Development of a Performance Envelope for Well Production Analysis

towards automated identification of problematic wells

B. Smorenburg

TU Delft: Applied Earth Sciences

Delft University of Technology

Challenge the future

Development of a Performance Envelope for Well Production Analysis

TOWARDS AUTOMATED IDENTIFICATION
OF PROBLEMATIC WELLS

by

B. Smorenburg

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Supervisor:	Prof. dr. ir. J.D. Jansen	Petroleum Engineering
Thesis committee:	Prof. dr. M. T. Kreutzer	Chemical Engineering
	Dr. A. Twerda	TNO & TU Delft
	Dr. F. Hollaender	Schlumberger

TU Delft Delft University of Technology

Abstract

Producing an oil well is a transient process, and although we like to assume there is a steady state phase in the production life, it is a fragile situation. Due to the many unknowns in the reservoir, changes in well production performance cannot easily be predicted. Changes in the subsurface will influence the production and lifetime of the well and need to be identified as soon as possible. Consequently, monitoring well performance is of great importance.

Identifying deviations from production forecasts is difficult, because mismatches between predicted and measured flow rates can have two causes: either the production prediction model is not valid, or the production test data is wrong. This research aims to quantify the uncertainty inherent to performance models caused by the uncertainty in input parameters and by the method used to establish the model. This is done by introducing the performance envelope, a range instead of a line in which the well is expected to produce for the given input parameters and the used method to establish it.

Two workflows are proposed to establish such a performance envelope, one for fitted models and one for simulated models. Additionally, a rate selection method is proposed, optimizing the test program by selecting the three rates which result in the narrowest confidence interval. The results show that a Performance Envelope can be computed for both fitted and simulated performance models, but that further research is needed to use them as an objective criterion. Furthermore, they show that rate selection has influence on the quality of the resulting model and that it can be used to optimize a test program.

Acknowledgements

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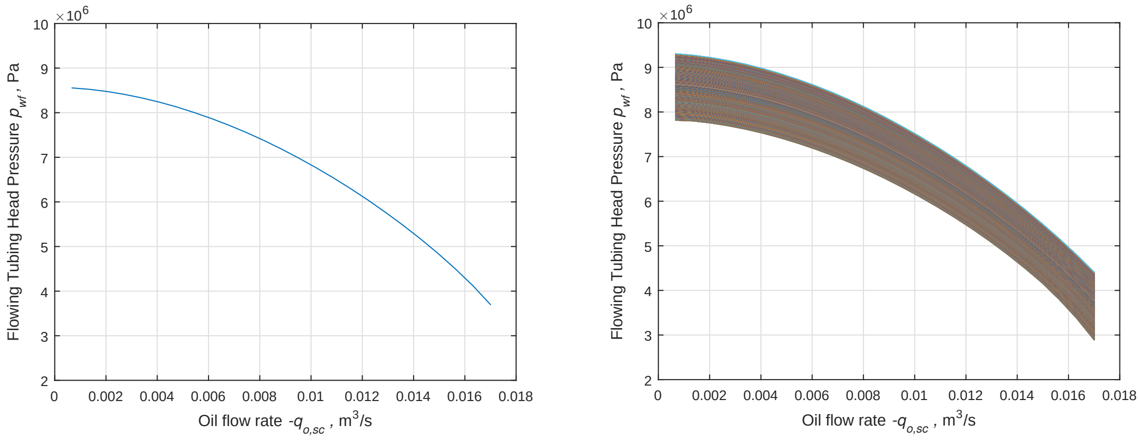
Introduction

Producing an oil well is a transient process and although we like to assume there is a steady state phase in the production life, it is a fragile situation. Due to the many unknowns in the reservoir, changes in well production performance cannot easily be predicted. Local heterogeneities can alter the water movements which can lead to an unexpected early increase in water cut. Migration of sands or salt precipitation can lead to a gradual or sudden change in the near-wellbore permeability, affecting the skin factor and thus productivity. These changes will cause deviations in production that can sometimes be solved by applying corrective measures (such as workovers) but they have to be identified in time before the production impairments become irreversible. Because of this narrow time frame it is of great importance to identify these deviations so that the production life of the well can be optimized.

Identifying deviations from production forecasts is difficult, because mismatches between predicted and measured flow rates can have two causes: either the production prediction model is not valid, or the production test data is wrong. In this modern age of simulation, the industry tends to trust production models since those form the basis for the economic value of an asset. An error in such critical business inputs can have many consequences, and thus the blame for a mismatch between predicted and measured production is usually assigned to an inaccurate measurement. With the daily use of reservoir simulators and nodal analysis software their results are becoming more and more seen as the truth and one tends to forget the basic rule of modeling: every model is as good as its input parameters. And here lies the crux of the matter: reservoir parameters are usually estimated values with attached uncertainty, more like distributions than single values. Some of them can be measured directly (such as permeability by coring), but such static measurements are not representative for fluid flow, and other properties (such as drainage area or skin) have to be determined by well test analysis. On top of this come the upscaling effects and assumptions made by the reservoir simulators for the sake of computational effiency. These assumptions lead to inherent model uncertainty which can be evaluated by doing sensitivity studies: running the simulator for a range of values. But as this is time consuming and the importance is not always recognized they are often omitted. Multiple simulations are run to determine the range of recoverable reserves, but this is a macroscopic analysis for the whole reservoir and does therefore not apply to a single well. This lack of sensitivity study leads to a false belief in the results of simulation software and in this case well performance modeling. This is illustrated in Figure 1.1: the simulated model (Figure 1.1a) is misleadingly represented by a line when in reality it is more like a cloud (Figure 1.1b).

Problem Statement

By treating the performance model as a line instead of a cloud or range, matching test results comes quite close: as well test results can have significant uncertainty (error in flow rate up to 10 % is a typically accepted uncertainty) it is obvious to assume a bad test in case of a big mismatch. Nowadays well test data is much more precise thanks to new technologies, improved operational procedures and validation methods. Nevertheless, a mismatch is still often dismissed as a bad test, not hesitating to discard them even as they may be representative. Validation of well test data is not a part of the scope of this research. While test data converged from a vague cloud into a better defined point, models are still not tested for their actual range of uncertainty. Because of its significant impact, the uncertainty inherent to the performance models has to be



(a) Simulated Tubing Performance Curve

(b) Multiple Realisations for a Simulated Tubing Performance Curve

Figure 1.1: Illustration of the cloud effect

characterized. In this manner it is possible to establish a performance envelope instead of a line, a confidence interval in which the well is expected to produce. Being able to characterize such uncertainty, it also becomes possible to design a test program that optimizes the predictive power. Combining those two approaches in a production analysis tool enables both an optimization of production prediction models but also provides an objective way of determining when a well is deviating from its predicted production trend.

OUTLINE

After this introduction follows the current situation and used methods for well design and well performance modeling in Chapter 2. This Chapter also identifies the issues with the current workflow and introduces the proposed solution: the Performance Envelope. The workflow to establish this Performance Envelope is presented in Chapter 3 as well as the proposed Rate Selector. Chapter 4 explains the practical execution of the proposed workflows and the simulation run. Results for these simulations are presented in Chapter 5. The concise conclusions of this research are presented in Chapter 6 and the road ahead and proposed follow up is presented in Chapter 7 .

2

Current Workflow

Much of the information regarding workflows for well design or well test monitoring are so called company knowledge: it is documented per company or section for internal use but not published to the outside world. Therefore multiple interviews with production, reservoir and well testing engineers where conducted to obtain this knowledge.

2.1. Well Design

Well performance prediction and analysis plays an important role in field development, either for designing a new well or for evaluation of an already producing one. Although every company or even production engineer has his own variations, all workflows use the same performance relations[1]:

- **Inflow Performance Relations** which describes flow from the reservoir to the near well bore area, computing the bottom hole pressure needed to induce flow in the reservoir. Flow in the reservoir can be divided in two phases, above and under bubble point shown in Figure 2.1a. The pressure drop in the reservoir above bubble point can be computed using Equation 2.1 [2].

$$\bar{p} - p_{wf} = \frac{q_{sc} B_o \mu}{2\pi k h} \left(\ln \frac{r_e}{r_w} - f_r + S \right) \tag{2.1}$$

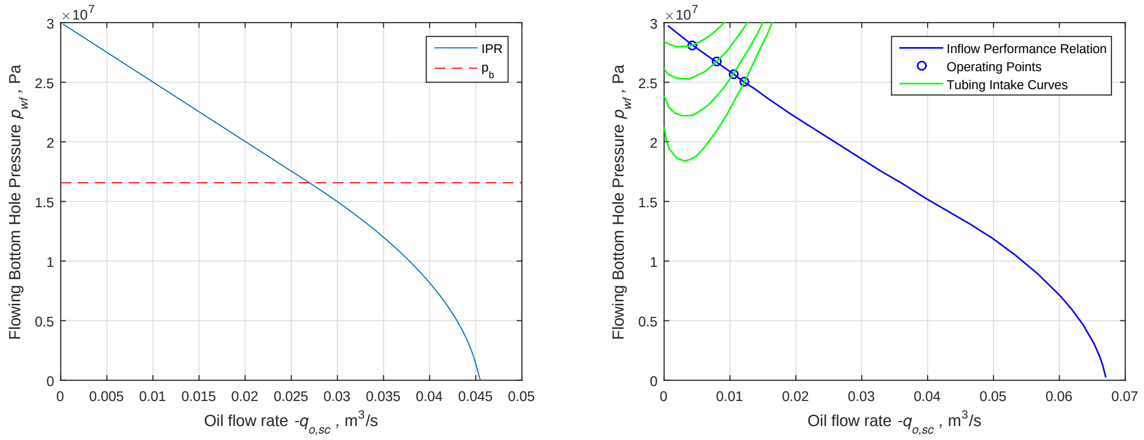
  And under bubble points using empirical equations such as Vogel[3].

- **Intake Performance Relations** which describes the flow from the well to surface, computing the bottom hole pressure needed to lift the flow to surface for a given and constant tubing head pressure. In combination with an Inflow Performance Relation the operating point for the well can be computed in the design phase by plotting multiple Intake Performance Relations for various tubing head pressures. (Figure 2.1b)

- **Tubing Performance Relations** which describe the flow from the well to surface, computing the tubing head pressure needed to lift the flow to surface for a given and constant bottom hole pressure

- **Total Performance Relations**, a combination of an Inflow- and a Tubing Performance Relation which overcomes the constant bottom hole pressure restriction by using an Inflow Performance Relation to compute the bottom hole pressures. This relation is most used for predicting well performance. As it also gives a relation between tubing head pressure and flow rate it is often wrongfully referred to as a Tubing Performance Relation

These relations can be used both for designing a new well, as well as for evaluating the production of an already producing well. The quality of their production prediction highly depends on the used input parameters, and their availability and degree of certainty depend on the lifetime of the field and the well: for a new field most parameters are only known to a limited extent, they are estimated from similar fields or from an exploration well, while for a new well in an already producing field most parameters are well-known by the input and measurements from previous wells. Some parameters such as skin can only be measured after

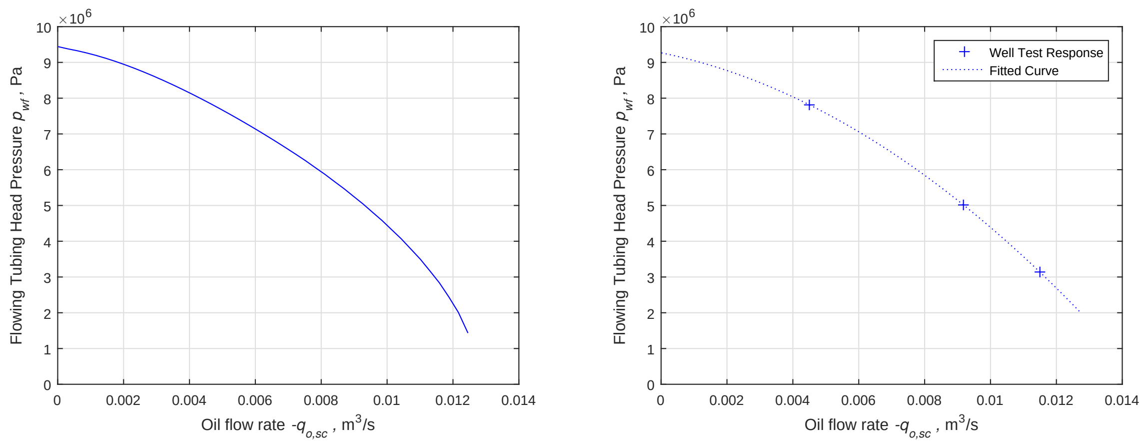


(a) Inflow Performance Curve with bubble point pressure, illustrating the two phases of flow

(b) Inflow Performance Curve with various Intake Performance Curves for various tubing head pressures.

Figure 2.1: The use of Inflow and Intake Performance Curves illustrated

completion and will remain highly uncertain during the design phase while parameters such as fluid properties will be well-known from other wells. In addition to simulating performance models, a different method of determining a Total Performance Curve is by using the results of multi rate well tests. In a multi rate test the well is tested at least at three rates from which one is the operating rate and then to establish the performance relation a curve is fitted through these three results, this method is illustrated in Figure 2.2b. The selection of rates is usually based on industry knowledge and consist of fractions of the operating rate, two widely used are operating rate*[1/3 2/3 3/3] and operating rate*[0.5 1 1.2]. An advantage of this method is that no input variables, assumptions or models are needed and as it is based on actual measurements it is used as a valuable alternative for a simulated performance model.



(a) Total Performance Curve from Pipesim

(b) Fitted Performance Curve from well test data

Figure 2.2: Illustrating the fitted workflow

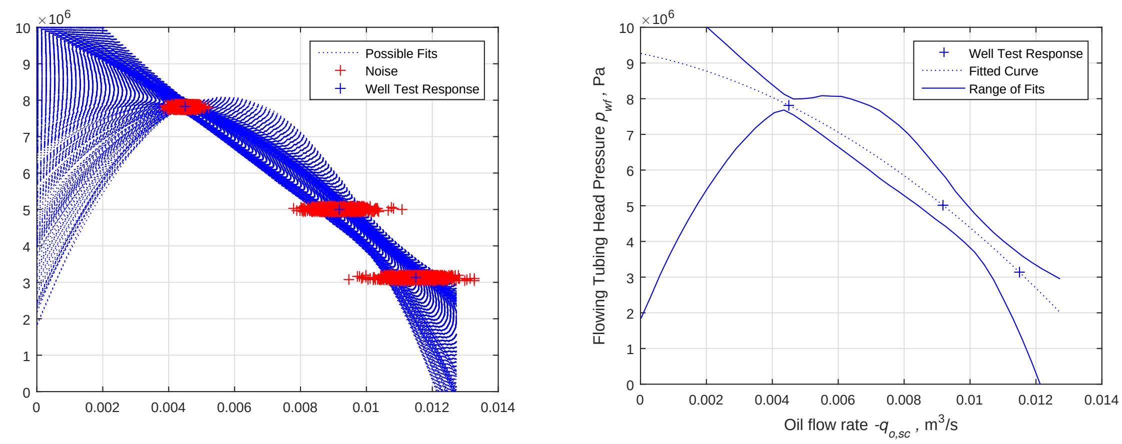
2.2. MONITORING WELL PERFORMANCE

Monitoring well performance can basically be done in three ways, either by comparing well performance models with real time production testing, history matching or by using decline curve analysis. Decline Curve Analysis was presented by Arps in 1944[4] and is based on recognition of a trend in recorded production data and forecasting future production by extrapolation. History Matching is based on a reservoir model which can be perfected using production data as new information, by adapting the model to minimize the difference between predicted production and actual recorded production. Until now, both decline curve analysis as history matching use the allocated results from monthly sales and delivery measurements. Real time production testing/monitoring focuses on measuring production parameters at live well conditions and then compares them with a well performance model. In recent history a complete well test package was needed but nowadays high resolution measuring devices with flow computers can measure production without interruption daily production and remaining permanent on site. In additions to this usability comes the increase in accuracy: traditional surface well tests where based on recording fluid production from test separators by hourly readings, resulting in measurement uncertainties in flow rate easily over 10%, while the new generation of multi-phase flow meters reduced this uncertainty to 2%.

All three monitoring methods have their downside in using them for daily production: Both for decline curve analysis as for history matching a large database of production history is needed and thus won't qualify for predictions in early production life. Due to the trend recognition character of decline curve analysis the time scale is in the order of quarters or even years and is therefore not suitable for identification of early deviations. For history matching an up to date reservoir model is needed and since in reservoir simulation precision for small timescales is a trade-off between computational efficiency, the current methods used are not suitable for day to day analysis either. Using production testing in combination with well performance modeling has neither of these disadvantages and is therefore the most used to evaluate well performance.

2.3. ISSUES WITH THE CURRENT WORKFLOW

Although well performance modeling is the current best solution for evaluating well productivity, it has one significant limitation. In the current used workflows, uncertainty in modeling parameters and in well test results are not incorporated in the well performance model while they have a significant influence: uncertainty in results from well test data can be up to 10% in flow rate, and Azi et al.[5] reported up to 20% in permeability from the interpretation of build up results. Until now, the uncertainty in well test results is only used to discard a test results in case of a mismatch, but never as an input for modeling. Take for instance the fitted workflow, where an empirical performance model is fitted to measurements as shown in Figure 2.2b: due to the measurement error the used well test responses in figure two are actually more like a range of values, as shown in Figure 2.3a. These ranges would result in a range of fits instead of just a line, as shown in Figure 2.3a and 2.3b. The same holds for simulated curves, uncertainty in input parameters results in ranges of simulated curves instead of one definitive line. These effects of uncertainty are commonly used e.g. the sensitivity analysis for STOIIP calculations, but never in production engineering. Therefore this thesis suggests a similar approach and introduces the performance envelope: a confidence interval, a range instead of a line in which the well is expected to produce for the given input parameters and the used method to establish it.



(a) Well test response, measurement noise and possible fits

(b) Well test response, range of possible fits and the initial fit

Figure 2.3: Illustrating the effect of measurement uncertainty for the fitted workflow

2.4. OBJECTIVES IN DESIGNING THE PERFORMANCE ENVELOPE

- Define a performance envelope: an uncertainty band "caused" by the method used to build a well performance model, and the uncertainty in input parameters:
  - For a simulated performance relation by running a sensitivity study and propagation of error analysis such as Monte Carlo. From the assumption of a range of uncertainty in input parameters, a possible range of outcomes can be generated leading to the definition of an uncertainty band on performance relation outputs corresponding to a given confidence interval.
  - The sensitivity analysis also gives information about the influence of various parameters and thus enables optimizing the selection of test points to resolve major uncertainties
  - Considering a performance relation established on the basis of fitting a mathematical or physical model to measurements (production test data), the evaluation of a confidence interval can be done by considering the effect of both the model fitting routine used and the presence of measurement error in the calibration points.
- Design a test advisor:
  - Use a simulated performance relation as a reference, and introducing measurement noise optimal test points can be selected to minimize residual uncertainty
  - As a deliverable, given the measurement uncertainty in pressure and flow-rate, the optimal rates that should be tested to achieve the best/narrowest confidence interval can be identified

3

Proposed Workflow

This chapter presents the proposed workflows (sections 3.1 & 3.2) to establish performance envelopes for well production predictions, by characterizing the uncertainty inherent to performance models and the used input parameters. Being able to characterize such uncertainty, it also becomes possible to design a test program that optimizes the predictive power by narrowing the confidence interval, presented in section 3.4. Combining those two approaches in a production analysis tool enables both an optimization of production prediction models but also provides an objective way of determining when a well is deviating from its predicted production trend. In this section the proposed workflows are presented with the aim to illustrate the workflow and the concept behind it, not to prescribe the exact steps, the used curves or distributions.

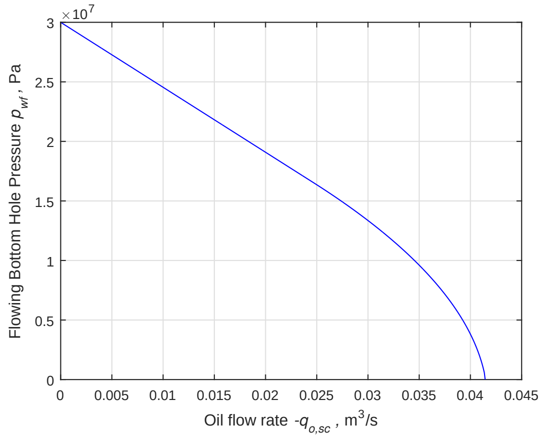
3.1. Workflow 1: Sensitivity analysis for simulated Performance Models

The main purpose of this workflow is to define a performance envelope and the associated uncertainty for a simulated performance curve in order to use these uncertainty bands as an objective criterion to check if a well is performing as predicted. In addition it can be used to evaluate and illustrate the influence of various input parameters on the predicted performance of the well.

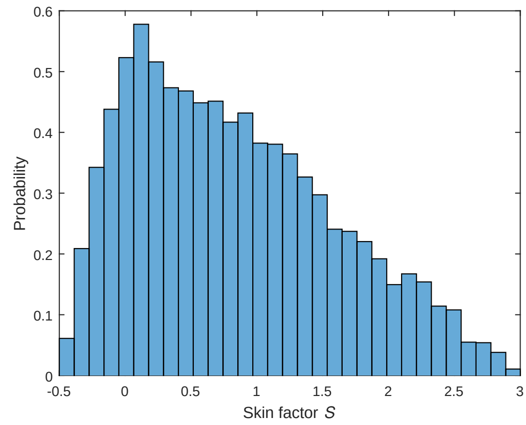
The workflow is schematically presented in Figure 3.1 and is similar to the workflows used for STOIIP sensitivity analysis and the work of Azi et al.[5] to evaluate confidence intervals in well interpretation results. As shown in Figure 3.1a, a basic Performance Model forms the base of this workflow and the purpose of the workflow specifies the type of Performance Model selected. As not every parameters manifests its influence in the same zone, the choice of the performance curve has to fit the parameter of interest. Skin for instance results in a pressure loss in the near wellbore area and manifests itself solely in bottom hole pressure so is studied best in an Inflow Performance Curve. Water cut on the other hand, influences the bottom hole pressure but also the lift model and needs to be studied in both an Inflow and a Tubing Performance Curve. Next comes the distribution for the input variable(s) of interest. Depending on the type of parameter and the software used it can either be in the form of an expected value with measurement error or a PDF as shown in Figure 3.1b. With the model and parameters in place Monte Carlo simulations can be run, building the model for the different input parameters, resulting in the curves shown in Figure 3.1c. Finally, the data has to be processed and sorted, resulting in the experimental confidence interval shown in Figure 3.1d. The last step is to define the envelope, which is explained in section 3.3.

3.2. Workflow 2: Sensitivity analysis for fitted Performance Models

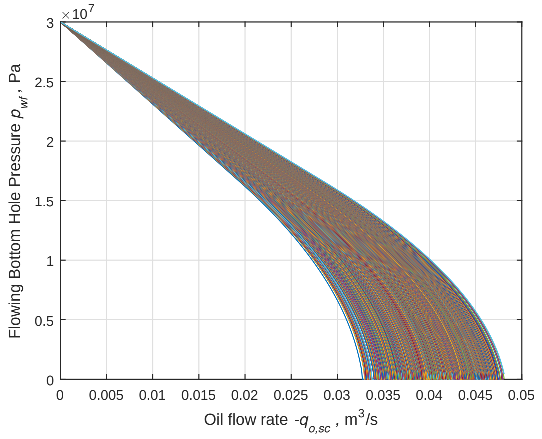
The main purpose of this workflow is to define a performance envelop and evaluate the associated uncertainty for a performance curve which is fitted to test data in order to use these uncertainty bands as an objective criterion to check if a well is performing as predicted. In addition it can be used to evaluate and illustrate the influence of measurement error, the value of anchor points such as shut in pressure or the effect of the chosen rates.



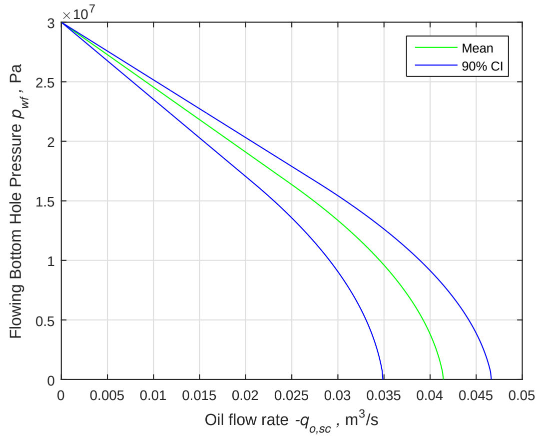
(a) Step 1: Selecting a performance model



(b) Step 2: Defining the parameter and its uncertainty as a pdf

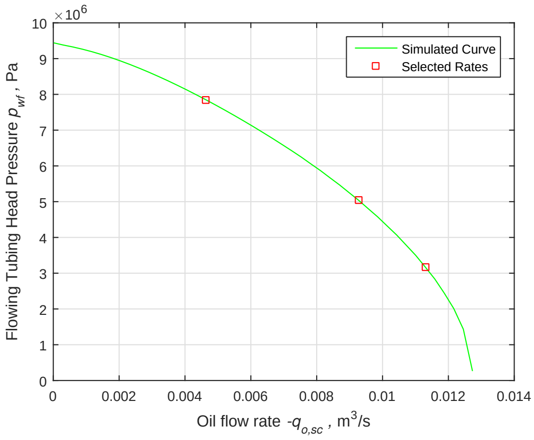


(c) Step 3: Run realisations

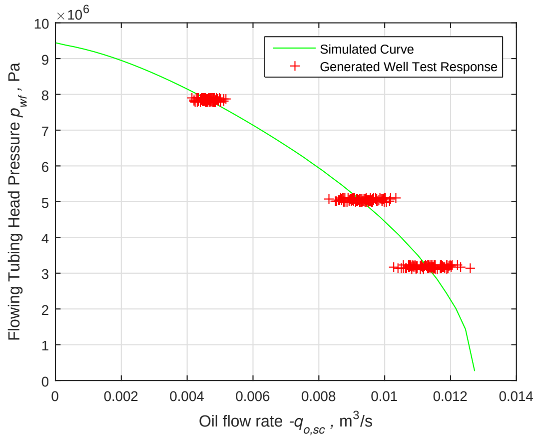


(d) Step 4: Process the data into confidence intervals

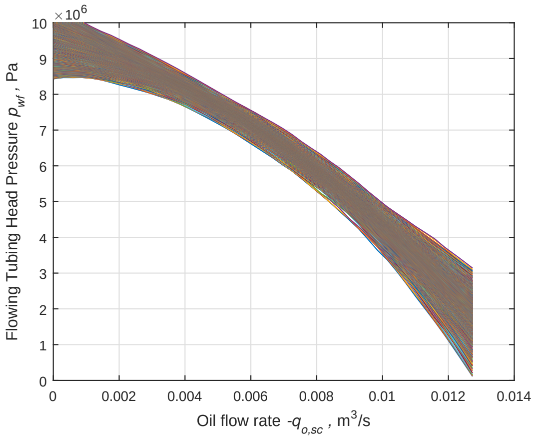
Figure 3.1: Workflow for simulated models visualized per step



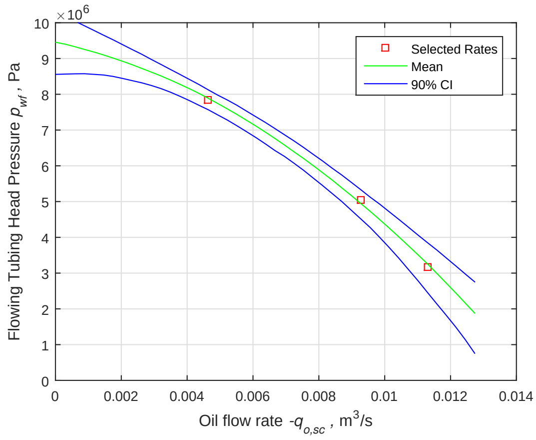
(a) Step 1: Using a simulated performance curve as a base



(b) Step 2: Introducing measurement noise



(c) Step 3: Fit realisiations



(d) Step 4: Process the data into confidence intervals

Figure 3.2: Workflow for fitted models visualized per step

The workflow is schematically presented in Figure 3.2 and is designed in the same manner as for the simulated curve: well test data for the selected rates is generated by adding noise from a pre-defined distribution to simulated Performance Relation (Figure 3.2a) results to include the effects of measurement errors, as shown in Figure 3.2b. Then Monte Carlo simulations are run, fitting a model through randomly selected values from the simulated data for every rate, resulting in the range of possible fits shown in Figure 3.2c. Finally the data has to be processed and sorted, resulting in the experimental confidence interval Figure 3.2d.

3.3. FORMULATION OF THE PERFORMANCE ENVELOPE

The last step to obtain objective boundaries for evaluating well performance is to transform the experimental confidence intervals presented in section 3.1 and 3.2 . These intervals represent, from a statistical point of view, experimental quartiles as the result of a sample and represent the range where for a certain percentage of repetitions the mean will fall in. Due to the big sample size the deviations from this mean even out and using these intervals to evaluate a single new observation is like comparing the weight of one student to the average of his class. Therefore the resulting intervals have no predictive power to evaluate a new individual well test results and need to be converted into prediction intervals. Expressed in statistical terminology this is converting a Confidence Interval in a Predictive Interval for a new observation. [6] To achieve this multiple approaches can be used. As this research works with results from simulated data, methods are needed to fit this experimental results in statistical tools. These methods are often used in social sciences to express the result of a large sample in statistical terms. For the simulated curves a distribution can be fitted to the data to obtain the standard deviation. After selecting a percentage for the prediction interval a p-value can be acquired from literature and the predictive interval can be computed by adding the standard deviation multiplied with the p-value to the mean. To make this predictive interval work practically the last step is to include the measurement uncertainty as well, which can be done in the same way as for the predictive interval, adding p-values multiplied with the standard deviation of the measurement noise to the interval, now using the predictive interval as mean. For the fitted intervals only the measurement error multiplied with the p-value has to be added. To exclude the subjective part of selecting percentages for p-values, this workflow for producing predictive intervals needs to be tested with real data. As this was not part of this research, nothing can be said about acceptable or advisable percentages. The further research needed is presented in Chapter 7.

3.4. WORKFLOW 3: RATE SELECTOR

The aim of this workflow is to design a test program by optimizing rate selection, resulting in the best fitted Performance Curve or the narrowest confidence interval in a region of interest and hereby enhancing the methods of defining the confidence bands for well performance prediction. This workflow is built on the assumption that every well test starts with a performance model that needs to be verified and gives a prediction of the expected performance. The start of this workflow is defining the goal for the test, the intended result, such as finding the narrowest confidence interval in the area around the operating point. Next comes the formulation of the boundary conditions such as the number of tests/rates, rate restrictions or imposed rates such as the operating point. Then for every combination of rates the workflow applies Workflow 2 (section 3.2) and checks for which combination of rates the confidence interval is the narrowest or provides the best fit compared to the pre simulated model.

4
METHODOLOGY

4.1. PRACTICAL IMPLEMENTATION OF THE WORKFLOWS

This chapter explains the scripts built and the procedures followed to get from the Proposed Workflows to the Results

4.2. PRACTICAL IMPLEMENTATION OF THE WORKFLOWS

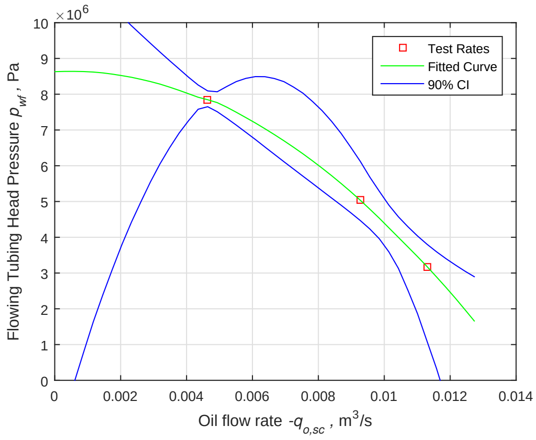
This section explains the scripts built to test and execute the method described in Proposed Workflows. As the focus of this research is to establish a performance envelope for production prediction, it focuses on Tubing Head Pressure Models. Although permanent downhole gauges are becoming more and more in fashion, this research only uses FTHP and flow rate as input parameters for the sake of applicability. Inflow Performance Curves are used to illustrate the effect of uncertainty, but for the establishment of Performance Envelopes the Total Performance Envelopes were used.

4.2.1. SIMULATED MODELS

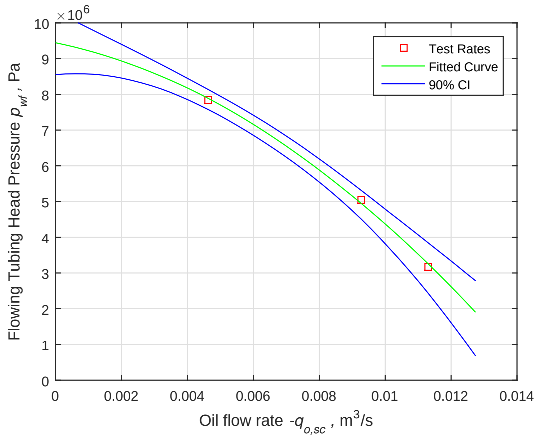
To execute the described workflows, the used nodal analysis software must be capable of running extensive sensitivity studies: many thousands of realizations for multiple parameters, preferably defined as distributions. Pipesim 2014 is not capable of running such simulations, therefore nodal analysis scripts coded in Matlab by Prof. Jansen for a course in Production Optimisation[7], where used as an alternative. An additional advantage of using a numerical computing environment such as Matlab over a commercial multiphase flow simulator like Pipesim is that Matlab has an open structure: Pipesim has a very strong engine which is completely obscured by the user interface, whereas in Matlab the code is accessible and adjustable. This accessibility makes it very efficient to use in sensitivity analysis, because the parameters can be provided as probability density functions and data can be formatted and plotted in a customized manner. The script used to compute an Inflow Performance Curve uses Darcy when above the bubble point and Vogel below for the analytical solution, and Runge Kutta integration for the numerical solution. It is capable of simulating multiphase flow and computes relative permeabilities for increasing water cut. The basic form of the Matlab code is presented in the Appendix. The script used to compute the Tubing Performance Curves and the Total Performance Curves uses Matlab's built in medium order method ODE45 for solving the multiphase flow equations along the wellbore with the input of a multiphase flow method. To produce a Total Performance Curve, an Inflow Performance Curve was used to compute the bottom hole pressures and these pressures were used as the input for the Tubing Performance Curve, resulting in a Total Performance Curve. Code is presented in the Appendix. Both scripts use temperature to compute the bubble point pressure and other fluid properties such as viscosity, but do not take temperature effects such as cooling along the wellbore in to account.

4.2.2. FITTED MODELS

The workflow for fitted curves is built in Matlab based on four basic ideas and assumptions: The well is tested for three different rates, usually including the operating rate, resulting in three data points to fit the curve. Polynomial functions of the 2nd degree were used to fit the curves because they are most widely used in the industry and numerically efficient. Different function types such as exponential were also considered and tested but were found to be less capable of using just three data points. Additionally, they proved to be computationally less efficient, resulting in up to hundredfold increases in computation times while not improving the quality of fit. To apply measurement uncertainty, the distributions where assumed known and constant and were implemented for both flow rate as well as pressure. The shut in pressure is known to a limited extent. This is mainly important from a numerical point of view: due to the significant error in flow rate, the best fit could be a parabola in the study area. From a physical point of view this make no sense as, it is known that the function has a starting point on the pressure axis and is monotonically decreasing from that point onwards. To implement this in the fitting routine, several options where tested such as restricting the fit parameters or simply discarding bad fits. Both results were unsatisfying: restriction lead to a significant growth in computing times and discarding bad fits resulted is loss of data. Implementing the knowledge from physics worked out best: include the (expected) shut-in pressure with an uncertainty as a fourth point, using it as an anchor. The results are shown in Figure 4.1.



(a) Without shut-in as an anchor



(b) With shut-in as an anchor

Figure 4.1: Effect of using the shut-in pressure as an anchor point for the fitting workflow

4.2.3. RATE ADVISOR

The rate advisor is built on the same principles as the Fitted Workflow and is based on the idea that according to the purpose or the input parameters a different set of rates will result in the best fit. The script computes a fit for every combination of three rates (three data entries) and compares this fit with the total performance curve. As the scripts uses the simulated performance curve as input to select the rates, the increment between the data points in the performance curve should be as small as possible, resulting in a big data vector. This precision of data conflicts with computational efficiency: increasing the number of rates results in an even bigger increase in combinations resulting in much longer computing times. Fortunately, two factors keep this increase to a minimum, one practical and one numerical. Firstly, using a small distance in flowrate might result in a precise result but is practically limited by the uncertainty in measured flowrate and the adjustability of the well. Secondly, by specifying one rate under operating rate and one rate above, the number of possible combinations is reduced by a factor two.

4.3. DIGITAL ASSET

All the simulations, both in Pipesim as in Matlab were run using a digital asset: a simple reservoir and well description which is summarized in Table 4.1. It consists of one horizontal well in a reservoir described in terms of thickness, outer range and permeability.

Table 4.1: Parameters of the Digital Asset

Reservoir Parameter	Value	**Well** Parameter	Value
Pressure P_{res} [Pa]	3,00E+07	Tubing Inside Diameter ID [m]	0,0762
Temperature T_{res} [C]	120	True Vertical Depth z [m]	3000
Permeabillity k [m^2]	1,00E-13	Tubing Head Temperature T_{wf} [C]	30
Thickness h [m]	20	Tubing Roughness e [m]	3,00E-05
Borehole Diameter r_w [m]	0.1524	Skin S	0
Drainage Radius r_e [m]	500		

The used fluid parameters are shown in Table 4.2.

Table 4.2: Used Fluid Parameters

Parameter	Value
Oil Density ρ_o [kg/m^3]	850
Gas Density ρ_g [kg/m^3]	0,95
Water Density ρ_w [kg/m^3]	1000
Gas Oil Ratio GOR [m^3]	90
Oil Parameter Correlations	Standing
Multi-phase Correlations	Mukherjee and Brill

4.4. SIMULATIONAL SET-UP

To test the proposed workflows and investigate the influence of parameters several cases were simulated, explained below in section 4.4.1 following the proposed workflows from Chapter 3. For all cases (except the uncertainty case) the measurement error in flowrate was assumed to be normally distributed with a standard deviations of 5% of the flowrate, the measurement error in pressure was assumed to be uniform distributed with an absolute error of $7 \cdot 10^4$ Pa and the error in shut-in was also assumed to distributed normal with an absolute error of $7 \cdot 10^4$ Pa. For the fitted workflows a Total Performance Curve computed in Pipesim was used with the operating rate at 0.0093 m3/s. To compare the results for the simulated workflow two criteria are used: The productivity index J as shown in Equation 4.1 and the flowrate at a flowing tubing head pressure of 5e6 Pa.

$$J = \frac{2\pi k h}{B_o \mu}\left(\ln\frac{r_e}{r_w} - f_r + S\right) \tag{4.1}$$

To compare the results for the fitted workflows two criteria were defined: 'Diff in Curve', computed as the sum of the squared residuals between the two confidence intervals and the input data used, and 'Diff in Oprange' computed as the sum of the squared residuals between the two confidence intervals and the input data used in the operating range, defined as operating rate ±15%.

4.4.1. SIMULATED CASES

Design Case The aim of the Design Case is to illustrate the effects of uncertainty in reservoir parameters prior to drilling. As no cores or well test results are available to estimate the value of certain parameters such as reservoir permeability with any precision, the uncertainty in these parameters is very large. The potential errors in these estimates are expected to have a profound impact on the size of the performance envelope. Using permeability k as the investigated parameter, simulations were run for a range of values between 0.2 $\cdot$ k and 5 $\cdot$ k. A triangular distribution was used as an approximation of the lognormal distribution that is typically found for permeability values.

Production Case In the later stages of constructing a well, well test data will be available to determine typical values of permeability and skin factor. Although available with a greater degree of accuracy than in the Design Case, there is inherent uncertainty in these parameters, mostly due to the uncertainties in well test interpretation. Simulations were run for a range of values for permeability and skin, using the uncertainties reported by Azi et al.[5] to create typical (uniform)distributions as shown in Table 4.3.

Skin Case: As opposed to investigating the effects of uncertainty in reservoir parameters, this case was simulated to illustrate the effect of the measurement uncertainties during the well test for both pressure and flow rate. By using the measurement error as an uncertainty on a simulated Total Performance Curve from Pipesim, one can investigate whether changes parameters such as the skin factor may remain unnoticed.

Table 4.3: Used parameters and distributions for the Simulated Cases

Case	Parameter	Distribution	Low	Mean	High	
Design	k	Triangular	20%	1	500%	Relative
Production	k	Uniform	80%	1	120%	Relative
Production	S	Uniform	-0,25	0	0,25	Absolute

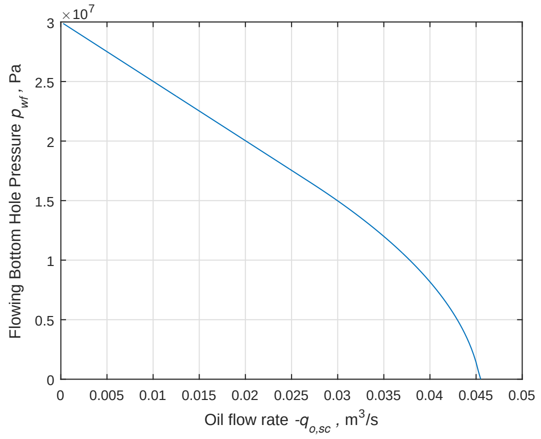
4.4.2. FITTED CASES

For the fitted cases three cases where compared:
Rate Selection compares the two rate selection methods as introduced in chapter 2.
Reducing Measurement Uncertainty illustrates the effect of reducing the uncertainties in flowrate and pressure and shut-in pressure.
Rate Advisor illustrates the added value of the rate selector, one result optimized for a narrow confidence interval over the whole curve and one for the operating range only.

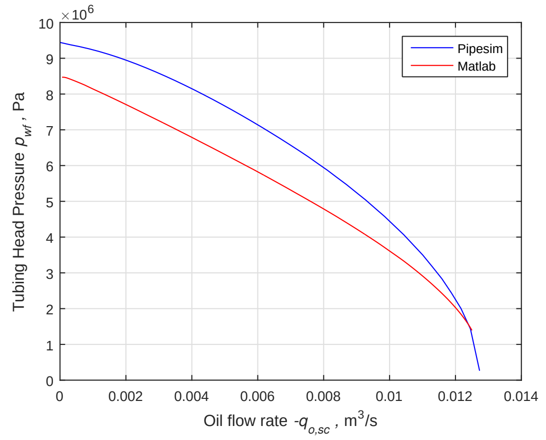
5
RESULTS

5.1. BASE CASE

The results for the base case scenario are shown in Figure 5.1. The difference between the two Total Performance Relations plotted in Figure 5.1b is notable.This difference is caused by multiple factors, and one of them is the fact that the Matlab model does not take temperature effects along the wellbore into account. This difference on its own illustrates how results coming from nearly the same model can differ greatly.



(a) Inflow Performance Relation



(b) Total Performance Relation computed in Pipesim and Matlab

Figure 5.1: Results for the basecase scenario

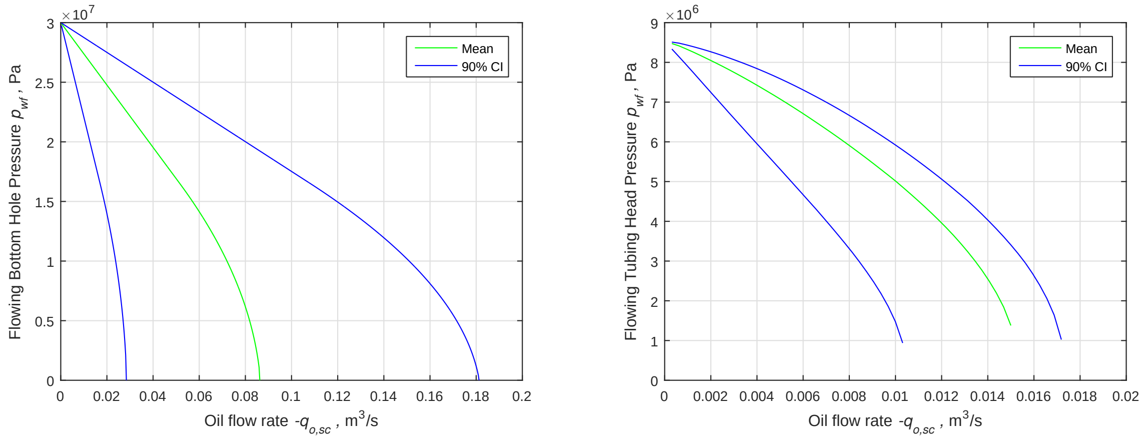
5.2. SIMULATED WORKFLOW

5.2.1. DESIGN CASE

As shown in Figure 5.2 and Table 5.1 the ranges for the results for the Design Case are quite large, which is expected due to the big uncertainty in input parameters. Although these results might seem obvious, they do illustrate the added value of simulating the whole range of possible outcomes, because these play an important role in designing the well.

Table 5.1: Productivity Index and flowrate at 50 bar for the Design Case

Parameter	Mean	Low	Percentage	High	Percentage
J	$3,82 \cdot 10^{-9}$	$1,26 \cdot 10^{-9}$	33	$8,01 \cdot 10^{-9}$	210
q	0,01	0,0055	55	0,0121	121

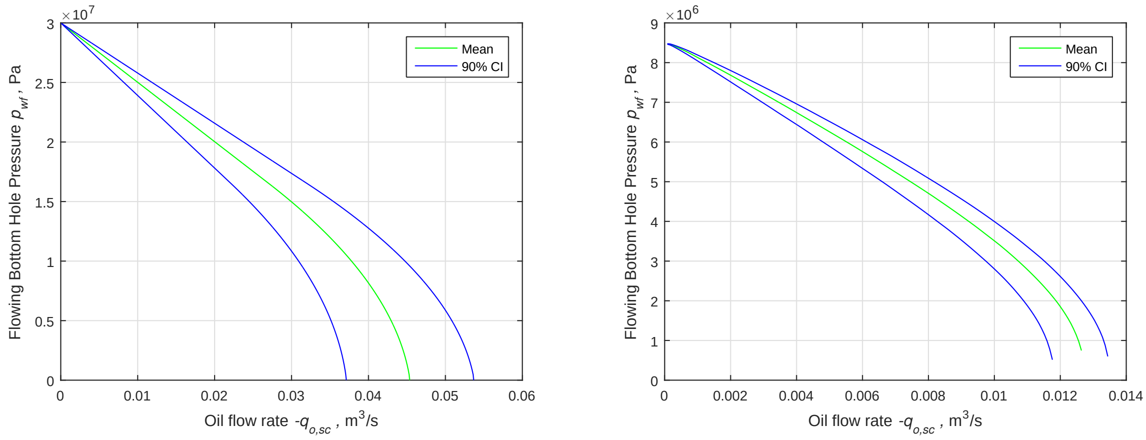


(a) Inflow Performance Relation (b) Total Performance Relation

Figure 5.2: Results for the simulated workflow with design uncertainties

5.2.2. Production Case

The results for the Production Case are shown in Figure 5.3 and Table 5.2. The uncertainty in input parameters results in an 11% spread in flowrate at the reference pressure and this illustrates the added value of the performance envelope.



(a) Inflow Performance Relation (b) Total Performance Relation

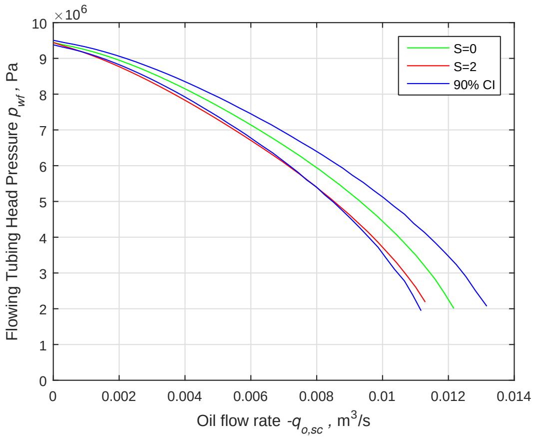
Figure 5.3: Results for the simulated workflow with the parameters from the Azi paper

Table 5.2: Productivity Index and flowrate at 50 bar for the Production Case

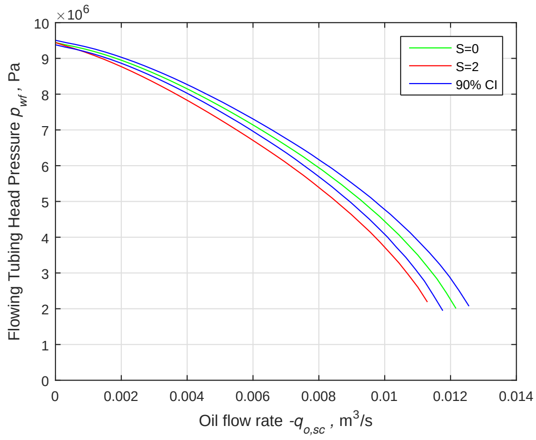
Parameter	Mean	Low	Percentage	High	Percentage
J	$2{,}01 \cdot 10^{-9}$	$1{,}64 \cdot 10^{-9}$	82	$2{,}37 \cdot 10^{-9}$	118
q	0,0074	0,0066	89	0,0082	111

5.2.3. Skin Case

Figure 5.4a illustrates that not only the input parameters cause uncertainty, but the measurement uncertainty does as well. With the reference uncertainty, it is not possible to determine if the skin factor has changed or if the measurements are affected by measurement noise and as a result it is not possible to distinguish a difference between a skin of zero and a skin of two. Figure 5.4b shows that by reducing the uncertainty in measurement error it becomes possible to determine if the skin factor changed.



(a) Results standard error in flowrate, 5%



(b) Results reduced error in flowrate, 2%

Figure 5.4: Results for the Skin Case

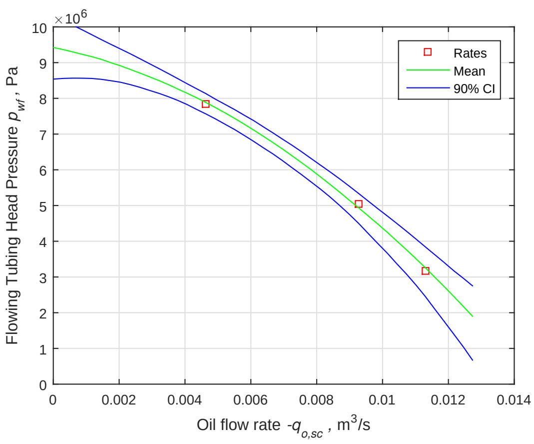
5.3. FITTED WORKFLOW

5.3.1. RATE SELECTION

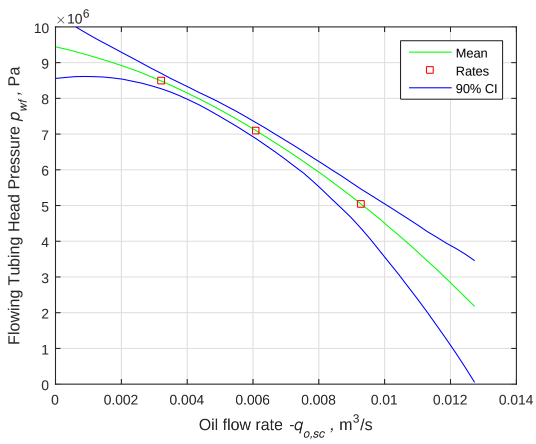
The performance envelope for the two different rate selection methods are shown in Figure 5.5. As the method illustrated in Figure 5.5b uses the operating rate as the highest rate, the confidence interval for higher rates is much wider than for the method shown in Figure 5.5a. This difference in confidence interval can also be seen from the significant difference in Diff in Curve and Diff in Oprange, as shown in Table 5.3 . From these values can be concluded that the confidence interval for both the whole curve as for the operating range is smaller/narrower for operating rate*[0.5 1 1.2] method and thus is a better rate selection method. Therefore the next simulations are run with the operating rate*[0.5 1 1.2] method. This case also shows that the rates selected to test and fit the model influence the quality of the fitted model.

Table 5.3: Comparison between the two rate selection methods

Rates	Diff in Curve	Diff in Oprange
operating rate*[0.5 1 1.2]	$3.06 \cdot 10^{13}$	$4.45 \cdot 10^{12}$
operating rate*[1/3 2/3 3/3]	$4.83 \cdot 10^{13}$	$8.77 \cdot 10^{13}$



(a) Results for operating rate*[0.5 1 1.2]



(b) Results for operating rate*[1/3 2/3 3/3]

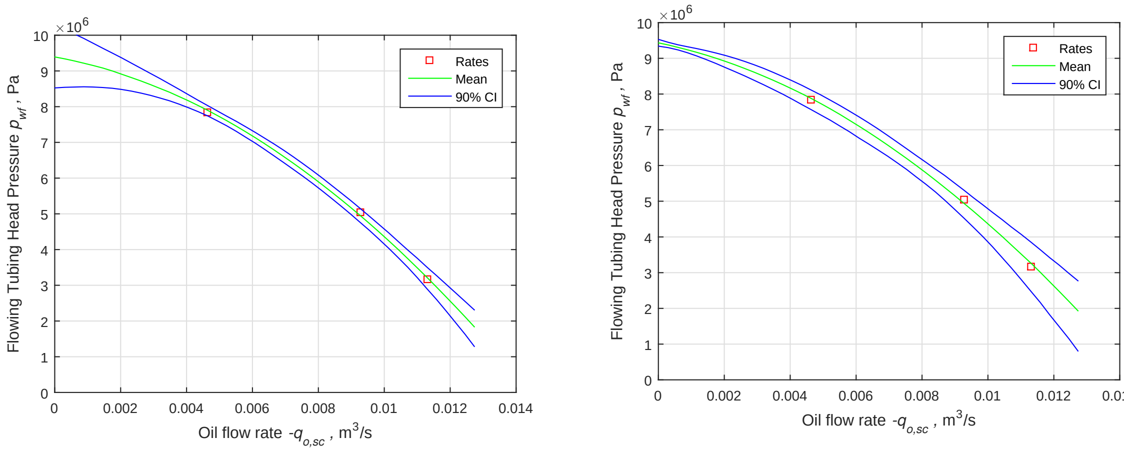
Figure 5.5: Results for the two different rate selection methods

Table 5.4: Comparison between reducing the error in flowrate and shut-in pressure

Uncertainty	Diff in Curve	Diff in Oprange
Flowrate	$1.77 \cdot 10^{13}$	$9.87 \cdot 10^{11}$
Shut-in	$2.21 \cdot 10^{13}$	$4.30 \cdot 10^{12}$

5.3.2. Reducing Measurement Uncertainty

The effect of reducing measurement uncertainty is shown in Figure 5.6. In Figure 5.6a the measurement uncertainty in flowrate is reduced for 5% to 2% and this has a significant effect as can be seen in Table 5.4: the Diff in Curve is reduced over 40% and the Diff in Oprange is reduced by a factor of 4.5. This enormous difference in result for the whole curve compared to the operating range is due to the error in shut-in pressure: since the error in shut-in is unchanged and significant, the reduction of flowrate uncertainty mainly effects the confidence interval for higher rates. Due to this locational effect, reduction of the error in shut-in has a limited effect for the operating range.



(a) Effect of reducing the uncertainty in flowrate from 5% to 2%

(b) Effect of reducing the uncertainty in shut-in pressure from 10e6 Pa to 7e4 Pa

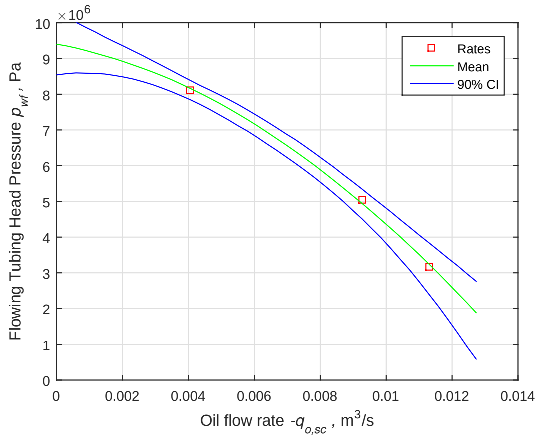
Figure 5.6: Results for reduction of the measurement uncertainties

5.4. Rate Advisor

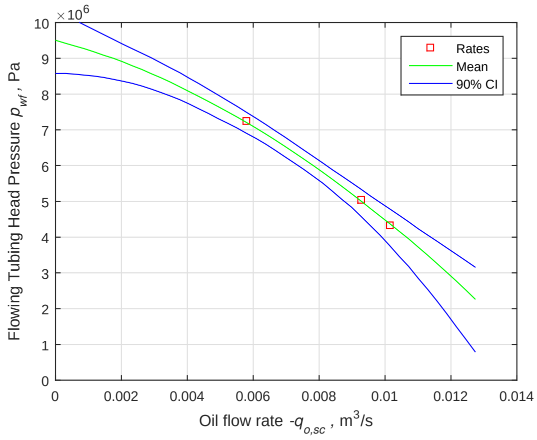
As already shown in the rate selection case the selected rates influence the outcome. The results for the rate advisor are shown in Table 5.5 and are illustrated in Figure 5.7. They show that optimizing for a given criterion does need different rates and also improves the model by narrowing the confidence interval. In addition, these results compared with the results for the rate selection method show that the operating rate*[0.5 1 1.2] selection method is quite precise for the whole curve. Only when the rate selector is optimized for a narrow confidence interval in the operating range it has significant added value, a decrease of 8% in Diff in Oprange.

Table 5.5: Comparison between the two used criteria for the rate advisor

Criterion	Adviced Rates	Diff in Curve	Diff in Oprange
Curve	op rate*[0.44 1 1.25]	$3.04 \cdot 10^{13}$	$4.64 \cdot 10^{12}$
Operating Range	op rate*[0.62 1 1.09]	$3.71 \cdot 10^{13}$	$4.07 \cdot 10^{12}$



(a) Results for optimalization for the whole curve



(b) Results for optimalization for the operating range

Figure 5.7: Results for the rate advisor

6 Conclusions

- By taking into account the uncertainties in the relevant parameters, we can generate a performance envelope and define associated uncertainty depending on the methodology used.
- Pre-simulation and sensitivity analysis have added value by illustrating the effects of uncertainty in parameters. The knowledge of what to expect makes it possible to anticipate: to design the test program optimized for the situation at hand.
- The rates used to test a well and establish a well performance model heavily influence the results, i.e. the shape and size of the performance envelope. Thinking about what rate to test helps to improve the quality of the resulting model. Using the proposed rate selector to optimize the well test, the three rates that result in the narrowest confidence interval can be determined.
- Simulation also shows the effects of reducing measurement uncercainty. Although this might seem trivial from a scientific point of view, the simulator was able to quantify the added value of reducing measurement uncertainty. The results prove the value of using high resolution multi-phase flow meters.
- Although the constructed performance envelopes provide insight into the effects of various uncertainties, further research is needed to use the performance envelope as an objective criterion to decide if a well produces as expected.

7
Recommendations

The next step towards identification of problematic wells requires the input of real production data, or at least full reservoir modeling. A big advantage of using full reservoir simulation is the controllability: it enables the control of parameters and the measuring of the effects, factoring real world uncertainty out of the equation. Reservoir simulators with the added possibility of simulating well test and production test data will prove to be especially useful. Using such simulators, we can apply changes in the reservoir and observe the response in the wells, to gain an understanding of the manifestation of the effects and the delay in reservoir effect and deviated production. Using this strategy, time effects such as increasing water cut and the decrease in reservoir pressure can be monitored in the well performance. Using such a time-based approach, it becomes possible to design experiments for the validity of a well performance model under changing circumstances. Another approach that can be tested with full reservoir simulators is a procedure similar to history matching for reservoir simulators: optimizing a well performance model based on the simulated production history and new simulated results.

A

Inflow and Total Performance Curve.mat

```
% ---------------------------------------------------------------------------------
% Input data:
% ---------------------------------------------------------------------------------
alpha = from_deg_to_rad(0); % wellbore inclination , rad
d = from_in_to_m(3); % tubing inside diameter, m
e = 30e-6; % tubing roughness, m
av          = 1; % use reservoir pressure at external boundary
beta        = 0; % Forcheimer coefficient, m^-1. Not relevant for fluid 1.
f_w_sc      = 0.0; % = q_w_sc/(q_w_sc+q_o_sc) = water cut, -. Not relevant for fluids ...
    1 and 2
fluid       = 4; % fluid  = 1: single-phase oil flow
% fluid  = 2: single-phase gas flow
% fluid ≥ 3: multi-phase gas-oil-water flow
h           = 20.0; % reservoir height, m
k      = 1e-13; % effective permeability for fluids 1 and 2, or absolute permeability
% for fluid 3, m^2
n_pt        = 200; % number of points in plot, -
oil = 1; % parameter to select black oil model or volatile oil table, -. Not relevant for
%           fluids 1 and 2
%           oil = 1: black oil; parameters computed with the aid of Standing correlations
%           oil = 2: black oil; parameters computed with the aid of Glaso correlations
%           oil = 3: volatile oil; parameters read from file 'vol_oil_table_01'
p_base         = 3e7; % reservoir pressure, Pa
q_o_sc_max = -0.0125; % maximum oil flow rate, m^3/s
r_e         = 500; % external radius, m
r_w         = from_in_to_m(6); % well bore radius, m
R_go        = 90; % producing GOR as observed at surface, m^3/m^3. Not relevant for ...
    fluid 2
rho_g_sc    = 0.95; % gas density at standard conditions, kg/m^3.
rho_o_sc    = 850;  % oil density at st. conditions, kg/m^3. Not relevant for fluid 2
rho_w_sc    = 1000; % water density at st. conditions, kg/m^3. Not relevant for fluids ...
    1 and 2
semi        = 0; % semi = 0: use steady-state conditions
%                  semi = 1: use semi-steady-state conditions
simp        = 1; % simp = 0: numerical solution using Runge Kutta integration
%                  simp = 1: simplified (semi-)analytical solution
S           = 0; % skin, -
T_R         = 120; % reservoir temperature, deg. C
T_tf = 30; % tubing head temperature, deg. C
T_wf = 120; % bottomhole temperature, deg. C
z_tvd = 3000; % true-vertical depth, m

% Relative permeability data (not relevant for fluids 1 and 2):
k_rg_0   = 0.7; % end-point relative permeability to gas, -
k_ro_0   = 0.9; % end-point relative permeability to oil, -
k_rw_0   = 0.5; % end-point relative permeability to water, -
```

```
n_g     = 3; % Corey exponent for gas, -
n_og    = 3; % Corey exponent for oil in gas-oil flow, -
n_ow    = 3; % Corey exponent for oil in oil-water flow, -
n_w     = 3; % Corey exponent for water, -
S_gc    = 0.00; % critical gas saturation, -
S_or    = 0.10; % residual oil saturation, -
S_wi    = 0.15; % immobile water saturation, -

n=10000;
p_R=p_base;
range=90; %in percentage
low=round((0.5*(100-range)/100)*n);
high=round((range+0.5*(100-range))/100*n);
% -------------------------------------------------------------
% End of input data
% -------------------------------------------------------------------
% [ mc_k ] = triangularmontecarlo( k_base, 0.2*k_base, 5*k_base, n);
%
% figure
% histogram(mc_k,101)
%
% pstore=zeros(22,n);
% entries=zeros(1,n);
% JS=zeros(1,n);

% for j=1:n;
%     k=mc_k(j);

% Check input:
if (simp == 1 && beta ≠ 0)
warning('Forcheimer flow only available numerically.')
warning('Parameter "simp" reset to 0.')
simp = 0;
end
if (simp == 0 && semi == 1)
warning('Semi-steady state solution only available analytically.')
warning('Parameter "semi" reset to 0.')
semi = 0;
end
if (simp == 0 && av == 1)
warning('Average reservoir pressure solution only available analytically.')
warning('Parameter "av" reset to 0.')
av = 0;
end

% Compute auxiliary variables:
s_tot = z_tvd/cos(alpha); % total along-hole well depth, m

% Create data vector:
rel = [k_rg_0,k_ro_0,k_rw_0,n_g,n_og,n_ow,n_w,S_gc,S_or,S_wi];
rho_sc = [rho_g_sc,rho_o_sc,rho_w_sc];

% Compute and print bubble point pressure (for info only):
if fluid ≠ 2
switch oil
case 1
p_b = pres_bub_Standing(R_go,rho_g_sc,rho_o_sc,T_R);
case 2
p_b = pres_bub_Glaso(R_go,rho_g_sc,rho_o_sc,T_R);
case 3
p_b = pres_bub_volatile_oil(T_R);
end
end

% Compute and plot IPR:

Δ_q_o_sc = q_o_sc_max/n_pt; % oil rate increment, m^3/s
p_wf = p_R;
results = zeros(n_pt,2);
for i=1:n_pt
q_o_sc = i * Δ_q_o_sc; % oil rate, m^3/s
```

```
q_g_sc = R_go * q_o_sc; % gas rate, m^3/s
q_w_sc = (f_w_sc/(1-f_w_sc)) * q_o_sc; % water rate, m^3/s
q_sc = [q_g_sc,q_o_sc,q_w_sc];
if simp == 0 % numerical solution
p_old = p_wf;
p_wf = res(beta,fluid,h,k,oil,p_R,q_sc,r_e,r_w,rel,rho_sc,T_R);
Delta_p = p_old - p_wf;
results(i,1:2)= [-q_o_sc p_wf];
if p_wf < 1e5 + Delta_p % to avoid pressures below atmospheric
break
end
else % Vogel solution
p_old = p_wf;
[p_wf J] = res_Vogel_BS(av,h,k,oil,p_R,q_sc,r_e,r_w,rel,rho_sc,semi,S,T_R);
if ¬isreal(p_wf) % p_wf is complex-valued
break
end
Delta_p = p_old - p_wf;
if p_wf < 1e5 + Delta_p % + Delta_p % to avoid pressures below atmospheric
break
end
results(i,1:3)= [-q_o_sc p_wf J];
end
end
nonzero_rows = results(:,1) ≠ 0; % select non-zero rows
results = results(nonzero_rows,:); % remove zero rows
p_bh=results(:,2);
figure
plot(results(:,1),results(:,2))

results = zeros(n_pt,2);
for i=1:(n_pt);
q_o_sc = (i) * ∆_q_o_sc; % oil rate, m^3/s
q_g_sc = R_go * q_o_sc; % gas rate, m^3/s
q_w_sc = (f_w_sc/(1-f_w_sc)) * q_o_sc; % water rate, m^3/s
q_sc = [q_g_sc,q_o_sc,q_w_sc];
p_th = pipe(alpha,d,e,fluid,oil,p_bh(i),q_sc,rho_sc,s_tot,0,T_wf,T_tf);
results(i,:)= [-q_o_sc p_th];
end

figure
plot(results(:,1),results(:,2))
xlabel('Oil flow rate\it -q_{o,sc} ,\rm m^3/s')
ylabel('Flowing bottom hole pressure\it p_{wf} ,\rm Pa')
xlim([0 0.02])
grid on
```

B

Rate Selector.mat

```
function [ advice, mid, sortsums, sortstore ] = rs_ci_curve_around( ...
    xdata,q_e,ydata,p_e,shutin_e,nc,nop,op)

%Rate selector based on Confidence Interval for the Operating Range with
%one point before and one points after op
%   Detailed explanation goes here
n_pts=length(xdata);

% %check variables
% if op>length(xdata);
%     error('Operating Point out of reach')
% elseif range>length(xdata)-op;
%     error('Operating Range to big')
% elseif range>op
%     error('Operating Range to big')
% end

count=0;
for i=2:op-1;
one=i;
for k=op+1:n_pts;
two=k;
t=count+1;
count=t;
end;
end;

pos=zeros(count,nop+1);

if nc<100
up=0.9;
low=0.1;
elseif nc==100
up=0.95;
low=0.05;
else
up=0.95;
low=0.05;
end

count=0;
for i=2:op-1;
one=i;
for k=op+1:n_pts;
two=k;
t=count+1;
count=t;
pos(t,1)=one;
pos(t,2)=two;
```

```
pos(t,3)=op;

store=zeros(n_pts,nc);
sortstore=zeros(n_pts,nc);

xdata_op=[xdata(1) xdata(one) xdata(two) xdata(op)];
ydata_op=[ydata(1) ydata(one) ydata(two) ydata(op)];
xdata_fit=sort(xdata_op,'ascend');
ydata_fit=sort(ydata_op,'descend');

[ xcloud ] = normalcloudp( xdata_fit, q_e, nc );
[ ycloud ] = cloudmaker( ydata_fit, p_e, nc );

shutinx= zeros(nc,1);
shutiny = cloudmaker( ydata(1), shutin_e, nc );
xcloud(1:nc)=shutinx;
ycloud(1:nc)=shutiny;

for k=1:nc;
xdatafit=[ xcloud(k) xcloud(nc+k) xcloud(2*nc+k) xcloud(3*nc+k)];
ydatafit=[ ycloud(k) ycloud(nc+k) ycloud(2*nc+k) ycloud(3*nc+k)];

[p] = polyfit(xdatafit,ydatafit,2);
[Y] = polyval(p,xdata);

store(:,k)=Y;
end

for k=1:n_pts;
sortstore(k,:)=sort(store(k,:));
end

ci_low=sortstore(:,(low*nc));
ci_high=sortstore(:,(up*nc));

sumsqr=sum((ydata-ci_low).^2)+sum((ci_high-ydata).^2);

pos(t,4)=sumsqr;
end
end


sortsums=sortrows(pos,nop+1);
one=sortsums(1,1);
two=sortsums(1,2);
drie=op;
points=[one two drie];
advice=sort(points);
one=advice(1,1);
two=advice(1,2);
drie=advice(1,3);

xdata_op=[xdata(1) xdata(one) xdata(two) xdata(drie)];
ydata_op=[ydata(1) ydata(one) ydata(two) ydata(drie)];

[ xcloud ] = normalcloudp( xdata_op, q_e, nc );
[ ycloud ] = cloudmaker( ydata_op, p_e, nc );

shutinx= zeros(nc,1);
shutiny = wolkmaker( ydata(1), shutin_e, nc );
xcloud(1:nc)=shutinx;
ycloud(1:nc)=shutiny;

for k=1:nc;
xdatafit=[ xcloud(k) xcloud(nc+k) xcloud(2*nc+k) xcloud(3*nc+k)];
ydatafit=[ ycloud(k) ycloud(nc+k) ycloud(2*nc+k) ycloud(3*nc+k)];

[p] = polyfit(xdatafit,ydatafit,2);
[Y] = polyval(p,xdata);

store(:,k)=Y;
```

```
end

for k=1:n_pts;
sortstore(k,:)=sort(store(k,:));
end

mid=(sortstore(:,nc/2)+sortstore(:,(nc/2)+1))./2;




end
```

Bibliography

[1] J. D. Jansen, *Nodal Analysis of Oil and Gas Wells* (Delft University of Technology, 2015).

[2] L. P. Dake, *Fundamentals of Reservoir Engineering* (Elsevier, 1978).

[3] J. V. Vogel, *Inflow performance relationships for solution-gas drive wells,* Journal of Petroleum Technology **20**, 83 (1968).

[4] J. J. Arps, *Analysis of decline curves,* Transactions of the AIME , 228 (1945).

[5] A. C. Azi, A. Gbo, T. Whittle, and A. C. Gringarten, *Evaluation of confidence intervals in well test interpretation results,* in *Europec/EAGE Conference and Exhibition* (Society of Petroleum Engineers, 2008).

[6] F. Dekking, *A Modern Introduction to Probability and Statistics* (Springer, 2005).

[7] J. D. Jansen, *AES1380 Production Optimalisation* (Delft University of Technology, 2015).