

The Successful Prediction of Waterflooding Using a Feed-Forward Algorithm

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Abstract – Waterflooding is one of the most frequently used Enhanced Oil Recovery (EOR) methods to increase oil recovery because it can increase 30% -60% of total production. It is necessary to apply a production system performance prediction approach to minimize uncertainty in increasing production figures, such as analytical and numerical methods. Artificial Intelligence in oil and gas is not new, but it has often been used in various fields such as exploration, drilling, production, and reservoirs. This is the basis for the Prediction of the success of waterflooding research carried out. This research aimed to predict the success rate of waterflooding using an Artificial Neural Network (ANN). The method used in this study is the simulation research method using CMG Imex for reservoir simulation modeling, running CMG CMOST for 500 sensitivity data with the input of seven parameters of compressibility, horizontal permeability, vertical permeability, pressure injection, injection rate, thickness, oil saturation, and the output is recovery factor using Artificial Neural Network (ANN) with a ratio of 70% of calculation model results for training and 30% model results for testing. In order to get optimal prediction results, trial, and error were carried out on the number of hidden layer nodes so that optimal and stable hidden layer nodes were obtained at node 10 with RMSE values of 0.339035 for training and 0.442663 for testing and MAPE for training 1.15% and 1.62% for testing. The statistical analysis value is 0.906139 for training and 0.899525 for testing data. It can be concluded from this study that the use of ANN in predictions using ten hidden layer nodes proved to be very good and successful, and predictions in this study were classified as highly accurate Predictions.

Keywords: Waterflooding, Artificial Intelligence, ANN, Prediksi, Feedforward

Introduction

Because reservoir pressure will continue to fall over time, it stands to reason that well production performance will suffer. The Enhanced Oil Recovery (EOR) method, which is a method with great prospects for oil recovery after primary recovery and secondary recovery, is one way to increase the production flow rate, which has decreased (Novriansyah & Khalid, 2016). This is consistent with the viewpoint (Alhuthali et al., 2006) that waterflooding is the primary method of secondary recovery utilized most frequently to boost production. The findings of (Li et al., 2020) The use of waterflooding in this area has a complicated process mechanism and multiple phenomena that affect it simultaneously, making it even more complicated. It is common practice in the oil and gas industry to anticipate outcomes and conditions prior to or following the execution of a wells work program in order to reduce the likelihood of failure or loss (Negash & Yaw, 2020). There are numerous analytical and numerical approaches to predicting the performance of oil production systems; however, when the prediction results are contrasted with actual field data, there are significant estimation errors and deviations. A comprehensive description of the reservoir and field fluid properties is required for the conventional oil and gas production prediction methods that are currently in use (Negash & Yaw, 2020). Because of the numerous operational uncertainties inherent in its application, efforts must be made to reduce the likelihood of failure and uncertainty. According to Jia & Zhang (2016), the ANN approach model is able to make predictions that are significantly more accurate than those made by the conventional empirical model.

According to (Shokir et al., 2002), the technique based on artificial neural networks can efficiently be used to predict the screening of various EOR methods based on field characteristics and evaluate technical implementation. An Artificial Neural Network (ANN) makes it possible for petroleum engineers to precisely select the EOR method that best suits the characteristics of the reservoir. This is consistent with the findings of (Ahmadloo et al., 2010) that the viscosity ratio, permeability, formation volume factor, reservoir depth, porosity,

initial gas/oil ratio, injection rate, initial reservoir pressure, and developed areas are the most important reservoir parameters in waterflooding.

Popa et al., (2017) use an artificial neural network and the backpropagation algorithm to predict waterflooding performance with a high accuracy (R^2) of 0.93. As can be seen from the preceding explanation, using an artificial neural network to make predictions simplifies the processing steps. This is in line with research conducted by Negash Yaw (2020), which found that using an artificial neural network to make predictions can improve both the efficiency of time spent and the level of accuracy of predictions made by methods that include complex predictions. So that researchers are interested in using one of the well-known Artificial Intelligence (AI) methods to analyze the parameters of waterflooding compressibility, horizontal permeability, vertical permeability, pressure injection, injection rate, thickness, oil saturation, and output in the form of recovery factor to predict the success of waterflooding. Using an Artificial Neural Network (ANN) to demonstrate how these parameters affect the flood's success. In addition, reservoir simulation with CMG IMEX, which is used for modeling, and CMG CMOST is utilized in this study to determine the sensitivity and running data of the established parameters.

According to Carpenter (2019), Artificial Intelligence is a process that derives its inspiration from the concept of understanding. In this process, the human brain and the computer work together to create a solution for a currently used system by utilizing input data from engineers or geoscientists. Artificial Intelligence has had a significant impact on a variety of business operations. According to Braswell (2013), five Artificial Intelligence methods can be used to simulate reservoirs, optimize production and packaging, optimize packaging, and control processes. (Aminian and others, 2019) on the use of ANN as an alternative to data-based models for predicting reservoir heterogeneity waterflooding. The purpose of this study is to identify relevant parameters for the Prediction of waterflooding in heterogeneous reservoirs. Based on a study (Xiong & Lee, 2020), ANN was used to predict the impact of a secondary recovery method, such as waterflooding in a heterogeneous reservoir. Popa et al. conducted a similar study, (2017) in which fluid properties, reservoir characteristics, and the design of operations for the distribution of water injection in an accurate surface network were used to model the performance of the distribution of water injection or to waterflood at the Lost Hills oil field. And efficient. A second related study by (Aminian et al., 2000) increased production in the West Virginia oil field by 25% using the Waterflooding recovery method by predicting permeability in complex formations using artificial neural networks. There are layers of neurons. An input layer, one or more hidden layers, and an output layer typically make up multilayer networks. According to Mohaghegh & U, 2000.

Temizel et al. (2020).) say that a learning approach is based on artificial neural networks and is influenced by the arrangement of neurons like those in the human brain. In addition, this method uses models with multiple layers and multilayer arrays to process and obtain data representation information at various levels of the data learning process (Temizel et al., 2020). An *artificial neural network* is a typical interconnection that functions as a multiplayer structure. The Feed Forward Neural Network (FFNN) is a model that is used more frequently among the various neural network models because it is known to have good approximation capabilities and is universal (Kurniawan, 2017). According to Nisa Afida Izati and Budi Warsito (2019), one of the main types of neural networks is the Feed Forward Neural Network (FFNN), and the FFNN method is the one that is used the most frequently for making predictions. Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) are two prediction evaluation parameters used to assess the accuracy and forecasting of model performance (Sari, 2018). is in line with the opinion (Janiaga, 2018) that the selection of MAPE and RMSE values the smallest is the selection of the best model, in which the model's performance will improve as the error value is small. The predicted MAPE (average absolute percentage error) is estimated as the average absolute percentage error. Function evaluate the evaluation parameters (Sari, 2018):

1. Root Mean Squared Error (RMSE)

Root Mean Square Error is a squared scoring rule that also measures the magnitude of the average error. The square root of the average of the squared differences between the predictions and the actual observations.

$$RMSE = \sqrt{\frac{\sum (Actual - Prediction)^2}{n}} \quad (1)$$

2. Mean Absolute Percentage Error (MAPE)

Mean Absolute Percentage Error is the most common measure of forecast error. The MAPE function is best when no extreme numbers exist in the data.

$$MAPE = \frac{\sum \frac{Actual - Prediction}{Actual} \times 100}{n} \quad (2)$$

According to Vivas' research in 2020, the percentage of MAPE values is categorized into several groups, as shown in Table 1. The predicted MAPE (average absolute percentage error) is estimated as the average absolute percentage error.

Table 1. Parameters MAPE

No.	MAPE %	Prediction Capability
1	< 10	Highly accurate Prediction (HAP)
2	10-20	Good Prediction
3	20-50	Reasonable Prediction
4	>50	Inmacurate Prediction

Source : (Vivas et al, 2020)

According to the literature review that the researchers have described above, using an Artificial Neural Network (ANN) to predict the success of the waterflooding method is very effective at minimizing the risk of failure. Therefore, the researchers approached the problem by employing a different algorithm, the Feed Forward Algorithm, whose use in predicting the success of waterflooding still needs to be improved.

Materials and Methods

This study was carried out at Riau Islamic University's Reservoir Simulation Laboratory, Faculty of Engineering, Petroleum Study Program. Secondary data were used. Using the CMG simulation software and the Python programming language, this study uses a combination of reservoir simulation and python programming language. Compressibility, horizontal permeability, vertical permeability, thickness, injection pressure, injection rate, and oil saturation with output Recovery Factor were tested in this study. Reservoir simulation is the mathematical modeling or imitation of a reservoir model so that future reservoir conditions can be predicted (Gunawan et al., 2018). Rock and formation properties are the data Table 2 needed to create a reservoir model.

Table 2. Characteristics of the Western Canadian Field Reservoir

Reservoir Data		
Rock Type	Carbonate	
Buble Point	4021	Psi
Density of water and oil	63	lb/ft ³
Porosity, Fraction	0.15	-
Reservoir Thikcness	250	Ft
Temperature of Reservoir (°F)	273	°F
Pressure of Reservoir (Psi)	4271	Psi
Reservoir Depth (feet)	8000	Feet
Rock Compresibility	5 x 10 ⁻⁶	1/psi
Water oil Contact (WOC)	8500	ft
Rock Wettability	Water wet	-

Source : (Kalam et al., 2021) (Xiong & Lee, 2020)

Reservoir Simulation Model

The CMG (IMEX) software was used to model the carbonate reservoir five wells in this study, which each have four injector wells and one producer well with the Normal-Five Spot pattern (Figure 1). Imuokhuede et al. say that in 2020), the purpose of modeling injection patterns like the standard 5-spot, 7-spot, and 9-spot is to assess the impact of reservoir water or oil saturation. The output of this reservoir model is the 500 data used in the prediction process using Network Artificial Neural (ANN) with a ratio of 70% model calculation results for training and 30% model results for testing.

The 5-spot injection pattern yields the best cumulative production results in shallow and diverse reservoir conditions. This is consistent with previous research (Jason et al., 2020) With an RF value of 30.18%, the adjusted usual five-spot injection method is the most effective for field X.

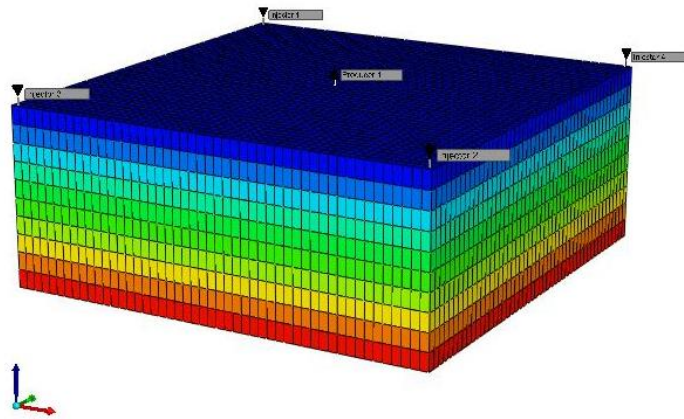
Table 3. Data Setting Parameters

Properties	Unit	Value	
		Lower Limit	Upper Limit
Compressibility	$\times 10^{-6}/\text{psi}$	0.1	18
Injection Rate	Bpd	0.72	4200
Injection Pressure	Psi	1800	2200
Thickness	ft	180	1000
Horizontal Permeability	mD	6.52	4500
Vertical Permeability	mD	1.08	2555
Oil Saturation	ha	0.1	0.75

Table 4. Reservoir model architecture

Parameter	Value
Waterflood pattern	5-Spot
Quarter pattern unit area, acres	132.23
Number of layers	10
Permeability in X direction, mD	1500
Permeability in Y direction, mD	1500
Permeability in Z direction, mD	100

The model in this study was made using CMG (IMEX) software, where the carbonate reservoir consists of 5 wells consisting of 4 injector wells and one producer well with the Normal-Five Spot pattern. Carbonate reservoirs generally have different porosity, permeability, or depth values, thus showing different colours in the reservoir model.

**Figure 1.** Model Reservoir

Reservoir Model Initialization

The initialisation results are based on reservoir properties and rock properties data from field X.

Table 5. Initialization Model

Parameter	Satuan	Nilai
Total Oil in Place	STB	2.7913E+08
Total Water in Place	STB	3.729E+07
Total Gas in Place	SCF	1.0150E+11

Results

The use of artificial Intelligence (AI) to predict success or even calculate the increase in the Recovery Factor's value has been the subject of numerous studies demonstrating that ANN is more efficient and quicker than other AI methods. Using the Artificial Neural Network method and the Feed Forward Neural Network (FFNN) algorithm, this study aims to either simplify the calculation of the Recovery Factor value for influencing parameters or predict whether waterflooding will be successful. This research flow begins with Reservoir modelling carried out with CMG Imex software with architectural data input of the reservoir model Table 4 and obtaining the initialization of the model and obtaining the results according to Table 5, after that the sensitivity of the data is carried out with CMG Cmost with the lower and upper parameters determined according to the Table 3, (the process of inputting parameter data is shown in Figure 2) then 500 data are formed.. The results of this run were then randomly and evenly sampled to get a representative data sample, and then the data were taken to be used to predict RF values with ANN FFNN.

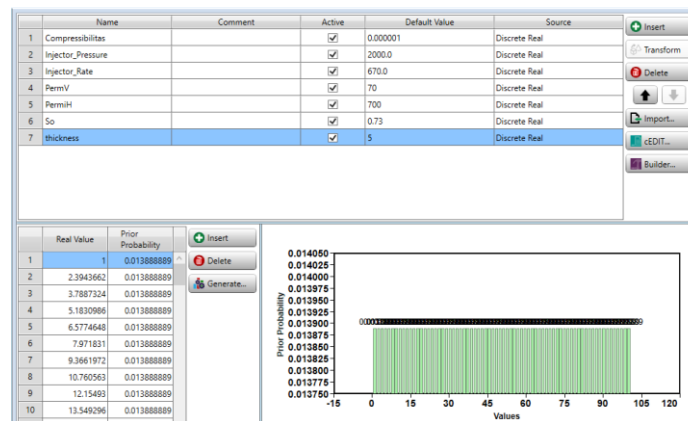


Figure 2. Setting Parameters at CMOST

Based Result of CMOST Sensitivity Test (Figure 3) demonstrates that the interaction between thickness and water injection pressure has the most significant impact on the success rate of water injection and the determination of fluid and oil mobility ratios (Rezaei et al., 2020) and that as the thickness 48% grows, so does the required injection pressure. This is consistent with previous research (Iqbal et al., 2017) that reservoirs with a thin net thickness will have issues with water injection in terms of water pressure and injection rate. That slight pressure and injection rate frequently result in less than more recovery.

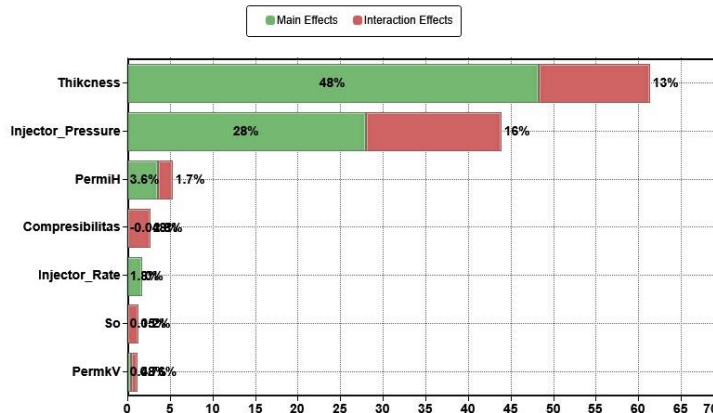


Figure 3. Prediction Results of CMOST Sensitivity Test

Anaconda Software, a Python-based application, and the Feed Forward Neural Network (FFNN) AI method are utilized in this study. The Python programming language, one of the relatively new programming languages of today, is a multipurpose interpretive language, according to Syahrudin & Kurniawan (2018). This programming language makes writing programs more manageable and takes less time. Each program will need

input and output results. In the studies that have been carried out (Chamidah et al., According to 2016), the input of an input dataset is the first step in developing the ANN programming language. After that, to normalize the output, data normalization is performed using a range of output values between 0 and 1. According to his research (Noureldien & El-Bambi, 2015), a good ANN model is created through trial and error, which is intended to determine the hidden layer's optimal number of nodes.

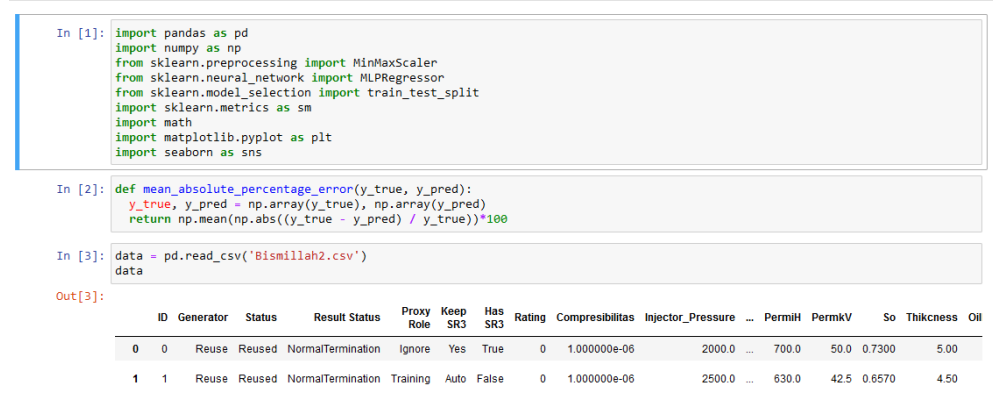


Figure 4. Setting Number of Nodes

In order to obtain 500 scenario data and the predicted data distribution using ANN FFNN, Figure 4 input parameters on the CMG CMOST require a 70 % of training and testing data 30% as the result of research (Shafiei et al., 2013). Whereas data testing is used to predict and measure the validation of the model's accuracy, data training is used to build and form data. RSME, R^2 , and MAPE values will be provided by each testing data and training data. The values of R^2 , RMSE, and MAPE will be affected by the number of hidden layers. Using a number of layers of 10 and trial and error, this study was conducted. The running results from the values of R^2 , RMSE, and MAPE using 500 datasets and a range of hidden layer nodes from 3 to 10 are presented in Table 6. The lowest MSE value will then be sought on training and testing data. The coefficient determination (R^2), which is the relationship between actual data and predictive data, demonstrates one level of data accuracy. The optimal value for hidden layer 10 was found to be 0.899525 for testing data and 0.906139 for training data in this study.

Table 6. Mean Square Error (MSE) and coefficient determination (R^2) values for different hidden layer nodes using 500 data.

The number of nodes in the hidden layer	R^2		RMSE		MAPE	
	Training	Testing	Training	Testing	Training	Testing
3	0.8906779	0.9154953	0.421143	0.366603	1.363064	1.268789
4	0.8906392	0.8451251	0.414995	0.515396	1.469261	1.722204
5	0.9040722	0.8484435	0.418256	0.416359	1.451774	1.409608
6	0.917590	0.8737312	0.363144	0.457977	1.231609	1.489910
7	0.917113	0.8651015	0.370886	0.4530733	1.243464	1.416860
8	0.903651	0.877257	0.403923	0.418801	1.297285	1.473380
9	0.926603	0.839540	0.361700	0.442663	1.173373	1.371404
10	0.906139	0.899525	0.339035	0.495983	1.151365	1.623697

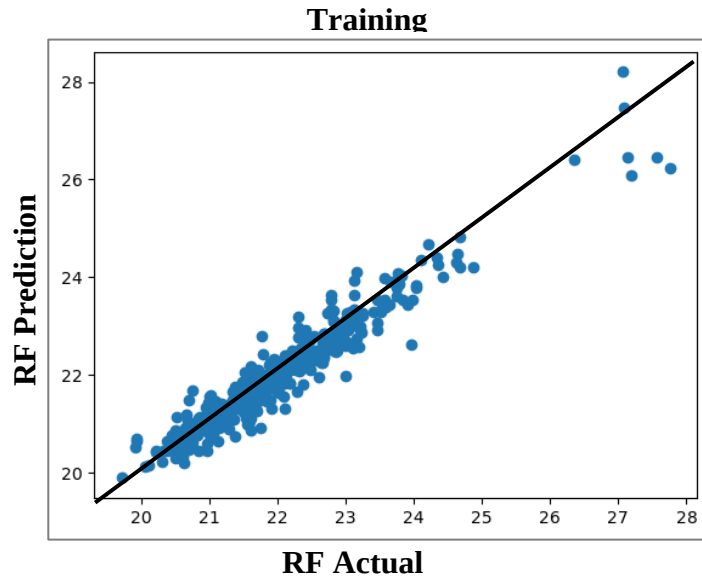


Figure 5. Coefficient of determination (R^2) 0.906139 between actual and predicted RF values of training data with 10 nodes layer.

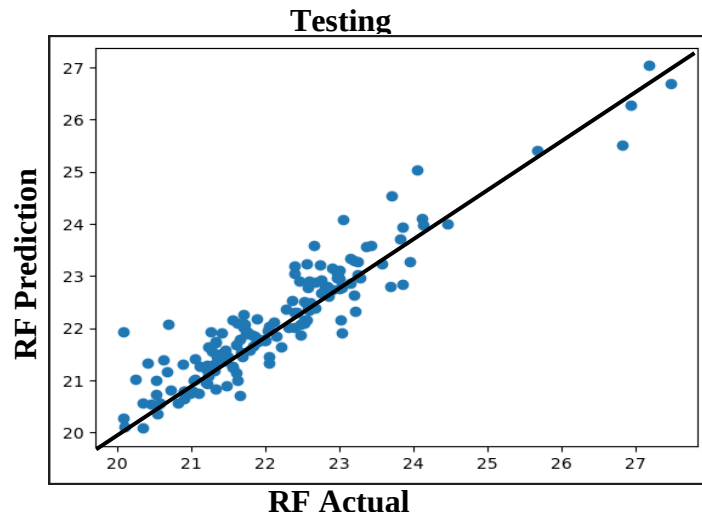


Figure 6. Coefficient of determination (R^2) 0.899525 between Actual RF and predicted RF values of testing data with 10 nodes layer.

Discussion

This study found that even though many nodes were created, there were still a lot of empty nodes and much optimal output. However, this resulted in a long day of data training and testing. The relation measured by RMSE and MAPE is comparable to that measured by the coefficient of thermal expansion (R^2). According to Wahyu Widayati (2013), when MSE is set to 0, and R^2 is set to 1, there is no correlation between output and Prediction. However, when R^2 is set to 1, there is no correlation. This is supported by the fact that MAPE (Mean Absolute Percentage Error) is used to calculate the ratio of absolute percentage to rata (Maricar, 2019). (Margi 2015) states that MAPE is a measurement of error that calculates the proportion of deviation sizes between actual data and forecasted data. Forecasting ability is very good if it has a MAPE value of less than 10% and has good forecasting ability if the MAPE value is less than 20%. According to (Vivas et al., 2020), "Forecasting Ability" is more

favorable if the MAPE value is less than 10%. In comparison, "Forecasting Ability" is more favorable if the MAPE value is more excellent than 20%.

Figure 5 and Figure 6 shows that the error values are 0.906139 and 0.899525, used for training and research testing data, each of which does not reach 1%. Shows that the accuracy of ANN modeling is considered good. This follows the opinion (Hammoudi et al., 2019), which states that the model used in this study has an almost perfect statistical correlation with an R-value close to the number "1". The data is a consistent simulation result, which makes it useful for ANN modeling. This shows that the prediction results of the FFNN ANN model in this study are pretty accurate and are almost identical to the prediction results of the CMG model in calculating the recovery factor. Based on this study, net thickness is the parameter that most influence the success of waterflooding or recovery factor. In contrast, the net thickness of the net will face the problem of water injection related to injection rate and injection pressure. Lower injection rates and injection pressures often lead to less-than-optimal waterflooding implementations.

Conclusion

Based on the results and discussion in this study, the conclusions are that the factors and parameters that have the most influence on the use of the water flooding method are a thickness of about 48% followed by an Injector Pressure of 28%. Implementing the Artificial Neural Network method for predicting the success of waterflooding results in a very high, effective and accurate validation. It is proven by analyzing 500 data samples using 11 hidden layer nodes. The RSME value for training is 0.339035, and for testing is 0.495983. The MAPE value is 1.151365 for training data and 1.623697 for testing data. The results of this Prediction are included in the High Accurate Prediction (HAP).

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