Arid Zone Journal of Engineering, Technology and Environment, October, 2017; Vol. 13(5):610-619

Print ISSN: 1596-2490, Electronic ISSN: 2545-5818, www.azojete.com.ng

OPTIMIZATION AND NON-LINEAR IDENTIFICATION OF RESERVOIR WATER FLOODING PROCESS

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Abstract

In this study, dynamic optimization and identification of petroleum reservoir waterflooding using receding horizon (RH) principles was examined. Two forms of the strategy were compared on a realistic reservoir model. Sequential quadratic programming (SQP) was applied to optimize net present value (NPV) using water injection rates as the variables. MRST from SINTEF was used for the reservoir modeling. The identification of the reservoir was performed using nonlinear autoregressive with exogenous input (NARX) neural network from MATLAB. Data for the network training and validation was obtained by carrying out a numerical experiment on a high fidelity model of the reservoir. This model was developed with Eclipse Reservoir Simulator from Schlumberger. From the results obtained, moving-end RH gave a higher NPV than fixed-end RH with a margin of $0.5 billion. The identification algorithm was very much effective and near perfect for the studied reservoir.

Keywords: Dynamic Optimization, Receding Horizon, Waterflooding, Nonlinear Identification, Neural Network

1. Introduction

The World energy statistical review by BP (British Petroleum) shows that most of the global energy consumption comes from fossil fuels. It has been estimated that global oil consumption grew by 890,000 barrels per day or 0.9% (BP , 2011). Unfortunately, oil and gas reserves are fixed and are depleting by the day, the chance of discovering new ones is also getting slimmer. So, there is prudent need to produce these resources in the most intelligent way possible. Oil and gas are hydrocarbons that are stored in underground formations called reservoirs. Reservoirs are porous in nature with the hydrocarbons found in the pores which are interconnected to ease their (hydrocarbon) flow. At the discovery, the reservoir pressure is usually high, and oil and gas can flow to the surface through a drilled well. The pressure decreases with production and reaches a point where it can no longer sustain it (Völcker *et al.*, 2011). This is called primary recovery phase. After this phase, the reservoir pressure is boosted by injection of certain fluids in a secondary recovery phase. When the injecting fluid is water, the process is called waterflooding and this is the commonest secondary recovery method. In tertiary or enhanced oil recovery, the phase properties of the fluids are altered by injecting more or less expensive fluids such as polymers and foams. Unfortunately, even with implementation of waterflooding, only about one third of the original oil in place is recovered using the conventional techniques.

Petroleum reservoirs are highly heterogeneous. This makes waterflooding non-uniform in the reservoir formation. In fact, the injected water will naturally flow through more conductive fractures and high permeable zones of the reservoir thereby bypassing the oil. The effect of this is premature water breakthrough and low sweep energy. Several methods of improving sweep efficiency were suggested by others (Mody *et al.*, 1989). One of such that is receiving great attention is the use of smart production and injection wells. A smart well is an unconventional well that is equipped down hole with inflow control devices (ICVs) which divide the well into segments so that fluid flow in various zones of the reservoir can be controlled independently (Brouwer *et al.*, 2001). This is achieved by redistributing injection and production among the sections so that early water break-through could be delayed or prevented (Meum *et al.*, 2008).

In the last two decades, studies on water-flooding optimization were focused mainly on rather simplified systems (Virnovsky, 1988 and Virnovsky, 1991). Over the last few years, several methods were applied for the optimization of water-flooding such as conjugate gradient (Yeten *et al.,* 2003 and Asadollah *et al.,* 2009), optimal control based on adjoint methods (Brouwer *et al.*, 2004) and ensemble Kalman filter techniques (Lorentzen, *et al.,* 2006). In all of these, the optimization was aimed at maximizing either the net present value (NPV) or recovery of oil. The variables usually used are injection rates and bottom-hole pressure of production wells.

In oil companies, a reactive measure is usually taken to curtail early water break-through by taking measurements of oil-water ratio. This strategy often leads to poor sweep efficiency. A proactive means was suggested by introducing a feedback into reservoir waterflooding management (Meum, *et al.,* 2008). A model predictive control (MPC) was designed to control the injection rates and production bottomhole pressure (Van Essen *et al.,* 2010). The prediction of the controller was performed by identifying a linear model using subspace identification technique. The identified model was assumed to have better short-term prediction accuracy than the available commercial reservoir simulators which are based on physical laws. A related work explained the benefit of using a data-driven model in formulating such control strategy (Van Essen *et al.,* 2012). It was stated that subsurface devices have high measurement frequencies (in the order of seconds or minutes) while physics-based models are constructed with time step size that ranges from days to several months. This time scale mismatch will lead to a loss of precious data used to capture fast dynamics. The prediction for the MPC controller was performed using Eclipse reservoir simulator which was treated as input-output black-box model. The simulator was interfaced with an in-house MPC software (Meum *et al.,* 2008).

In the downstream of oil and gas, as well as other industries, the application of linear MPC has been successful. However, MPC depends on linear models even though most processes are nonlinear (Cao *et al.,* 2003). Despite the numerous advantages offered by identified models, the use of linear models in conjunction with MPC has some drawbacks especially when it comes to waterflooding management. Waterflooding process is nonlinear and as such the prediction accuracy of the identified linear model will decrease as the prediction horizon increases. In the past, total liquid rate had been used as the output instead of individual oil and water rates because of the very strong nonlinear relationship that exists between water cut and the inputs to the model (injection rates and producer bottomhole pressure), (Van Essen *et al.,* 2010). For this reason, research into nonlinear MPC (NMPC) is receiving attention over the years. One of the shortcomings in using NMPC is the task associated with the solution of highly nonlinear equations. This necessitated investigations into the possible use of artificial neural networks (ANN) for identification and control purposes.

The use of ANN in the upstream oil and gas has been reported in the literature. Juniard *et al.,* (1993) used ANN in well test analysis. Dang *et al.* (1993) used NN to model rock lithology. ANN was also applied to a field wise waterflooding problem where wellhead pressure was predicted as a function of injection rate and vice versa (Nikravesh *et al.,* 1996). History matching and prediction was performed using the identified model and the best injection strategy was determined that maximized recovery with decreased formation damage (permeability impairment). In another work, Nikravesh *et al.* (1996) employed feedforward with back propagation neural networks to model reservoir performance under steam and water injection. Garg *et al.* (1996) used ANN to model water imbibition. Demiryurek *et al.* (2008) used ANN to establish injector-producer relationship. Also, Nakutnyy *et al.* (2008) has been reported to utilize ANN in modeling waterflooding.

The choice of ANN as a method of identification is based on some of its inherent advantages over other methods. For instance, it has the ability to approximate any nonlinear relationship to any degree of accuracy. It also has the ability to learn how to perform certain task based on supplied data, which can be processed in parallel and applied to multivariable systems (Nakutn *et al.*, 2008). Apart from this, ANN can be trained easily using past data (Garg *et al.*, 1996).

This study is in two folds: dynamic optimization of reservoir waterflooding was carried out using the principles of receding horizon (RH). Although, the approach of RH was reported (Grema *et al.*, 2013), only a simplified reservoir was considered. Present work has considered a realistic reservoir. The second aspect of the paper deals with nonlinear identification of the waterflooding process used in the optimization by applying nonlinear autoregressive with exogenous input (NARX) neural networks. This is a part of methodology to create NMPC for waterflooding in order to investigate the effect of feedback into long term reservoir production planning. This is shown in Figure 1. The NMPC consists of the identified model and optimization module which computes the control, u' that minimizes an objective and the optimal control, u is applied to the reservoir. The reference trajectory, y_r is computed through the dynamic optimization. The real reservoir is represented here by the large-scale physics-based reservoir model.

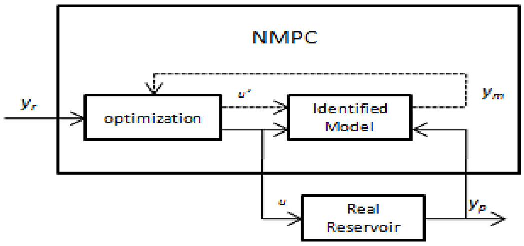

Figure 1: NMPC for Waterflooding

2. Problem Formulation

2.1 Reservoir Description and Dynamics

The reservoir model used in this work is the SAIGUP (Sensistivity Analysis of the Impact of Geological Uncertainties) model that is a part of MATLAB Reservoir Simulator Toolbox (MRST) software suit. SAIGUP model is a synthetic but realistic model with faults, inactive cells and disconnected component. It mimics progradational shallow marine reservoirs with heterogeneous permeability and porosity. There are five each of injection and production wells. For the optimization case, the reservoir was modeled with MRST from SINTEF while Eclipse commercial simulator was used for the data-driven model. In both cases Cartesian gridding system was used. For the case of modeling using MRST the fluid system was assumed to be incompressible while black oil simulation was applied with Eclipse model. Figures 2a and 2b show the reservoir models developed from the two softwares. The difference in the two models is from the assumption of the fluid properties. For the MRST model (Figure 2a), the fluid was assumed to be incompressible while black oil model was adopted for Figure 1b.

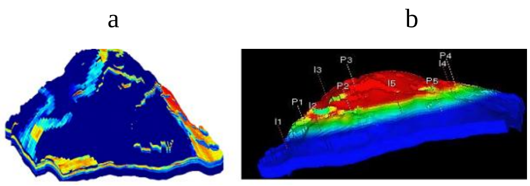

Figure 2: Reservoir model (a) MRST (b) ECLIPSE

Reservoir model can be represented in discrete form in terms of states and input variables as follows (Jansen, *et al.*, 2008):

$$g_{k+1}(u_{k+1}, x_k, x_{k+1}) = 0, \ k = 0, \dots K-1 \tag{1}$$

where: g is a nonlinear function, *u* is the input vector which represents variables such as injection rates and/or bottomhole pressure, *x* is the reservoir states which include pressure, water and oil saturation. The discrete time is denoted by *k* while *K* is the end of production time. Usually, an initial condition such as Equation 2 is supplied to complete the model.

$$x_0 = \check{x}_0 \tag{2}$$

The output vector consisting of production rates is a function of state and input variables as follows:

$$y_{k+1} = h(u_{k+1,} x_{k+1}) \tag{3}$$

2.2 Optimization using Receding Horizon

In previous works, optimal control *u* was obtained to optimize an objective functional *J* (Brouwer *et al.*, 2004 and Völcker *et al.*, 2011). In this work, receding horizon (RH) was used for the optimization of waterflooding. RH is an extension of optimal control algorithms that was applied for both linear and nonlinear systems. It involves solving a fixed horizon optimization problem where a sequence of predicted inputs is determined over a prediction horizon (for instance T time steps) and then implementing only the first step in the series. The prediction time is moved one step forward and the whole process is repeated (Goodwin *et al.*, 2006). Sequential quadratic programming (SQP) was adopted for solving the optimization problem.

2.3 Nonlinear Identification of Waterflooding using Artificial Neural Network

System identification is a process of formulating a mathematical model of a system based on observed data (Ljung, 1999). ANN has been proven to be powerful tool for nonlinear identification. ANNs are composed of simple computing elements called neurons. One of the most common type of ANNs used for nonlinear identification is feed forward neural network (FFNN) with back propagation (Centilmen *et al.*, 1999). But some authors are of the opinion that FFNN can only predict for a predefined number of steps, in most cases single step, and as such are not good for applications that may require a multiple step predictions (Cao *et al.*, 2003). Recurrent or dynamic networks are found helpful in overcoming this shortcoming of single-step prediction. These are multilayer FFNN with feedback. There are several architectures of dynamic NN. One of such is Nonlinear Autoregressive with Exogenous Input (NARX). NARX networks are computationally powerful with a more effective learning of gradient descent algorithms than other recurrent networks, hence, our choice of NARX in this work. For a given *d* past values of *y(t)* and *u(t)*, NARX can predict subsequent series of *y(t)* as follows:

$$y(t) = f(u(t-1), \dots, u(t-d), y(t-1), \dots y(t-d)) \tag{4}$$

3. Methodology

3.1 Optimization

Dynamic optimization was performed using RH strategy. Two forms of RH were compared; moving-end and fixed-end strategies. The objective function used in this study is optimizing a net present value (NPV) of the venture (Jansen *et al.*, 2009). The optimization variables are the various injection rates.

$$J_k = \left\{ \frac{\sum_{i=1}^{N_{inj}} r_{wi}(u_{wi,i})_k + \sum_{j=1}^{N_{prod}} \left[r_{wp}(y_{wp,j})_k + r_o(y_{o,j})_k \right]}{(1+b)^{\frac{t_k}{\tau}}} \right\} \Delta t_k \quad (5)$$

Here, N_{inj} and N_{prod} are the number of injectors and producers respectively. u_w, y_w, and y_o are water injection, water production and oil production rates respectively. The oil selling price, r_o was fixed at \$80/m^3 while water injection and production costs, r_w and r_{wp} were both fixed at \$5/m^3. The discount factor b was taken as 10% per year. The time interval is Δt_k at time t_k where k denotes the step.

There were five each of injection and production wells for the considered reservoir which were placed arbitrarily. Eight-year total production period was used for the two optimization cases with two years of sampling period. The prediction period of moving-end was also two years. The NPV was optimized using sequential quadratic programming (SQP).

3.2 Numerical Experiment for Identification

To obtain data for identifying the reservoir, a high fidelity model was created using Eclipse reservoir simulator. A stair case experiment was conducted by injecting various rates of water and fixing the producers bottomhole pressures at varying values over a period of 5,110 days at an interval of 730 days. The water injection rates were initially fixed at 500 m^3/day which were increased by 200 m^3/day twice and then to the peak of 1000 m^3/day. This was followed by a one-step decrease of 100 m^3/day and then a two-step decrease of 200 m^3/day to reach the minimum of 500 m^3/day. For the case of producers' bottomhole pressures, the minimum and maximum pressures were set at 3 and 9 bars respectively. There were 3 steps each of increment and decrement pegged at a value of 2 bars. These are shown for producer 1 and injector 1 in Figures 3 and 4 respectively.

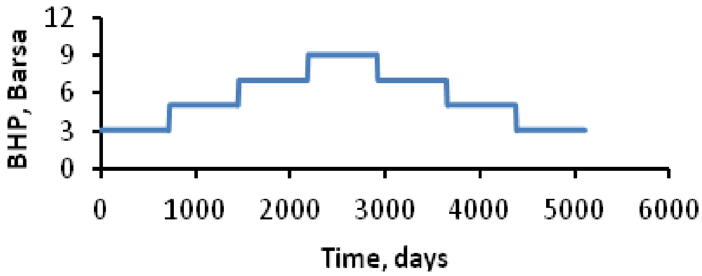

Figure 3: Producer BHP Experimental Input

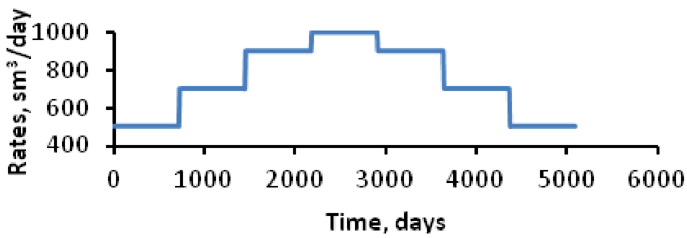

Figure 4: Injection Rate in m^3/day Experimental Input

3.3 Nonlinear Identification using Neural Network

The data collected from the numerical experiment were first processed into a form suitable for time-series identification. MATLAB neural network toolbox was used for the identification using NARX algorithms. The network has two layers. Different number of neurons in the hidden layer was tested ranging from 5 to 12 while fixing the number in the output layer to 10. The input and the feedback have two delays each. Sigmoid and linear transfer functions were adopted in the hidden and output layers respectively. Training of the network was performed using the Levenberg-Marquardt algorithms while performance of the network was computed using mean squared error (MSE). The data were divided into three parts for training, validation and testing.

4. Results and Discussion

4.1 Optimization

From Figure 5, it can be seen that water injection rates remain relatively constant for all the wells in the case of moving-end RH while there are considerable fluctuations for the case of fixed-end RH with peak attainment after 1460 days (4 years). The same pattern of flow is observed for oil production (Figure 6). The total amounts of oil and water productions are higher for moving-end than fixed-end RH (Figures 7 and 8). The difference in total oil production is 1.27 million m^3 and 4.5 million m^3 for water. This difference in production results to a NPV margin of $0.5 billion in favour of moving-end strategy as can be seen in Figure 9. In general, the computational time for this optimization is very high, in the order of days.

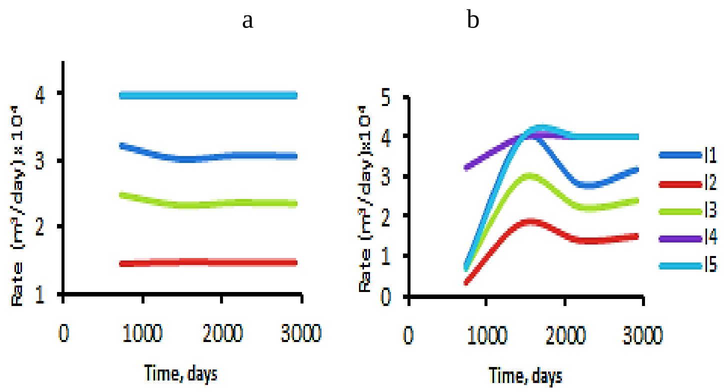

Figure 5: Injection Rates (a) Moving-end (b) Fixed-end

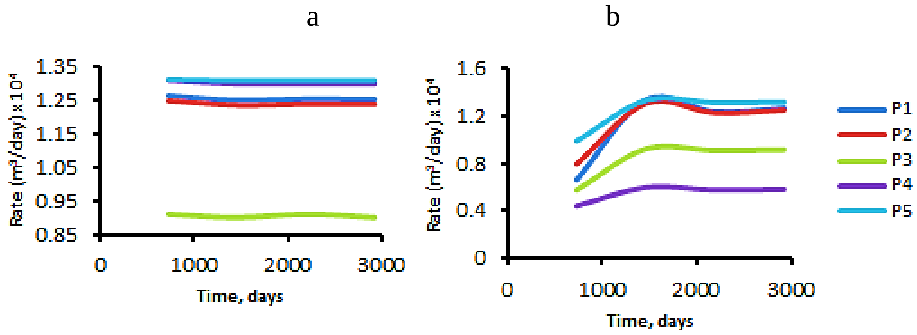

Figure 6: Oil Production Rates (a) Moving-end (b) Fixed-end

4.2 Identification

The stair case experiment performed using Eclipse is shown in Figures 10 and 11. It can be seen that both oil and water productions (outputs) responded to the changes in injection rates and producers bottomhole pressures.

a b

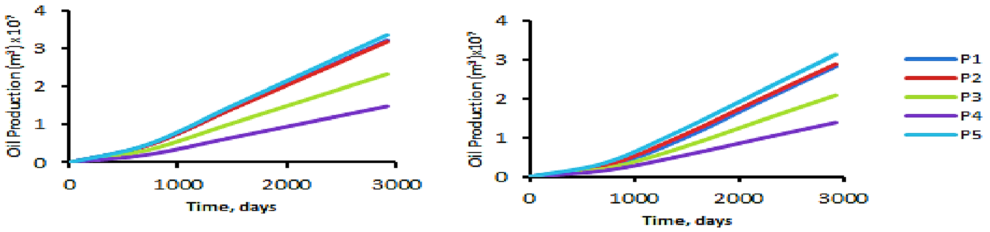

Figure 7: Total Oil Production (a) Moving-end (b) Fixed-end

a b

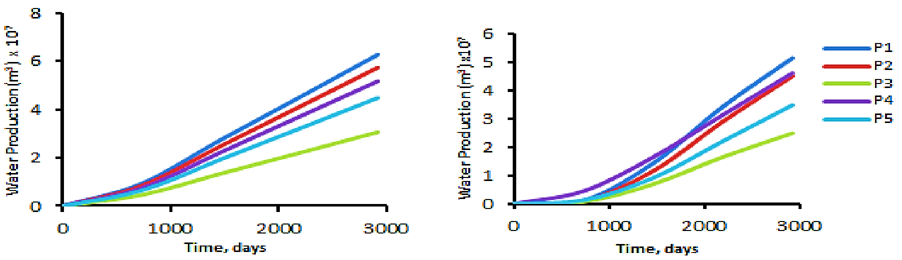

Figure 8: Total Water Production (a) Moving-end (b) Fixed-end

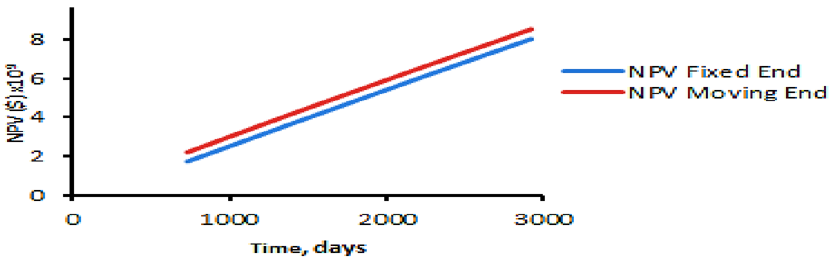

Figure 9: NPV Comparison for the Two Strategies

Hence, the obtained data show that they are good candidate for identification.

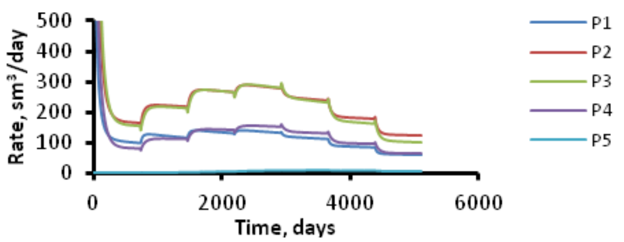

Figure 10: Oil Production Rates Experimental Outputs

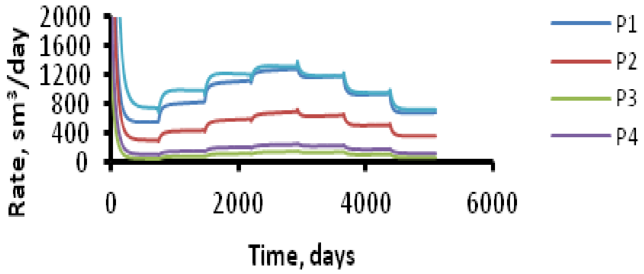

Figure 11: Water Production Rates Experimental Outputs

Figure 12 shows the network structure with 10 neurons each in the hidden and output layers. In Figure 13, the R-value is 0.9868 which shows a near perfect correlation. The time-series response is also seen in the figure where the targets, outputs and errors are shown. There are no much variations between the targets and the network outputs. The error line confirms this also.

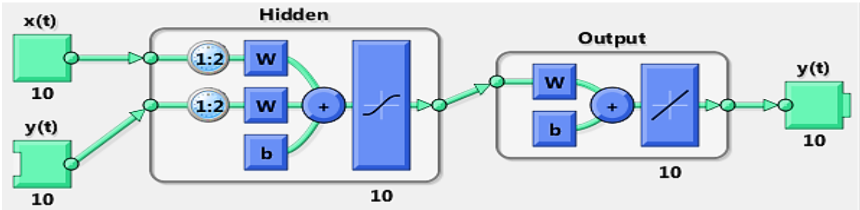

Figure 12: NARX NN Structure for the Reservoir Identification

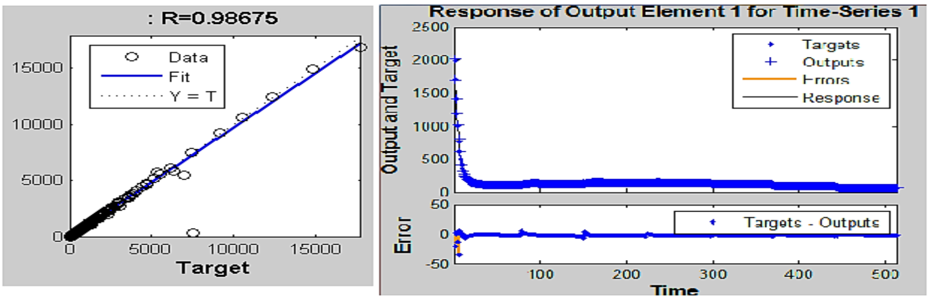

Figure 13: Regression and Time-Series Response

5. Conclusion

Two different forms of RH optimization on a realistic but synthetic reservoir from SAIGUP study group was carried out. The optimization considered water injection as a variable during waterflooding of the reservoir. Moving-end RH strategy gave a higher NPV than the fixed-end. Both high oil and water productions were recorded for the case of moving-end RH due to high water injection rates. The effect of high water production did not cause the NPV by this method (moving-end RH) to be less than that obtained by fixed-end RH due to high volume of oil production recorded.

Although the methodology appeared to be effective as far as dynamic optimization is concerned, it is however computationally prohibitive. This is because due to the complex nature of the physics-based reservoir models on one hand, and the multiple function evaluations required by the optimization algorithms on the other hand. For this reason, a NARX neural network was chosen to identify a reservoir model which can be used for subsequent studies. From the results obtained, the identified model showed a very good prediction power with negligible error and good R-value.

Acknowledgement

We acknowledge Schlumberger and SINTEF for the free licenses of ECLIPSE and MRST respectively.

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