as more optimal inputs require less change of the manipulated variables for optimal operation.

1.2 Goal and Method

The main goal of this thesis is to investigate how a data-driven methodology can be implemented in SEPTIC. The data-driven methodology includes step response model gain updating based on online process data from a simulation. The proposed method will be tested on a simulated single subsea well system, which is highly nonlinear.

As mentioned, SEPTIC uses step response models to model the input-output behavior of the process. A step response model assumes linearity, an assumption that is not satisfied in the example system used in this thesis. Because of this, the step response models will lose their accuracy if the process parameters change from the area where the model was created. For an MPC dependent upon having an accurate mathematical model of the system it controls to perform optimally, the performance of the MPC will degrade with decreasing model quality.

Depending on critical parameters, the proposed method will excite the process to identify updated model gains. Updating a model gain is done by scaling the initial step response model. The model gain is equivalent to the steady-state gain in a step response model. A process excitement is necessary, as one cannot identify an updated model gain for a process in steady-state. Critical parameters for process excitation include the age of the current step response models and changes in the process parameters and disturbances. It is assumed that the step response models lose their accuracy with changing process parameters and that the system operates over a wide range of operating conditions. Because the subsea well system is highly nonlinear, the assumption that a current model will lose its accuracy if the process parameters and disturbances change a certain amount is reasonable. Due to, among others, tighter environmental regulations and demanding operating conditions, it is also a reasonable assumption that the system operates over a wide range of operating conditions.

During steady-state optimal operation, the process will be in steady-state given that the process has reached its setpoint(s)/ideal value(s). Mathematically, this is when the cost function of the MPC is minimized. During a process excitation for model gain identification, the process will not be in steady-state. Therefore, one must carefully consider the value of a process excitation for model gains identification. During a process excitation for model gain identification, the process will not be optimal, but updated model gains will yield increased controller performance in case of changes in operating conditions. This thesis assumes that the value of the model gains being up to date and correct outweighs the disadvantage of briefly not operating in steady-state. A process excitation is not necessary not optimal operation, as a process excitation might be needed to operate in another area in the state-space.

The goal is to implement an automatic model gain identifier during running operation while satisfying all constraints in the system. The goal is to show that the implementation automatically excites the process, when needed, to identify updated model gains. An additional goal is to show that the updated model gains are more accurate than the initial models, ultimately yielding improved and sustained MPC performance.

SEPTIC is used as the MPC software. SEPTIC can use data from a running simulation to construct algorithms. The algorithms constructed in SEPTIC are called calcs and are used for designing the proposed solution in this thesis.

1.3 Outline of Report

This thesis is divided into 8 main chapters.

In **Chapter 2: Data-driven MPC** a brief literature review about data-driven MPC will be given. Current challenges for MPC in industrial applications are described, motivating data-driven control schemes in industrial processes.

Chapter 3: Theory will introduce essential concepts used in this thesis and provide a fundamental theoretical understanding in order to follow the approach provided in Chapter 5.

In **Chapter 4: Model Aspects and Software** describes the subsea well system on which the data-driven methodology is implemented. The available tools available in the software will be briefly described.

Chapter 5: Controller Design will give an overview of how a data-driven methodology might be implemented on the subsea well system described in Chapter 4.

The methodology will be implemented in Equinor's in-house software for MPC, SEPTIC, which is described in Chapter 3.

The main results from applying the data-driven methodology will be presented in **Chapter 6: Results**. The results are divided into two parts. The first part seeks to illustrate improved performance from the MPC after a model gain identification, compared to using the initial step response models. The second part illustrates how the implemented application automatically when deemed necessary, excites the process and subsequently identifies and updates the model gains.

A discussion is covered in **Chapter 7: Discussion**. The data-driven methodology and its results will be discussed regarding the achieved results and what eventually could be done differently. Proposals for further work will also be provided. The discussion focuses on how the proposed method presented in the thesis could be implemented for an industrial application.

The thesis is summed up and concluded in Chapter **8: Conclusion**.

Chapter 2

Data-driven MPC

This section presents current challenges for MPC in industrial applications, motivating data-driven control in industrial applications. A brief literature review about data-driven control, and more specifically, data-driven MPC will be covered. Data-driven control is a current research area within the process control community, and data-driven control is not yet well understood, which contrasts with achievements obtained regarding system identification.

2.1 Challenges for MPC in Industry

According to [2], practitioners usually spend up to 80 % of the overall MPC design effort to obtain an adequate model for MPC for nonlinear systems. Using step response models for model identification reduces the design effort dedicated to obtaining an adequate model. However, the obtained model assumes linearity, which is a drawback when controlling nonlinear systems. An adequate model is essential for good MPC performance since poor model quality is often an essential source of performance degradation [8]. Despite obtaining an initial model with good performances from an MPC application, the mathematical model of the system which the MPC control may change with changing operating conditions. Models with decreasing model quality due to changing operating conditions will decrease MPC performance as inputs from the MPC cannot be optimally predicted. As offline model maintenance for the entire plant leads to high maintenance costs, acquiring an accurate mathematical model of the plant to decrease plant-model mismatch by learning from online data is a prime issue in industrial process control.

[9] conducted a survey to clarify state of the art in process control applications, including MPC. The survey was conducted in Japan in 2009, and the results will be used to showcase some of the challenges that MPC faces in industrial applications. The survey was conducted on engineers from industry and researchers from universities in Japan. Results from the survey are shown in Table 2.1.

It is clear from the results in Table 2.1 that problems and needs for improvement related to modeling and model errors are highly present. Response to performance deterioration and coping with changes in process characteristics are problems related to decreasing model quality. The motivation for learning from data is clear from the results in the survey.

[5] states that decades of successful application of MPC to industrial processes has shifted the focus of practitioners to ease of commissioning and automation of maintenance, including continuous performance monitoring and automated model re-identification and updating. Model updating means applying mathematical methods (e.g., calibrating model parameters and bias-correction) to match model predictions with the physical observations [10]. Data-driven MPC is at the forefront of the focus shift and is a trending research area within the process control community.

2.2 Data-driven MPC

MPC has seen decades of successful applications to industrial processes. It has a wide adaptation in diverse fields, including process control, automotive systems, and robotics, and has become the standard approach for implementing constrained, multivariable control in the process industries today [11].

Due to successes in the field of machine learning and increased computational and sensing capabilities in modern control systems, there has been a growing interest in data-driven control techniques [12]. This interest is also strengthened by challenges in the current MPC implementations today in industrial applications.

According to [13], data-driven control may be defined as:

Problem: general	
Low robustness against model error	26%
Difficulty in tuning	23%
Inability to cope with specific objective	15%
Difficulty in modeling	12%
Others	24%
Problem: maintenance	
Transfer of engineering technology	44%
Response to performance deterioration	33%
Education of operators	7%
Difficulty in tuning	7%
Others	9%
Need for improvement: general	
To improve modeling technology	28%
To clarify method of estimating effect	25%
To simplify implementation	22%
To increase process control engineers	14%
Others	11%
Need for improvement: theory	
To cope with changes in process characteristics	26%
To clarify relations between model accuracy and control performance	24%
To cope with unsteady operation (SU/SD)	16%
To incorporate know-how in control system	16%
To cope with nonlinearity	13%
Others	5%
Need for improvement: response to changes/nonlinearity	
To switch multiple linear models	28%
To improve robustness of linear MPC	25%
To use time-varying/nonlinear model	18%
To add adaptive function to linear MPC	18%
To integrate other technique with MPC (e.g. knowledge-based control)	11%

Table 2.1: Industry survey of MPC challenges.

> all control theories and methods in which the controller is designed by directly using online or offline I/O data of the controlled system or knowledge from the data processing but not any explicit information from the mathematical model of the controlled process, and whose stability, convergence, and robustness can be guaranteed by rigorous mathematical analysis under certain reasonable assumptions.

As the citation describes, data-driven control directly utilizes I/O(input/output)-data for control of the system, without needing explicit information from a mathematical model of the process. Data-driven control is suitable for applications where first-principle models are not conceivable when models are too complex for control design and when detailed modeling and parameter identification is too costly [14]. A plant-model mismatch is inevitable in practice and is highly desirable to minimize such discrepancies to ensure good control performance [15].

The literature on data-driven control is vast, so an approach is highlighted. There are several different data-driven control methods and techniques which use different approaches. An approach based on the Willems fundamental lemma [16] will be highlighted, as approaches based on this lemma have received attention in the last few years. The lemma answers how to replace process models with data by learning the systems' "behavior". With the systems "behavior", one is not concerned with a system representation but rather the whole set of trajectories that a linear system can generate. The lemma stipulates that the set of trajectories can be represented by a finite set of system trajectories, provided that such trajectories come from sufficiently excited dynamics.

If a component of the response signal of a controllable linear time-invariant system is persistently exciting of a sufficiently high order, then the windows of the signal span the full system behavior. The windows of the signal are then applied to obtain conditions under which the state trajectory of a state representation spans the whole state-space. [14] presents a data-enabled algorithm, based on the Willems fundamental lemma, that can be applied to unknown linear time-invariant systems. The algorithm uses a finite data set to learn the behavior of the unknown system and computes optimal controls using real-time feedback to drive the system along a desired trajectory while respecting system constraints. The algorithm's performance was superior compared to offline system identification on the same system followed by MPC. Other examples of data-driven control design based on Willems fundamental lemma can be found in [17] [18] [19] [20].

Chapter 3

Theory

3.1 Optimization

Mathematically speaking, optimization is the minimization or maximization of a function subject to constraints on its variables [21].

An optimization problem is described mathematically in Equation 3.1.

$$
\begin{aligned}
&\min_{x \in \mathbb{R}^n} f(x) \\
&\text{subject to} \\
&c_i(x) = 0, \qquad i \in \mathcal{E} \\
&c_i(x) \geq 0, \qquad i \in \mathcal{I}
\end{aligned}
\tag{3.1}
$$

x is a vector of decision variables, $f(x)$ is the objective function that we want to minimize, and c_i are constraint functions that define certain equations and inequalities the vector x must satisfy. $\mathcal{I}$ and $\mathcal{E}$ are sets of indices for inequality and equality constraints, respectively.

Dynamic optimization is a category of optimization where the decision variables are a function of time ($x(t)$). The solution is, therefore, also a function of time.

Dynamic optimization is necessary when dynamics play a significant role, which often is the case for systems with frequent changes in the operating conditions [22].

Convexity

An essential concept in optimization is convexity. A convex optimization problem is easier to solve both in theory and practice. For this reason, it is a desirable property in optimization problems. If both the objective function in Equation 3.1 and the feasible region are convex, any local solution will be a global solution. The feasible region is the area in which all constraints are satisfied.

Both sets and functions can be convex. A set, $S \in R^n$, is convex if a straight line segment connecting *any* two points in S lies entirely inside S. This can be formulated mathematically as:

$$\begin{aligned}
&\alpha x + (1-\alpha)y \in S, \qquad \forall \alpha \in [0,1] \\
&\text{and} \\
&x, y \in S
\end{aligned}$$

A function, f, is a convex function if its domain S is a convex set and the following property is satisfied:

$$\begin{aligned}
&f(\alpha x + (1-\alpha)y) \leq \alpha f(x) + (1-\alpha) f(y), \qquad \forall \in [0,1] \\
&\text{and} \\
&x, y \in S
\end{aligned}$$

QP

A quadratic program (QP) is an optimization problem with a quadratic objective function and linear constraints. A fundamental understanding of quadratic programming is essential for understanding the use of a linear MPC (see Section 3.2) in this thesis.

The general QP is shown in Equation 3.2.

$$
\begin{aligned}
&\min_x q(x) = \frac{1}{2}x^\top Gx + x^\top c \\
&\text{subject to} \\
&a_i^\top x = b_i, \qquad i \in \mathcal{E} \\
&a_i^\top x \geq b_i, \qquad i \in \mathcal{I}
\end{aligned}
\tag{3.2}
$$

G is a symmetric $n \times n$ matrix, $\mathcal{E}$ and $\mathcal{I}$ are finite sets of indices, and c, x, and a_i, $i \in \varepsilon \cup I$, are vectors in R^n. n is the number of decision variables in x.

If the matrix G is positive semi-definite, Equation 3.2 is a convex QP, and any solution to the optimization problem in Equation 3.2 will yield a global solution.

Any solution x^* of Equation 3.2 satisfies the first-order KKT conditions shown in Equation 3.3.

$$Gx^* + c - \sum_{i \in \mathcal{A}(x^*)} \lambda_i^* a_i = 0, \tag{3.3a}$$

$$a_i^\top x^* = b_i, \quad \text{for all } i \in \mathcal{A}(x^*), \tag{3.3b}$$

$$a_i^\top x^* \geq b_i, \quad \text{for all } i \in \mathcal{I} \setminus \mathcal{A}(x^*), \tag{3.3c}$$

$$\lambda_i^* \geq 0, \quad \text{for all } i \in \mathcal{I} \cap \mathcal{A}(x^*), \tag{3.3d}$$

where λ_i^* is the Lagrange multipliers and $\mathcal{A}$ is the active set.

3.2 Model Predictive Control

Model predictive control (MPC) is a method of process control. This section will briefly introduce MPC to establish a theoretical foundation for understanding the control approach to be presented later in this thesis.

For a more comprehensive discussion on MPC, the reader is referred to [23].

An MPC is based on solving a dynamic optimization problem at every sampling instant. The optimization problem seeks to minimize the sum of a quadratic cost function over a finite prediction horizon. The optimization problem is subject to state trajectories provided by a model of the real system, the current state of the real system, and state and input constraints. The dynamic optimization problem to be solved at every sampling instant is shown in Equation 3.4.

MPC combines dynamic optimization with feedback control, which yields closed-loop optimization. Closed-loop optimization is achieved when computing the optimal control move at each sampling instant.

$$\min_{z \in \mathbb{R}^n} f(z) = \sum_{t=0}^{N-1} \frac{1}{2} x_{t+1}^\top Q_{t+1} x_{t+1}^\top + d_{xt+1} x_{t+1} + \frac{1}{2} u_t^\top R_t u_t^\top + d_{ut} u_t + \frac{1}{2} \Delta u_t^\top R_t \Delta u_t^\top \tag{3.4a}$$

subject to

$$x_{t+1} = A_t x_t + B_t u_t \tag{3.4b}$$
$$x_0, u_{-1} = \text{given} \tag{3.4c}$$
$$x^{\text{low}} \leq x_t \leq x^{\text{high}} \tag{3.4d}$$
$$u^{\text{low}} \leq u_t \leq u^{\text{high}} \tag{3.4e}$$
$$\Delta u^{\text{low}} \leq \Delta u_t \leq \Delta u^{\text{high}} \tag{3.4f}$$

where

$$Q_t \geq 0 \tag{3.4g}$$
$$R_t \geq 0 \tag{3.4h}$$
$$R_{\Delta t} \geq 0 \tag{3.4i}$$

Equation 3.4a is the quadratic cost function to be minimized, Equation 3.4b represents the model of the real system, Equation 3.4c represents the current state while Equations 3.4d-3.4f represents state and input constraints. Equation 3.4g-3.4i are weighting matrices. These are normally diagonal, and penalizes the corresponding state variable.

A basic MPC algorithm is provided in [22] and is shown in Algorithm 1. The algorithm requires an exact measure of the current state, x_t, at each time step

Algorithm 1: State feedback (N)MPC procedure

for t = *0,1,2...* **do**
  Get the current state x_t.
  Solve a dynamic optimization problem on the prediction horizon from t to $t + N$ with x_t as the initial condition.
  Apply the first control move u_t from the solution above.
end for

which is unrealistic in industrial processes. The current state is, therefore, usually an estimate, $\hat{x}_t$, based on measured data.

The general objectives of an MPC controller are to [24]:

1. Prevent violation of input and output constraints.
2. Drive the CVs to their optimal steady-state values (dynamic output optimization).
3. Drive the MVs to their optimal steady-state values using remaining degrees of freedom (dynamic input optimization).
4. Prevent excessive movement of MVs.
5. When signals and actuators fail, control as much of the plant as possible.

Furthermore, the main reasons for the success of MPC in industrial process control are, according to [25]:

1. It handles multivariable control problems naturally.
2. It can take account of actuator limitations.
3. It allows operation closer to constraints, which frequently leads to more profitable operation.
4. Control update rates are relatively low in these applications so that there is plenty of time for the necessary online computations.

A visual representation of an MPC is shown in Figure 3.1.

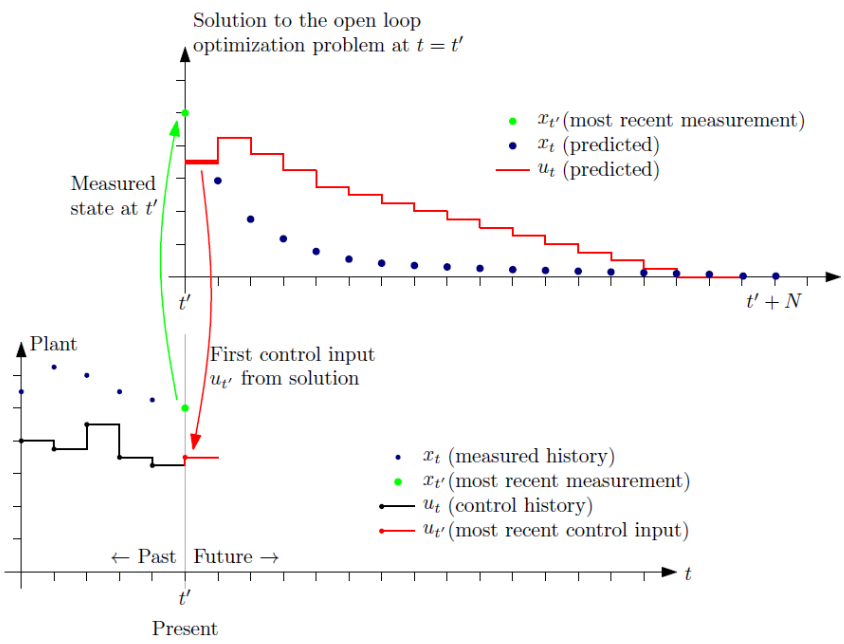

Figure 3.1: Illustration of the MPC principle [22].

3.3 SEPTIC

SEPTIC (Statoil Estimation and Prediction Tool for Identification and Control) is an in-house control software developed by Equinor and has been successfully used in many process control applications. It is a software for MPC, real-time optimization, dynamic process simulation, and offline and online parameter estimation in first principle-based process models. A more comprehensive description is given in [3] and [26].

For clarification purposes, a brief description of the MPC application in SEPTIC will be given as some notation will vary from the general MPC description in Section 3.2.

The dynamic optimization problem to be solved at each sample instant in SEPTIC is given in Equation 3.5.

$$\min_{\Delta u} y_{dev}^\top Q_y y_{dev} + u_{dev}^\top Q_u u_{dev} + \Delta u^\top P \Delta u \tag{3.5a}$$

subject to

$$u_{\min} < u < u_{\max} \tag{3.5b}$$

$$\Delta u_{\min} < \Delta u < \Delta u_{\max} \tag{3.5c}$$

$$y_{\min} < y < y_{\max} \tag{3.5d}$$

$$y = M(y, u, d, v) \tag{3.5e}$$

The subscript *dev* denotes deviation.

y (output) is referred to as a controlled variable (CV), while u (input) is referred to as a manipulated variable (MV).

The cost function, Equation 3.5a, penalizes CV deviations from setpoint, MV deviations from ideal value, and MV moves. It seeks to minimize the rate of change for the MV's, while respecting the constraints given in Equations 3.5b-3.5d.

The model is given in Equation 3.5e. d represents disturbance variables (DV), while v is estimated and optionally predicted unmeasured disturbances.

The models in SEPTIC are built with experimental (single-input single-output) SISO step response models, which are described in Section 3.4. These are easy to build, understand and maintain, but still have some drawbacks. They are linear and based on the superposition principle. Step response models where linearity is assumed may be a challenge when controlling nonlinear systems with constantly changing process parameters, as the models may become inaccurate.

There is a priority hierarchy in SEPTIC to avoid dynamical and stationary infeasibilities due to state constraints. The priority hierarchy is as follows:

1. MV rate of change limits
2. MV high and low limits
3. CV hard constraints, hardly ever used
4. CV setpoint, CV high and low limit and MV ideal value with priority level 1
5. CV setpoint, CV high and low limit and MV ideal value with priority level n

6. CV setpoint, CV high and low limit and MV ideal value with priority level 99

Level n is manually adjustable in SEPTIC as part of the tuning procedure.

For SEPTIC to function optimally, it is crucial to have an appropriate tuning. Correct tuning will yield the best performance from the MPC application.

The parameters in SEPTIC for tuning the weighting matrices are:

- Fulf
- Span
- MovePnlty

Fulf and span are unique for each respective MV or CV. The diagonal elements of $Q_{y_{n\times n}}$ and $Q_{u_{n\times n}}$ from Equation 3.5a, are calculated as follows:

$$Q_{y_{n\times n}} = (\frac{\text{Fulf}_n}{\text{Span}_n})^2 \tag{3.6}$$

$$Q_{u_{n\times n}} = (\frac{\text{Fulf}_n}{\text{Span}_n})^2 \tag{3.7}$$

n is the respective CV or MV.

For MVs, there is also a weighting matrix that penalizes MV moves. The diagonal elements of P are calculated as follows:

$$P_{n\times n} = (\frac{\text{MovePnlty}_n}{\text{Span}_n})^2$$

A CV bias update captures the discrepancy between the process and model response in SEPTIC to include integral action in the controller (more in Section 3.5). If the process being controlled is subjected to noise, the discrepancy may have a high rate of change, which leads to aggressive control actions from the

MV(s) affected by process noise. SEPTIC can low-pass filter the bias updating to avoid issues with process noise disrupting the MV moves and allow the MV to choose smoother inputs. The low-pass filter is configured using BiasTfilt for the respective CV to filter the bias update. If there is noise on the CV measurements, a typical choice for BiasTfilt would be 2-10 times the sample time. The value of BiasTfilt is the time constant of the low-pass filter.

For computational efficiency, SEPTIC calculates the prediction horizon automatically, such that each of the CVs has reached steady-state after the last MV move. The prediction horizon may therefore differ between the CVs. SEPTIC also has implemented MV (input) blocking. Most often, 4 to 8 blocks provide a good balance between computational effort and performance.

Other examples of implementations of SEPTIC can be found in [27][28][29][30][31].

3.4 Process Models

Many control approaches rely upon having a precise model of the system to be controlled. These control approaches may be referred to as model-based control (MBC). MBC includes theory for both linear and nonlinear systems and is well established in industrial applications. The first step in MBC is modeling and system identification of the industrial process to be controlled. In this section, a brief description of model identification in industrial applications is covered.

In academic literature, most processes are described by state-space representation, and there exist several system identification methods for finding these models. However, with industrial systems becoming more substantial and more complex, plant modeling becomes more expensive and challenging. Therefore, describing the input-output behavior of the system using step responses is a common approach for industry applications.

As mentioned in Section 3.3, SEPTIC develops models between a CV and an MV by using step response models, i.e., a step in an MV yields a response in a CV. SEPTIC has an option to use the offline commercial product Tai-Ji [32] to identify the dynamic models and produce the correct model file format directly. Another option in SEPTIC is using an identification module for directly identifying step response models. An example of a step response model is shown in Figure 3.2.

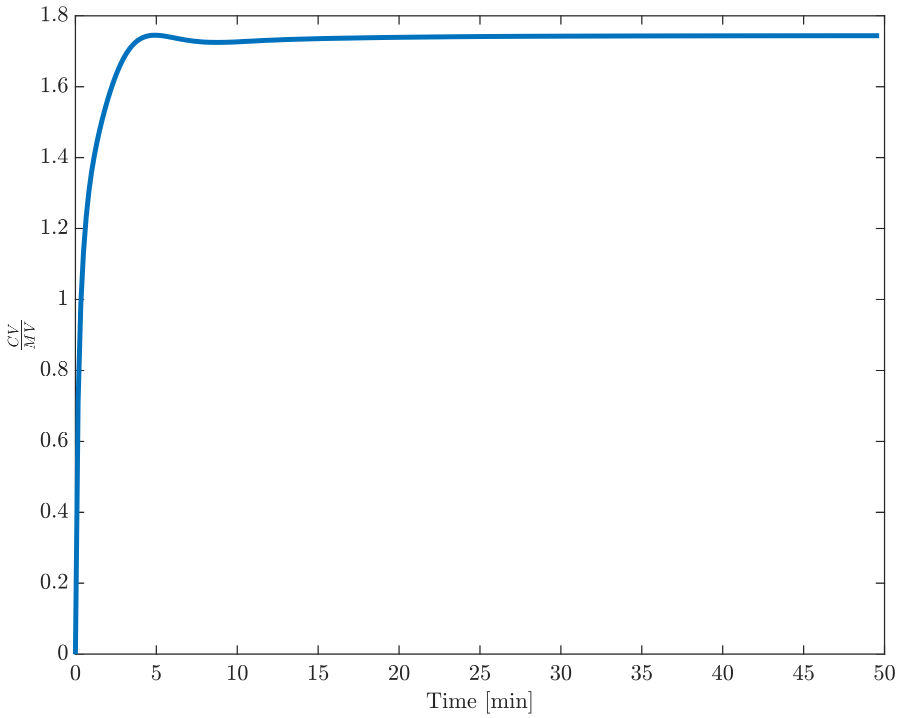

Figure 3.2: An example of a step response model in a SISO-system. A unit step in the MV yields the following response in the CV.

Tai-Ji identification is based on the asymptotic method (ASYM) of identification based on theory in [33]. The theory explains the frequency domain properties of high-order models obtained using the prediction error method.

Identification consists of at least four steps:

1. Identification test
2. Model order/structure selection
3. Parameter estimation
4. Model validation

The idea of a step response model for a single input variable is to apply a step at the input variable and record the open-loop response of the outputs until it settles at a constant value. Linearity is assumed, such that the response of any other input signal can be deduced by knowing the step responses of the process because of the superposition principle.

Because linearity is assumed, a drawback of step response models is that, for nonlinear systems, the step response model would only be accurate in and around the area the model was created. The predicted response of any other input signal might be incorrect if the process has moved from where the step response model was created. Another drawback is that the plant to be modeled needs to be asymptotically stable.

The step response is discussed in [34] and [35].

By assuming that the process is in steady-state (Section 3.7), and applying a step on the input j, this can be mathematically expressed as:

$$\{u_j(t) = a | t \geq 0\},$$

where a is the value of the step. The recorded step response on output i becomes

$$y_i(t) = \sum_{k=0}^{t} h_{ij}(t-k)u_j(t) = \sum_{k=0}^{N} h_{ij}(k)u_j(t).$$

The response $y(t)$ to an input vector $u(t)$ is given by

$$y(t) = \sum_{k=0}^{N} \mathbf{H}(k)u(t),$$

where

$$\mathbf{H}(t) = \begin{bmatrix} h_{11}(t) & h_{12}(t) & \dots & h_{1m}(t) \\ h_{21}(t) & h_{22}(t) & \dots & h_{2m}(t) \\ \vdots & \vdots & \ddots & \vdots \\ h_{p1}(t) & h_{p2}(t) & \dots & h_{pm}(t) \end{bmatrix}.$$

p is the number of outputs, while m is the number of inputs.

The step response matrix is defined as

$$\mathbf{S}(t) = \sum_{k=0}^{N} \mathbf{H}(k).$$

Since the input change $\Delta u(t) = u(t) - u(t-1)$ is used rather than the input itself, the equation used by the MPC controller to model the plant is given by

$$y(t) = \sum_{k=0}^{t} \mathbf{S}(k)\Delta u(t-k).$$

3.5 Model Quality

Modeling is an approximation of the real system, and modeling errors are therefore inevitable. Modeling errors lead to less robustness and less stability in a controller. Model quality is the main factor that affects the control performance of model-based controllers, such as an MPC. Predictions in an MPC from an inadequate model can result in computed inputs far from optimal control moves. Output feedback (bias updating) is commonly used as compensation for poor model quality, which means that an MPC might still perform sufficiently. To ensure that the models used in the controller are adequate, an approach for assessing model quality is necessary.

Poor model quality may be caused by poor model design, unmodeled disturbances, or decreasing model quality due to changes in the process. If the control performance of the MPC degrades over time, it may be due to plant-model mismatch or tuning factors, which without a model assessment method is challenging to tell. The alternative of offline model maintenance for the entire plant leads to a high cost of MPC maintenance and is desirable to avoid. An online model assessment method to estimate model quality is therefore desirable.

As mentioned, integral action is included in SEPTIC. Integral action is added by including a CV bias update that captures the discrepancy between the process and model response. The integral action removes the steady-state offset to the CVs. This bias should be constant, such that the rate of change between the process response and model response is constant, which implies that the process models are correct.

When the process is stable, the bias rate of change will be close to zero. A bias rate of change close to zero implies that the current input-output models are of high enough quality to control the process with the current noise and disturbances.

Bias

Output bias captures the discrepancy between the process and the model response. This provides integral action to the controller, and removes steady-state offsets to produce a corrected prediction, $\tilde{y}(k+j)$. The corrected prediction is defined as [36]:

$$\tilde{y}(k+1) \triangleq \hat{y}(k+1) + b(k+1)$$

where $\hat{y}(k+1)$ is the predicted nominal model value (model output value without corrections from measurements), while $b(k+1)$ is the bias correction.

In practice, the bias is often specified to be the difference between the latest measurement $y(k)$, and the corresponding predicted value, $\hat{y}(k)$:

$$b(k+1) = y(k) - \hat{y}(k)$$

This strategy is referred to as output feedback [24]. The bias is added to the model for use in subsequent predictions:

$$\tilde{y}(k+1) \triangleq \hat{y}(k+1) + b(k+1) = \hat{y}(k+1) + [y(k) - \hat{y}(k)]$$

This feedback form is equivalent to assuming that a step disturbance enters at the output and remains constant. This constant output disturbance provides integral action to the controller for stable processes, removing steady-state offset due to disturbances and plant-model mismatch.

A perfect input-output model of a SISO-system would yield the following response:

$$\dot{\hat{y}}(k) = \dot{y}(k) \quad \Rightarrow \quad \dot{b}(k+1) = 0.$$

The model response matches the process output measurement given an arbitrary input. Therefore, a measure for assessing model quality could be to monitor the rate of change of bias, $\dot{b}(k)$. The closer $\dot{b}(k)$ is to zero, the higher is the model quality.

Figure 3.3 and Figure 3.4 show CV responses from a change of input, following a change of setpoint value for the oil rate. An example of poor model quality is shown in Figure 3.3, while an example of the same system with near-perfect model quality is shown in Figure 3.4. Figure 3.3 and Figure 3.4 are nonlinear systems controlled using an MPC, whose performance is dependent upon model quality. The systems are modeled using step response models.

In Figure 3.3, there are considerable variations of bias when the process is subjected to a change of input. The output value also converges slowly towards the setpoint due to the inadequate step response model.

In Figure 3.4 the model is better, as can be seen with less change in bias than in Figure 3.3. The output also converges faster to the setpoint value. Because the controlled system is highly nonlinear, the step response model of higher quality will still be inaccurate when subjected to a considerable input change. Therefore,

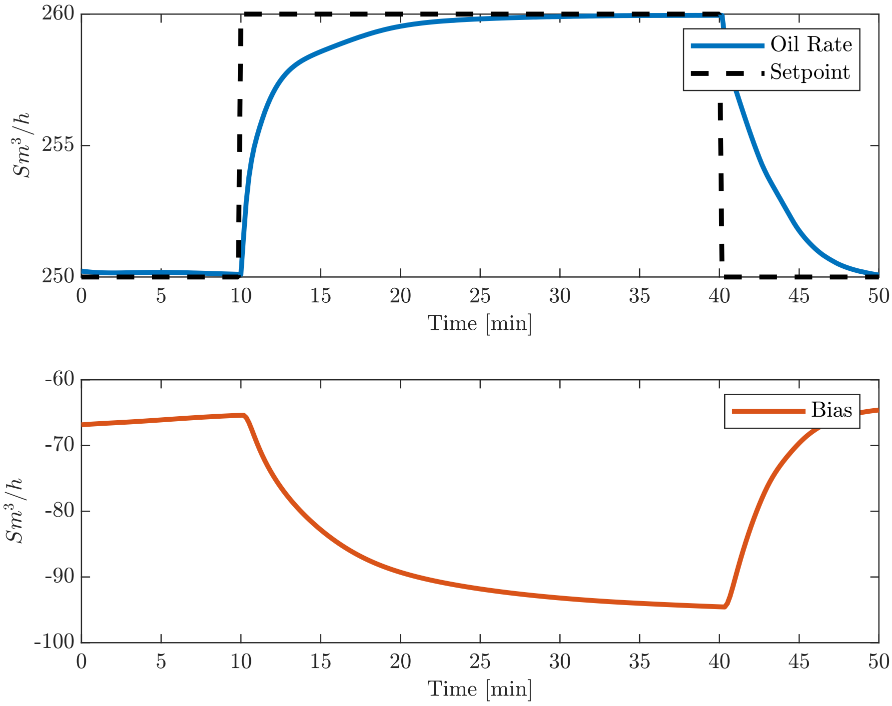

Figure 3.3: A process excitation with a poor mathematical model.

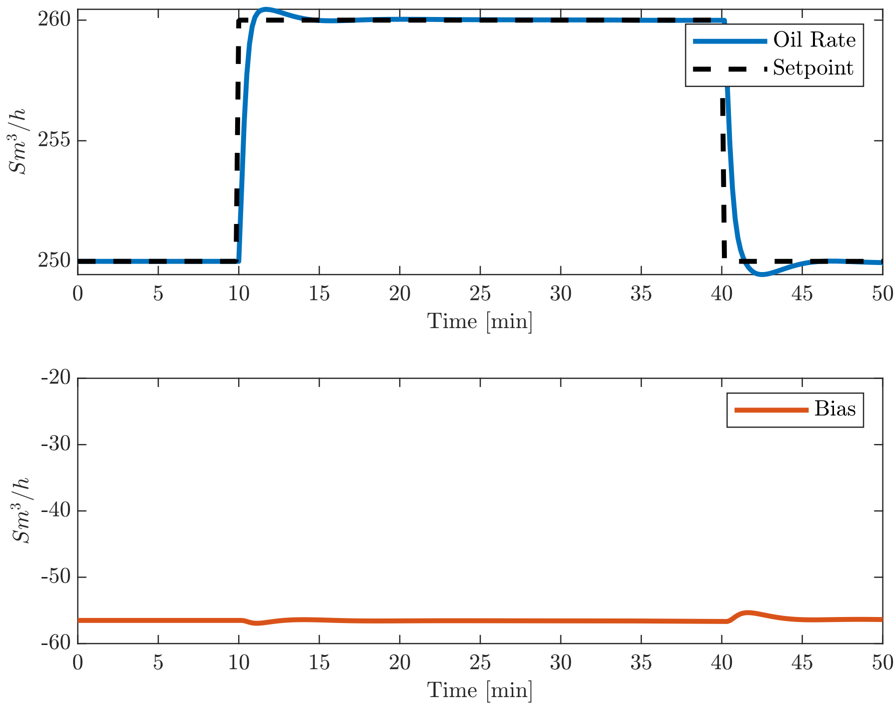

Figure 3.4: A process excitation with a near perfect mathematical model.

it is observable that the response overshoots, and there is still some change of bias.

3.6 Linear vs. Nonlinear Systems

A linear system will satisfy the superposition property [37]. The superposition property holds if the additivity property and the homogeneity property holds. The additivity property is described as shown in Equation 3.8, and the homogeneity property is shown in Equation 3.9.

$$\left.\begin{array}{l}\mathbf{x}_1(t_0)+\mathbf{x}_2(t_0)\\ \mathbf{u}_1(t)+\mathbf{u}_2(t), \quad t\geq t_0\end{array}\right\} \rightarrow \mathbf{y}_1(t)+\mathbf{y}_2(t), \quad t\geq t_0 \tag{3.8}$$

$$\left.\begin{array}{l}\mathbf{x}_1(t_0)\\ \mathbf{u}_1(t), \quad t\geq t_0\end{array}\right\} \rightarrow \mathbf{y}_1(t), \quad t\geq t_0 \tag{3.9}$$

Combining the additivity property and the homogeneity property shown in, respectively, Equation 3.8 and Equation 3.9 yields the superposition property:

$$\left.\begin{array}{l}\alpha_1\mathbf{x}_1(t_0)+\alpha_2\mathbf{x}_2(t_0)\\ \alpha_1\mathbf{u}_1(t)+\alpha_2\mathbf{u}_2(t), \quad t\geq t_0\end{array}\right\} \rightarrow \alpha_1\mathbf{y}_1(t)+\alpha_2\mathbf{y}_2(t), \quad t\geq t_0$$

for any real constants α_1 and α_2.

In a linear system the total response from an input $\mathbf{u}(t)$ is the sum of the zero-input response and the zero-state response:

$$\begin{aligned}\text{Output due to } &\begin{cases}\mathbf{x}(t_0)\\ \mathbf{u}(t), \quad t\geq t_0\end{cases} = \text{output due to } \begin{cases}\mathbf{x}(t_0)\\ \mathbf{u}(t)=\mathbf{0}, \quad t\geq t_0\end{cases}\\ &+ \text{output due to } \begin{cases}\mathbf{x}(t_0)=\mathbf{0}\\ \mathbf{u}(t), \quad t\geq t_0\end{cases}\end{aligned}$$

A linear system time-invariant can described as:

$$\dot{\mathbf{x}}(t) = \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}(t)$$

This system is described by state-space representation. $\mathbf{x}$ is a state vector, and the state vector elements are state variables. State-space representation is to describe systems using vector notation [38].

In a linear system, the change of the output is proportional to the change of the input.

A system is said to be nonlinear if the superposition property is not satisfied [39]. The change of the output would not be proportional to the change of input. Nonlinearity adds complexity to the system and demands analysis tools with more advanced mathematics. A nonlinear system may be described mathematically as:

$$\dot{\mathbf{x}}(t) = f(t, \mathbf{x}, \mathbf{u})$$

There are many methods and control techniques available for linear systems [40]. Therefore, it is preferable to linearize nonlinear systems to use control techniques for linear systems. Linearization consists of forming locally valid linear approximations of nonlinear systems.

However, if a system deviates from the point (in state-space) where the linearized model was created, the inaccuracy of the linearization increases. If the system dynamics change with time (e.g., change of disturbances), the mathematical model no longer reflects the actual dynamics [41]. As stated in [4], higher product quality specifications and increasing productivity demands, tighter environmental regulations, and demanding economic considerations require operating systems over a wide range of operating conditions and often near the boundary of the admissible region. Operating systems over a wide range of operating conditions and often near the boundary of the admissible region also increases the likelihood of linearized models losing their accuracy.

The reason for the linearized mathematical model of a nonlinear system losing its accuracy is that the superposition property is not satisfied in nonlinear systems. An input at one area of the process point may yield a different output response than the predicted output response, making such nonlinear systems more challenging to control.

A resource for nonlinear control is given in [42]. Some control techniques for nonlinear systems are:

- Feedback linearization
- Nonlinear model predictive control (NMPC)
- Adaptive control
- Gain scheduling

3.7 Steady-state

Steady-state is a description of a system or a process where the variables are constant. If a process has reached steady-state, it is considered to be stable. In steady-state, the observed behavior will continue if the system or process is not subjected to external disturbances.

In continuous time, steady-state is described as:

$$\dot{x} = f(x, u) = 0$$

where x is a vector containing the state variables.

In discrete time, steady-state is described as:

$$x_k - x_{k-1} = 0$$

In an industrial process subjected to process control, the aim for a state variable may be to reach and stay at a setpoint. If a process has reached its setpoint(s) and/or ideal value(s), and $\Delta u = 0$ the cost function in Equation 3.5 is minimized and operating in steady-state. The process is then said to be in steady-state optimal operation [43].

Steady-state Gain

The models generated in SEPTIC are step response models, where a step in an MV will yield a response in the CVs. This procedure is covered in Section 3.4, with an example in Figure 3.2.

The steady-state gain corresponds to the ratio between a constant input and the steady-state output [44] and is a relevant quantity only when a system is stable about the corresponding equilibrium point.

The steady-state gain in a SISO-system is calculated using Equation 3.10.

$$\text{Steady-state gain} = \frac{\text{CV}_{\textit{Steady-state}} - \text{CV}_0}{\text{MV}_{\textit{Steady-state}} - \text{MV}_0} \tag{3.10}$$

The subscript 0 corresponds to the CV- and MV-values before a change of MV. These are steady-state values before a change of input. The subscript Steady-state corresponds to the constant MV (input) value and the steady-state CV (output) value after an input change.

In Figure 3.2 the steady-state gain is 1.74. In this case, a unit step in the input would increase the output with the magnitude of 1.74 if the system is linear and the step response model is correct.

Steady-state gain may be referred to as zero frequency gain or DC gain in electrical engineering.

Chapter 4

Model Aspects and Software

The single subsea well system provided by Equinor is modeled in Dymola. Dymola is a complete tool for modeling and simulation of integrated and complex systems [45]. The model is then exported as an FMU (Functional Mock-up Unit) [46] to SEPTIC. Exporting the model as an FMU allows SEPTIC to control the process model, providing inputs to the simulation generated using the MPC software in SEPTIC. In industrial applications for Equinor, SEPTIC is used as a regulator to control a real process using MPC. However, in this thesis, SEPTIC is used as a combined simulator and regulator. The model is a single subsea well system to simulate subsea well control and is highly nonlinear.

A simplified version of the system is shown in Figure 4.1. There are three CVs, one MV, and two DVs in the process. These are shown in Table 4.1, along with their upper and lower limits.

		Lower limits	Upper limits	Unit
MV	Production choke	0	100	%
DV	Gas lift rate	0	12500	Sm^3/h
DV	Downstream pressure	1	20	bar
CV	Oil rate	100	300	Sm^3/h
CV	WHP	17	25	bar
CV	BHP	155	170	bar

Table 4.1: Variables in the single subsea well system.

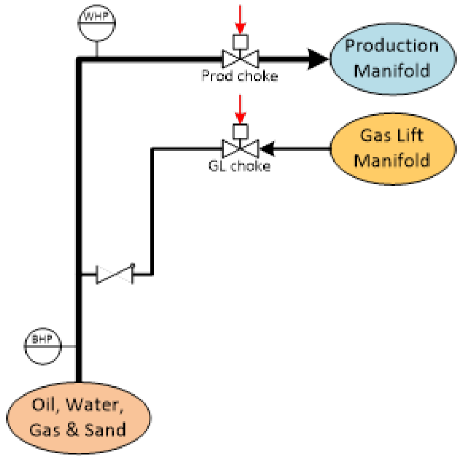

Figure 4.1: Simplified version of the subsea well system which the automatic model gain identifier is tested on [1].

In a subsea well system, gas lift is an artificial lift method that uses external high-pressure gas to lift the well fluids. Gas is injected into the production tubing to reduce the hydro-static pressure of the fluid production column. Reduction of the hydro-static pressure of the fluid production column results in a reduction of bottom hole pressure (BHP) which is an enabler for production, resulting in higher production rates. In reality, this is an MV in the system, but it is modeled as a DV for this case.

If the gas lift rate increases, wellhead pressure (WHP) will also increase. An increase of WHP may present an extra challenge in SEPTIC as it directly affects the differential pressure ΔP over the production choke.

The disturbances are manually adjustable (for simulation purposes) in SEPTIC, but it is unknown how they affect the process as they are unmodeled. Unmodeled disturbances pose a challenge for the controller, as it is impossible to predict the optimal controller input if the disturbances are changing. Manually adjustable disturbances allow for flexibility in simulating operation over a broader range of process parameters. Simulating operation over a broader range of process parameters contributes to the opportunity of highlighting differences in model gains across a wide range of operating conditions and highlighting how poor model quality affects the prediction of optimal inputs in SEPTIC.

The oil rate is subjected to noise. The noise is added to the simulation to simulate the subsea well system more realistically. The noise added is white noise with an amplitude of 1.

The downstream pressure is the pressure downstream of the production choke (to the right of the production choke in Figure 4.1). The downstream pressure may be pressure in a separator downstream of the production choke.

The process only has one degree of freedom (DOF), which means it only has one MV to control the CVs. A process having fewer MVs than CVs may be referred to as a thin plant [24]. In this case, one cannot guarantee optimal solutions and constraint satisfaction at all times. A thin plant poses extra challenges, and appropriate tuning and establishing correct priority levels in SEPTIC would contribute to solving these challenges.

If the gas lift rate could be modeled and manipulated, making the gas lift rate an MV, the process would be a square plant, which leads to the dynamic optimization in Equation 3.5 having a unique solution. The most desirable situation would be to have more MVs than CVs, which would lead the MPC to have further optimize the process [47].

The mass flow rate $[kg/s]$ of fluids from the reservoir into the model is constant. The constant mass flow rate is a simplification during the simulations.

The step response process models between the production choke and the CVs are shown in Appendix B, and a schematic overview of the subsea well system in Dymola is shown in Appendix A.

4.1 The Production Choke

As it is the only MV in the system, a brief description of the production choke used in the Dymola-model is provided. The production choke controls the flow of fluids in the process through the production pipe. The production choke opening varies from 0 to 100%. Typical choke characteristics from the production choke opening u to the flow Q through the choke are linear, quadratic, and equal percentage. The production choke used in this model has a linear characteristic. The flow through a choke with linear characteristic is given by Equation 4.1 [48].

$$Q = uA_vY\sqrt{\rho\Delta P}, \quad \Delta P \geq 0. \tag{4.1}$$

The choke valve used in the model is a check valve. A check valve only allows for the flow of fluids in one direction. If the differential pressure, ΔP, is below 0, the flow Q through the choke is 0. The flow through the production choke in this model is

$$Q = \begin{cases} uA_vY\sqrt{\rho\Delta P} & \Delta P \geq 0 \\ 0 & \Delta P < 0 \end{cases}$$

where $Q[m^3/s]$ is the flow through the production choke, $u \in [0, 100\%]$ is the choke opening, $A_v[m^2]$ is a flow coefficient, $Y[m^2/kg]$ is the compressibility factor, $\rho[kg/m^3]$ is the mean density of all the fluids through the choke and $\Delta P[Pa]$ is the pressure drop over the choke. The pressure drop ΔP over the production choke in this model is given by:

$$\Delta P = \text{WHP} - \text{Downstream pressure.}$$

Downstream pressure is a DV in the system, while WHP is a CV. If the downstream pressure increases, WHP will also increase to maintain the pressure drop over the choke. If the oil rate setpoint is active, the pressure drop ΔP needs to remain constant to ensure constant flow, Q, at the oil rate setpoint through the production choke, given a constant production choke opening. However, the production choke opening is regulated to give the pressure drop ΔP to yield the desired oil rate.

If the downstream pressure increases above the upper limit of WHP, $25bar$, constraint satisfaction is infeasible. As the production choke is a check valve, the pressure drop ΔP needs to be positive to have production flow through the valve. For ΔP to be positive, the WHP needs to be higher than the downstream pressure. If the gas lift rate could be manipulated, making the process a square plant (the number of MVs equals the number of CVs), these infeasibilities could be avoided.

4.2 Tools in SEPTIC

The data-driven methodology, i.e., the automatic model gain identifier, is, as mentioned, implemented in SEPTIC.

A useful feature in SEPTIC for updating controller design based on online process data is called calc. The definition for a calc from the SEPTIC reference documentation [26] are as follows:

> "Algorithms for intermediate calculations"

Algorithms for intermediate calculations imply that one can construct algorithms for updating process parameters using online data from running simulations. The calcs are necessary for implementing a data-driven methodology by including online process data for intermediate calculations. The calcs used for implementing the data-driven methodology are described in Appendix C.

The figures presented later in this report are generated in Matlab unless stated otherwise. To export data to Matlab from SEPTIC, the Matlab function dta2matlab3.m, provided by Equinor, is used. From a .dta-file generated from a SEPTIC simulation, the function returns data from the simulation.

Chapter 5

Controller Design

In this chapter, the proposed method for implementing a data-driven methodology as an automatic model gain identifier in SEPTIC will be described. The different elements of the automatic model gain identifier are thoroughly described, and examples of the implementation will be shown.

The steady-state gain, described in Section 3.7, will be referred to as model gain when discussing the steady-state gain in the step response models.

As mentioned in Section 3.4, the models for input-output behavior generated in SEPTIC are step response models, i.e., a step in the input yields a response in the output. If a process is in steady-state and the input value is changed and remained constant at this value, and subsequently the output reaches steady-state, the model gain is the ratio between output change and input change. Because the step response models assume linearity, the step response models will lose their accuracy if process parameters change from where the step response models were generated. Since an MPC's performance depends on having an accurate mathematical model of the process it controls, the performance of the MPC will decrease if the step response models lose their accuracy. This thesis will propose a data-driven methodology to combat non-linearity in the system, and at the same time, identify and implement more precise model gains, yielding improved and sustained MPC performance.

The proposed method for implementing a data-driven methodology is to exploit the online data available from the process simulation to update the model gains for the initially generated step response models. Utilizing the online data for designing the controller is a data-driven control technique. The proposed method excites the process and updates the model gains automatically during simulation, based on both process parameters and the model's age. The process can be excited by moving a CV setpoint or an MV ideal value. Both methods will be implemented and compared.

Some initial assumptions are made for simplification purposes.

Assumptions:

- The initial step response models are accurate enough to ensure that the process reaches steady-state, given initial conditions. Accurate initial models are necessary for the process to become stable and controllable. The initial step response models are shown in Appendix B.
- The process reaches steady-state after 30 minutes, with known and constant disturbances.

5.1 Initial Setup

The process is subject to constraints. The constraints include minimum/maximum values and maximum rate of change for the MV, which is of the highest priority level in SEPTIC and thus always respected. The production choke, which has a maximum opening of 100 %, can not, for obvious reasons, exceed 100%. The same also applies to the maximum rate of change, which is included to reflect a realistic behavior of the production choke valve. The MV constraints are of the highest priority in the priority hierarchy in SEPTIC to respect the actual limitations of MVs.

There are also minimum and maximum constraints for the CVs. These are mainly included to protect the process, as process values outside these limits may damage equipment and be sources of safety hazards. Safety is of utmost importance in a subsea well system, and the CV constraints must be respected. The minimum and maximum constraints of the CVs are of priority level 1, which is the highest priority level outside of the MV constraints. Respecting the CV constraints is seen as one of the most essential role of an MPC, which is reflected in the chosen priority level in SEPTIC for this thesis. The priority hierarchy in SEPTIC is described in Section 3.3.

The desired setpoint for the oil rate is 250 Sm^3/h, while the desired ideal value for the production choke is 31 %. BHP and WHP do not have a setpoint value, but their constraints need to be respected. Either the setpoint for the oil rate or the ideal value for the production choke is activated, depending on how the process is excited. The setpoint and ideal value will have priority level 2, i.e., less critical to reaching the setpoint/ideal value than respecting the CV constraints.

The initial step response models are generated in SEPTIC. The disturbances are kept constant at their initial values, and the production choke opening is moved from 30% to 35%. A production choke opening between 30% and 35% was the preferred area for the production choke to operate by experimentation and observation, given the initial conditions. Therefore, the step from 30 % to 35 % is chosen to generate the initial step response models. The responses in the CVs were recorded, and the step response models were saved in SEPTIC to use as initial models for this thesis. The initial values for gas lift rate and downstream pressure during the generation of the step response models were respectively $5000Sm^3/h$ and $13bar$.

The process is tuned during initial conditions to ensure satisfactory performance with the initial step response models. The tuning process includes tuning of weighting matrices and filtering. Tuning parameters in SEPTIC are mentioned in Section 3.3. The tuning procedure for the process in this thesis will not be covered in detail, as it is not crucial for the automatic model gain identifier.

The sample time in the controller is

$$N_{secs} = 10s$$

which limits the simulation time of the model. The integration time of the model must be much lower than the sampling time of the controller since the model is simulated over a prediction horizon for each sample.

The cost function in SEPTIC is given in Equation 3.5a. The cost function can be used as a measure of how the controller performs. The dynamic optimization problem in Equation 3.5 tries to minimize the cost function. A lower value, therefore, implies a more efficient and better-performing controller.

The cost function depends upon the method of process excitement. As mentioned in Section 3.3, the cost function penalizes CV deviations from setpoint, MV deviations from the ideal value, and MV moves. When the process is excited by moving the oil rate setpoint, there is no deviation from MV ideal value, as there is no ideal value active. The same logic applies when exciting by moving the ideal value of the production choke. Then there is no setpoint active.

When the process is excited by moving the oil rate setpoint, the cost function becomes as shown in Equation 5.1.

$$\begin{aligned} \min_{\Delta u} \ J_{SP} = (\text{Oil rate} - \text{oil rate setpoint})^2 * (\frac{\text{Fulf}_{Oilrate}}{\text{Span}_{Oilrate}})^2 + \\ \Delta\text{Choke}^2 * (\frac{\text{MovePnlty}_{Choke}}{\text{Span}_{Choke}})^2. \end{aligned} \tag{5.1}$$

When the process is excited by moving the ideal value for the production choke, the cost function becomes as shown in Equation 5.2.

$$\begin{aligned} \min_{\Delta u} \ J_{IV} = (\text{Choke} - \text{choke ideal value})^2 * (\frac{\text{Fulf}_{Choke}}{\text{Span}_{Choke}})^2 + \\ \Delta\text{Choke}^2 * (\frac{\text{MovePnlty}_{Choke}}{\text{Span}_{Choke}})^2. \end{aligned} \tag{5.2}$$

These are included in SEPTIC to monitor the current performance of the controller. The value of J_{SP} and J_{IV} is calculated for each sample and gives the cost of the current sample. If the process has reached steady-state, and either the production choke ideal value or the oil rate setpoint is reached, the cost will be 0. Mathematically, steady-state optimal operation minimizes J_{SP} and J_{IV} [43].

5.2 Process Excitation

Process excitation provides the process with an input signal to ensure that the process is not in steady-state. A process not being in steady-state is necessary as an updated model gain cannot be identified if the process is in steady-state. From Equation 3.10, it is clear that the model gain could not be calculated without a change of MV.

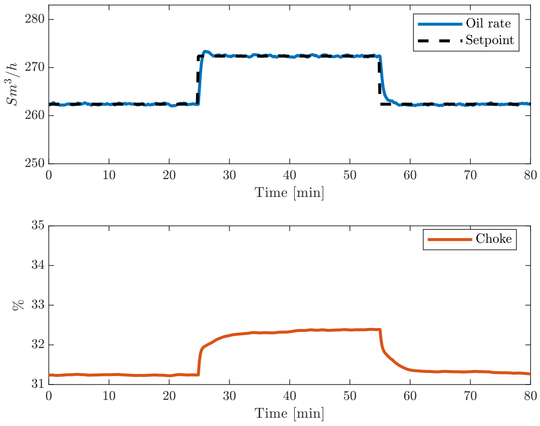

Figure 5.1: Excitation by moving the oil rate setpoint.

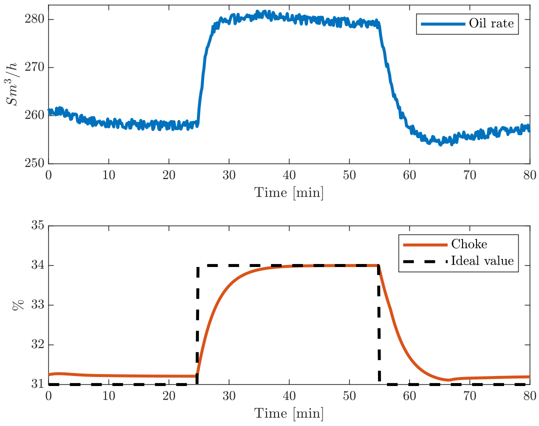

Figure 5.2: Excitation by moving the production choke ideal value.

The process may either be excited by moving a setpoint value for a CV or moving the ideal value for the MV. Moving of a setpoint or an ideal value for process excitation will be referred to as an excitation step, where the size of the excitation step is the difference between the initial setpoint/ideal value and the setpoint/ideal value after the process excitation. Both methods will be implemented for process excitation. A change of ideal value or setpoint will, if the constraints are respected, ignite a change of MV. If a given change in an MV yields a response in all CVs, it will be sufficient to calculate an updated model gain for all step response models for the MV. A desired oil rate set is often used as a specific production goal in a subsea well system. This process aims to control the oil rate as well; consequently, moving the oil rate setpoint is used for excitation. The production choke ideal value is used for excitation by moving the ideal value, as it is the only MV in the process.

When the process is excited by moving the oil rate setpoint value, the priority level in SEPTIC of the oil rate setpoint will be 2, i.e., less critical than CV high and low limits. This choice of priority level is to ensure that the other CV constraints are respected during an excitation. When the process is excited by moving the ideal value of the production choke, the priority level will be 2 for the same reasons as for the setpoint excitation.

The different excitation methods yield different responses and subsequently different model gains. This will be highlighted in Chapter 6, but examples of the difference in excitation method are illustrated in Figure 5.1 and Figure 5.2.

By moving the oil rate setpoint, the process response is more comfortably controlled, as can be seen in Figure 5.1. When the process is excited by moving the production choke ideal value, shown in Figure 5.2, the response in the oil rate will be more subjected to noise, as the production goal is to keep the production choke at its ideal value. The production goal when exciting by moving the oil rate setpoint is to reach and stay at the setpoint. Minor changes in the production choke will counteract the process noise.

Depending on the disturbance values, situations where either the oil rate or the production choke cannot reach their respective setpoint or ideal value, may arise. Figure 5.1 is an example of this situation, as the desired oil rate is $250Sm^3/h$. Situations where the setpoint or ideal value cannot be reached may arise if another CV will not satisfy its constraint if the oil rate or production choke moves closer to its respective setpoint or ideal value. It is desirable to excite the process from where the oil rate or ideal value currently is, as this gives control of the size of the excitation step. Given a situation where the desired setpoint or ideal value cannot be reached, the setpoint or ideal value is temporarily changed to where the process has stabilized. The process excitation will begin from the temporarily changed setpoint or ideal value. The process in Figure 5.1 excites from an oil rate setpoint of $262Sm^3/h$. In Figure 5.2, the production choke cannot stabilize at its desired ideal value, 31%. The process still excites from the value it stabilizes at, since the production choke stabilizes close to its desired ideal value, and a margin of ±0.5% is added. After the process excitation and updated model gains have been identified, the setpoint or ideal value returns to its original value.

An initial assumption in the automatic model gain identifier was that the process reaches steady-state after 30 minutes, given constant disturbances. In Figure 5.1 and Figure 5.2, the disturbances are constant for the whole duration of 80 minutes. The processes are excited at 25 minutes, and reaches steady-state. The setpoint or ideal value is moved and stays constant for 30 minutes, due to the assumption, before the setpoint or ideal value is reversed. To ensure that the process has actually reached steady-state, two extra conditions are added for steady-state verification. The first condition is to check if the oil rate has reached its steady-state value, by comparing the steady-state value with the current oil rate. The steady-state value can be found with the SEPTIC calc "getssval". If the current oil rate is within $\pm 1Sm^3/h$ of the steady-state value, the condition is considered to be satisfied. The second condition is to compare the current production choke opening to the optimal production choke opening in the next sample. The optimal production choke opening can be found the SEPTIC calc "mvmget". If the production choke is within 0.01% of the optimal production choke at the next sample, the condition is satisfied. If the production choke is within 0.01%, it is assumed that the process is in steady-state.

5.3 Updating the Model Gain

The model gain can be updated during simulation by implementing the calc "mod-set":

$$\text{Alg} = \text{"modset(CV,MV,scale,apply)"}$$

where apply = 1 commands to set scale, and any other value gives unaffected scale. If the scale is set, the updated model gain is implemented. Scale is calculated by:

$$\text{Scale} = \frac{\text{Model gain}_{calculated}}{\text{Model gain}_{initial}}$$

Model $\text{gain}_{initial}$ is the initial model gain. By using the calc "modget" at $N = 0$, the initial model gains can be acquired:

$$\text{Alg} = \text{"if(N=0,modget(CV,MV))"}$$

The Model $\text{gain}_{calculated}$ is calculated by using Equation 3.10, which is repeated below:

$$\text{Model gain} = \frac{\text{CV}_{\textit{Steady-state}} - \text{CV}_0}{\text{MV}_{\textit{Steady-state}} - \text{MV}_0}$$

CV_0 and MV_0 are the respective CV- and MV-values before the process excitation, while $\text{CV}_{Steady-state}$ $\text{MV}_{Steady-state}$ are the CV- and MV-values after the process has reached steady-state after the excitation.

For added robustness, the CV- and MV-values to calculate the model gains are calculated using the values from every sample for the past 5 minutes. The CV- and MV-values will be the average of the values from the past 5 minutes. Using

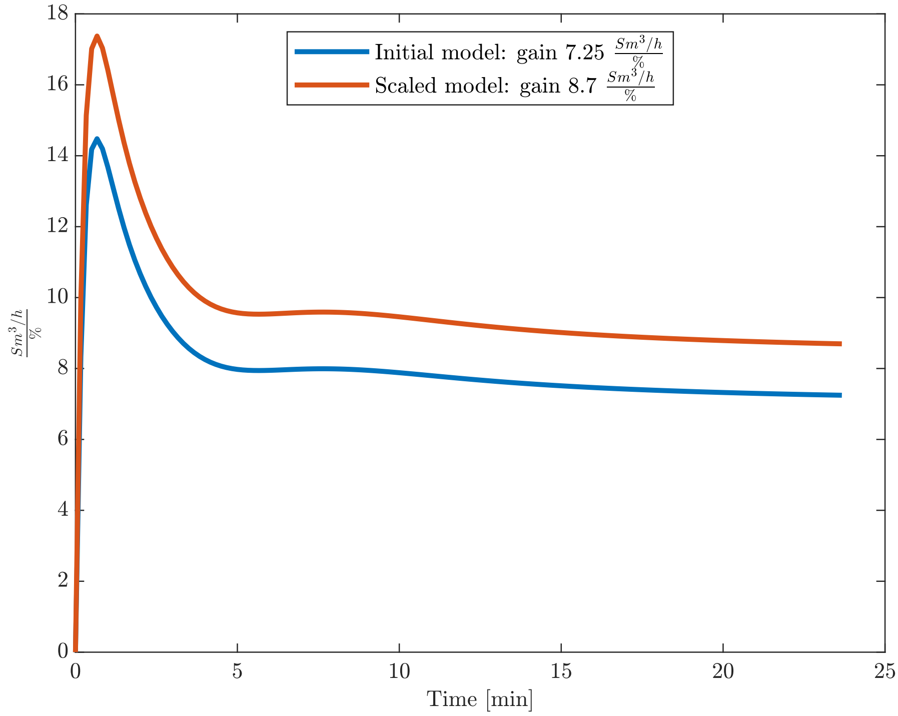

Figure 5.3: The initial step response model between oil rate and production choke, compared with the same step response model scaled by a factor of 1.2.

the values of the past 5 minutes to calculate the average improves the robustness of the gathered value, as it will be less affected by process noise. Using more values to calculate an average value is common practice in industrial applications.

An example of a scaled model is shown in Figure 5.3. The figure shows the initial step response model between oil rate and choke, compared to the same step response model, scaled by a factor of 1.2.

After the process has been excited and has reached steady-state, the setpoint/ideal value is reversed to the desired setpoint/ideal value.

The calculated model gains are verified before they are implemented. The calculated gain may suffer from noise, or the assumption of time to reach steady-state does not hold. An easy verification procedure is therefore added. The verification procedure is primarily a safety measure to ensure that the updated model gains will not be implemented if there is a risk of them being subjected to miscalculations.

The verification procedure is as follows:

Obtain the values for the CV and MV (CV_{after} and MV_{after}) after the excitation step has been reversed. Calculate an additional model gain value by using the following equation:

$$\text{Model gain}_{after} = \frac{\Delta\text{MV}}{\Delta\text{CV}} = \frac{\text{MV}_{Steady\text{-}state - \text{MV}_{after}}}{\text{CV}_{Steady\text{-}state} - \text{CV}_{after}}$$

The values for MV_{after} and CV_{after} also use the average values for the past 5 minutes after the process has reached steady-state.

This value is then compared to Model $\text{gain}_{calculated}$:

$$\text{Gain Ratio} = \frac{\min(\text{Model gain}_{calculated},\text{Model gain}_{after})}{\max(\text{Model gain}_{calculated},\text{Model gain}_{after})} \quad \in \langle 0, 1]$$

If the gain ratio is above 0.8, the model gain is updated. The first calculated model gains, Model $\text{gain}_{calculated}$, are then implemented. If the gain ratio is below 0.8, the initial model gain from before the process excitation is kept. It is then assumed that the process is too affected by noise or does not reach steady-state either before or after the excitation.

5.4 Constraint Satisfaction During Excitation

The expected steady-state CV-values (referred to as expected CV-values here) after an excitation step can be calculated from the online data available from the simulation. The expected CV-values help decide which direction the excitation step should be. Because of the priority levels in SEPTIC, the constraints are satisfied at all times given feasibility. However, the identified model gains will be more robust if the setpoint/ideal value is reached after the process excitation.

The default excitation step is positive. A positive excitation step means that when a process excitation is deemed necessary, either the oil rate setpoint or the production choke ideal value, depending on the excitation method, will change in a positive direction. When the process is excited by moving the oil rate setpoint, the default step for the setpoint will be +10 Sm^3/h. When the process is excited by moving the production choke ideal value, the default step will be +3 %.

The excitation steps of $+10Sm^3/h$ and +3% for the oil rate setpoint and the production choke ideal value were used as the model gains calculated were not too affected by process noise. Smaller excitation steps could not ensure consistency in the calculated model gains, which were avoided with larger excitation steps. It is also not desirable to have too large excitation steps either, as not to disrupt the process too much.

Before each process excitation, the expected CV-values after the excitation step is calculated. The motivation behind calculating the expected CV-values is that the default positive excitation step might yield expected CV-values that do not respect the constraints. Because of the priority levels in SEPTIC, the CV constraints will still be respected. However, the process might not reach either the oil rate setpoint or the production choke ideal value after an excitation step. The reason for the process not reaching the setpoint/ideal value is that respecting the constraints is of higher priority.

If the process does not reach a setpoint/ideal value after a process excitation, the calculated model gains are less accurate and less robust because of a reduced excitation. The expected CV-values are calculated for excitation steps in both positive and negative directions. When exciting the process by moving the production choke ideal value, the expected CV-values are calculated using Equation 5.3.

$$\mathrm{CV}_{expected} = \mathrm{CV}_0 + \mathrm{Gain}_{CV} * \pm\Delta\mathrm{MV} \tag{5.3}$$

ΔMV is the excitation step for the production choke, and the expected CV-values will be calculated for both positive and negative excitation steps, yielding two expected values for each CV. The expected values indicate in which direction the excitation should be.

If the expected CV-values when ΔMV is positive respects the CV-constraints, the excitation step will be positive (+3 % change of production choke). If a positive ΔMV yields expected CV-values which do not respect the CV-constraints, while a negative ΔMV yields expected CV-values which respects the constraints, the excitation step will be negative (-3 % change of production choke).

When the process excitation is done by moving the oil rate setpoint, the expected CV-values is calculated by first calculating the expected movement of the production choke:

$$\Delta\text{MV}_{expected} = \pm\frac{\text{Oil rate}_{Steady\text{-}state} - \text{Oil rate}_0}{\text{Gain}_{OilRate}} = \pm\frac{\Delta\text{Oil rate}}{\text{Gain}_{OilRate}}$$

ΔOil rate is a setpoint change of 10 Sm^3/h. The expected CV-values (BHP and WHP) from both a positive and negative excitation step can then be calculated by using Equation 5.3 ($\Delta\text{MV} = \Delta\text{MV}_{expected}$). As with process excitation by moving the ideal value of the production choke, both the positive and the negative excitation steps will be investigated to detect which direction the excitation step is expected to respect the constraints.

Situations where neither a positive or a negative excitation step expects constraint satisfaction may occur. In these situations, the deviations for all expected CVs which do not respect the constraints are calculated. The deviations are the difference between the constraint limit and the expected CV-value which violates the constraint:

$$\text{Deviation}_{CV_n} = \text{CV}_{n_{expected}} - \text{CV}_{n_{High}}$$

$$\text{Deviation}_{CV_n} = \text{CV}_{n_{Low}} - \text{CV}_{n_{expected}}$$

$\text{CV}_{n_{expected}}$ is calculated using both positive and negative excitation steps. A positive value for Deviation_{CV_n} imply that constraint satisfaction is not expected. For these CVs, a maximum allowable excitation step is calculated. If a positive excitation does not expect constraints satisfaction, the maximum allowable expected excitation step is calculated as:

$$\frac{\text{CV}_{n_{High}} - \text{CV}_{n_0}}{\text{Gain}_{CV_n}} * \text{Gain}_{Oilrate}$$

CV_{n_0} is the current value of the CV. If neither a positive or negative excitation step yields constraint satisfaction, the excitation step will go in the direction which the maximum of the expected maximum allowable excitation step is.

For illustration purposes, an example is presented. In this example, the process is excited by moving the oil rate setpoint. The initial model gains and the initial disturbance conditions are shown in Table 5.1.

Model gain oil rate	7.25 $\frac{Sm^3/h}{\%_{choke}}$
Model gain WHP	-1.74 $\frac{bar}{\%_{choke}}$
Model gain BHP	-0.37 $\frac{bar}{\%_{choke}}$
Gas lift rate	$5000 Sm^3/h$
Downstream pressure	$13 bar$

Table 5.1: Initial model gains and disturbances.

Oil rate_0	$290.9 Sm^3/h$
WHP_0	$25 bar$
BHP_0	$164.7 bar$

Table 5.2: Steady-state CV-values after disturbance changes.

The gas lift rate and downstream pressure change to, respectively, $12000 Sm^3/h$ and $5 bar$, such that the model gains need updating. The CV-values then stabilizes at the values shown in Table 5.2. The oil rate cannot reach its desired setpoint of $250 Sm^3/h$, and the WHP is at its high limit.

In this situation the expected movement of the choke is:

$$\Delta \text{MV}_{expected} = \pm \frac{\Delta \text{Oil rate}}{\text{Gain}_{Oilrate}} = \pm \frac{10 Sm^3/h}{7.25 \frac{Sm^3/h}{\%_{choke}}} = \pm 1.38\%_{choke}$$

A negative excitation step (moving the oil rate setpoint $-10\ Sm^3/h$) would lead to the following expected WHP:

$$\begin{aligned} \text{WHP}_{expected} &= \text{WHP}_0 + Gain_{WHP} * -\Delta \text{MV}_{expected} \\ &= 25 bar + (-1.74 \frac{bar}{\%_{choke}} * -1.38\%_{choke}) = 27.38 bar \end{aligned}$$

The WHP high limit is not respected, yielding a deviation of:

$$\text{Deviation}_{WHP} = \text{WHP}_{expected} - \text{WHP}_{High} = 27.38 bar - 25 bar = 2.38 bar$$

A positive excitation step would lead to a deviation of the oil rate upper limit:

$$\begin{aligned}\text{Deviation}_{Oilrate} &= \text{Oil rate}_{expected} - \text{Oil rate}_{High} \\ &= 300.9Sm^3/h - 300Sm^3/h = 0.9Sm^3/h,\end{aligned}$$

as $\text{Oil rate}_{expected} = \text{Oil rate}_0 + \Delta\text{Oil rate} = 300.9Sm^3/h$. The maximum allowable expected excitation step in positive direction becomes:

$$\text{Oil rate}_{High} - \text{Oil rate}_0 = 300Sm^3/h - 290.9Sm^3/h = 9.1Sm^3/h.$$

Comparing this with the maximum allowable expected excitation step in negative direction:

$$\frac{\text{WHP}_{High} - \text{WHP}_0}{\text{Gain}_{WHP}} * \text{Gain}_{Oilrate} = \frac{25bar - 25bar}{-1.74\frac{bar}{\%_{choke}}} * 7.25\frac{Sm^3/h}{\%_{choke}} = 0Sm^3/h$$

As the maximum allowable expected step in the negative direction is 0, the process would not move if the oil rate setpoint was moved in a negative direction. To perform a successful process excitation, the setpoint would therefore have to be moved in a positive direction.

In these situations, the oil rate setpoint would be set to 300 Sm^3/h instead of 300.9 Sm^3/h, such that the setpoint is not set outside of the high/low limits.

The example is shown in Figure 5.4.

As the disturbances change, it is seen that the oil rate stabilizes at $290.9Sm^3/h$, while WHP reaches its high limit of $25bar$. The process excitation will begin from where the oil rate stabilizes if the oil rate cannot stabilize at the desired setpoint of $250Sm^3/h$. When the process stabilizes, it is calculated which direction the excitation should be for maximum possible excitation. As has been explained, the direction which would yield the maximum allowable excitation step was in the positive direction. This is shown in Figure 5.4. If the excitation step was in the opposite direction, the process would remain in steady-state and the process would not be excited, with the reason being that the oil rate cannot be reduced (as the production choke opening would need to be reduced) without breaking the upper limit of WHP.

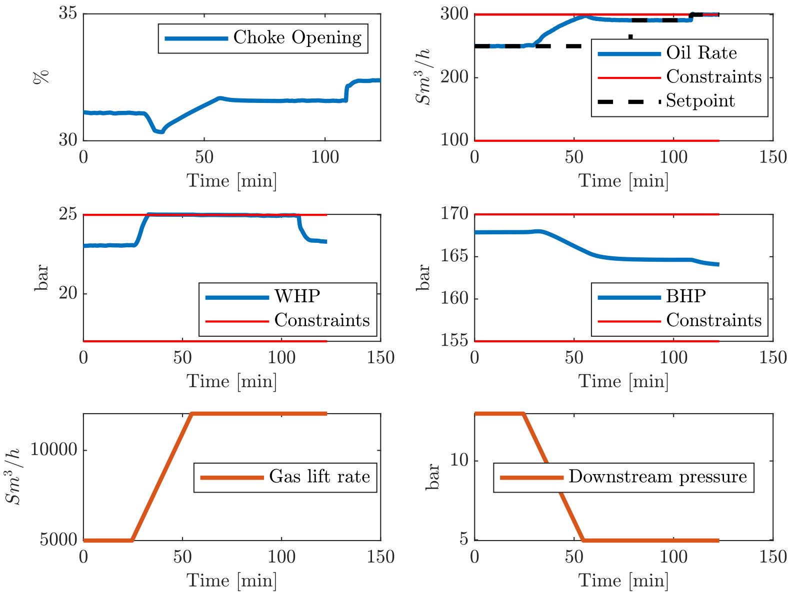

Figure 5.4: The disturbances changes and WHP reaches its upper limit. The automatic model gain identifier recognizes this, and the direction of the excitation step is positive as this is the direction which yields the maximum available excitation step. Excitation by moving the oil rate setpoint. The oil rate reaches its upper limit.

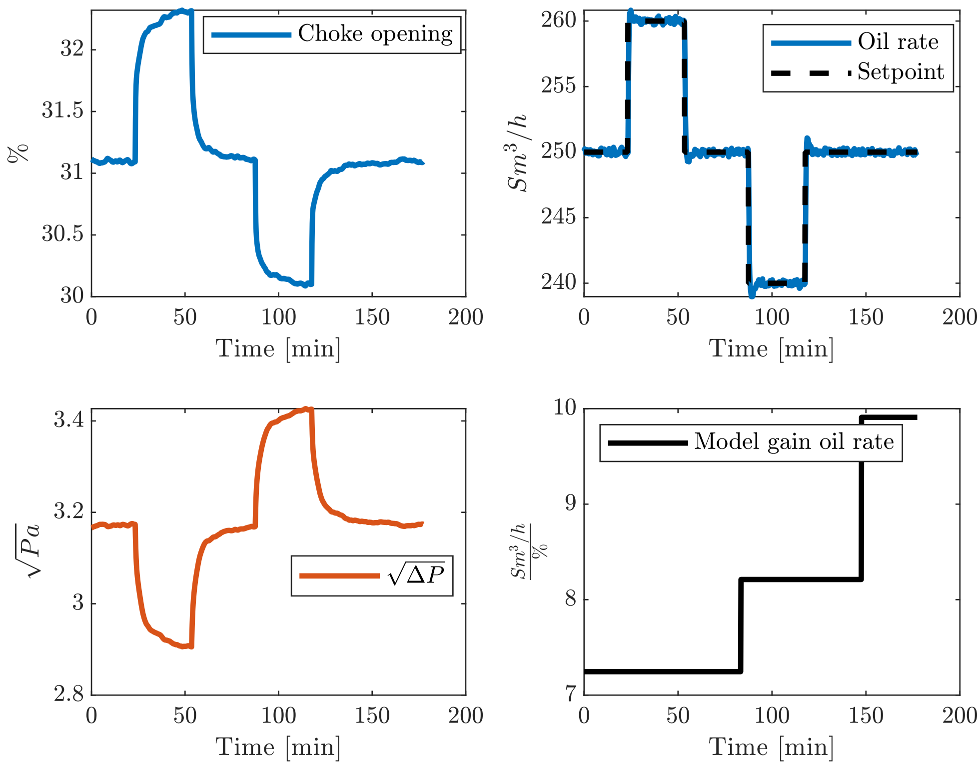

Figure 5.5: The process is first excited by moving the oil rate in positive direction, and then in negative direction. This yields two different model gains, respectively, $8.2 \, \frac{Sm^3/h}{\%_{choke}}$ and $9.9 \, \frac{Sm^3/h}{\%_{choke}}$.

The automatic model gain identifier will identify different model gains depending on the direction the excitation step will be, even if the disturbances are constant during the two identification periods. An example is shown in Figure 5.5, where a movement of the oil rate setpoint is used as the excitation method. In the example, the gas lift rate is $5000 Sm^3/h$ and the downstream pressure is $13 bar$. When the excitation step is in a positive direction, the production choke opening increases to reach the setpoint, while the production choke decreases to reach the setpoint if the excitation step is in a negative direction. If the production choke decreases, WHP pressure increases. However, if the production choke increases, WHP pressure decreases. As the downstream pressure is kept constant, the pressure drop ΔP over the production choke depends upon which direction the excitation step is. As the square root of ΔP determines the production choke opening needed to reach a specified oil rate (Equation 4.1), the change of production choke opening will differ depending on the direction of the excitation step. Because the production choke opening differs, the identified model gains will also differ.

	Initial conditions	Acceptable movements
Gas lift rate	$5000 Sm^3/h$	$\pm\ 2000 Sm^3/h$
Downhole pressure	$13 bar$	$\pm\ 3 bar$

Table 5.3: Disturbances: initial conditions and acceptable movements.

5.5 Excitation Triggers

In a best-case scenario for an industrial process, it is preferable to avoid a process excitation if production rates are satisfactory. During operation, it is preferable to keep the process in steady-state to avoid wear and tear on the equipment. It is therefore essential to carefully select in which scenarios to excite process for model gain identification.

An excitation trigger added to the data-driven methodology is the age of the current model gains. This excitation trigger is added to have a continuous model gain identification to verify the current model gains. The process will excite and identify updated model gains if the existing model gains has not been updated in the last 24 hours.

Due to the non-linearity in the process, the model gains will differ from where in the state-space the process currently is. Therefore, an excitation trigger is added based on the value of the disturbances, as a change of disturbance values corresponds to a process moving in the state-space.

The disturbances in the process are gas lift rate and downhole pressure, as mentioned in Chapter 4. Initial conditions and acceptable movements in the state-space for each of the disturbances are listed in Table 5.3.

The acceptable movements are the minimum and the maximum change of the disturbances before the current model gains are deemed unacceptable. From these acceptable movements, an area of model acceptance is created. If the process disturbances are within these limits, the current process models are considered acceptable and kept. The initial acceptable area for the disturbances is shown in Figure 5.6.

An excitation is triggered if the process disturbances moves outside of this area. A percentage for each disturbance is calculated based on where in the state-space the disturbance is. This is implemented as follows:

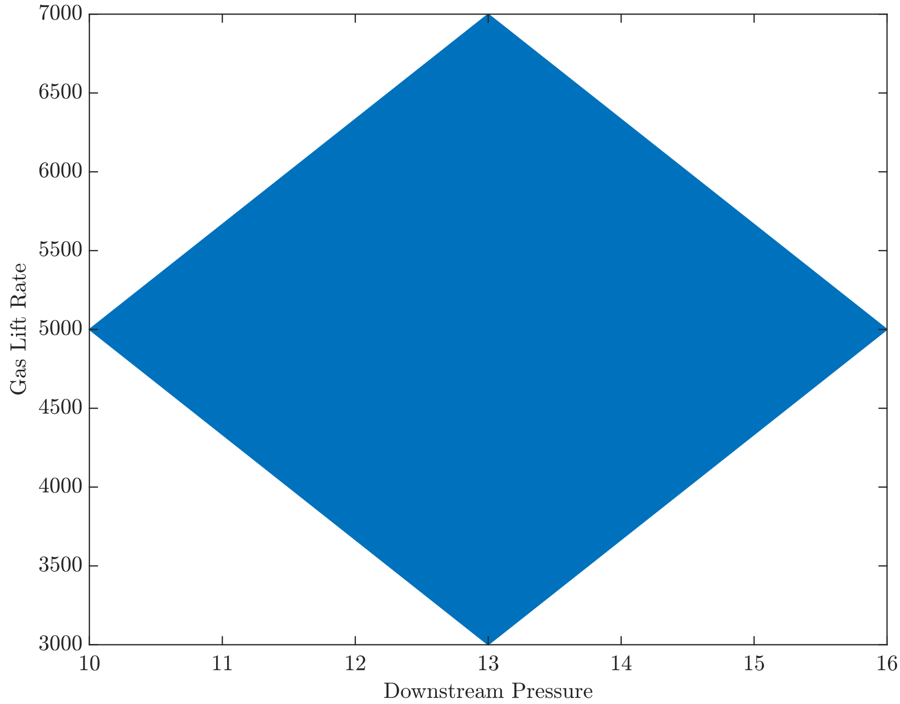

Figure 5.6: Initial acceptable area for the disturbances, with a gas lift rate of $5000Sm^3/h$ and a downstream pressure of $13bar$.

$$\% = 100 * \frac{|DV - DV_{init}|}{DV_{\pm}}$$

where DV is the current disturbance value, DV_{init} is the initial disturbance value, and $DV_{\pm}$ is the acceptable movements for the disturbances. The percentage is calculated for both disturbances, and summed to a total percentage:

$$\%_{\text{total}} = \%_{\text{Gas lift rate}} + \%_{\text{Downhole pressure}}$$

If $\%_{total}$ exceeds 100%, the process is outside of the acceptable area, and the process is subsequently excited.

If the model gains are updated, the initial conditions are also updated such that the acceptable area is updated. The acceptable movements are kept for further creation of a new acceptable area.

When the disturbances are manually adjusted in SEPTIC, the disturbances reach their adjusted values after 30 minutes with a constant rate of change. This is to avoid sudden changes to the process, as this is not realistic during a real life environment during normal operation. The gas lift rate (normally an MV) are limited in rate of change. The downstream pressure may change suddenly in a real life scenario, however this is not expected during normal operation, and therefore outside of the scope of this thesis.

Chapter 6

Results and Simulations

In this chapter, the main results of this thesis will be presented. The aim is to show increased performance from the MPC using the automatic model gain identifier. The gain identifier will automatically excite the process to identify model gains if the existing model gains are deemed unacceptable.

The main results will be presented in two parts. The first part illustrates how a set of previously implemented model gains affects the process, compared to how the process is affected after the model gains have been updated. The model gains will first be identified from a process excitation by moving the oil rate setpoint. The responses with the previous model gains and the updated model gains from a setpoint procedure will be compared. The oil rate setpoint will be set to its upper limit of $300Sm^3/h$ from its initial setpoint of $262Sm^3/h$. When the process has stabilized and reached steady-state, the setpoint will be set to its lower limit of $100Sm^3/h$. The model gains will then be identified and updated, and the same setpoint procedure with updated model gains is repeated. The goal is to illustrate increased performance from the MPC, given correct model gains. The model gains are updated with the automatic model gain identifier presented in Chapter 5. The same procedure will be repeated by exciting the process by changing the production choke ideal value. The ideal value is then first set to 100% from its initial ideal value 31% and then to 0% after reaching steady-state. A brief discussion of the difference between excitation by ideal value and setpoint follows.

The second part aims to illustrate that the model gain identifier is automatic. The disturbances will change with time, and the process will excite, when necessary,

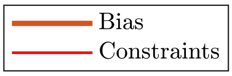

Figure 6.1: Common legends in the plots.

Model gain oil rate	3.1 $\frac{Sm^3/h}{\%_{choke}}$
Model gain WHP	-0.4 $\frac{bar}{\%_{choke}}$
Model gain BHP	-0.2 $\frac{bar}{\%_{choke}}$

Table 6.1: Initial model gains from setpoint excitation for model gains identification, identified with a gas lift rate of $2500Sm^3/h$ and a downstream pressure of $15bar$.

and model gains will be identified and updated. An additional aim is to show the consistency of identified and updated model gains, i.e., the model gains identified at a set of process parameters will be equal if the process returns to this set of process parameters. An additional aim is to illustrate that the excitation steps do not lead to constraint dissatisfaction. In case of a risk of constraint dissatisfaction, the excitation step will be in the direction that allows the maximum allowable excitation step size. The automatic model gain identifier is presented using both setpoint excitation and ideal value excitation separately.

6.1 Part 1

The first part shows that the identified model gains from a process excitation improve the MPC performance compared with the previously implemented model gains.

6.1.1 Setpoint Excitation

The initially identified model gains are shown in Table 6.1. The model gains are identified with a gas lift rate of $2500Sm^3/h$ and a downstream pressure of $15bar$.

The updated acceptable area is shown in Figure 6.2.

The disturbances are then adjusted. The gas lift rate is set to $7500Sm^3/h$, while

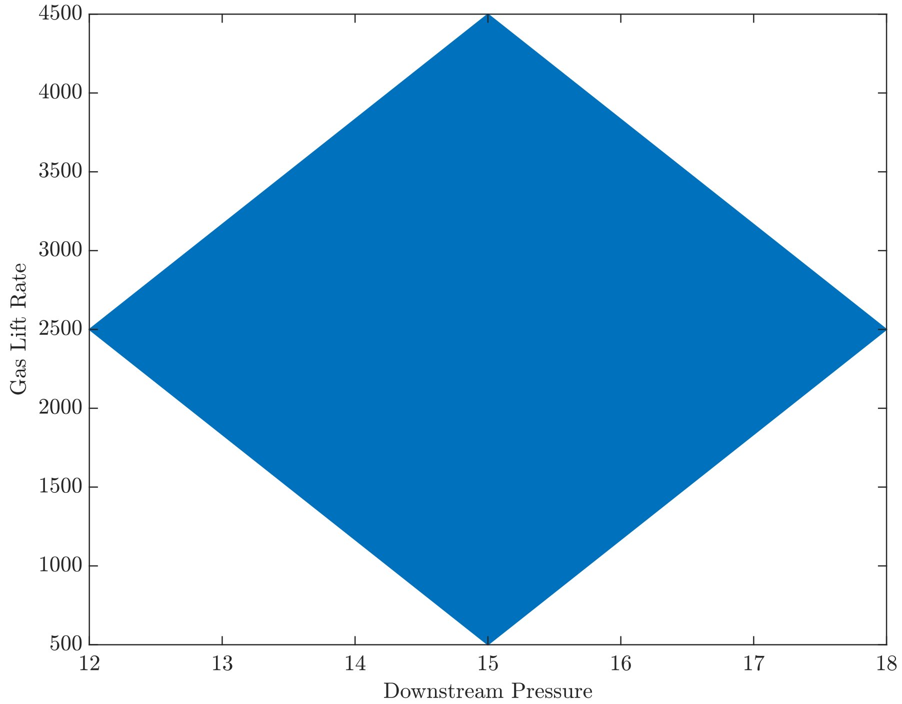

Figure 6.2: Updated acceptable area for the disturbances, after model gains identification at a gas lift rate of $2500 Sm^3/h$ and a downstream pressure of $15 bar$.

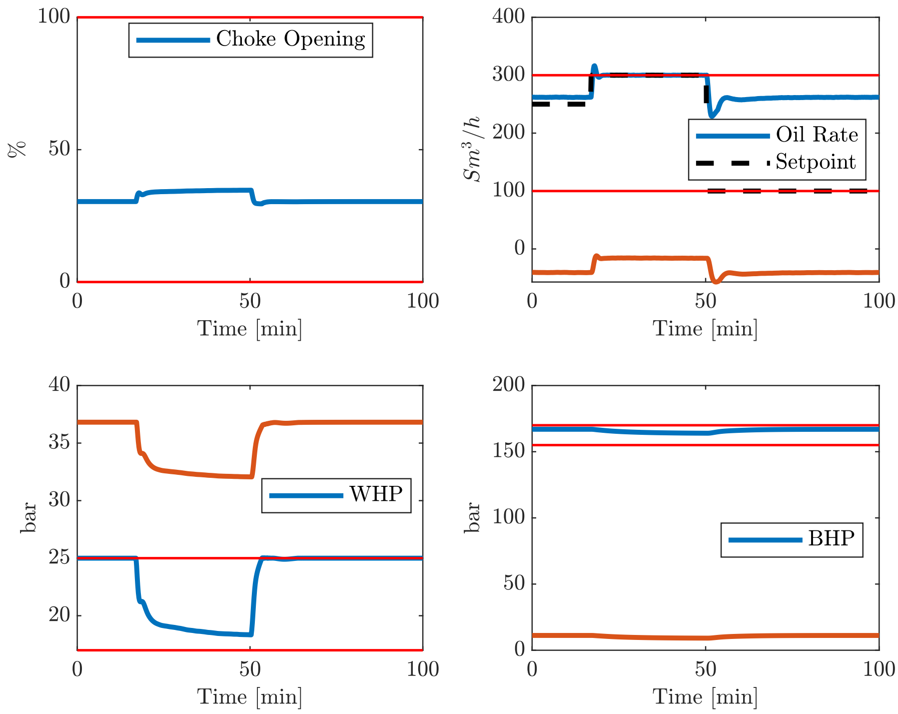

Figure 6.3: Setpoint procedure, with a gas lift rate of $7500Sm^3/h$ and a downstream pressure of $9bar$, using the initial model gains. Model gains identified with oil rate setpoint excitation, with a gas lift rate of $2500Sm^3/h$ and a downstream pressure of $15bar$.

the downstream pressure is set to $9bar$. The disturbance values are outside of the acceptable area in Figure 6.2 as the total percentage $\%_{total}$ is above 100%, and the model gains are therefore not considered acceptable. Given the value of the disturbances, the oil rate cannot reach the desired setpoint of $250Sm^3/h$ but stabilizes at $262Sm^3/h$. The oil rate cannot reach the setpoint of $250Sm^3/h$ because WHP is at its upper limit of $25bar$. This constraint would not be respected if the oil rate would decrease because the production choke opening would have to decrease. A reduction of production choke opening leads to increased WHP.

The model gains are tested in a procedure where the oil rate setpoint is set first to its upper limit $300Sm^3/h$ and then to its lower limit of $100Sm^3/h$. This setpoint procedure is used as large process excitations are optimal to illustrate the comparison in performance between the updated model gains and the initial model gains. The responses from the setpoint procedure using the initial model gains are shown in Figure 6.3.

Model gain oil rate	11.5 $\frac{Sm^3/h}{\%_{choke}}$
Model gain WHP	-2.0 $\frac{bar}{\%_{choke}}$
Model gain BHP	-0.9 $\frac{bar}{\%_{choke}}$

Table 6.2: Updated model gains from setpoint excitation for model gains identification, identified with a gas lift rate of $7500 Sm^3/h$ and a downstream pressure of $9 bar$.

The process is then excited, and new model gains are identified. The updated model gains are shown in Table 6.2.

To test the updated model gains, the setpoint procedure is repeated. The responses from the setpoint procedure using the updated model gains are shown in Figure 6.4.

In Figure 6.3 the oil rate goes outside of the upper limit of $300 Sm^3/h$ when adjusting the setpoint to the upper limit. Because the model gains are not optimal given the process parameters, the MPC cannot predict optimal inputs from the mathematical model of the process, which leads to constraint violation. The production choke takes aggressive control actions as a direct consequence of not predicting optimal inputs. Aggressive control actions from the production choke are not desirable in an industrial process, as the production choke will wear out quicker. When the oil rate setpoint is set to its lower limit of $100 Sm^3/h$, a slight overshoot in WHP is also observed.

Figure 6.4 shows smoother input values from the choke with less aggressive control actions. The MPC can predict more optimal values from the mathematical model of the process. The oil rate converges quicker to the upper limit, compared with Figure 6.3. The constraints are respected throughout the oil rate setpoint procedure.

The bias and the bias rate of change throughout the procedure from the old model gains are compared with the bias and the bias rate of change throughout the procedure from the new model gains. The comparisons are shown in Figure 6.5-6.7. A lower bias rate of change corresponds to higher model quality, as explained in Section 3.5.

The total bias rate of change from the setpoint procedure is shown in Table 6.3.

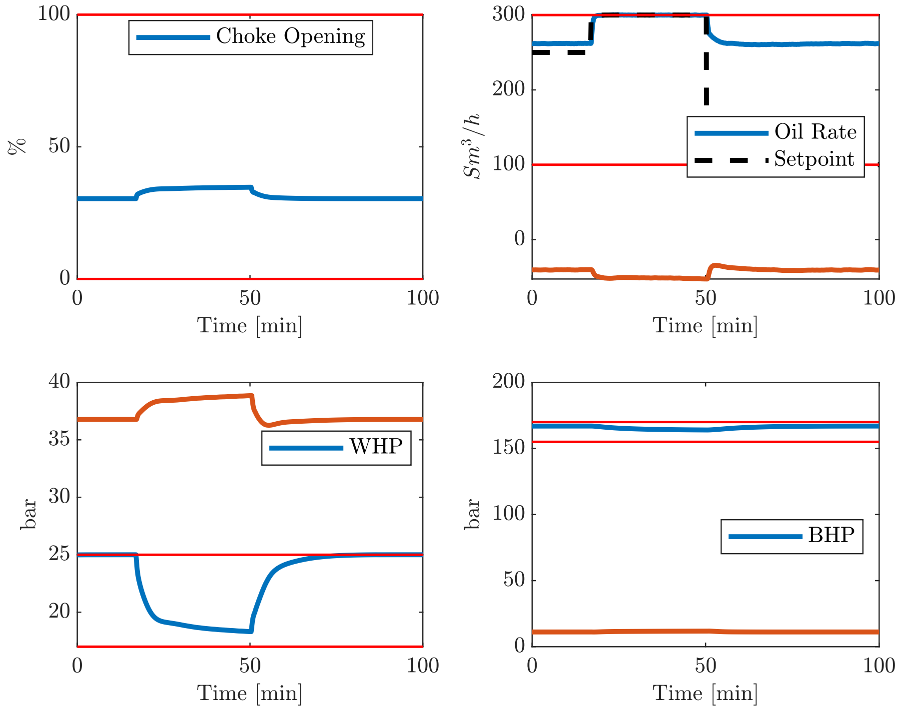

Figure 6.4: Setpoint procedure, with a gas lift rate of $7500Sm^3/h$ and a downstream pressure of $9bar$, using the updated model gains. Model gains identified with oil rate setpoint excitation, with a gas lift rate of $7500Sm^3/h$ and a downstream pressure of $9bar$.

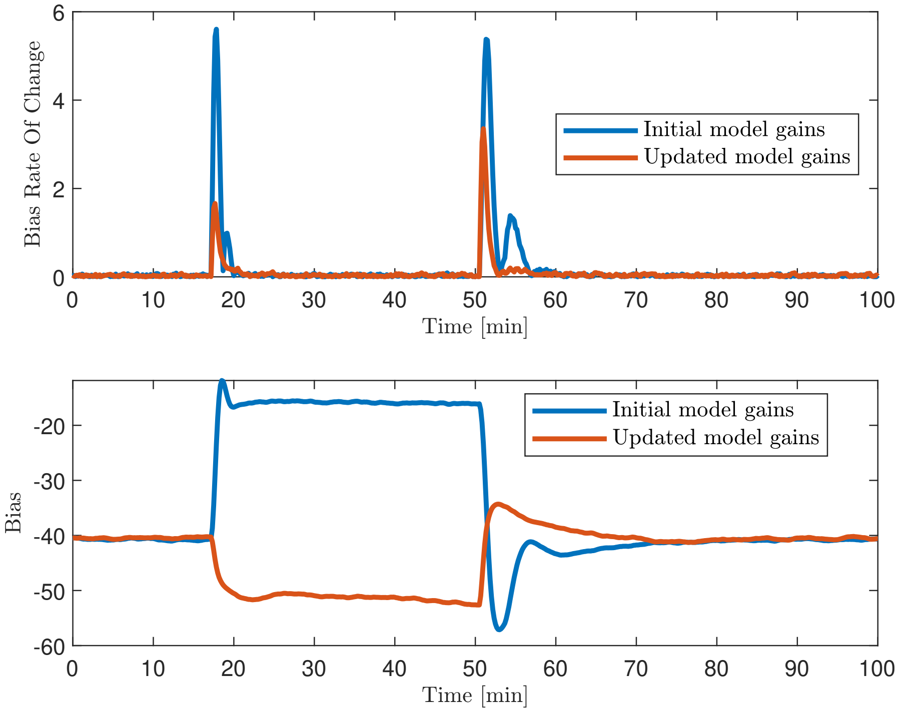

Figure 6.5: Comparing oil rate absolute value of bias rate of change and bias between the initial and the updated model gains for the oil rate setpoint procedure.

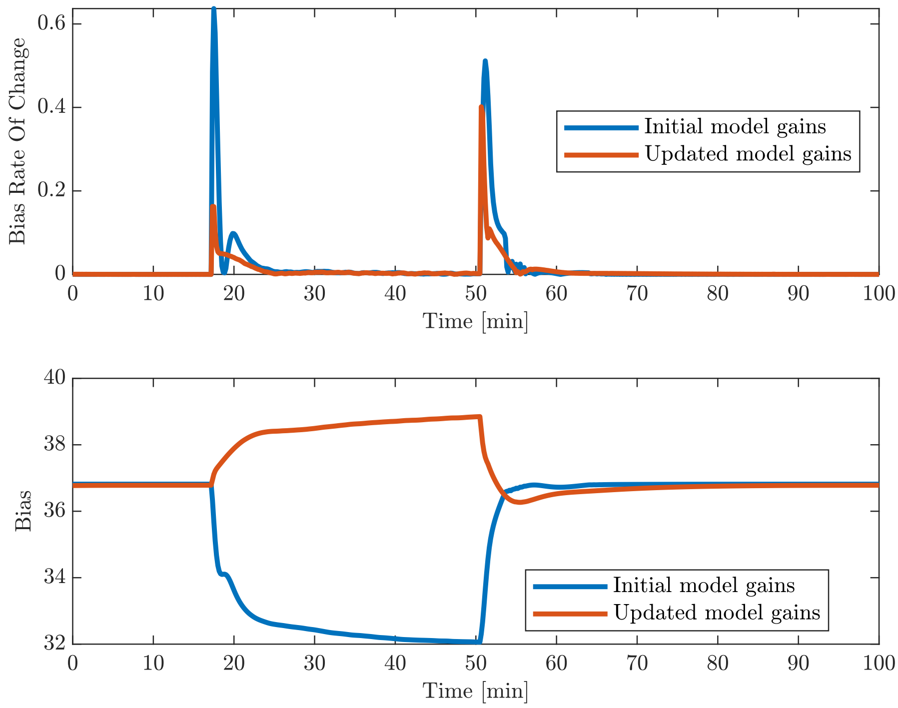

Figure 6.6: Comparing WHP absolute value of bias rate of change and bias between the initial and the updated model gains for the oil rate setpoint procedure.

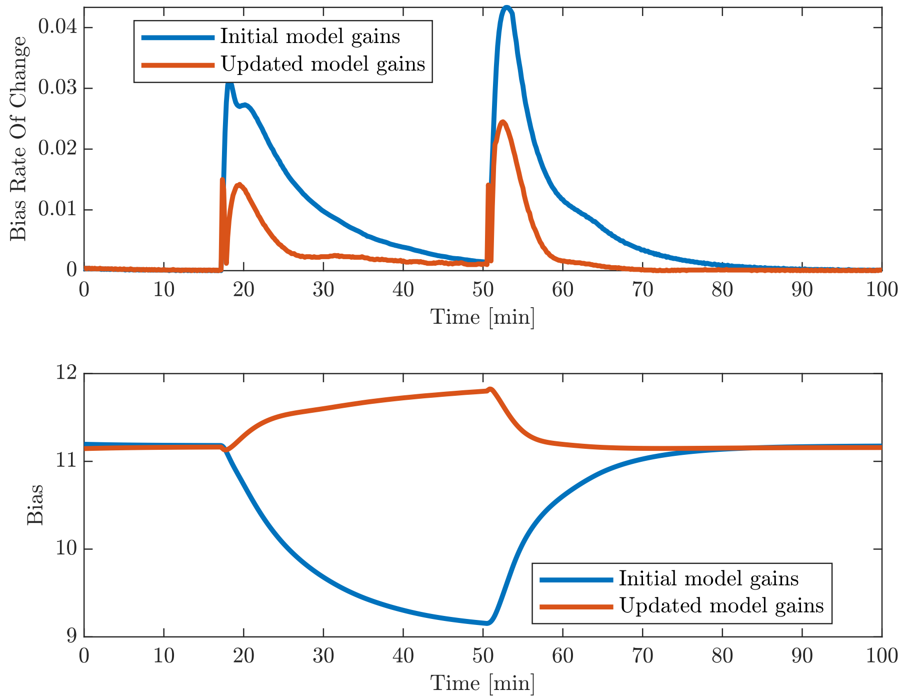

Figure 6.7: Comparing BHP absolute value of bias rate of change and bias between the initial and the updated model gains for the oil rate setpoint procedure.

	Total bias rate of change		
	Oil rate	WHP	BHP
Initial model gains	108.37	9.73	4.06
Updated model gains	50.19	5.17	1.44
Reduction	53.69 %	46.87 %	64.53 %

Table 6.3: Comparison of total bias rate of change for the oil rate setpoint procedure.

The total bias rate of change is calculated using Equation 6.1.

$$|\sum_{k=0}^{N-1} b(k+1) - b(k)| \tag{6.1}$$

$b(k+1)$ is calculated using Equation 3.5. The absolute value of the bias rate of change is used, as it better illustrates the differences in the bias rate of change between old and new model gains. As explained in Section 3.5, a perfect input-output model of a SISO-system would yield $\dot{b}(k) = 0$. A bias rate of change closer to zero corresponds to higher model quality. When comparing the bias rate of change from the old and new model gains, the absolute value is ideal for illustrating the bias rate of change.

The reduced total bias rate of change shows that the updated model gains perform better than the old model gains. Using the updated model gains yields a reduction of 53.69 % of the total bias rate of change for the oil rate, a reduction of 46.87 % total bias rate of change for the WHP, and a reduction of 64.53 % total bias rate of change for the BHP.

With constraint satisfaction despite considerable process excitations and great reductions of the total rate of change of bias, the updated model gains show promising results. The gain identification used process data from the simulation to identify the gains. The results presented show that the gains acquired from the gain identification are better performing than using initial gains identified at different process parameters.

Model gain oil rate	5.6 $\frac{Sm^3/h}{\%_{choke}}$
Model gain WHP	-0.8 $\frac{bar}{\%_{choke}}$
Model gain BHP	-0.4 $\frac{bar}{\%_{choke}}$

Table 6.4: Initial model gains from ideal value excitation for model gains identification, identified with a gas lift rate of $2500Sm^3/h$ and a downstream pressure of $15bar$.

Model gain oil rate	8.7 $\frac{Sm^3/h}{\%_{choke}}$
Model gain WHP	-1.5 $\frac{bar}{\%_{choke}}$
Model gain BHP	-0.7 $\frac{bar}{\%_{choke}}$

Table 6.5: Updated model gains from production choke ideal value excitation for model gains identification, identified with a gas lift rate of $7500Sm^3/h$ and a downstream pressure of $9bar$.

6.1.2 Ideal Value Excitation

The ideal value for the production choke is used instead of setpoint for the oil rate for process excitation in this section. This yields slightly different initial model gains at the initial disturbance values. The initial model gains at the initial disturbances are shown in Table 6.4.

The disturbances are adjusted, i.e., the gas lift rate is set to $7500Sm^3/h$, and downstream pressure is set to $9bar$. The responses from an ideal value procedure using the initial model gains with adjusted disturbances are shown in Figure 6.8. First, the ideal value procedure moves the production choke ideal value to 100% and then to 0% after the process has reached steady-state.

The process is then excited, and model gains are updated. The updated and implemented model gains are shown in Table 6.5.

The responses using the updated model gains with adjusted disturbances are shown in Figure 6.9.

The bias from the old model gains is compared with the bias from the new model gains and the bias rate of change. This is shown in Figure 6.10-6.12.

The total bias rate of change and reduction in total bias rate of change from using

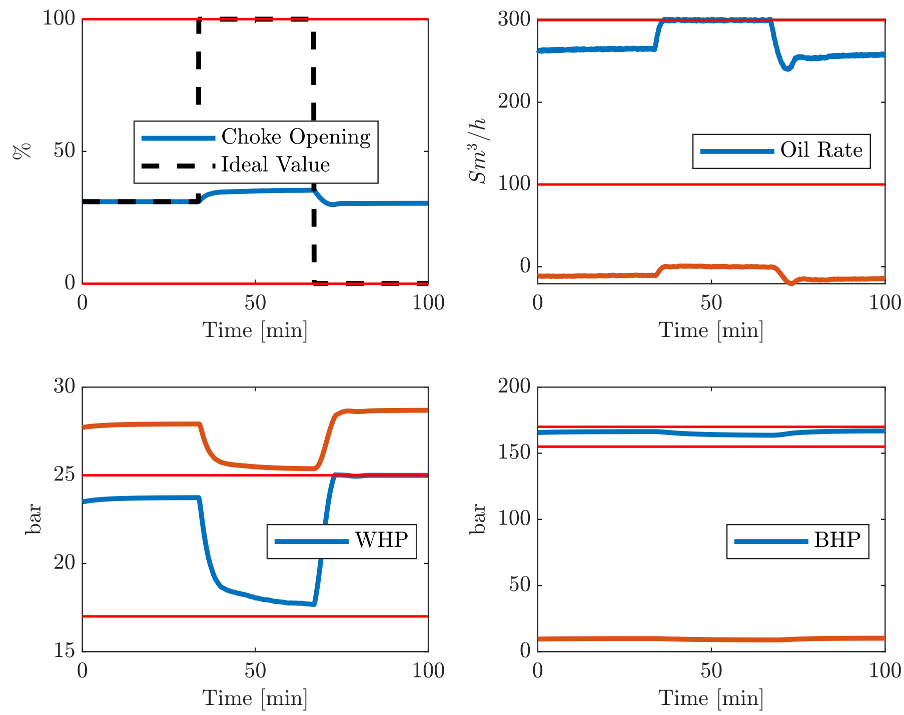

Figure 6.8: Ideal value procedure, with a gas lift rate of $7500 Sm^3/h$ and a downstream pressure of $9 bar$, using the initial model gains. Model gains identified with production choke ideal excitation, with a gas lift rate of $2500 Sm^3/h$ and a downstream pressure of $15 bar$.

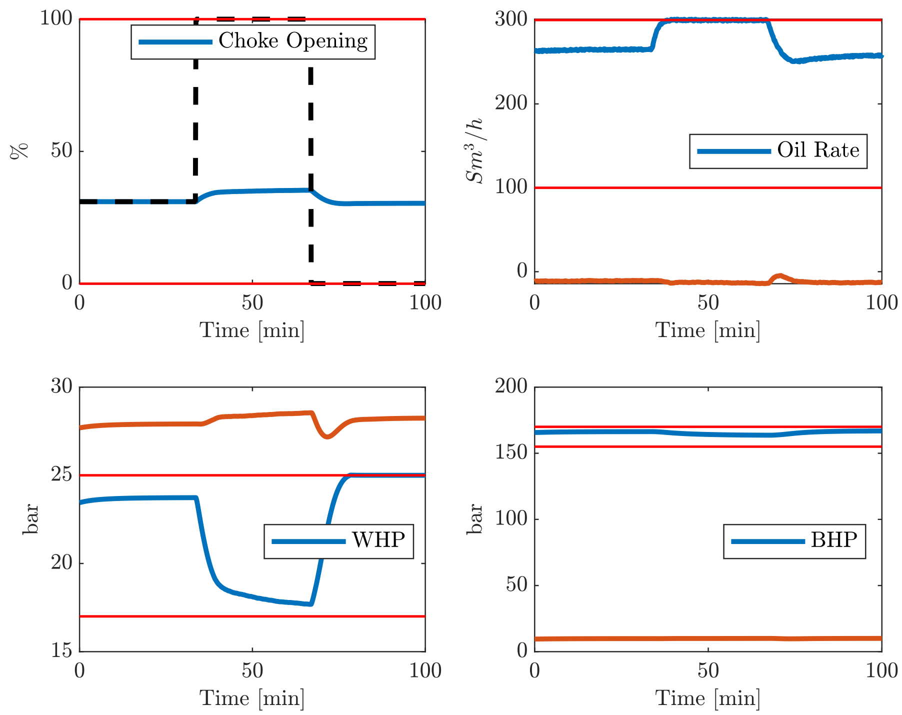

Figure 6.9: Ideal value procedure, with a gas lift rate of $7500 Sm^3/h$ and a downstream pressure of $9 bar$, using the updated model gains. Model gains identified with production choke ideal value excitation, with a gas lift rate of $7500 Sm^3/h$ and a downstream pressure of $9 bar$.

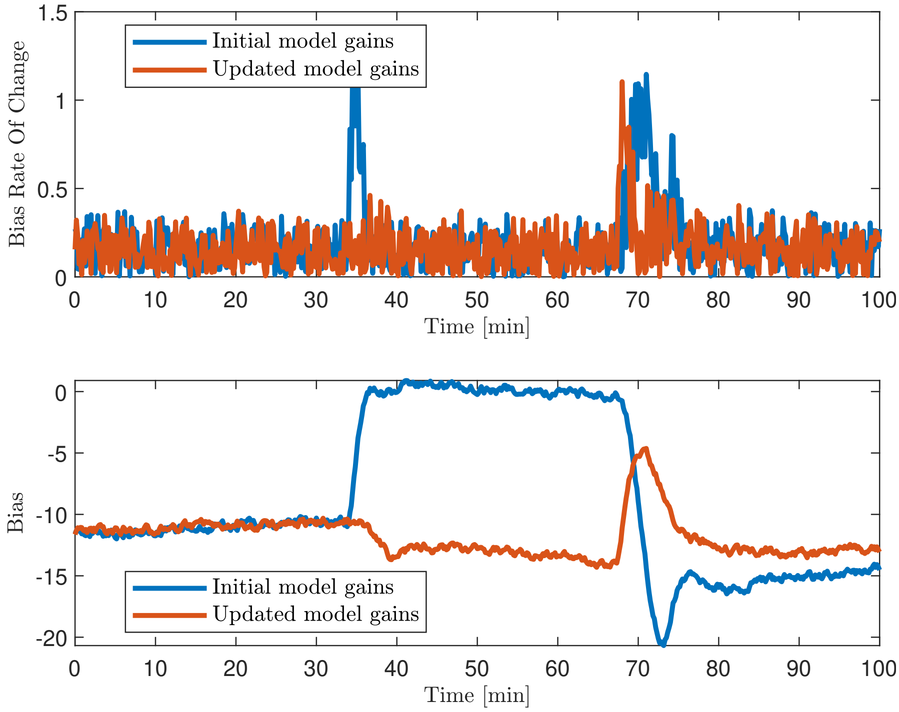

Figure 6.10: Comparing oil rate absolute value of bias rate of change and bias between the initial and the updated model gains for the ideal value procedure.

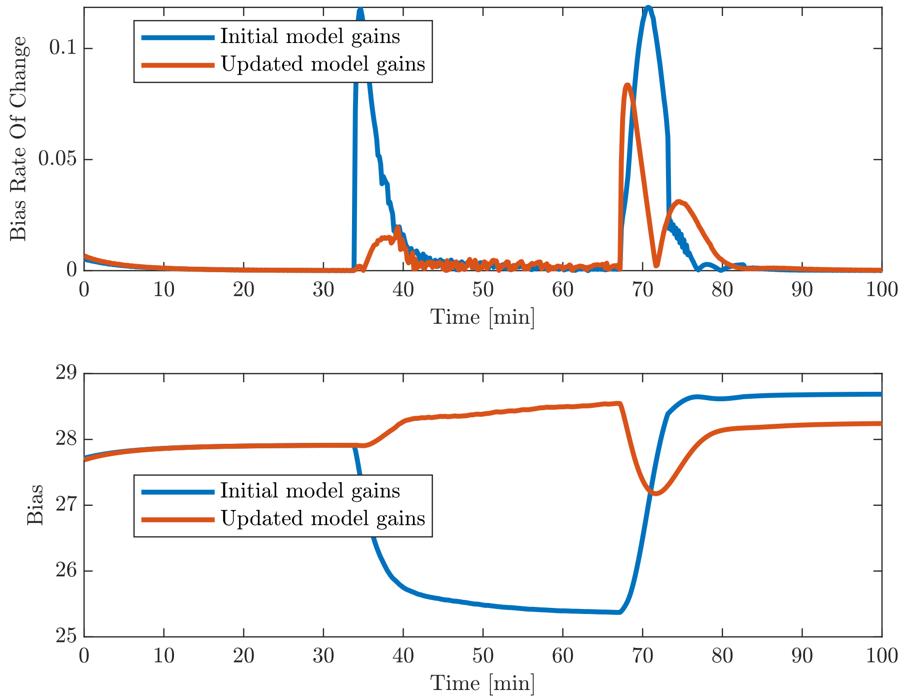

Figure 6.11: Comparing WHP absolute value of bias rate of change and bias between the initial and the updated model gains for the ideal value procedure.

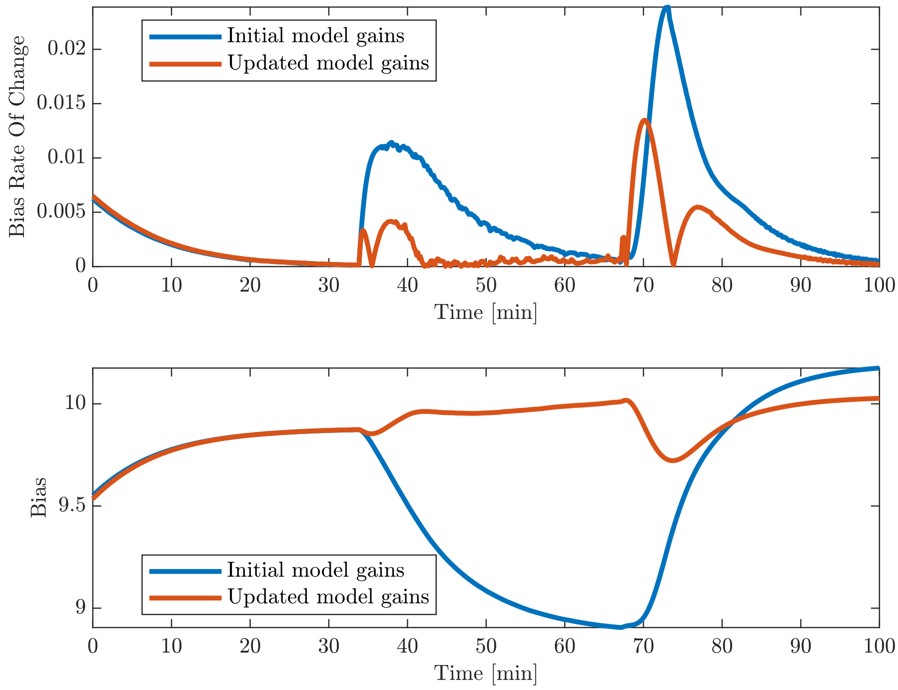

Figure 6.12: Comparing BHP absolute value of bias rate of change and bias between the initial and the updated model gains for the ideal value procedure.

	Total bias rate of change		
	Oil rate	WHP	BHP
Initial model gains	120.65	6.13	2.57
Updated model gains	99.71	3.43	1.15
Reduction	17.36 %	44.05 %	55.25 %

Table 6.6: Comparing total bias rate of change in initial and updated model gains for the ideal value procedure.

updated model gains is shown in Table 6.6.

6.1.3 Discussion

Both excitation methods yield increased performance after identifying and updating model gains, both in terms of less aggressive control actions and reduced total bias rate of change. The excitation methods yield slightly different model gains, and using an ideal value for excitation leaves the oil rate more exposed to process noise.

If the subsea well system were linear, the model gains from the excitation methods would be equal, as the superposition principle (explained in Section 3.6) would be satisfied. When exciting the process using the oil rate setpoint, the model gain for the oil rate was $11.5\frac{Sm^3/h}{\%_{choke}}$. This yields an expected change of production choke opening ΔMV of $\frac{10Sm^3/h}{11.5\frac{Sm^3/h}{\%_{choke}}} = 0.87\%$. When the process is excited by changing the ideal value of the production choke, the total expected change of oil rate was $3\% * 8.7\frac{Sm^3/h}{\%_{choke}} = 26.1Sm^3/h$. The values used in the calculations are from Table 6.2 and Table 6.5, and using default excitation step values. The reduction of total bias rate of change are shown in Table 6.3 for setpoint excitation and Table 6.6 for ideal value excitation. The reduction is overall greater for setpoint excitation. A greater reduction of the total bias rate of change implies that the model gains identified from setpoint excitation yield better performance than the model gains identified from ideal value excitation.

Comparing the excitation methods in terms of bias, using setpoint excitation yields better results in the total rate of change in bias for the oil rate. Since the oil rate is subjected to process noise and there is no active setpoint for the oil rate, the process noise can be observed in Figure 6.8 and Figure 6.9. The process noise can be indirectly observed in Figure 6.10. The term indirectly is used, as the process noise does not directly influence the bias or bias rate of change but is observable in both the bias and the bias rate of change. When the process is excited by changing the oil rate setpoint, the process noise is counteracted, i.e., the production choke takes control actions to counteract the process noise to ensure that the oil rate reaches its setpoint. When the ideal value for the production choke is active, the production choke takes no control actions to counteract the process noise. The control actions are to ensure constraint satisfaction, preferably at the production choke ideal value. If all constraints are satisfied and the production choke is at its ideal value, no control actions will be taken. The process noise is then more easily observed, and the total bias rate of change will not be as much reduced.

6.2 Part 2

The second part will show that SEPTIC will automatically excite the process if disturbances move outside of the acceptable area, and the acceptable area will subsequently be updated if the model gains updates. The disturbances are adjusted and kept constant while model gains are identified. The initial model gains are identified with a gas lift rate of $6500 Sm^3/h$ and a downstream pressure of $14 bar$. The gas lift rate is then adjusted to $6000 Sm^3/h$, while the downstream pressure is adjusted to $11.5 bar$. The initial acceptable area with a gas lift rate of $6500 Sm^3/h$ and a downstream pressure of $14 bar$ is illustrated in Figure 6.13, where the asterisk shows the adjusted disturbances. The asterisk is outside of the acceptable area, which triggers a process excitation. Part 2 is divided into two parts, where the first part uses oil rate setpoint for process excitation, while the second part uses production choke ideal value for process excitation.

After the model gains have been identified with a gas lift rate of $6000 Sm^3/h$ and a downstream pressure of $11.5 bar$, the disturbances are adjusted back to where the initial model gains were identified. When the disturbances are adjusted back, the consistency of the updated model gains can be verified.

The initial state of the process is shown in Table 6.7. The initial state is the same for both oil rate setpoint excitation and production choke ideal value excitation.

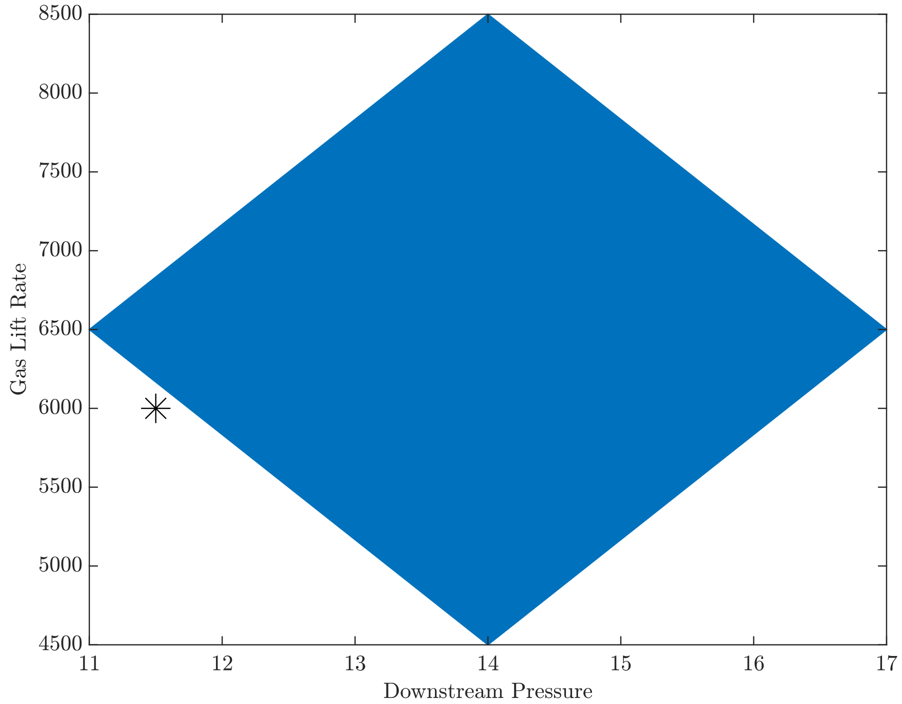

Figure 6.13: Initial acceptable area, with a gas lift rate of $6500Sm^3/h$ and a downstream pressure of $14bar$. The asterisk shows where the disturbances are adjusted to after the initial model gains identification.

Gas lift rate	$5000Sm^3/h$
Downstream pressure	$13bar$
Model gain oil rate	7.25 $\frac{Sm^3/h}{\%_{choke}}$
Model gain WHP	-1.74 $\frac{bar}{\%_{choke}}$
Model gain BHP	-0.37 $\frac{bar}{\%_{choke}}$

Table 6.7: Initial state of the process in Part 2.

Model gain oil rate	8.47 $\frac{Sm^3/h}{\%_{choke}}$
Model gain WHP	-1.47 $\frac{bar}{\%_{choke}}$
Model gain BHP	-0.65 $\frac{bar}{\%_{choke}}$

Table 6.8: Initial model gains from oil rate setpoint excitation, identified at a gas lift rate of 6500 Sm^3/h and a downstream pressure of 14bar.

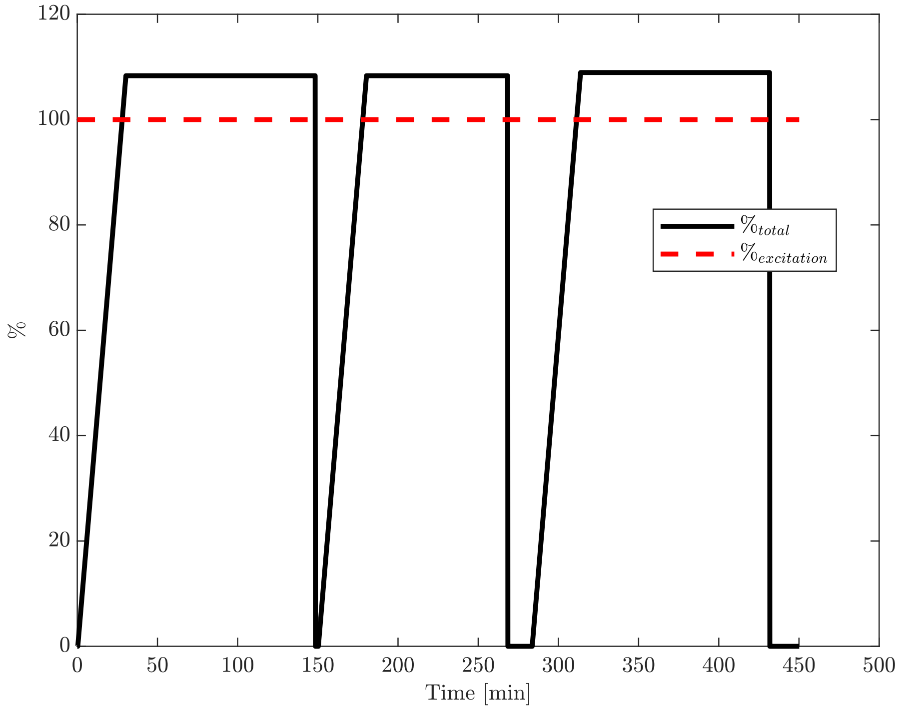

Figure 6.14: $\%_{total}$ during the setpoint excitation simulation in Part 2. $\%_{total}$ resets to 0 after implementing identified model gains.

6.2.1 Setpoint Excitation

The initially identified model gains, identified at a gas lift rate of $6500Sm^3/h$ and a downstream pressure of $14bar$, are shown in Table 6.8.

Figure 6.14 shows $\%_{total}$ changing with time during simulation. When updated model gains have been identified and implemented, the $\%_{total}$ resets to 0. When $\%_{total}$ first and third exceeds 100%, the gas lift rate reaches $6500Sm^3/h$, and the downstream pressure reaches $14bar$. On the second occasion, $\%_{total}$ exceeds 100%, the gas lift rate reaches $6000Sm^3/h$, and the downstream pressure reaches $11.5bar$.

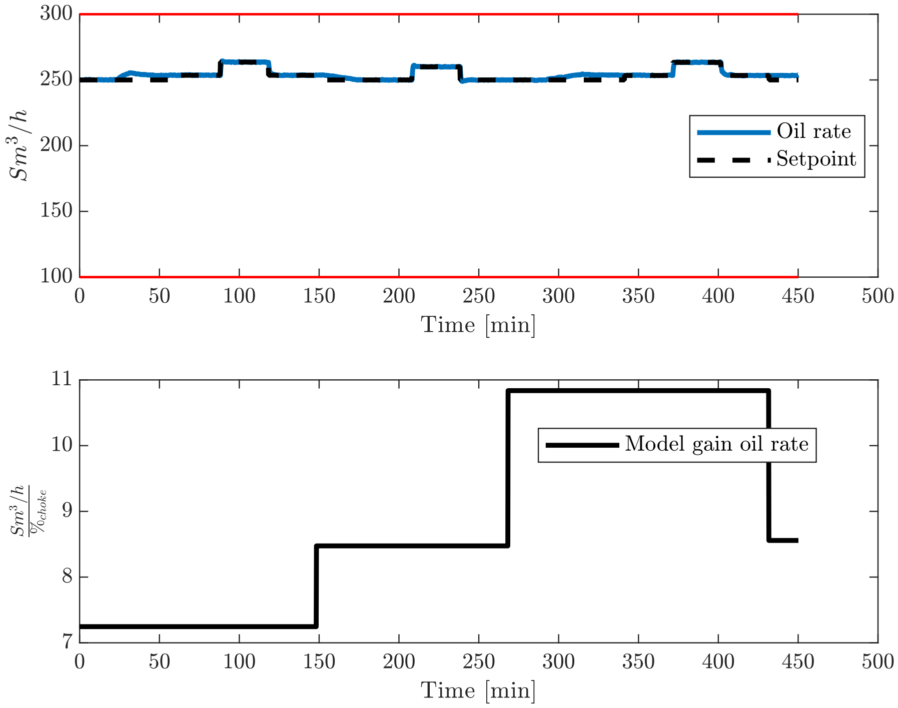

Figure 6.15: Process simulation of oil rate and the model gain updates, through disturbance changes. Oil rate setpoint excitation.

Figure 6.15-6.17 shows the process simulation during changing disturbances, with process excitations and model gains identification. The initial model gains are identified from the first process excitation at 88 minutes and implemented at 148 minutes. The process is excited from an oil rate of $253.6 Sm^3/h$ as the process cannot stabilize at the desired oil rate setpoint of $250 Sm^3/h$ because the WHP has reached its upper limit.

The disturbances are adjusted to the asterisk in Figure 6.13 at 150 minutes when the model gains have been implemented after the first excitation. The disturbances reach their final values of $6000 Sm^3/h$ and $11.5 bar$ for the gas lift rate and the downstream pressure, respectively, after 30 minutes, i.e., at 180 minutes. The process then stabilizes at 208 minutes, and the process is then excited as the disturbance values are outside of the acceptable area. The identified model gains are shown in Table 6.9.

The reduction of gas lift rate allows the oil rate to reach its desired setpoint of $250 Sm^3/h$ without breaking the upper limit of WHP. As the downstream pressure decreases and WHP is still at its upper limit, the pressure drop ΔP over the

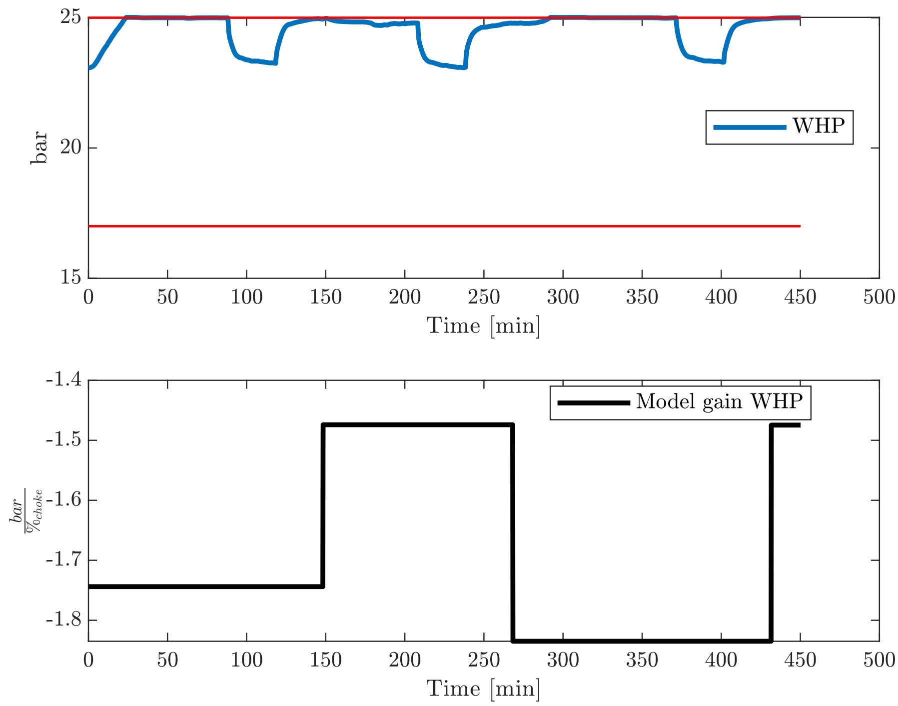

Figure 6.16: Process simulation of WHP and the model gain updates, through disturbance changes. Oil rate setpoint excitation.

Model gain oil rate	10.84 $\frac{Sm^3/h}{\%_{choke}}$
Model gain WHP	-1.83 $\frac{bar}{\%_{choke}}$
Model gain BHP	-0.81 $\frac{bar}{\%_{choke}}$

Table 6.9: Model gains identified using oil rate setpoint excitation, identified at a gas lift rate of 6000 Sm^3/h and a downstream pressure of $11.5 bar$.

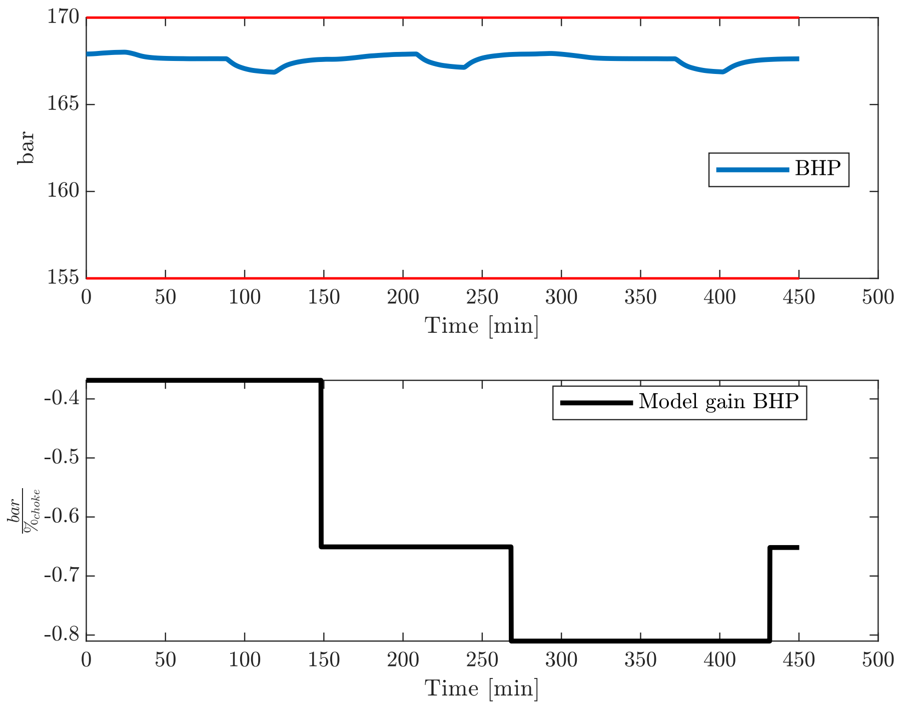

Figure 6.17: Process simulation of BHP and the model gain updates, through disturbance changes. Oil rate setpoint excitation.

Model gain oil rate	8.56 $\frac{Sm^3/h}{\%_{choke}}$
Model gain WHP	-1.48 $\frac{bar}{\%_{choke}}$
Model gain BHP	-0.65 $\frac{bar}{\%_{choke}}$

Table 6.10: Model gains identified using oil rate setpoint excitation, identified at a gas lift rate of $6500Sm^3/h$ and a downstream pressure of $14bar$.

	Initial identification	2nd identification
Model gain oil rate	8.47 $\frac{Sm^3/h}{\%_{choke}}$	8.56 $\frac{Sm^3/h}{\%_{choke}}$
Model gain WHP	-1.47 $\frac{bar}{\%_{choke}}$	-1.48 $\frac{bar}{\%_{choke}}$
Model gain BHP	-0.65 $\frac{bar}{\%_{choke}}$	-0.65 $\frac{bar}{\%_{choke}}$

Table 6.11: Comparison of model gains identified at equal disturbances: a gas lift rate of $6500Sm^3/h$ and a downstream pressure of $14bar$. Model gains identified using oil rate setpoint excitation.

production choke increases. When ΔP increases, the ΔChoke necessary to reach the desired setpoint after the excitation step decreases (see Equation 4.1). It is therefore expected that the (absolute) values of the model gains increases:

$$\text{Model gain} = \frac{\Delta CV}{\Delta \text{Choke}}.$$

The disturbances are then adjusted back to a gas lift rate of $6500Sm^3/h$ and downstream pressure of $14bar$. The disturbances are adjusted back to verify that the identified gains are equal at equal disturbance values. The model gains identified when returning to the previous disturbance values are shown in Table 6.10. The model gains are identified in the last process excitation in Figure 6.15, which begins at the 253rd minute.

The aim of part 2 was to show that the model gain identifier was automatic. Additionally, an aim was to show the consistency of identified gains and constraint satisfaction throughout the simulation by correctly choosing the direction of the excitation steps. The presented results show that no process excitations violate any constraints. Correctly chosen directions of the excitation steps ensure that the setpoints after the excitation steps were reached during simulation, which could not happen with constraint satisfaction if the directions of the excitation steps were opposite. Figure 6.14 shows $\%_{total}$ throughout the simulation. Figure 6.5-6.7 shows that when $\%_{total}$ exceeds 100%, the process reaches steady-state and is excited to

Model gain oil rate	7.81 $\frac{Sm^3/h}{\%_{choke}}$
Model gain WHP	-1.32 $\frac{bar}{\%_{choke}}$
Model gain BHP	-0.6 $\frac{bar}{\%_{choke}}$

Table 6.12: Model gains identified using production choke ideal value excitation, identified with a gas lift rate of 6000 Sm^3/h and a downstream pressure of 11.5bar.

identify updated model gains. The identified model gains were consistent given consistent disturbances, and the process excitations were automatic when $\%_{total}$ exceeded 100%.

Comparing Table 6.8 with Table 6.10, consistency in the model gains are acquired when identifying model gains at equal disturbances. A direct comparison is shown in Table 6.11. The results are promising, yielding consistent model gains given equal disturbance values.

6.2.2 Ideal Value Excitation

The same procedure is repeated as in Subsection 6.2.1, using production choke ideal value excitation instead of oil rate setpoint excitation. The disturbance changes are equal, with first reaching the center in Figure 6.13, then reaching the asterisk after a process excitation, and then back to the center. The process simulations for the oil rate, the WHP, and the BHP are shown in Figure 6.18-6.20, along with the model gains updates. The figures show automatic model gains identification after the process has reached steady-state after $\%_{total}$ exceeds 100%.

The model gains identified with a gas lift rate of 6000Sm^3/h and downstream pressure of 11.5bar (the second process excitation) is shown in Table 6.12, while Table 6.13 shows the comparison between model gains identified with a gas lift rate of 6500Sm^3/h and a downstream pressure of 14bar.

The identified gains using production choke ideal value excitation with a gas lift rate of 6500Sm^3/h and a downstream pressure of 14bar yielded consistent gains between the first and the second excitation with these disturbance values.

Figure 6.18-6.20 shows that the process automatically excites when $\%_{total}$ exceeds 100% and after the process has stabilized, and that all constraints are satisfied throughout the process simulation. There is no constraint violation despite only

	Initial identification	2nd identification
Model gain oil rate	7.19 $\frac{Sm^3/h}{\%_{choke}}$	7.19 $\frac{Sm^3/h}{\%_{choke}}$
Model gain WHP	-1.25 $\frac{bar}{\%_{choke}}$	-1.25 $\frac{bar}{\%_{choke}}$
Model gain BHP	-0.56 $\frac{bar}{\%_{choke}}$	-0.56 $\frac{bar}{\%_{choke}}$

Table 6.13: Comparison of model gains identified at equal disturbances: a gas lift rate of $6500 Sm^3/h$ and a downstream pressure of $14 bar$. Model gains identified using production choke ideal value excitation.

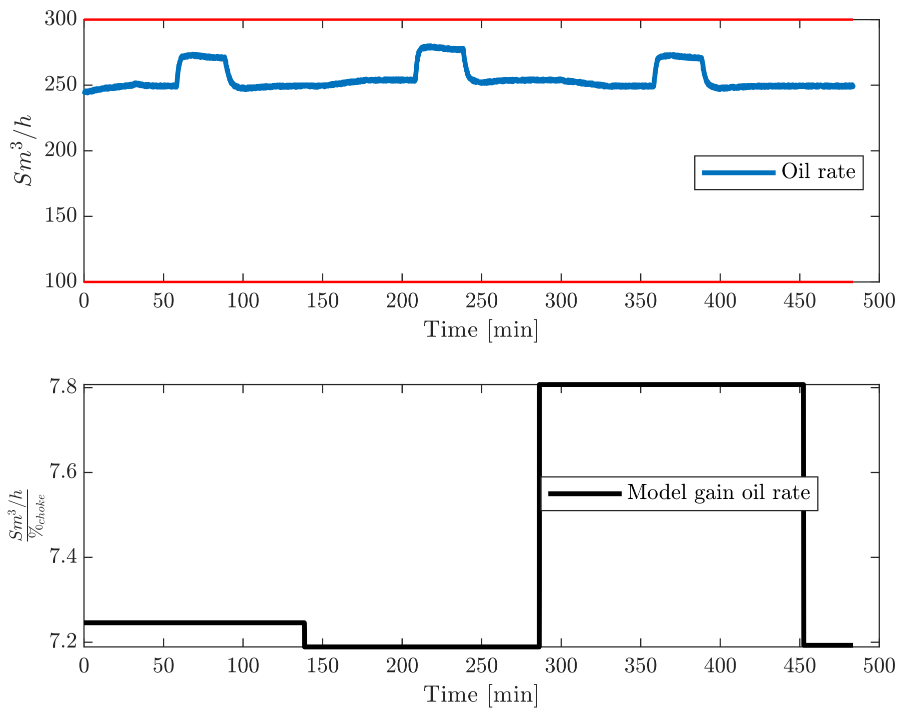

Figure 6.18: Process simulation of oil rate and the model gain updates, through disturbance changes. Production choke ideal value excitation.

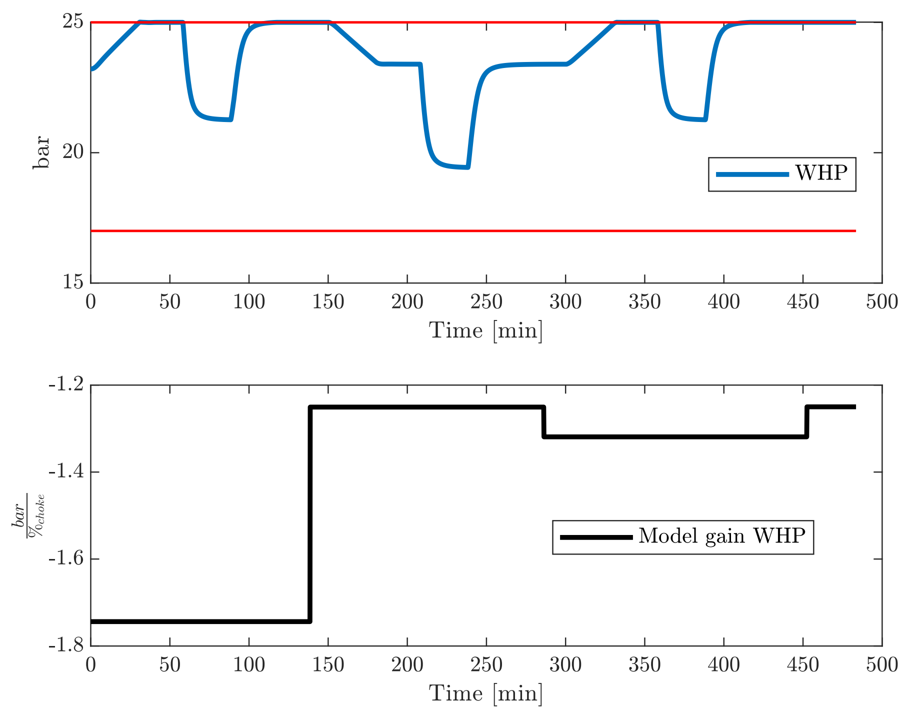

Figure 6.19: Process simulation of WHP and the model gain updates, through disturbance changes. Production choke ideal value excitation.

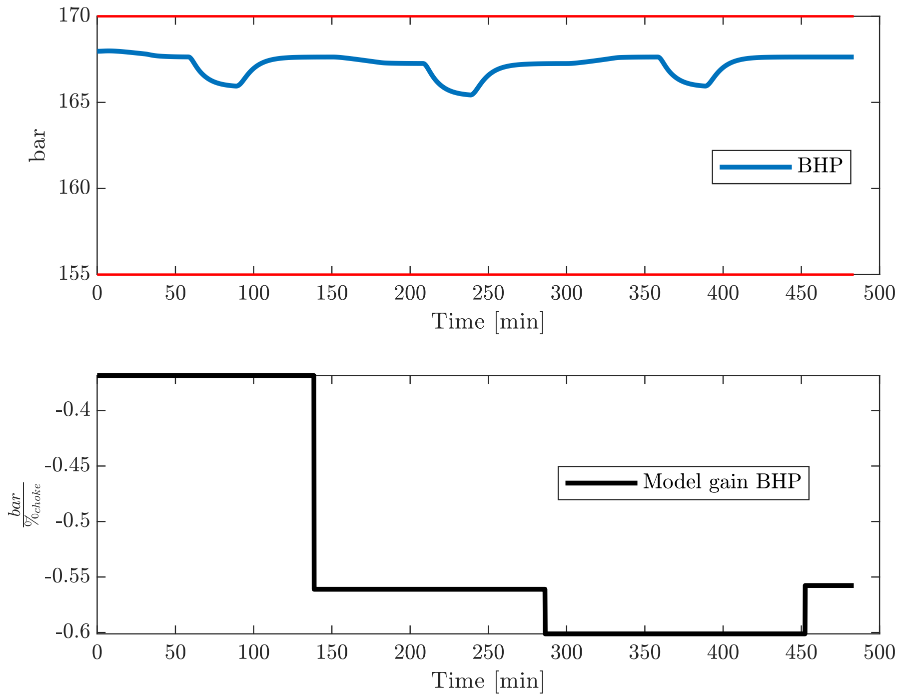

Figure 6.20: Process simulation of BHP and the model gain updates, through disturbance changes. Production choke ideal value excitation.

the production choke ideal value is active.

The results are similar to the results presented in Subsection 6.2.1. The simulation was subjected to the same disturbance changes. Both methods yielded consistent model gains and no constraint violation through the process simulations.

Chapter 7

Discussion

The goal of this thesis was to implement an automatic model gain identifier in SEPTIC. The automatic model gain identifier was tested on a simplified subsea well system with a single subsea well. Gas lift rate was modeled as a disturbance, further simplifying the gain identification process. MPC performance was improved, and the bias rate of change decreased. These results are promising, and the results from this thesis should inspire further work. Despite showing promising results in this thesis, simulations are limited compared to a real-life environment. In a real-life environment, there is more uncertainty as unexpected events might occur. The process would likely be exposed to more random process noise and be affected by other wells in a subsea well cluster.

The gas lift rate was modeled as a DV in the simulations. Gas lift rate modeled as a DV gave the advantage of manually adjusting the variable in SEPTIC to simulate over a wide operating range. However, in a real-life environment, the gas lift rate is an MV. Gas lift rate as an MV introduces an extra degree of freedom which yields overall better performance from the MPC. However, identifying model gains with more than one MV active adds a challenge. The other MV(s) other than the one for which the models are identified needs to be constant to identify model gains correctly.

Simulating the subsea well system in more complex situations could verify the automatic model gain identifier further. As mentioned in Chapter 4, the mass flow rate from the reservoir is kept constant during the simulations. A non-constant mass flow rate could have been added to the system as another DV to simulate the subsea well system more realistically. In a real subsea well system, the mass flow rate from the reservoir would decrease as the reservoir ages and influence the model qualities.

A process excitation moves a process away from steady-state. However, the process excitation is necessary for model gains updating. The value of updated model gains must be carefully compared with the value of a process in steady-state, as a process in steady-state yields optimal operation. In this thesis, the DVs were used as excitation triggers. The DVs were used, as a change of DVs means that the system moves in the state-space. If the system moves in the state-space, the step response models lose their accuracy as they assume linearity. Other excitation triggers may be considered instead of the DVs. From Equation 4.1, ΔP is decisive for the flow through the production choke. The differential pressure ΔP could instead be used as an excitation trigger, as it is dependent upon both gas lift rate and downstream pressure. The gas lift rate influences ΔP, as the gas lift rate increase also increase WHP. Alternatively, the movement of the production choke itself could trigger an excitation. If the production choke moves to sustain the current oil rate at its setpoint, one can conclude that the process moves in the state-space.

In this thesis, the size of the excitation steps was decided from the process noise added to the simulation. The chosen size of the excitation steps was found to produce consistent model gains, as they were large enough not to be too affected by the process noise. In an actual process, the process noise may change in size with time. The size of the excitation steps could therefore be a function of the current process noise. Size of excitation steps dependent upon the process noise can ensure that the ratio between the size of the excitation step and the process noise is large enough to ensure the robustness of the calculated model gains.

As a process excitement is preferable to avoid, a gain scheduling method could be added. The gain scheduling method could be implemented as follows: when a model gain is updated, the value is saved along with the respective disturbance variables. If the process returns the area where this was previously acceptable, the model gain could be implemented without a process excitement. For example, the model gain can be saved for 24 hours, as the model gain is considered outdated after 24 hours.

As mentioned in Chapter 1, the thesis assumes that the value of the process excitations to identify correct model gains outweighed the disadvantage of briefly not operating in steady-state. This assumption was necessary for the thesis' subject.

However, in an industrial application, this assumption needs to be thoroughly discussed. The gain scheduling method mentioned above would reduce the number of process excitations. The size of the excitation steps being a function of the current process noise would yield more effective excitation steps.

Another element to consider for reducing process excitations would be to utilize natural variations during the process simulation for model gain identification. Natural variations may arise from external disturbance changes, i.e., a change of incoming mass flow rate. If the process is naturally excited, the model gain identifier could recognize this and identify updated model gains. Implementing a model gain identifier that recognizes natural changes in the process would further utilize available data from the process.

Chapter 8

Conclusion

In this thesis, a data-driven inspired approach has been presented. The approach has been implemented in Equinor's in-house software for MPC, SEPTIC. Online data from running operations have been utilized in SEPTIC calcs, where one can construct algorithms for intermediate calculations. The approach comprised of process excitations for updating model gains in the step response models in SEPTIC. The process excitations were necessary to calculate updated model gains. The implemented approach identifies when an update of model gains is necessary, based on process parameters and disturbances.

The results show that the identified model gains yield better performance by monitoring the bias rate of change. It is shown that the process automatically excites the process to identify model gains when $\%_{total}$ exceeded 100%. When the $\%_{total}$ exceeds 100%, the current model gains were deemed unacceptable. The value of $\%_{total}$ was calculated based on disturbance variables, as a change of disturbances corresponds to movement in the state-space. When model gains were identified at equal disturbance variables, the model gains were consistent. Consistent model gains show robustness from the model gain identifier.

Online data from process simulations were used for constraint satisfaction during process excitations and model gain identification. The online data were used to recognize when process excitations for model gain identification were necessary. Utilizing the online data for controller design is a data-driven control-inspired implementation implemented in SEPTIC using calcs; algorithms for intermediate calculations.

The automatic model gain identifier was implemented using two different excitation methods; moving the production choke ideal value, or moving the oil rate setpoint. The results were similar; however, the oil rate was more subjected to noise when using the production choke for process excitation.

The automatic model gain identifier was implemented on a simulation of a single subsea well system. The results are promising; however, improvements can be made before implementing in industrial applications. Improvements include:

- Modeling the gas lift rate as an MV without affecting the identified model gains for the production choke.
- Utilizing the online data more efficiently, reducing the number of process excitations.
- Size of excitation steps based on process data
- Alternative excitation triggers.

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Appendix A

Dymola Model

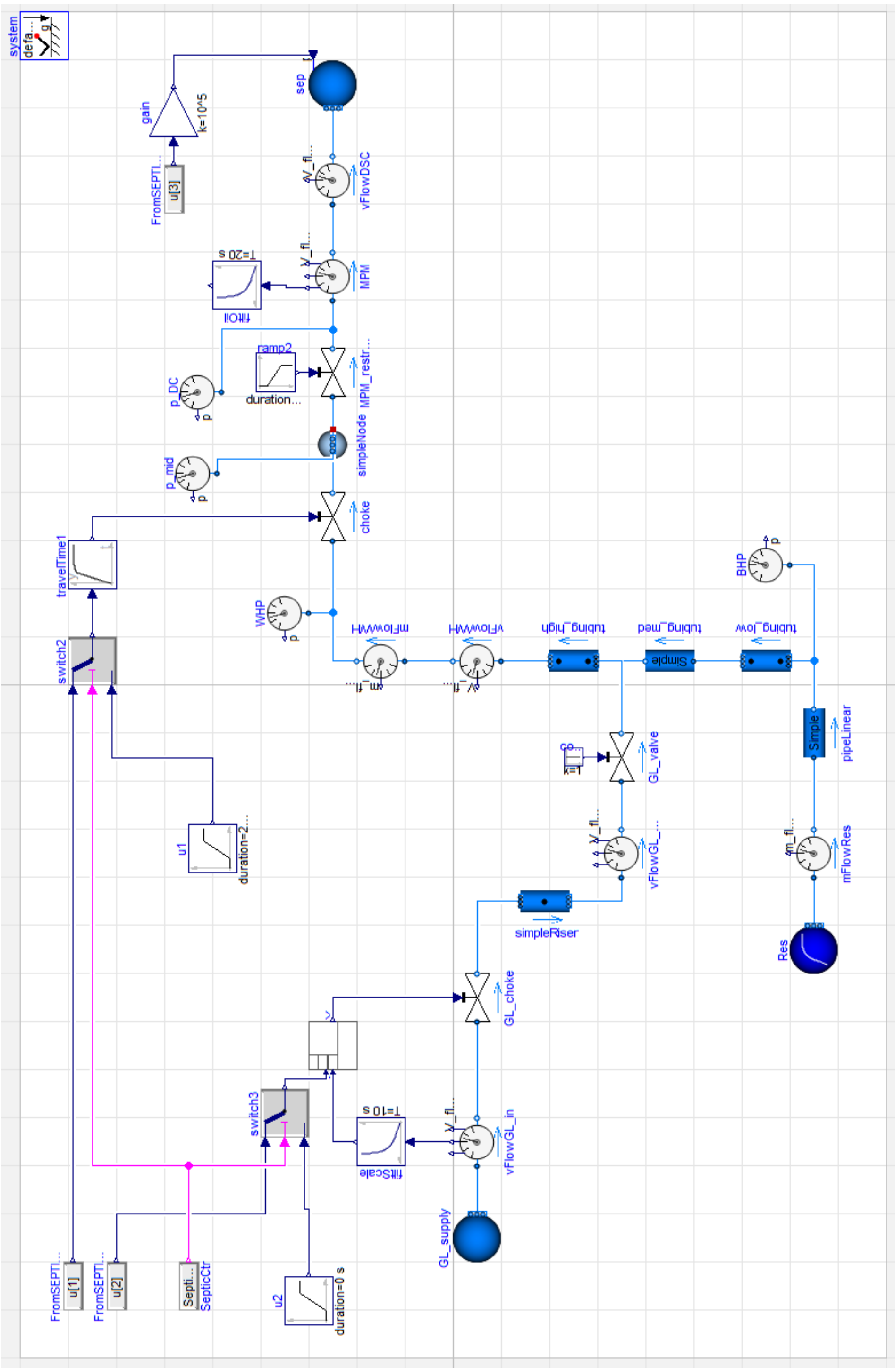

Figure A.1: Dymola model

Appendix B

Initial Step Response Models in SEPTIC

The initial step response models are shown in Figure B.1-B.3. The responses in the CVs are generated from a step in the choke. As seen in the figures, the step response models reach steady-state after approximately 30 minutes, which supports the initial assumption in Section 5.

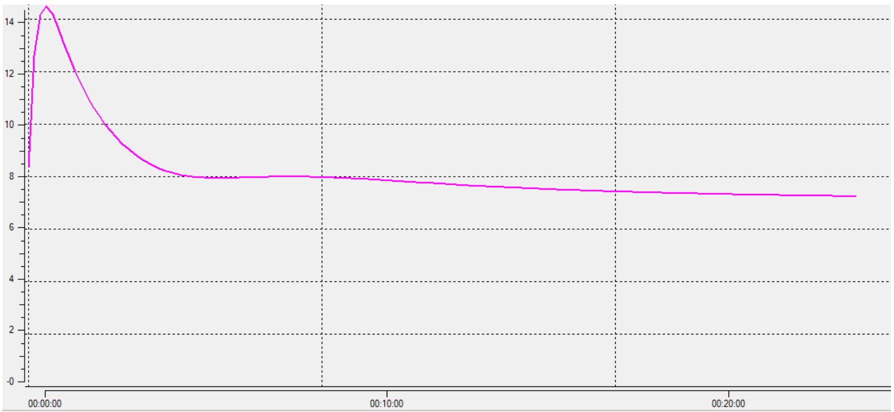

Figure B.1: Step response model, oil rate and choke. Steady-state gain: $7.25\frac{Sm^3/h}{\%_{choke}}$.

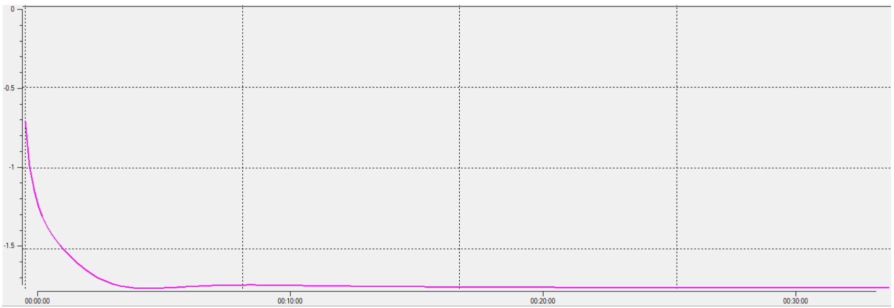

Figure B.2: Step response model, WHP and choke. Steady-state gain: $-1.74\frac{bar}{\%_{choke}}$.

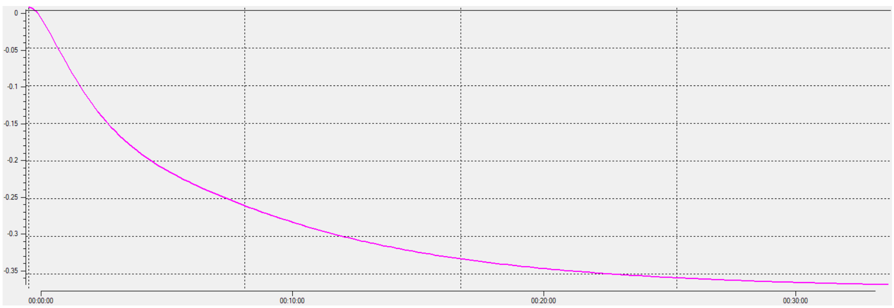

Figure B.3: Step response model, BHP and choke. Steady-state gain: $-0.369\frac{bar}{\%_{choke}}$.

Appendix C

Calcs in SEPTIC

As mentioned in Section 4, calcs are algorithms for intermediate calculations in SEPTIC. In this section, an overview of the calcs used in the implementation will be provided.

The descriptions are given in the SEPTIC Reference Documentation [26].

The algorithms may be combined, where a typical example may be to include an if-calc to decide when to apply the model scaling for modset (for example:
Alg = "modset(OilRate, Choke, if(condition=true, apply, do not apply))").

If

Alg = "if(A,B,C)"

A is a logical test. If A is true, the output of the algorithm is B; else, it is C.

Modget

Alg = "modget(CV,MV)"

An algorithm for acquiring the steady-state gain from the step response model between a CV and an MV.

Modset

Alg = "modset(CV,MV,Scale,Apply)"

An algorithm for updating the steady-state gain of a step response model between a CV and an MV. Scale is the value that is multiplied with the current steady-state gain for setting the new steady-state gain. The scale is applied if Apply = 1.

Setsetpnt

Alg = "setsetpnt(CV,Setpoint)"

An algorithm for changing the setpoint of a CV during simulation.

Gethist

Alg = "gethist(Xvr,n,x)"

An algorithm for getting a historic value or an average value of historic values. Xvr is the variable or member of a variable. n is the sample number from the current value and backward. x is the number of values to include for calculating the average.

Getappln()

Alg = "getappln()"

The output is the current sample number in the simulation.

Mvmget

Alg = "mvmget(MV)"

The output is the calculated optimal MV (input) value for the following sample.

Delta

Alg = "delta(Xvr,n)"

Calculates the difference between a historic Xvr-value at sample n and n-1.

Abs

Alg = "abs()"

Returns the absolute value.

Getbias

Alg = "getbias(CV)"

Returns the current bias of the CV.

Setmeas

Alg = "setmeas(CV, CV-value)"

Can set the measured CV-value. Used for adding noise to the process.

Min

Alg = "min(a,b,c...)"

Returns the minimum value.

Max

Alg = "max(a,b,c...)"

Returns the maximum value.

Getssval

Alg = "getssval(CV)"

Returns the current predicted steady-state CV-value.

Setiv

Alg = "setiv(MV,Ideal value)"

An algorithm for changing the ideal value of an MV during simulation.