Vol. 10(2), pp. 14-22, March 2019
DOI: 10.5897/JPGE2018.0299
Article Number: 533242B60367
ISSN: 2141-2677

http://www.academicjournals.org/JPGE

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Journal of Petroleum and Gas Engineering

Full Length Research Paper

Prediction of the water saturation around wells with bottom water drive using artificial neural networks

Muhammad Alrumah[1]* and Turgay Ertekin[2]

[1]Public authority for Applied Education and Training, Kuwait.
[2]Institute for Turgay Ertekin is Pennsylvania State University, USA.

Received 1 October, 2018; Accepted 28 January, 2019

This study is concerned with the water coning phenomenon that takes place around production wells of hydrocarbon reservoirs. In this paper, the development of artificial neural networks to predict the water saturation buildup around vertical and horizontal wells with a good level of accuracy is described. In the development of expert systems, it is assumed that water encroachment originates from an active aquifer which is located under the hydrocarbon reservoir (reservoir with bottom water drive). A high-fidelity numerical model is utilized in generating training data sets that are used in structuring and training the artificial neural networks. The artificial expert systems that are developed in this paper are universal and are capable of predicting the change of water saturation around the wellbore as a function of time and the prediction process is faster than a reservoir simulator and requires less data, which saves time and effort. With the help of these models, it will be possible to predict the position of high water saturation zones around the wellbore ahead of time so that remedial actions such as closing the perforations that produce the water can be implemented on a timely basis.

Key words: Bottom water drive, water coning, neural network, water saturation, vertical well, horizontal well.

INTRODUCTION

Many hydrocarbon reservoirs contain an active water aquifer. The drilled wells are always completed to produce only hydrocarbons. As oil production continues, water starts to appear in the wellbore. This water is undesirable as its presence around the wellbore decreases the well productivity and needs more facilities to be handled, treated and disposed of at the surface resulting in extra investments and operating costs. The height of the water cone stops increasing if the upward dynamic flow forces become equal to the downward gravitational forces. The water will be produced once the height of the water reaches the wellbore. By continuing to produce the hydrocarbon with water, formation around the wellbore will be saturated with water in the shape of a cone, a phenomenon that is referred to as water coning. This study analyzes the water coning phenomenon. The water coning behavior has significant importance in hydrocarbon production, and the ability to predict its future behavior will improve and help in better managing reservoirs experiencing water encroachment. The behavior of the water coning in an oil reservoir is predicted successfully using Artificial Neural Networks (ANN) by predicting the change of the water saturation distribution in the reservoir over time, and the prediction

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*Corresponding author. E-mail: mk.alrumah@paaet.edu.kw.

process is faster than a reservoir simulator and requires less data, which saves time and effort. The developed neural networks were designed to be used for vertical and horizontal wells in communication with a bottom water aquifer. These developed neural networks can be useful in optimizing production by finding the optimum perforation interval or the optimum production rate to delay the water production.

The first paper discussed the water coning phenomenon and its physics was done by Muskat and Wyckoff (1935). Muskat and Wyckoff (1935) indicated that some of the factors that affect the water coning are production rate and length of perforated interval. Others performed numerical studies on the effects of various parameters on water coning in vertical wells (Blades and Stright, 1975; Byrne and Morse, 1973; Mungan, 1975). Also, Kuo (1983) studied the effects of various parameters on water coning in vertical wells, and developed correlations to predict critical rate, breakthrough time, and watercut after water production. Yang and Wattenbarger (Yang and Wattenbarger, 1991) studied the water coning effects in vertical and horizontal wells and developed a method to calculate the critical rate, break- through time, and the water-oil ratio after breakthrough. Van (1994) investigated the water coning behavior for a fractured reservoir in a vertical well and studied various parameters and their effects on water coning. Helle and Bhatt (2002) developed artificial neural networks that predict the underground fluids (water, oil and gas) and their partial saturation directly from the well logs. Shokir (2004) presented new artificial neural networks that predict water saturation in shaly formation using the well log data and the core data as the inputs. Al-Bulushi et al. (2009) developed artificial neural network based models to predict water saturation from well log data and core data. Mahmoudi and Mahmoudi (2014) developed artificial neural network that predicts porosity and water saturation of an Iranian oil field using well logs as an input data. Zendehboudi et al. (2014) developed a hybrid artificial neural network with particle swarm optimization to estimate breakthrough time and critical production rate for fractured system. Hamada et al. (2015) used neural network, optimized by particle swarm optimization, to determine the parameters of Archie’s formula, and then use the formula to calculate water saturation. Finally, Gholanlo et al. (2016) used radial basis function neural network improved by genetic algorithm to predict formation water saturation using conventional well-logging data. Gharib et al. (2018) developed artificial neural network to predict water saturation and porosity for shaly sand using core and log data. Baziar et al. (2018) performed a comparative study using four intelligent methods to determine water saturation in a tight gas sandstone reservoir and the methods are support vector machine, multilayer perceptron neural network, decision tree forest, and tree boost. Alimoradi et al. (2011) pointed out that one of the most important parameters in reservoir characterization procedure is water saturation, and the aim of this study is the future prediction performance of water saturation.

MODELS DEVELOPMENT

Numerical model

Data used to train the artificial neural networks were generated from a numerical reservoir simulation model. Two reservoir numerical models were implemented in radial and rectangular coordinates. The reservoir properties are assumed to be homogeneous and isotropic. In terms of fluid properties, the reservoir conditions are assumed to be above the bubblepoint pressure to ensure that no free gas is present in the reservoir. Furthermore, capillary forces were ignored assuming no transition zone. The reservoirs are assumed to be horizontal with uniform thicknesses. The radial reservoir model was used to generate data for vertical wells and the rectangular reservoir model was used to generate data for horizontal wells. The gridding for the radial system was in three dimensions, where the number of grid blocks was 30×1×25. The thickness of all the grid blocks is equal and the spacing of grids in the r-direction was designed according to the following equation:

$$r_i = r_w \left(\frac{r_e}{r_w} \right)^{(i/30)} \tag{1}$$

The rectangular reservoir gridding was 25×25×15 with $\Delta x = \Delta y =$ 61 m. The reservoir properties for the radial and the rectangular models are tabulated in Tables 1 and 2. For the vertical well scenario, six key parameters were selected to be changed to create different oil reservoirs. The parameters with their ranges are shown in Table 3 for the vertical well scenarios and in Table 4 for the horizontal well scenarios.

Artificial neural network vertical well scenario

A total of 233 data sets were generated randomly. Each combination was used to create a new reservoir model. All of the runs were designed for 10 years. The water saturation data, for all the blocks as generated by the simulation runs, were collected and prepared for the ANN training process. The ANN used for training is a feedforward network. The principal inputs are six parameters, which are:

(1) Oil density (ρ_O),
(2) Oil viscosity (μ_O),
(3) Vertical permeability (k_V),
(4) Total liquid flow rate (q_L),
(5) Reservoir thickness (h),
(6) Open interval to the flow (h_p).

The outputs are the water saturation values for all the blocks in the reservoir model at the end of each year. The 233 scenarios were divided into three sets; 210 scenarios were used for training, 11 for validation and 12 for blind

Table 1. Reservoir properties for the radial system.

Porosity (φ)	0.25
k_r, m^2	500×10^{-15}
Reservoir radius (r_e), m	1,829
Oil formation volume factor, Rm^3/Sm^3	1.0
Oil compressibility (c_o), MPa^{-1}	145×10^{-6}
Initial pressure (p_i), MPa	34.5
Temperature, °C	54
Initial oil saturation (S_{oi})	1.00

Table 2. Reservoir properties for the rectangular system.

Porosity (φ)	0.25
k_x, m^2	500×10^{-15}
k_y, m^2	500×10^{-15}
Reservoir length, m	1,524
Reservoir width, m	1,524
Oil formation volume factor, Rm^3/Sm^3	1.0
Oil compressibility (c_o), MPa^{-1}	145×10^{-6}
Initial pressure (p_i), MPa	34.5
Temperature, °C	54
Initial oil saturation (S_{oi})	1.00

Table 3. The selected reservoir properties were changed within their ranges for the vertical well study.

S/N	Parameter	Range
1	Oil density (ρ_o), kg/m^3	769 - 929
2	Oil viscosity (μ_o), cp	1 - 10
3	Vertical permeability (k_v), m^2	5×10^{-15} - 500×10^{-15}
4	Total liquid flow rate (q_L), m^3/Day	79.5 - 1,590
5	Reservoir thickness (h), m	7.6 - 76
6	open to flow interval of pay zone (h_p), m	0.04 - 0.96 h

testing. Training and validation data are used in the training of the ANN and the testing data are only introduced to the network after the end of the training process to test the new ANN. Training the neural network started by including all water saturation values for all the blocks of each reservoir, which will produce a network that can predict the water saturation for the entire reservoir. However, this did not result in a capable network that could predict the water saturation values with a good level of accuracy. The next trial was to reduce the amount of data to simplify the problem for the neural network, and at the same time not to generate a large catalog of neural networks. The volume of data was reduced more to simplify the problem by taking the data for only one layer instead of the 25 layers, but these efforts were not successful once again. Then again, the data was reduced by taking the data of a single layer and considering only the 6 blocks. This time, a good network was generated and the absolute error was less than 10% for all the predicted water saturation values. The absolute error is calculated using the following equation:

$$Error = |S_w - S_w(ANN)| \qquad (2)$$

After succeeding in designing a satisfactory network, the goal now is to increase the complexity of the problem and reduce the number of the networks needed to predict the water

Table 4. The selected reservoir properties were changed within their ranges for the horizontal well study.

S/N	Parameter	Range
1	Oil density (ρ_O), kg/m^3	769 - 929
2	Oil viscosity (μ_O), cp	1 - 10
3	Vertical permeability (k_V), m^2	5×10^{-15} - 500×10^{-15}
4	Total liquid flow rate (q_L), m^3/Day	79.5 - 1,590
5	Reservoir thickness (h), m	4.6 - 73
6	Depth of the horizontal well from top of formation (h_d), m	0.067 - 0.53 h
7	Length of the horizontal well (h_L), m	183 - 1,036

saturation for the reservoir.

The complexity was increased by including the data for the 10 years and not only for one year. The produced networks were good. Increasing the number of blocks to 16 blocks was tried, but the efforts were not successful. At the end, 25 networks were considered, where each network predicts the water saturation for each layer at the end of each year for 10 years.

Horizontal well scenario

A total of 314 combinations were generated randomly and for each combination, a reservoir was created. The horizontal well was always placed in the center of the square reservoir. This created a symmetry, which reduces the amount of data to be considered, and in return, will reduce the time needed to train the neural network.

After running the numerical simulation for all the 314 reservoirs for 10 years, water saturation data was collected and prepared for training the neural networks.

The input list required to generate the blocks' water saturations as outputs, contains seven parameters, which are:

(1) Oil density (ρ_O),
(2) Oil viscosity (μ_O),
(3) Vertical permeability (k_V),
(4) Total liquid flow rate (q_L),
(5) Reservoir thickness (h),
(6) Depth of the horizontal well (h_d),
(7) Length of the horizontal well (h_L).

The data collected was only from the vertical plane (x-z plane) which contains the horizontal well. The water saturation for each block at the end of each year was collected. Training the neural network using the water saturation values for the blocks in a single column, produced 13 different neural networks. The data for the 314 reservoirs were divided into 3 groups: 284 for training, 15 for validation, and 15 for blind testing. The resulting ANN is considered good when the predicted water saturation of the testing data has an absolute error of less than 10% for all values. The structure of the ANN was selected after trial and error. The network with the lowest error found was the feedforward network. The learning function with the lowest error was the gradient descent with momentum weight and bias learning function. The training function with the lowest error was the conjugate gradient backpropagation with Polak-Ribiére updates. The transfer functions which showed the lowest error was the hyperbolic tangent sigmoid transfer function. The neural network structure consists of the input and the output layers and two or more hidden layers. In each layer (input, output and hidden), the number of neurons must be specified. The number of neurons in the input layer is 7. The number of neurons in the output layer is 150. A table of 150 neurons is required because each column has 15 blocks and the water saturation value for a single block was taken at the end of each year for 10 years.

RESULTS AND DISCUSSION

Vertical well

As explained earlier, in this case, 25 ANN were created. They were tested using data from 12 different reservoirs. The average absolute error was less than 10% for all the layers of all 12 reservoirs. The structure of all the networks consists of one input layer, one output layer and two hidden layers. For each network, the outputs were the water saturation values for the blocks at the end of each year, for 10 years. Figure 1 shows the structure of the generated ANN for the first layer. The network has 6 inputs in the input layer, 46 neurons in the first hidden layer, 37 neurons in the second hidden layer, and 60 outputs in the output layer. The average absolute error for each layer of the reservoirs is found to be between 0.07 and 1.67%. Two reservoirs (reservoir #230 and #233) were selected, from the reservoirs used to test the generated ANN, to show the capability of the ANN in predicting the water saturation. Reservoir #230 has the highest average absolute error (Figure 3c), among the 12 tested reservoirs, for the predicted water saturation values, and reservoir #233 was randomly selected. Figure 2a shows the surface map of the water saturation distribution for reservoir #233 from numerical simulation data. Figure 2b shows the same water saturation distribution but with predicted data from ANN. The prediction has a very low error, and the water cone shape is captured clearly. Figure 2c shows the absolute error on a surface map to give a better way of visualizing the error and its location. The highest error is 5.9% and it is observed in a very small area. Figure 3a is for the

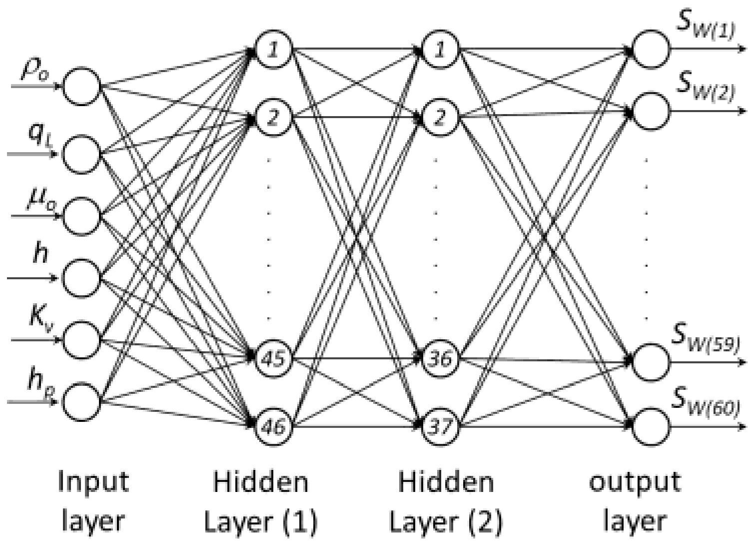
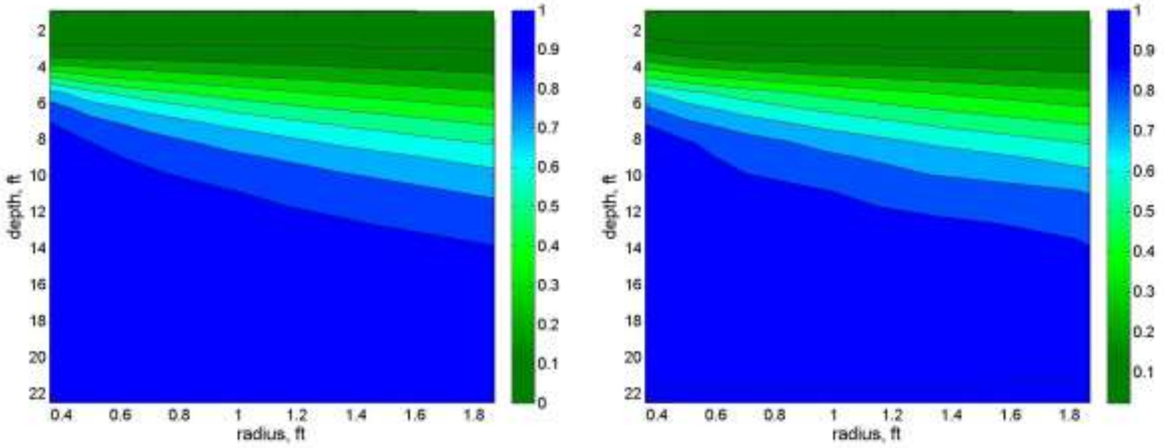
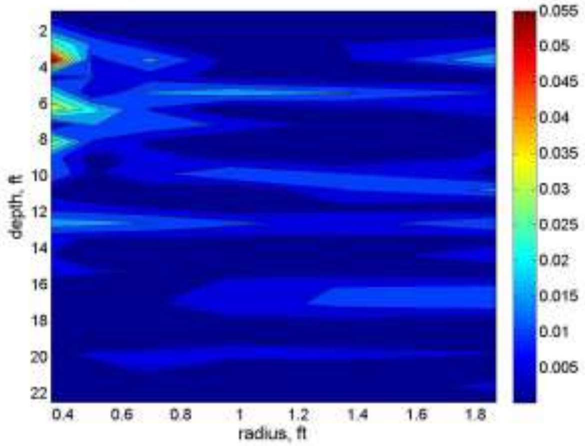


Figure 1. ANN structure generated for the fi layer for the vertical well.



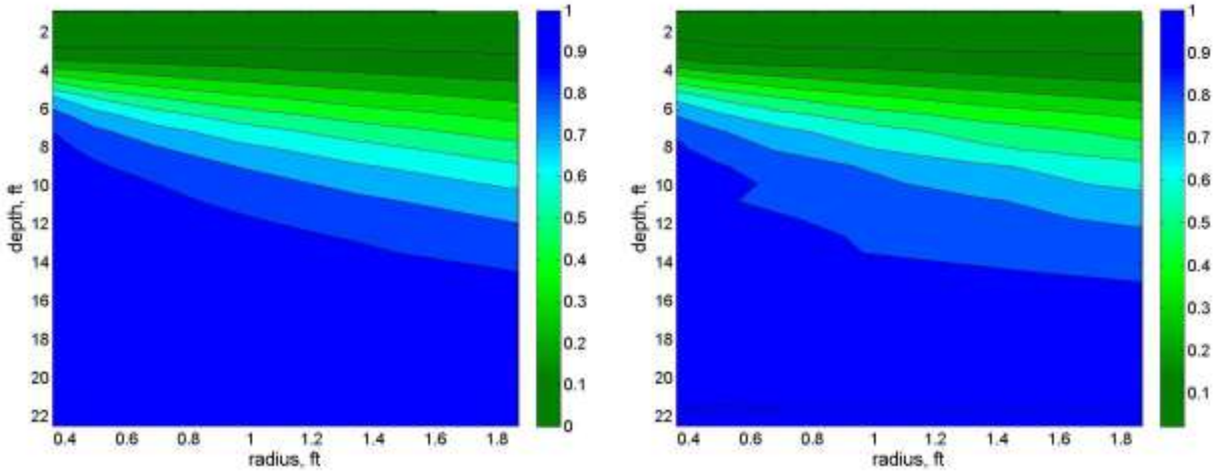
(a) Numerical simulation

(b) Artificial neural network

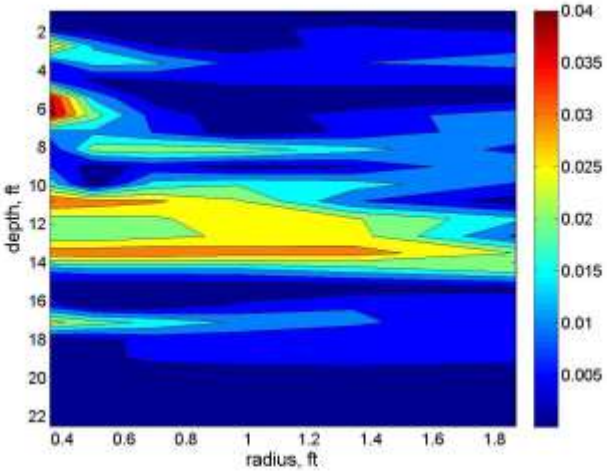


(c) Absolute error

Figure 2. Surface map of S_W for reservoir #233 at the end of the 6th year.



(a) Numerical simulation (b) Artificial neural network



(c) Absolute error

Figure 3. Surface map of S_W for reservoir #230 at the end of the 5th year.

surface map for reservoir #230 for the water saturation using the data from the numerical simulation. Figure 3b is the surface map for the same reservoir using data predicted with the ANN. Figure 3c shows the absolute error. Prediction for this reservoir has the highest error among the 12 reservoirs used for testing, but the shape of the cone has developed, which is clearly visible from the ANN model.

Horizontal well

Twelve ANNs were generated. Each network predicts the water saturation for each column. The structure of all the networks consists of one input layer, one output layer and 2 or 3 or 4 hidden layers. The output layer has the water saturation values for the blocks at the end of each year, for 10 years.

Figure 4 shows the structure of the generated ANN for the first column. The network has 7 input neurons, 31 neurons in the first hidden layer, 37 neurons in the second hidden layer, and 150 neurons in the output layer. The average absolute error encountered in the 15 reservoirs was found to be very low (between 0.34 and 2.72%).

Fifteen reservoirs were tested using the neural networks developed in this study and two reservoirs were selected to illustrate the results of the ANN predictions. The two selected reservoirs are reservoirs #8 and #10. Figure 5a shows the surface map of reservoir #8 of water saturation from numerical simulation. The horizontal well is at a depth of 12.5 m and the horizontal section is 1,036 m long extending from 244 to 1,280 m. Figure 5b shows the surface map of the same reservoir with water

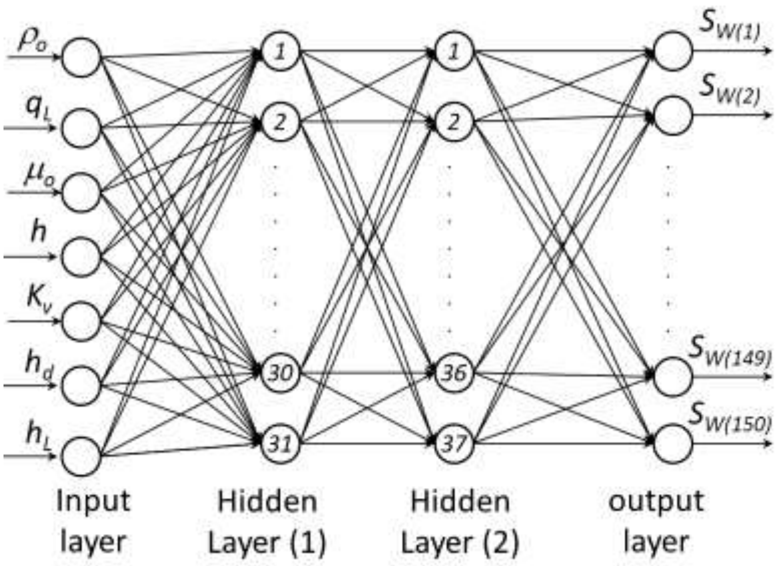
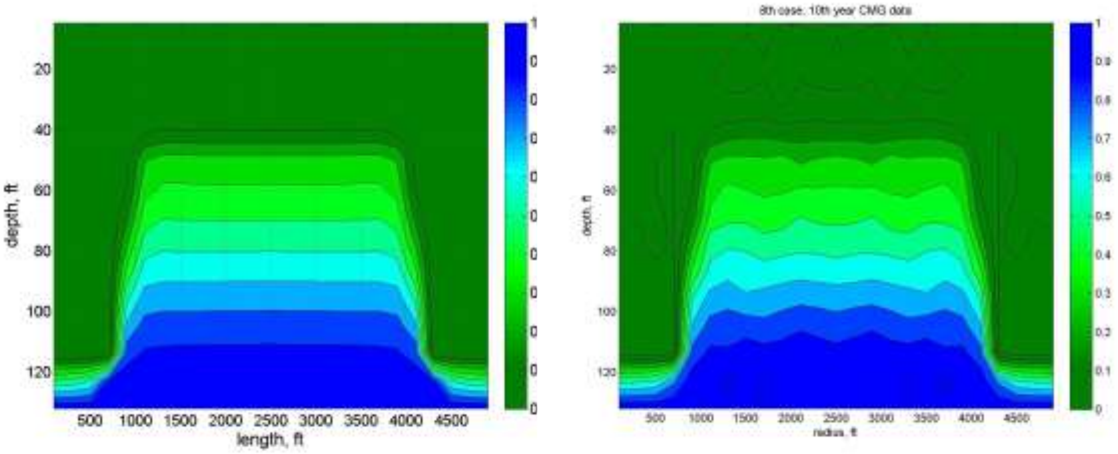
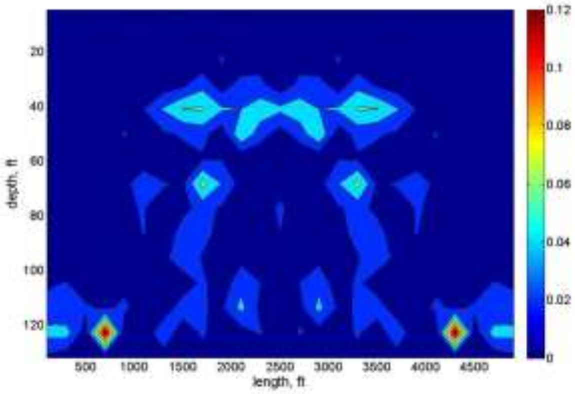


Figure 4. ANN structure generated for the fi column for the horizontal well.



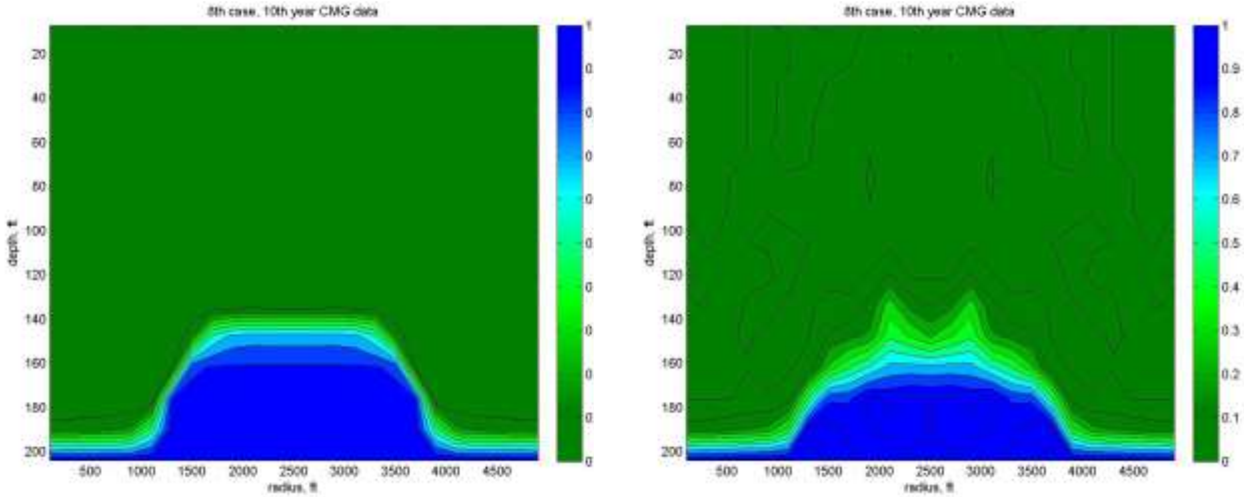
(a) Numerical simulation

(b) Artificial neural network

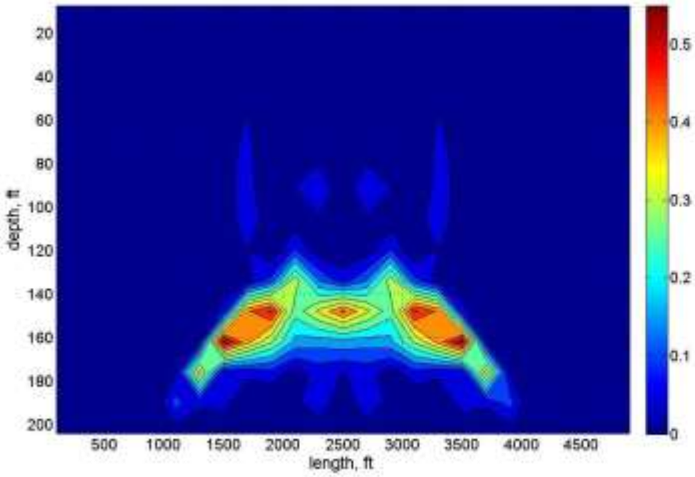


(c) Absolute error

Figure 5. Surface map of S_W for reservoir #8 at the end of the 10th year.



(a) Water saturation from numerical simulation (b) Water saturation from artificial neural network



(c) Absolute error

Figure 6. Surface map of S_W for reservoir #10 at the end of the 10th year.

saturation data predicted from ANN. Figure 5c shows the absolute error of the ANN predicted water saturation for reservoir #8.

The ANN was able to predict the shape of water crest very effectively. There are areas which show an absolute error larger than 10%, but they are all at the bottom of the water cone which is not critical in performance calculations (Figure 5c). The more important areas are those which show where the water front has reached. The high error zones occur at the transition zones, similar to results of the vertical wells, and the high error occurs because saturation gradients are high over a small area, which creates a greater challenge to the ANN to predict the water saturation values accurately.

The second example to illustrate the ability of the ANN to predict the water coning phenomena is for reservoir #10. Figure 6a shows the surface map of water saturation for the reservoir with the numerical simulation data, and Figure 6b shows the surface map for the same reservoir with the ANN predicted data. The ANN was able to predict the cone shape, and also to predict the sharp decrease of water saturation at the bottom sides of the cone. Figure 6b shows two identical peaks. This is an overestimate of the water saturation values and this is because the horizontal section of the well, which is off the center, is having more flow than the center section. The ANN was successful in predicting this behavior, but the values of water saturation were overestimated. Figure 6c shows the absolute error of the ANN predicted water saturation for reservoir #10, and it shows very low error (less than 10%) in most areas.

Conclusions

This study is concerned with predicting the rate of increase of water saturation in the immediate vicinity of the production wells using ANN based models. The developed ANNs are for vertical wells located in a radial flow geometry, and horizontal wells located in a rectangular reservoir system with active bottom water drives. A total of six input parameters are needed for the ANN to predict the water saturation distribution for a period of 10 years. The predicted water saturation values for the vertical well represent the water saturation distribution around the wellbore at the end of each year while the well is under production. In the case of horizontal wells, the water saturation predictions are made in the vertical plane of symmetry that cuts through the centerline of the horizontal well.

The examples of the applications described in this paper show that accurate saturation predictions matching the numerical simulation results effectively have been attained. With the help of the expert systems developed in this paper it will be possible to generate results showing the development of water saturation profiles as a function of time without resorting to reservoir simulators which require large amount of data and large computational times.

The developed ANNs can be used to optimize production strategies, by running the ANN under different production scenarios to find the production rate that will effectively delay water production. Furthermore, ANN based reservoir models developed in this study can be used in selecting the optimum perforation interval that will increase production of water-free oil by delaying water production or reducing it.

CONFLICT OF INTERESTS

The authors have not declared any conflict of interests.

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