SSRG International Journal of Recent Engineering Science
ISSN: 2349–7157 / https://doi.org/10.14445/23497157/IJRES-V8I3P101

Volume 8 Issue 3, 1-6, May-Jun, 2021

Original Article

Neural Network Based Performance Evaluation of a Waterflooded Oil Reservoir

Mahlon Marvin Kida[*1], Zakiyyu Muhammad Sarkinbaka[2], Abdulhalim Musa Abubakar[3], Aminullah Zakariyyah Abdul[4]

[1]*Department of Chemical Engineering, Faculty of Engineering, University of Maiduguri, Maiduguri, Nigeria.*
[2,4]*Department of Chemical Science, Faculty of Pure and Applied Science, Federal University, Wukari, Nigeria.*
[3]*Department of Chemical Engineering, School of Engineering and Engineering Technology, Modibbo Adama University of Technology, Yola, Nigeria.*

Received: 10 April 2021 Revised: 20 May 2021 Accepted: 01 June 2021 Published: 16 June 2021

Abstract *- In this paper, we considered the use of neural networks in the identification and prediction of a waterflooded reservoir consisting of eight injection wells and one production well with a 40% porosity. The data used for the non-linear identification was generated from a reservoir modelled in MATLAB Reservoir Simulation Toolbox (MRST). Likewise, in this study, the effect of the number of hidden neurons on the accuracy, Mean Squared Error and oil production prediction of the reservoir were investigated. The study asserted the efficacy of the neural networks as regards their predictive capacity. For the oil production rate, a mean squared error was recorded to be minimal for 2 hidden neurons as compared to the other three cases of neuron number. For water production rate, 8 hidden neurons were observed to be optimal compared to other cases. Oil and water production rate for a peak NPV value of 3 billion US dollars was recorded to be 2000m^3/day and 4500m^3/day, respectively. The response was optimal for all cases except for the net present value, which requires a more substantial amount of data for the neural network model.*

Keywords *- MRST, Artificial Neural Networks, Net Present Value, Oil Reservoir, Oil production, Water production.*

1. Introduction

Reservoir waterflooding is a secondary recovery technique used in the production of oil through the use of an enhanced pressure-driven state. This pressure-driven state is enforced by subjecting the reservoir to a waterflood, which in turn increases the reservoir pressure forcing the trapped oil to flow out to the surface [1]. This enhanced technique is applied when the reservoir pressure in its natural state has been depleted overtime due to early recovery. The waterflooding technique is commonly used due to its effectiveness and the fact that water is easily available and cheap to implement [2]. Due to large geological uncertainties in reservoirs, simulation models will greatly require more sophisticated prototypes so as to meet up with the geological intricacies [3].

Technological innovation has become increasingly prevalent in making scientific research more efficient and accurate. Reservoir engineers are faced with finding suitable tools that will enhance the productivity of oil, and as such, knowledge expansion on uncertain reservoirs is [4]. New ways of making oil recovery efficient and profitable have gained traction over the years. Such kind of technology, like the use of machine learning and deep learning, has become predominant in the oil and gas industry. Conventional techniques might pose a drawback in modelling approaches, especially when a more complex reservoir is studied [5]. In model processing, engineers are faced with constitutive data modelling problems, and this sometimes may result in trial and error estimation. But with the advent of function approximation, precision is identified, mostly in problems such as well log data, seismic surveys etc. [6].

Computational limitations have become one major challenge in identifying reservoirs, especially those with complex geological properties [7]. Investigating efficient production or Net Present Value might be rigorous and time taken. Monumental oil well data, rock and fluid properties will require extensive study for cases of modelling. However, sophisticated prototyped reservoir models might pose design intricacies due to geological uncertainties and modelling inaccuracies. This key limitation will require substantial computational techniques such as Artificial Neural Networks.

1.1. Artificial Neural Networks

Artificial intelligence is a field of computer science that mimics the behaviour of the human brain, not necessarily in its complete state but at some level of accuracy and usability [8]. Artificial Neural networks are basically mathematical structures depicting the biological neurons [9], used mostly in function approximation. Studies have shown that Engineering models have to be considerably less complex than the brain [10], and as such complex systems are easily identified.

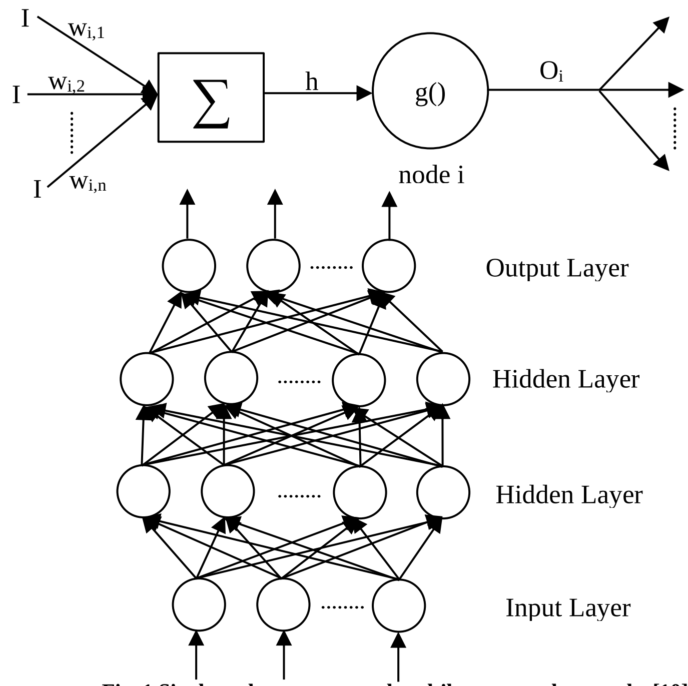

Fig. 1 Single node structure and multilayer neural networks [10]

Neural networks are able to fix data in an input and output fashion [11]. The earliest neural network is the perceptron network, designed by Frank Rosenbalt. It is made up of input and output layers, although the major setback of the perceptron model is that it is unable to model a non-linear system. Various neural network models have been designed for specific purposes. Such are the feed-forward neural networks used in most literatures [11]. Neural network is defined by its ability to model nonlinear systems without the use of an inherent model. Based on the stipulation by [12], a machine exhibits an autonomous ability when it is able to perceive, process and execute. These paradigms give neural networks their inherent ability to perform complex tasks efficiently without recourse to the underlying nature of the system being studied. Neural networks are identified based on their learning techniques [13], which are supervised and unsupervised learning. Supervised learning requires an input and output or target datasets, while unsupervised requires only the input datasets. It is mostly used in identifying discrepancies within data. Supervised learning is used in modelling regression problems, while unsupervised learning is used in modelling classification and clustering problems. Obtaining qualitative models is solely dependent on the inherent nature of available data [14].

Research papers on the application of artificial neural networks to oil reservoir systems have being identified by several authors. [9] applied artificial neural networks to model an oil and gas production rates as a function of measured pressure, injection and production data. [2] predicated a water flooding reservoir performance in stratified reservoirs by the use of a cheap corelation derived from a proxy model. Other predication techniques were observed and compared by reviewing their applicability.

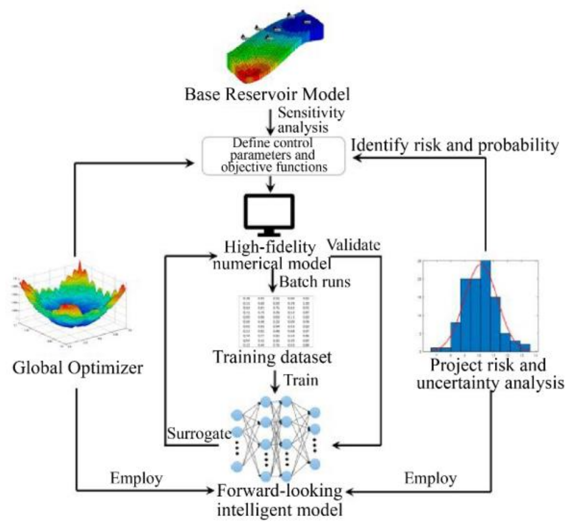

Fig. 2 General feedforward workflow model [6]

[15] applied a nonlinear Autoregressive with exogenous input (NARX) neural network model to identify a certain waterflooding reservoir for the purpose of optimization. [3] proposed a data-driven modelling approach to predict production efficiency by reducing computational and observational costs. The prediction was carried out as a function of heterogeneity and injection well placements. [5] applied artificial neural networks to predict reservoir porosity, saturation and lithofacies identification. [16] implemented the use of artificial neural network function approximation to address reservoir challenges such as reservoir fluid properties

in the absence of PVT analysis, average reservoir pressure and oil production prediction. [17] investigated a neural networks-based study on an oilfield situated at Stringtown, West Virginia, were the result of the simulation was compared with five years of actual field data. [18] applied artificial neural networks in predicting oil recovery and CO_2 storage capacity in residual oil zones, where the training data were generated from well operations, geological factors and parameter uncertainties.

In this paper, we considered the use of neural networks in the identification and prediction of a waterflooding reservoir. The data used for the non-linear identification was generated from a reservoir modelled in MATLAB Reservoir Simulation Toolbox (MRST). Likewise, in this study, the effect of the number of hidden neurons on the accuracy, Mean Squared Error and oil production prediction of the reservoir were investigated.

2. Methodology

The reservoir modelled in MATLAB Reservoir toolbox consists of a 400ft by 400ft by 100ft reservoir grid divided into 20 by 20 by 10 cells, respectively. 8 horizontal injection wells and 1 production well were used, where a permeability with a porosity of 40% was generated. The reservoir is heterogenous in phase, having both oil and water. Other reservoir properties specified were the fluid viscosity and density.

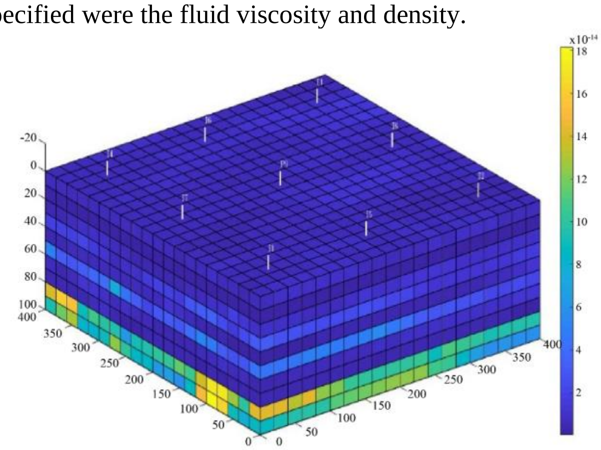

Fig. 3 Reservoir grid with permeability distribution

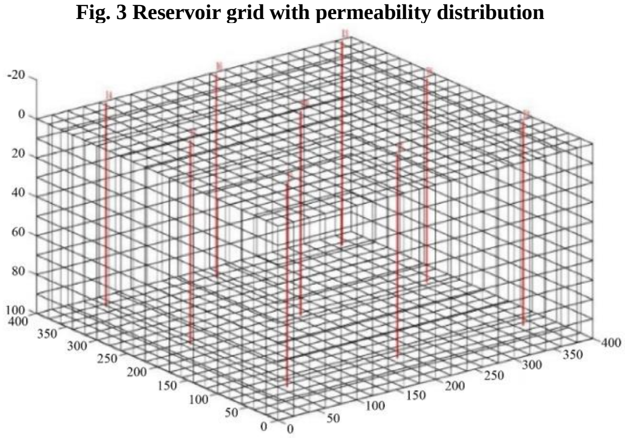

Fig. 4 Reservoir grid with wells

2.1. Neural Networks Configuration

There are different neural network models built for specific purposes. Such models can be the feedforward neural networks for regression or classification or recurrent neural networks for time series analysis. However, these models are inherent design limitations as a result of the nature of the data. For example, an autoregressive with Moving-Average (ARIMA) model cannot be used for nonlinear time series forecasting due to its linear nature. For such cases, the Non-linear Autoregressive with Exogenous Inputs (NARx) model is implemented. For situations where there is an estimate in error feedback, Non-linear Autoregressive Moving Average with Exogenous Inputs (NARIMAx) model is best suited.

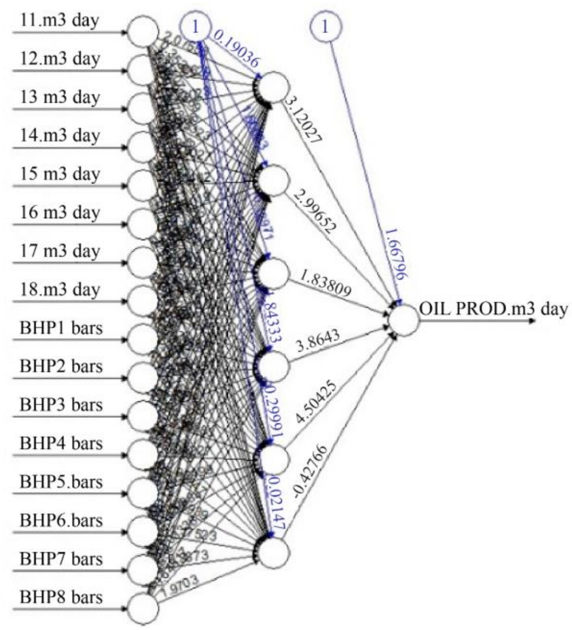

Fig. 5 Neural networks architecture for oil production

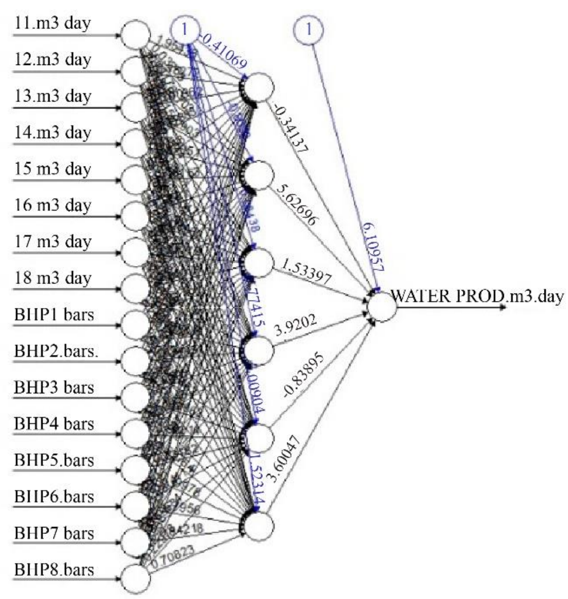

Fig. 6 Neural networks architecture for water production

For most reservoir engineering problems, the nature of data is time controlled, such that its approximation is intrinsic to time lags. Recurrent neural network is known for its dynamic and recursive driven condition. For our work, we implemented a NARx neural network architecture for non-linear identification.

A NARx model is a kind of recurrent neural network that operates on the bases of a feedback network [18]. The network's output is fed back into the network as the new input for a given time step. A nonlinear system is described by the equation:

$$y_t = f\left(y_{t-1}, y_{t-2}, \dots \dots . y_{t-p}\right) + \varepsilon_t \qquad (1)$$

were $f\left(y_{t-1}, y_{t-2}, \dots \dots . y_{t-p}\right)$ is the non-linear function mapping the previous observation to the next output. ε_t is the error at each estimated time interval. The recursive nature of a time series neural networks follows a differential equation given as: [19]

$$\tau \frac{dy_i}{dt} = -y_i + g\left(x_i + \sum_j w_{ij} v_j\right) \qquad (2)$$

Were τ denotes the time coefficient, x_i denotes the external input of the network, $g(\dots)$ denotes the activation function, y_i denotes the network's output, v_j denotes the output of the hidden neurons.
For the reservoir system, the well injection rates and bottom hole pressure for injection wells were used as the network's input data, while the well production rates, Net present value, and oil formation volume factor was used as the network's output data. Here, the first network has 2 hidden neurons, the second network has 4 hidden neurons, the third network has 6 hidden neurons, and the fourth network has 8 hidden neurons.

60% data was used for training, while 15% and 25% were used for validation and testing, respectively. The Levenberg – Marquardt training algorithm was used likewise.

3. Discussion of the Result

Figure 7 - 8 shows the neural networks performance variation of water production rate, oil production rate, Net present value and oil formation volume factor, respectively, with a change in the number of hidden neurons.

In Figure 5, the mean squared error recorded for the water production rate was seen to be slightly reduced with an increase in hidden neurons for the test and validation data, although the peak increase was not instantaneous for the validation data. A rapid error increase and decrease were recorded for the training data. At 4 hidden neurons, the error was slightly high, but with 8 hidden neurons, the error was reduced. The model accuracy was constant at about 99%, with an increase in hidden neurons.

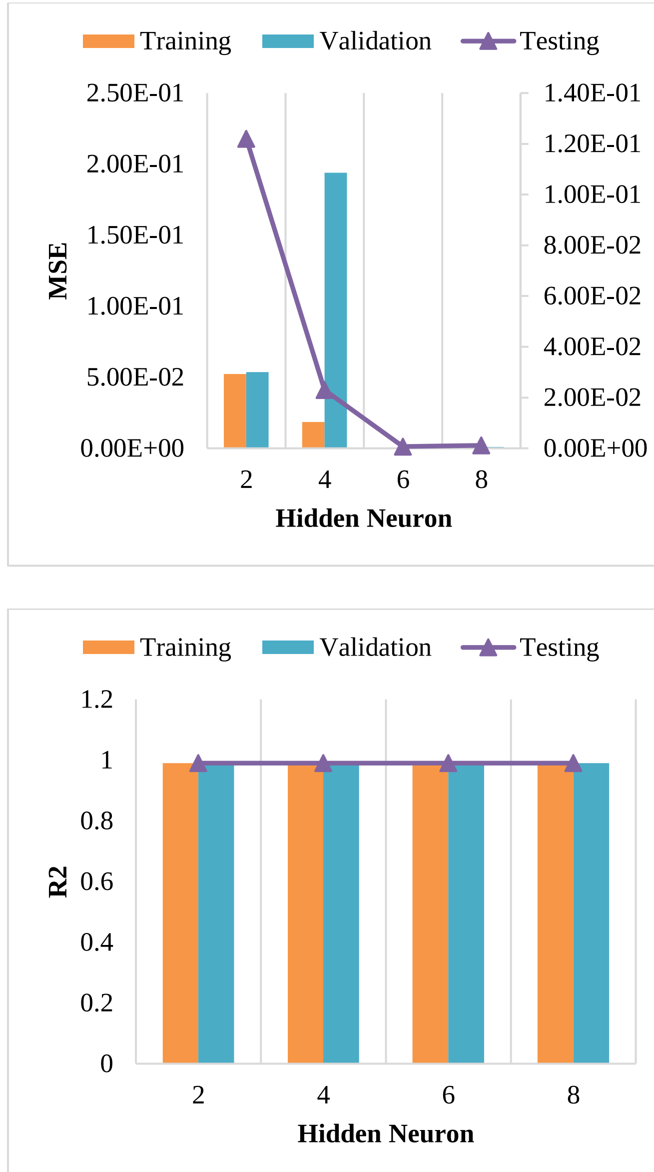

Fig. 7 Network's performance for water production rate

The oil production rate's network was shown to have a reduction in mean square error (Fig. 8). Although with 2 neurons, the test data was shown to have a greater error but subsequently reduced with more hidden neurons. The model accuracy was also shown to be 99% percent for the training, validation and test data, respectively.

Model accuracy is necessary for a good prediction. It requires extensive optimal formulation and generation of good data. Sometimes, data inaccuracies could pose a challenge in identifying proper model properties that depict the studied process. Nonlinear systems are complex to identify. No matter the flexibility of a neural network, if it is not properly modelled to suite the process data, it will equally produce poor results.

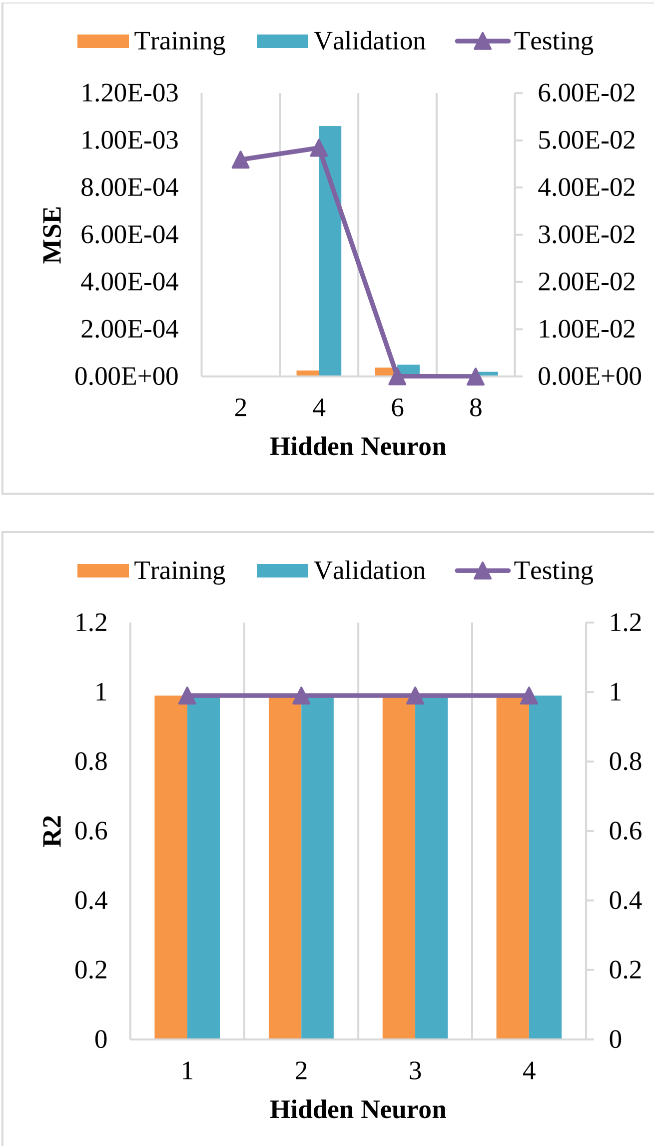

Fig. 8 Network's performance for oil production rate

The validity of the neural network was confirmed for the oil and water production rate. The neural network for oil and water production rate can be used and tested on future data due to its minimal error and good accuracy.

Minimal error was recorded for the water production rate for a simulation period of 450 seconds (Fig. 7). Random error value was also shown to be insignificant. This implies that the prediction accuracies of the model will be substantially high. The error variation for the oil production rate was obvious with minimal effect, which makes it good for prediction. The NPV response error was recorded as high for the first 50 seconds of simulation but reduced with more simulation time.

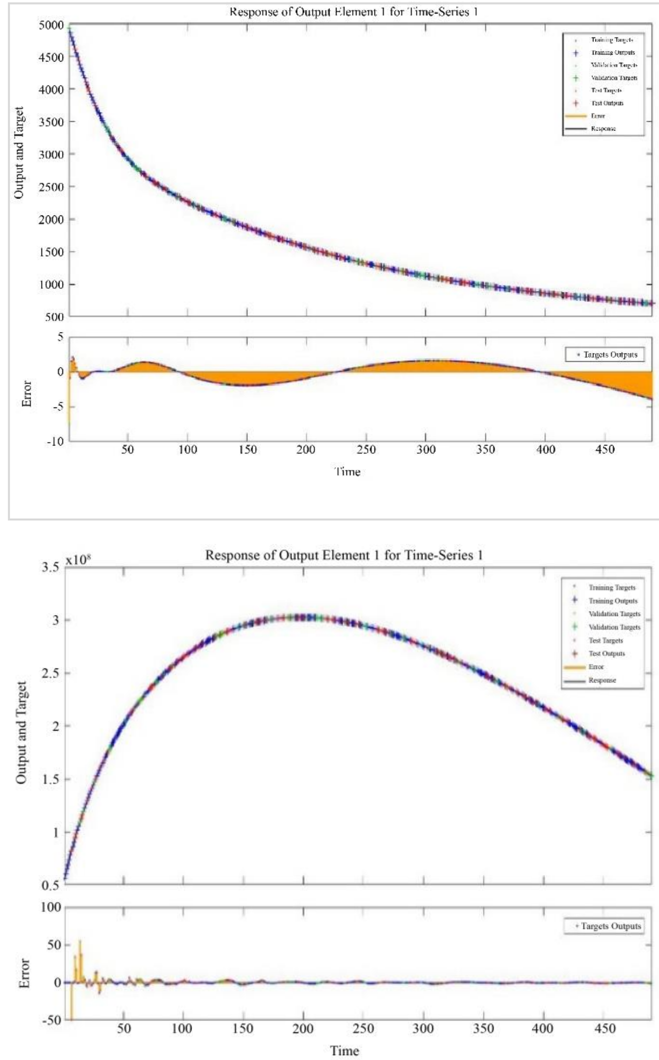

Fig. 9 Network's response to oil production rate and net present value, respectively (8 Hidden neurons)

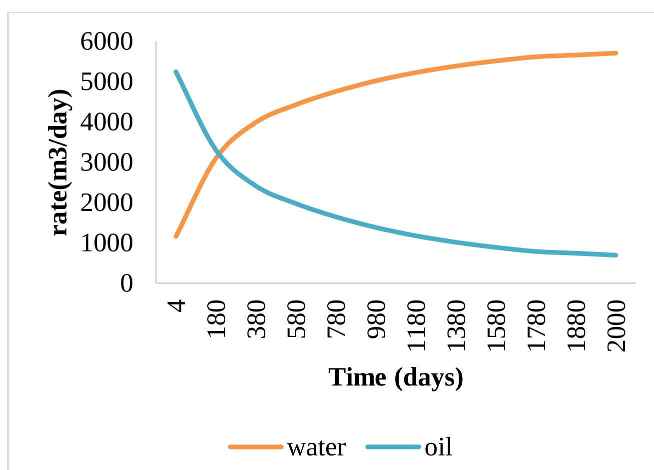

Fig. 10 Oil and water production rate

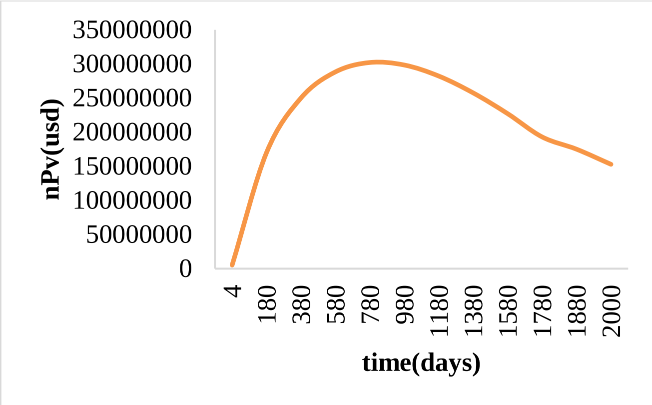

Fig. 11 Net present value

3.1. Reservoir Simulation

The reservoir simulation results are given in Figure (10 - 11). More production time might, in some cases, reduce the economic value of the reservoir, possibly due to depleting oil rate in the reservoir. This implies that production time will be reduced for a reservoir with the given configuration. A Peak NPV value of 800 million dollars was recorded at a period of about 850 days but began decreasing exponentially. For the NPV, no cumulative was taken.

The oil production rate is recorded to be 2000 m^3/day for the next 1000 days and later began decreasing due to depleting reservoir bottom hole pressure. However, neural networks will require a large amount of data to validate the efficacy of the reservoir in terms of its net present value and oil and water production rate.

4. Conclusion

A waterflooding reservoir was studied, and data were generated and used for neural network modelling. Significant model accuracy was recorded for 500 simulation data points consisting of the injection rates for all wells, oil and water production rate, net present value, and oil and water formation volume factor.

The neural network was found to be effective for the studied data but might require a large dataset to improve the prediction efficacy of the reservoir. Complex reservoirs will require a more sophisticated neural network. The model simulation showed that with more large data, more hidden neurons might be needed. Future studies should be carried out on the optimal analysis of the neural network that consists of monumental datasets.

References

[1] Jude Emeka Nwaozo, "*Dynamic Optimization of a Water Flood Reservoir*," MSc Thesis, Mewbourne School of Petroleum and Geoligical Engineering, University of Oklahoma, 2006. [Google Scholar]

[2] Ahmed I. Omar, Zhangxing Chen, and Abdulhadi E. Khalifa, "Predicating Water-flooding Performance into Stratified Reservoirs using a Data Driven Proxy Model," *Journal of Petroleum and Gas Engineering*, vol. 8, no. 7, pp. 60-78, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[3] Xinwei Xiong, and Kyung Jae Lee, "Data Driven Model to Optimize the Injection Well Placement for Waterflooding in Heterogeneous Reserviors Applying Artificial Neural Networks and Reducing Observation Cost," *Energy Exploration & Exploitation*, vol. 38, no. 6, pp. 2413–2435, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[4] Mohammad Ali Ahmadi et al., "Determination of Oil Well Production Performance Using Artificial Neural Network (ANN) Linked to the Particle Swarm Optimization (PSO) Tool," *Petroleum*, vol. 1, no. 2, pp. 118–132, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[5] M. Hamada Ghareb, Elsakka Ahmed, and Y. Nyein Chaw, "Artificial Neural Network (ANN) Prediction of Porosity and Water Saturation of Shaly Sandstone Reserviors," *Advances in Applied Science Research*, vol. 9, no. 2, pp. 26–31, 2018. [Google Scholar] [Publisher Link]

[6] Turgay Ertekin, and Qian Sun, "Artificial Intelligence Applications in Reservoir Engineering: A Status Check," *Energies*, vol. 12, no. 15, p. 2897, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[7] Udy Jackson et al., "Review of Field Development Optimization of Waterflooding, EOR, and Well Placement Focusing on History Matching and Optimization Algorithm," *Process*, vol. 5, no. 34, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[8] Rene Y. Choi et al., "Introduction to Machine Learning, Neural Networks and Deep Learning," *Translational Vision Science & Technology*, vol. 9, no. 14, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[9] Berihun Mamo Negash, and Atta Dennis Yaw, "Artificial Neural Network Based Production Forecasting for a Hydrocarbon Reservior Under Water Injection," *Petroleum Exploration and Development*, vol. 47, no. 2, pp. 383–392, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[10] David M. Himmelblau, "Application of Artificial Neural Networks in Chemical Engineering," *Korean Journal of Chemical Engineering*, vol. 17, no. 4, pp. 373–392, 2000. [CrossRef] [Google Scholar] [Publisher Link]

[11] Zhihao Zhang et al., "Real Time Optimization and Control of Non-linear Processe Using Machine Learning," *Mathematics*, vol. 7, no. 10, pp. 890–915, 2019. [CrossRef] [Publisher Link]

[12] G. Rzevski, "Artificial Intelligence in Engineering: Past, Present and Future," *WIT Transactions on Information and Communication Technologies*, vol. 10, 1995. [CrossRef] [Google Scholar] [Publisher Link]

[13] Ehsan Amirian, and Zhangxing John Chen, "Cognitive Data Driven Proxy Modelling for Performance Forecasting of Waterflooding Process," *Global Journal of Technology & Optimization*, vol. 8, no. 1, pp. 1-8, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[14] Robert J. May et al., "Non-linear Variable Selection for Artificial Neural Networks Using Partial Mutual Information," *Environmental Modelling & Software*, vol. 23, no. 10-11, pp. 1312–1326, 2008. [CrossRef] [Google Scholar] [Publisher Link]

[15] A. S. Grema et al., "Optimization and Non-linear Identification of Reservior Water Flooding Process," *Arid Zone Journal of Engineering, Technology and Environment*, vol. 13, no. 5, pp. 610–619, 2017. [Google Scholar] [Publisher Link]

[16] E. Saber Khaled, "*Application of Function Approximations to Reservoir Engineering,"* Degree of Doctor of Philosohpy in Process Systems Engineering, University of Regina, 2012. [Google Scholar] [Publisher Link]

[17] G. Edison, "*Improving the Simulation of a Waterflooding Recovery Process Using Artificial Neural Networks,"* MSc Thesis Submitted to the College of Engineering and Mineral Resources, West Virginia University, Morgantown, West Virginia, 2000. [Google Scholar] [Publisher Link]

[18] Sandhya Samarasinghe, *Neural Networks for Time series forecasting, in Neural Networks for Applied Sciences and Engineering : From Fundamentals to Complex Pattern Recognition,* Auarbach publications, Taylor and Francis Group, 2006. [Google Scholar]

[19] Daniel Graupe, *Principle of Artificial Neural Networks*, 3rd edition, Singapore: World Scientific Publishing Co. Pte. Ltd, 2013.[Google Scholar]