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A simple model for control and optimisation of a produced water re-injection facility

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ABSTRACT

Model-based control and optimisation strategies can play a key role in improving energy efficiency and reducing emissions into produced water re-injection facilities. However, building a model that adequately describes the plant is challenging and can also be used in online decision-making procedures. This work proposes a simple model based on a real water re-injection facility operating on the Norwegian continental shelf. The results demonstrate the model's flexibility, which could be fitted to different plant operating points while being fast to solve when embedded in optimisation problems. The developed model is expected to aid the implementation of strategies like self-optimising control and real-time optimisation on produced water re-injection facilities.

Keywords: Modelling, Water Injection, Subsea, Control, Optimisation.

INTRODUCTION

Water injection (or water flooding) is an enhanced oil recovery technique that injects water into the reservoir to maintain pressure. The injected water can come either from the sea or the water separated from the oil and gas production (produced water). The reservoir engineers typically decide the amount of injected water in each well, and many methodologies have been proposed so far in the literature where reservoir models are usually applied [1]. Once the injection targets have been defined, the water injection network system can be optimised.

A relevant optimisation problem in this context may consist of the optimal operation of the pump system topside while ensuring the integrity of the subsea water injection system by maximising the lifetime of the equipment. Usually, the works in that phase are modelling the system at a macro-level where each unit is represented as a node in a network [2-3].

The use of simple and lower-level models where the manipulated variables and measured variables can be directly connected proved to be useful in the design of new control strategies [5-6] as well as in real-time optimisation formulations where the model parameters can be updated in real-time [4].

Several requirements should be fulfilled when a model-based control and optimisation strategy is developed: 1) The formulated model should adequately describe the target plant behaviour [5]; 2) The model should be able to be fitted to the plant available measurements considering the intrinsic uncertainty [7]; 3) A optimisation problem embedding the model should be able to be reliably solvable in the required time [4].

This work proposes a simplified mechanistic model of a produced water re-injection facility that aims to meet all those requirements. The model is shown to be capable of matching real industrial data. Furthermore, this work provides original insights into the challenge of training models with real operation data.

BACKGROUND

Oil and gas offshore production

Offshore oil and gas production has been used for over a century and is expected to still play a role in the next decades years. A typical offshore oil and gas production facility consists of a reservoir containing oil, gas and water. The reservoir's high pressure is the driving force to make the mixture flow through the production wells. A manifold connects all the wells through a riser that will transport the mixture to a separator that is usually located topside, but subsea separators may also be applied [5]. A three-phase separator is used to separate the oil, which is then transported to the shore through the production lines or ships. The same is done with the produced gas.

After years of operation, the reservoir starts to decrease in natural pressure, resulting in production reduction. Production can be kept at a plateau using enhanced recovery (EOR) techniques. The gas-lift technique is one of the most common methods and consists of recirculating part of the produced gas using compressors and re-injecting it into the bottom of the well [7]. This reduces the hydrostatic pressure of the mixture in the well, and a higher production. Another technique commonly applied in addition to gas-lift, is to inject the water into the reservoir in separate injection wells. This keeps the reservoir pressure high, such that a high production can be maintained.

Produced water (PW) re-injection facility

The outflow of water from the separator is called the produced water (PW). The destination of the PW has been the topic of many government regulations [8]. The simple solution would be to discharge the PW into the sea. However, since the separator is not 100 % efficient, drops of oil are carried into the PW. Therefore, the PW needs to be submitted to treatment before discharge, in a way that complies with the regulations [2,8].

Another possible destiny for the PW is to re-inject it into the reservoir. This strategy also has the advantage of being an enhanced oil recovery technique and can increase the revenues from the asset. However, the amount of water injected into each well must be carefully chosen. If too much water is injected into a well, the water cut (ratio of produced water compared to other liquids) will increase, potentially making oil production infeasible [9]. On the other hand, if insufficient water is injected, the reservoir pressure will decrease, lowering production [9]. As a complement, seawater can also be used for water injection.

Produced water model-based optimal control and optimisation

Many tools were developed for subsea operations, multi-phase flow control [5], gas-lift optimal injection [7], electric submersible pump operation [10] and separator control [6]. Sometimes, the models were used to develop simple feedback solutions [10]. In other cases, the model was used to generate predictions in a Model Predictive Control structure [7].

The decision-making process in PW management is made on different layers [2,11]. On higher layers, decisions are made over the long horizon of many years, where the equipment's health condition should be considered, such as pump and valve degradation. A health-aware control strategy can be applied if a degradation model is available [12]. The injection targets are typically updated over months.

On a faster time scale, the production optimisation decisions are taken. Here the optimal flow rates and pump speeds are decided [2]. Those flow rates are typically sent to the lowest layer, the control and automation layer, where feedback loops and simple controllers are used to track the setpoints coming from the layer above.

RELATED WORK

Many studies have been conducted to control and optimize PW facilities. Most use reservoir models to obtain the optimal injection flow rates based on reservoir dynamics [1,9]. Another set of works assumed that the injection targets were given and worked only on the production optimisation layer. The main goals of those works were to efficiently operate the pumping system and consider the seawater discharger regulation. The system is treated as a network, where the nodes can be pumping stations, tanks, valves or wells.

[9] proposed a mixed integer linear programming method to solve the PW system operating optimization problem. [2] proposed an economic model predictive control formulation for optimizing daily injection, with a strong focus on compliance with environmental regulation of PW sea discharging. As far as we are concerned, no work on lower-level layers of control and automation was developed.

Motivation and contribution of the paper

We have two main motivatiors for building a new model for the PW re-injection facility: i) Obtaining a model that can be used on real-time control and optimization strategies; ii) To address the challenges of obtaining a model that can be easily fitted to real facility data. To address those goals, a static model for the PW was developed in this work.

The model is designed to be applied to operation and production strategies that are not fully explored and adapted yet in the industry. For example real-time optimisation Here, the optimal valve openings, pump speeds, and flows can be computed to minimize energy consumption while operating within the pump envelopes and reducing the risk of cavitation on the injection valves. The model is also suitable for obtaining insights on how a simple optimizing control structure may be implemented (e.g. self-optimizing control [14]).

MATHEMATICAL MODEL

System description

The system to be modelled is presented in Figure 1. It is based on a real reinjection facility operated on the

Norwegian continental shelf. The system in consideration has nine boundaries: three inflows and six outflows. The outflows consist of the reservoir injection wells placed in distinct locations. The inflows consist of a seawater return, and two produced water streams. Since the goal is to obtain a simple model, the focus was to include only the primary operations that can contribute to achieving the water injection targets or the energy efficient optimisation. Therefore, the PW treatment and the separators were excluded from the model development. The interested reader is referred to [6].

The overall water injection system is divided into two parts: the topside part (on a platform or a ship) and the subsea part. A topside tank is used to store the seawater inflow, which is mainly used to complement the PW streams. The tank guarantees a steadier flow and are connected to a fixed-speed pump C. Two variable-speed pumps A and B are used to pump water to the different injection wells of the reservoirs. The second part of the model is the subsea injection system, which uses flow modules and choke valves on top of the well to precisely control each well's injection flow rate.

Main assumptions

The main assumption made was that a steady-state model can well describe the system. This decision was based on analysing past process data and the system's relative fast dynamics. Besides, it was discussed previously that static models suffice in most cases of daily production optimisation [11]. Model accuracy was another reason for building a steady-state model, as calibrating dynamic models can be challenging in real facilities [7] and requires state estimators. Besides, steady-state models can be more easily applied in real-time optimisation (RTO) approaches [4].

Another important assumption made is the description of the reservoir behaviour, which is considered to behave linearly based on the pressure gradient between the bottom hole pressure and the reservoir pressure. That assumption is commonly used since reservoir dynamics are much slower than pumping system dynamics, and the injection parameter can be obtained experimentally by operators through injectivity tests [2].

Topside equations

The first part of the equations describes the topside of the water injection facility. The inlet flow on the tank is controlled by a valve. Since the goal was to obtain a steady-state model, we assumed a perfect control of the tank level (h_{tank}). Therefore, the ordinary differential equation originating from the mass balance in the tank was not included explicitly in the model.

The pump located downstream of the tank has a fixed speed (Pump C) and the outlet flow (F_s) can be computed using the pump equations, where the pressure in the bottom of the tank (P_{out}^{tank}) is computed using a static pressure equation. Another control valve is used for manipulating the flow (P_{out}^{c}) downstream Pump C. The Pump C head (H_c) is provided by the pump curve equation.

$$F_s = CV_s z_s \sqrt{P_{out}^{c} - P_{out}^{valve}} \quad (1)$$

$$P_{out}^{tank} = P_{tank} + \rho g h_{tank} \quad (2)$$

$$P_{out}^{c} = P_{out}^{tank} + \rho g H_1 \quad (3)$$

$$H_c = a_{10} + a_{11} F_s + a_{12} F_s^2 \quad (4)$$

Downstream the pump, the flow is split into two separate lines that will connect with the two PW streams. The

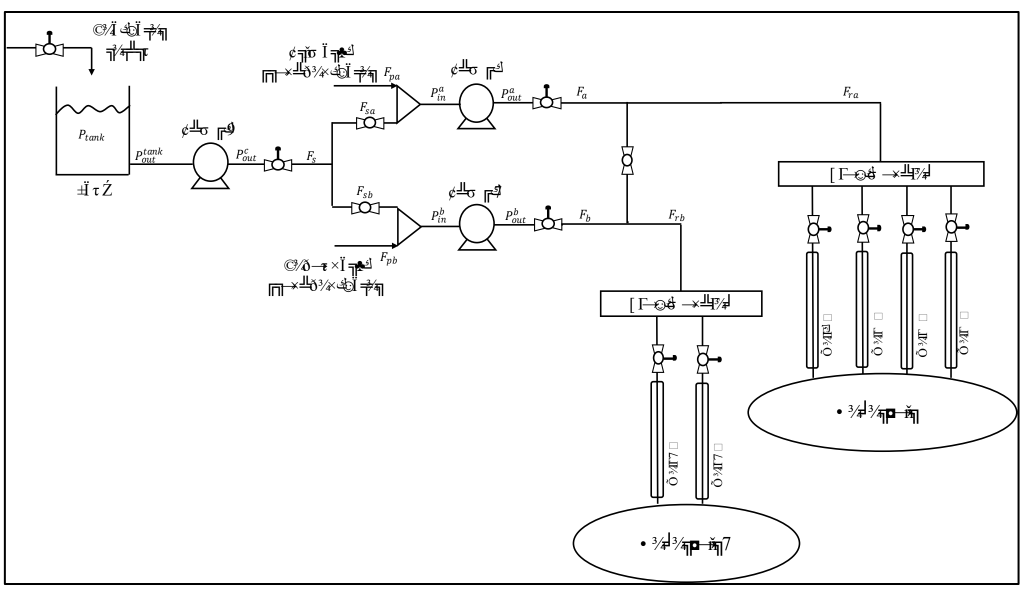

Figure 1 – Illustration of the modelled produced water facility.

mass balances on those nodes are described as follows:

$$F_s = F_{sa} + F_{sb} \tag{5}$$

$$F_a = F_{sa} + F_{pa} \tag{6}$$

$$F_b = F_{sb} + F_{pb} \tag{7}$$

The two variable speed injection pumps are described using the pump equations, as well as the respective control valves.

$$H_a = a_{20}\omega_a^2 + a_{21}\omega_a F_a + a_{22}F_a^2 \tag{8}$$

$$H_b = a_{30}\omega_b^2 + a_{31}\omega_b F_b + a_{32}F_b^2 \tag{9}$$

$$F_a = CV_a z_a \sqrt{P_{out}^a - P_n^a} \tag{10}$$

$$F_b = CV_b z_b \sqrt{P_{out}^b - P_n^b} \tag{11}$$

$$P_a^{out} = P_a^{In} + \rho g H_1 \tag{12}$$

$$P_b^{out} = P_b^{In} + \rho g H_2 \tag{13}$$

Subsea system equations

The second set of equations describes the flow modules, wells and reservoirs. The pressure on the flow modules as well as the mass balance are described as follow:

$$P_m^a = P_i^a + \rho g h_{riser}^a \tag{14}$$

$$F_{ra} = F_a + F_{an} \tag{15}$$

$$P_m^b = P_i^b + \rho g h_{riser}^b \tag{16}$$

$$F_{rb} = F_b + F_{bn} \tag{17}$$

Each well (i = B1, B2, A1, A2, A3 and A4) is described by the pressure in the top of the well (P_{top}^i) computed using the static valve equation, the bottom hole pressure (P_{bhp}^i) and the linear water injection on the reservoir's equation:

$$F_i^{valve} = CV_i z_i \sqrt{P_m^i - P_{top}^i} \tag{18}$$

$$P_{bhp}^i = P_{top}^i + \rho g h_i \tag{19}$$

$$F_i^{res} = (P_{bhp}^i - P_{res}^i) J_i \tag{20}$$

$$F_i^{res} = F_i^{valve} \tag{21}$$

DATA GATHERING AND PARAMETER ESTIMATION

The industrial data was gathered from a PW facility operated on the Norwegian continental shelf. The available measurements were pressures, volumetric flow rates and pump and valve operating data. Outliers were removed, and all the data set was normalized. Figure 2 shows the water flow rate for pumps A and B during the collected period. Since the model to be fitted is static, five different steady-state operating points were selected to evaluate the model's capability of describing different scenarios.

The model comprises of 44 algebraic variables and nonlinear equations, 14 inputs and 31 parameters. Model parameters related to equipment dimensions and the valve's flow coefficient were fixed as in the real industrial system. The remaining 15 parameters were estimated using least squares regression from the field data (P_{tank}, P_a^{In}, P_b^{In}, P_{res}^i and J_i).

A nonlinear weighted least-square problem was solved, where the weight used was the inverse of the variance of each measurement. Pump envelops and valve operation ranges were used to constrain the optimisation problem. The problem was implemented in MATLAB using the CasADi tool with automatic differentiation and the NLP solver IPOPT.

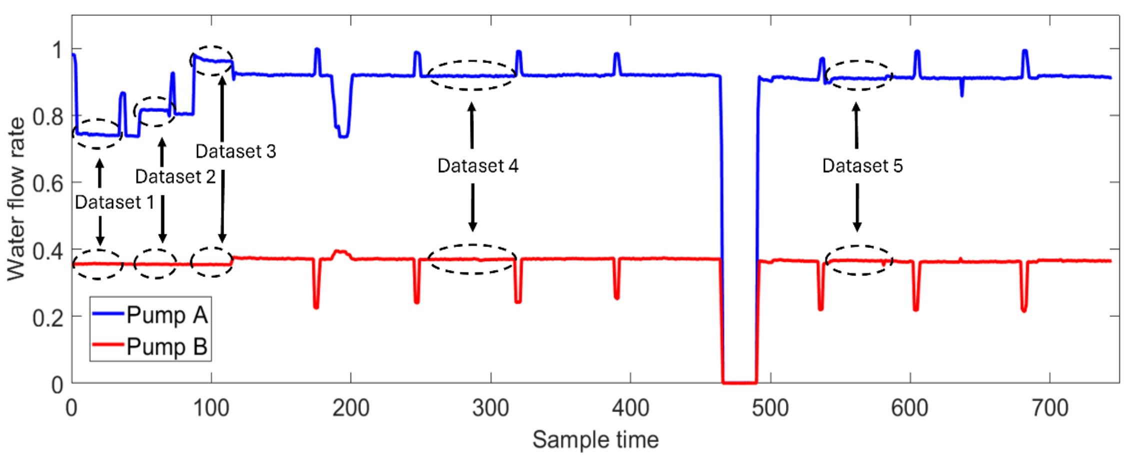

Figure 2 – Five datasets used for parameter estimation.

RESULTS

The fitted pump curves for pumps A and B are visualised in Figure 3, as well as the pumps operation envelopes that were used to constrain the problem feasible region. This is a crucial part of the model for future applications, because many optimal operation strategies try to optimise the pump performance [2].

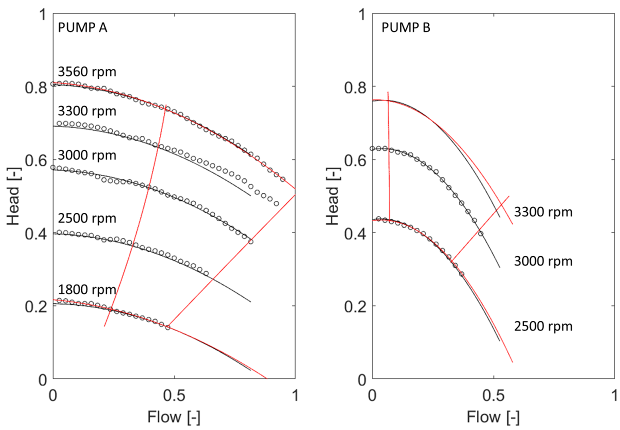

Figure 3 –Normalized pump curves: Pump curves datapoints (circles), model predictions (black line) and operation envelopes (red line).

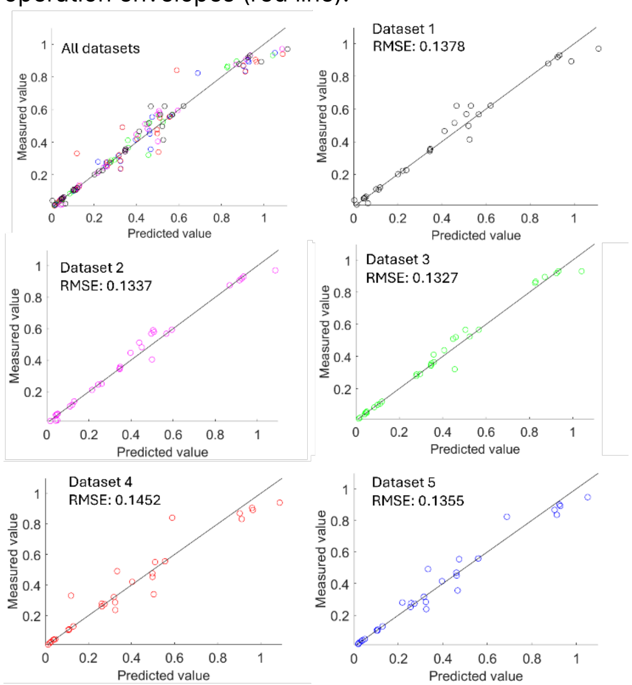

Figure 4 – Scatter plot of the predicted and measured values for the five datasets.

A scatter plot comparing the model predictions and measurements for the five different steady state datasets can be visualized in Figure 4. All the five operating points could be described by the model with a relative equal root-mean square error (RMSE), with a slightly difference for dataset four.

The water injection rates for the different wells are the most relevant variables for optimizing water injection, since the rates should be driven to their respective targets provided by upper layers decision makers. Therefore, in Figure 5 a closer look on the predicted and measured water injection rates are shown.

Overall, the model could describe the injection rates satisfactorily, with a few exceptions. Operating points 1 and 2 have a distinct feature since either well A1 or A2 were shut down. However, the model predicted a low remnant injection rate on those wells. Furthermore, the model underpredicted wells B1 and B2 rates in almost all cases.

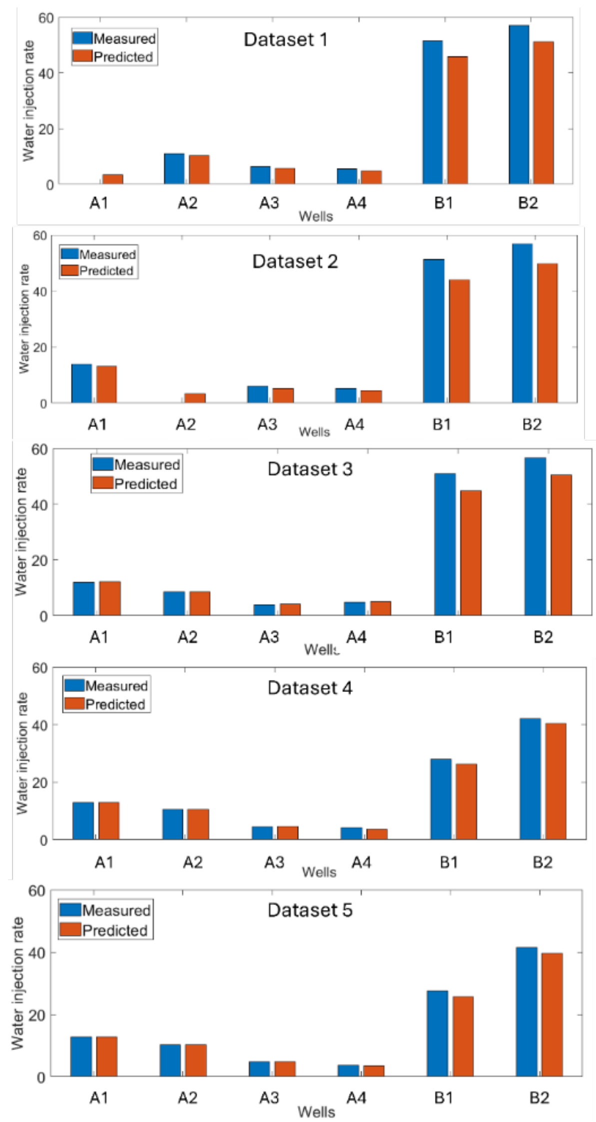

Figure 5 – Measured and predicted water injection rate of all the wells on the five different data-sets.

CONCLUSIONS

A simple steady-state model could be fitted to datasets from a real produced water re-injection facility. Overall, the model was flexible enough to fit different operating points with relatively small prediction errors.

Future work will focus on applying the developed model to applications such as real-time optimisation [4] and health-aware control by adding equipment degradation models [12]. Furthermore, an Economic Model Predictive Control strategy can also be explored. For that purpose, a dynamic model of the facility can be built based on the developed steady-state model.

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