Dynamic Well Bottom-Hole Flowing Pressure Prediction Based on Radial Basis Neural Network

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Abstract Reservoir simulation provides information about the behaviour of a reservoir in various production and injection conditions. Reservoir simulator is used to predict the future behaviour and performance of a reservoir field. However, the heterogeneity of reservoir and uncertainty in the reservoir field cause some obstacles in selecting the best calculation of oil, water and gas components that lead to the production system in oil and gas. This paper presents a dynamic well Surrogate Reservoir Model (SRM) to predict reservoir bottom-hole flowing pressure by varying the production rate constraint of a well. The proposed SRM adopted Radial Basis Neural Network to predict the bottom-hole flowing pressure of well based on the output data extracted from a numerical simulation model in a considerable amount of time with production constraint values. It is found that the dynamic SRM is capable to generate the promising results in a shorter time as compared to the conventional reservoir model.

1 Introduction

Multiphase flow in oil and gas field generally refers to simultaneous flow of more than one fluid in a reservoir [1] and it is commonly encountered as the flow of oil-gas-water is the reservoir. The physics involved in multiphase flow is very intricate due to the interaction between different fluids [2] and it is generally experienced during the production of oil and gas field. This indicates that oil and gas field is

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getting more complicated and challenging, having one or more reservoirs and many numbers of injection and production wells in its geological structure. The complexity of a reservoir leads the system to a dynamic nature and the recovery process changes from natural depletion to water-flooding as well as switches to an enhanced oil recovery process [3]. In order to deal with this complexity, large amount of researches has been done and performed with the introduction of mechanistic models [4] to predict the fluids and gas flow by changing their pressure and temperature value etc. This phenomena also leads to many numerical simulation models that are used as potential candidates to estimate the accurate flow characteristics of oil, gas and water in the production system [2]. Numerical simulation models that are used to simulate the behavior of production system in multiphase flow reservoir requires considerable amount of time on some parallel computer processing units. On the other hand, surrogate reservoir model (SRM) can also be considered as a potential solution to address this necessity. SRM can be used to predict the results of a reservoir, such as pressure, production rate and gas-oil ratio in less amount of time as compared to the other numerical simulation models. The objective of this paper is to develop a dynamic well SRM to predict the bottom-hole flowing pressure (BHFP) of a well based on production rate constraints that mines the output data from reservoir model. In real scenario the BHFP of a well always changes based on time period. This is because sometimes the reservoir and petroleum engineers prescribe (fix) the value of a well BHFP for some specific years and they do not want to put the well BHFP for those years into consideration. In order to cater for this kind of common scenarios, dynamic well SRM is proposed in this paper. Dynamic well SRM has the capability of producing the results of BHFP for all or specific years.

The structure of this paper is as follows: Sect. 2 explains the related work of SRM in oil and gas fields, Sect. 3 details the development of the proposed dynamic well SRM, while Sect. 4 shows a case study which is under consideration of this research and Sect. 5 spells out the results and discussion, followed by a conclusion in Sect. 6 of this paper.

2 Related Work

In 1999, the first surrogate reservoir model (SRM) was developed for hydraulic fracturing simulator in oil and gas. It was able to reproduce the results of hydraulic fracturing simulator called FracPro in less amount of time using artificial intelligence technique [5]. In later years, other attempts of SRM can be found in literature articles. For instance, SRM was able to calculate the porosity and permeability distribution in a heterogeneous and multiphase reservoir by matching the static and dynamic data that are available [6]. The surrogate model was also developed for Steam Assisted Gravity Drainage process in heterogeneous and multiphase petroleum reservoir [7]. Based on the previous work on surrogate model, another SRM was built for a giant oil in the Middle East, in that development full field simulation model was taken, which includes millions of grid blocks and more than 165 wells in its geological structure. The SRM was able to replicate the results of full field simulation model based on time complexity [5, 8, 9]. Besides that, SRM was also developed for uncertainty analysis of coalbed methane (CBM) production to optimize the performance of reservoir [10]. In the same year, well SRM was developed to examine against the two-and-a-half year production of a reservoir. The SRM was used to accurately predict the simultaneous cumulative oil production and water cut for every well at each given time [11]. Pertaining to that work, SRM was also built for CBM reservoir to predict the cumulative production, that includes thirteen well to produce fifteen years production [12]. In subsequent years, well based SRM was developed for a reservoir that includes both natural and hydraulic fractures. SRM has been used to optimize the recovery process and predict the cumulative oil production [13, 14]. On the other hand, SRM was also used to predict the pressure and CO_2 distribution throughout the reservoir with good accuracy [15]. Recently, well based SRM was developed to generate a production rate as a function of time for all wells over the next 25 years with promising accuracy [16].

The success of SRM development is due to the state of the art technology in Artificial Intelligence, such as Artificial Neural Network (ANN). And the use of the ANN has been increasing in oil and gas industry over the past few years to solve many complex and highly non-linear problems [17]. ANN is considered as a non-linear tool and are good at predicting the complex and nonlinear system behavior. ANN is also used to solve many different kinds of problems related to reservoir engineering, such as, reservoir characterization [18], permeability prediction [19, 20], prediction of bottom-hole flowing pressure in vertical multiphase flow [21, 22], predicting the water inflow performance in solution gas drive [23]. In the past few years, some of the ANN study has been done on the history matching process [24] and the application of surrogate reservoir modeling [9, 25]. The benefit of ANN over other conventional techniques such as, response surface and reduced models in reservoir engineering, is its ability to perform complex and highly non-linear task accurately and rapidly. In most of the previous work related SRM, researchers have adopted backpropagation neural network (BPNN) in constructing the reservoir model. However, in the study of BPNN, there is a problem of trapping in local minima during training time because one needs to specify the number of hidden neurons in the network. In most of the time, the network will not reach at the global minima to find the minimum error value. However, another type of ANN which is known as radial basis neural network (RBNN), in which the non-existence of local minima problem will not occur because the number of hidden neurons increases automatically until the error value reaches its minimum value, which is considered as more objective based.

In this paper, we propose to adopt RBNN after comparisons were done on the performance of BPNN and RBNN, to construct the dynamic well SRM based on production rate constraint which defer from the previous developed SRM. The developed dynamic well SRM may cater the changes with respect to each time step on the specific task. Dynamic well SRM is considered as a complex task to be implemented because it generates the reservoir response based on the time complexity which may vary in an inconsistent pattern. Dynamic well SRM is used to calculate the results of BHFP by prescribing the production rate value at all or some specific time steps.

3 Dynamic Well Surrogate Reservoir Model

Dynamic well surrogate reservoir model (SRM) is the collection of reservoir well constraints such as, well bottom-hole flowing pressure (BHFP, p_{wf}) and production rate, which changes with respect to the time span. In most of the real scenarios, the BHFP of a well always changes based on time period and sometimes reservoir and petroleum engineers have already known the value of a well BHFP for some specific years and hence they do not need to calculate the well BHFP for those specific years but only consider those unknown period of time. In order to predict BHFP for such a scenario, dynamic well SRM can be used to predict BHFP for all or specific years. In this paper, a dynamic well bottom-hole flowing pressure with prescribed production rate is developed. Equation 1 represents the BHFP value of a well using the BOAST simulator and well SRM with production rate is used to replicate the result of BHFP using Eq. 1. In the equation, p_{wf} represents the bottom-hole flowing pressure of well, Q_o represents the production rate, PI represents a productivity index of the reservoir's ability to transfer fluid to the well, λ_o shows mobility of the oil phase, B_o explains the volume factor of oil phase and p represents reservoir pressure.

$$p_{wf} = p + \frac{B_o}{PI \cdot \lambda_o} Q_o \tag{1}$$

Figure 1 represents the steps involved to build the surrogate reservoir model (SRM) for this paper. The first step to build the SRM requires data collection. In this paper, we use Black Oil Simulation Tool (BOAST) to build a spatio-temporal database and generate the output responses based on the input values which are tuned to the BOAST simulator.

BOAST is developed and provided by the Department of Energy (DOE) United States in 1982 as an open source package. It is considered as an implicit pressure-explicit saturation (IMPES) simulator [26], which finds the pressure distribution for a given time step first then calculates the saturation distribution for same time step. It is a three dimensional (X, Y, Z) and three phase (oil-gas-water) simulator for modeling the multiphase flow in porous channel and used in oil and gas field to simulate different scenarios. For example, primary (natural) depletion, secondary depletion in which pressure is maintained by water injection and tertiary depletion is considered as enhanced oil recovery such as gas injection is used to maintain the pressure. The well model in BOAST has the flexibility to change the operational constraints such as production rate specifications or well flowing pressure value on the well behavior and performance, and the user is permitted to add or replicates the wells during the simulation time [27].

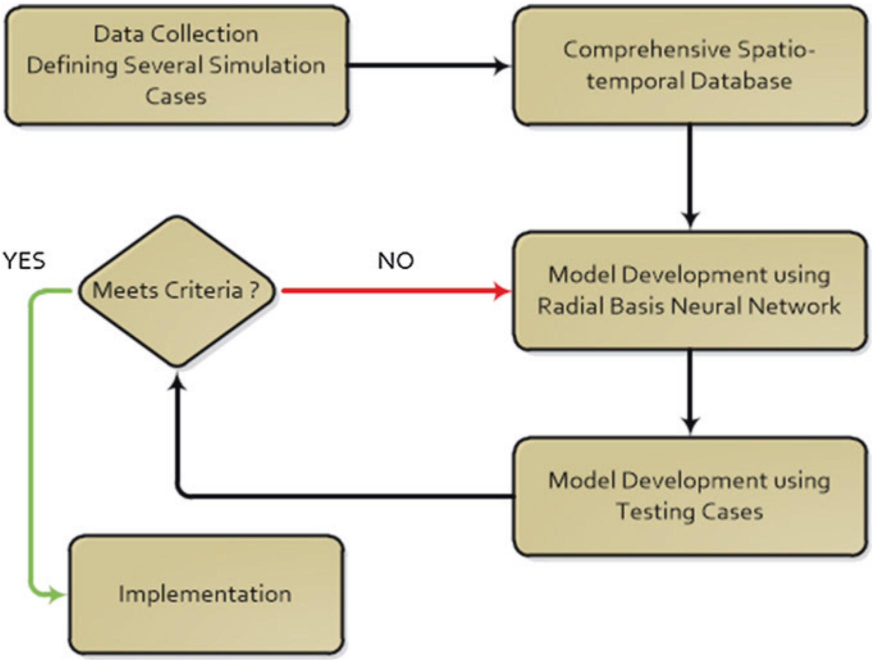

Fig. 1 Basic flow chart to build surrogate reservoir model

The spatio-temporal database represents the characteristics and behavior of the reservoir with its input-output parameters, which is considered as the training data sets for SRM. It is developed using the static and dynamic data, such as, porosity, permeability, pressure and production value at any time the reservoir.

Before the training starts in RBNN, all the training datasets can be divided into two matrices. One is assumed to be input data sets and another is considered as the output data sets. The input and output data sets are normalized in a specific range. In this research, a standard normalization function such as tangent sigmoid function is used to confine all the input and output data sets within the specific range of -1 and 1 before the training starts [28, 29]. The mathematical representation of this function is given in Eq. 2:

$$y = \frac{e^{2x} - 1}{e^{2x} + 1} \tag{2}$$

During the training of RBNN, the training data set is always divided in three phases: training, validation and testing. The training data is used during the training of the neural network where as validation data is also used during the training process, but it is not used to train the neural network rather it is used to check the network learning during the training. Both training and validation data that used during the training time is considered as non-blind data [16].

3.1 Radial Basis Neural Network

Radial Basis Neural Network (RBNN) is used to develop a network with good generalization capabilities having a less number of hidden neurons in its structure [30]. A RBNN is considered as the special type of the ANN because it only requires one hidden layer in its architecture and it allows the input space to be represented in a new space with different hidden layer neurons. During the training process of RBNN, it behaves as a linear model because all the hidden neurons center and computations are fixed. The RBNN hidden layer neurons perform non-linear transformations and maps all the inputs into new input space satisfactory. The output layer is considered as linear transformer, which is applied to new input space so that only weights of hidden neurons can be adjusted. The performance of the RBNN can be determined by adjusting the centers (widths) of the hidden neurons and there is no specific formula available to select the width of the radial basis function (RBF). But one should select the width of the RBF larger than the distance between two adjacent inputs and smaller than the distance all over the input space in order to get good generalization [31]. RBNN has been used in wide range of applications, such as, system prediction, pattern recognition, system approximation, signal processing and system equalization, system identification, speech recognition and adaptive control, etc. [32]. And it has been used to solve the problems of oil and gas field, i.e. gas-oil ratio (GOR) of reservoir, seismic, electromagnetic, resistivity, [33], well log data inversion [34], prediction of log properties from the seismic attributes of the reservoir [35] as well as the nonlinear relationship between the reservoir property and seismic attributes [36].

The growth and general architecture of the RBNN has been influenced by the RBF. Figure 2 represents the general architecture of the RBNN. In Fig. 2, $x = [x_1, x_2, \ldots, x_m]$ represents the input vectors of the network and $y = [y_1, y_2, \ldots, y_n]$ represents the final net output of the network and in hidden layer there are a number of neurons. Inside each hidden neurons there is a RBF [37], the RBNN inputs are directly connected to the each basis function that generates an output Φ_i as shown in the Eq. 3, which depends upon the input vectors.

$$\phi_i = \exp\left[-\frac{(\| x - u \|)^T (\| x - u \|)}{\sigma^2}\right] \tag{3}$$

where, x represents the input data points of network, u is the center of the radial basis function ($u = 0$), σ represents the radius of the RBF ($\sigma > 0$). Once the hidden neuron is calculated based on radius of RBF. Then it is passed to the output layer, where the sum of the product between the hidden layer neuron and weight vector is computed to produce final network output y_n.

$$y_n = \sum_{m=1}^{M} w_i \cdot \phi_i \tag{4}$$

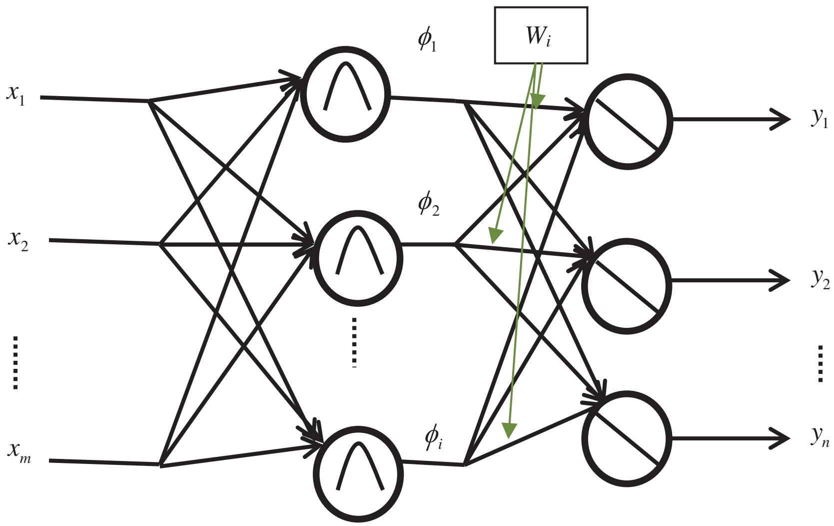

Fig. 2 Radial basis neural network with m-dimensional inputs and n-dimensional outputs

Once the model is developed using the training, it is ready to be tested with testing data, that the network never uses during the training process. This testing data is used to check the predictive capability of constructing a network [38]. If the network generalized this testing data with good accuracy, it means that the network has a capability to predict the output of new data with good approximation and this network is considered as a validated network model to serve the SRM.

4 Case Study

The base case study, which is considered in this paper has been taken from the Society of Petroleum Engineering (SPE) [39] to build the dynamic well SRM with production rate constraints. Figure 3 represents the grid view and configuration of the reservoir which is under consideration. In the figure, each grid block consists of 1,000 ft and the reservoir consists of 10 × 10 grid block in x and y directions. The total area occupied by the reservoir is considered as 100,000,000 ft^2. Figure 4 reveals the diagonal cross section model of the reservoir properties.

The reservoir model is based on the three layers labeled as LAYER 1, LAYER 2 and LAYER 3. The 8,325 ft is considered as the top value of the model, while H, FT represents the depth of the reservoir, which varies as 20, 30, 50 ft in LAYER 1, LAYER 2 and LAYER 3 respectively. Φ represents the porosity value of the reservoir, which is assumed to be homogeneous in whole reservoir. It represents the tiny spaces in the rock that hold oil or gas and is measured of total rock which is taken up by pore space [40]. Kx, Ky and Kz represents the permeability value of

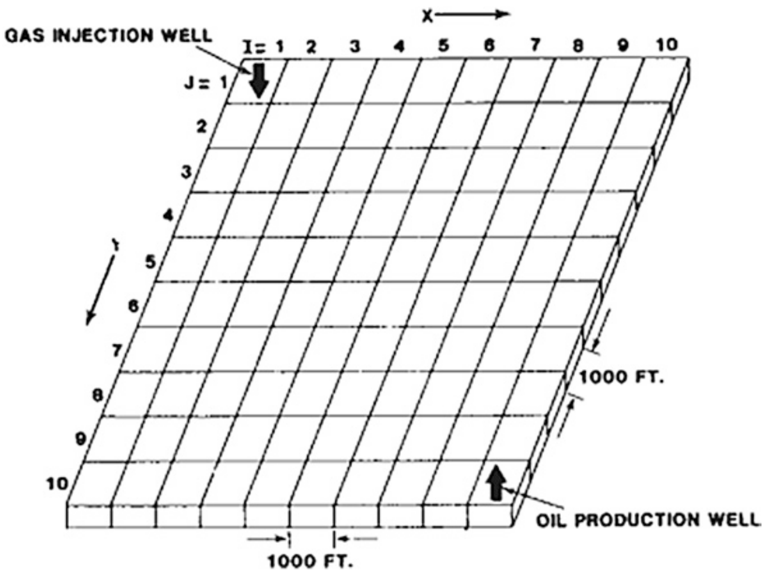

Fig. 3 Grid configuration and problem specification to build well SRM [39]

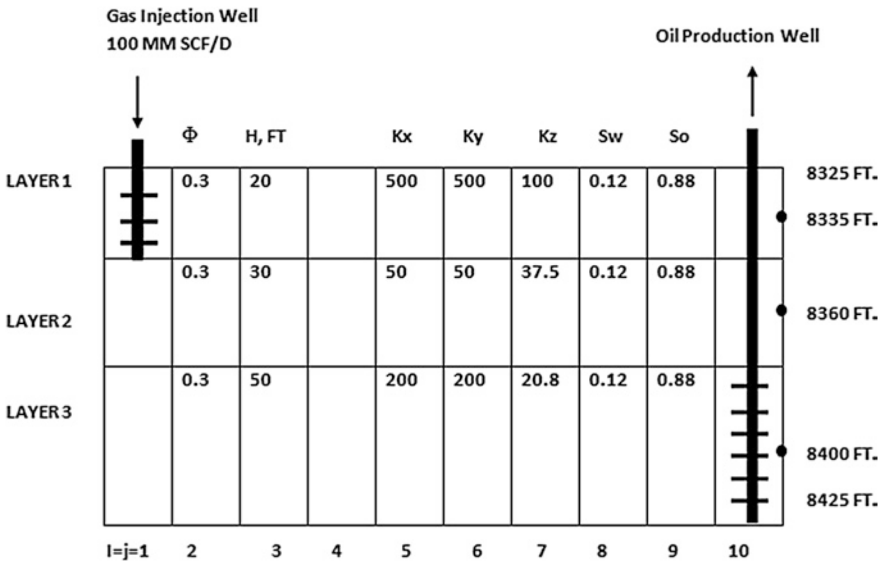

Fig. 4 Diagonal cross section of reservoir grid model [39]

reservoir in *x*, *y* and *z* direction respectively. The value of permeability is considered as homogeneous in *x* and *y* direction, but heterogeneous with respect to *z* direction. Permeability is considered as the ability of a reservoir to pass the fluid from the

Table 1 Reservoir characteristics used to build database for dynamic well SRM

Input parameters	Range
Porosity in Layer 1 (%)	2–4
Porosity in Layer 2 (%)	2–4
Porosity in Layer 3 (%)	2–4
Permeability in Layer 1 X direction (md)	470–530
Permeability in Layer 1 Y direction (md)	470–530
Permeability in Layer 1 Z direction (md)	70–130
Permeability in Layer 2 X direction (md)	40–60
Permeability in Layer 2 Y direction (md)	40–60
Permeability in Layer 2 Z direction (md)	30–45
Permeability in Layer 3 X direction (md)	170–230
Permeability in Layer 3 Y direction (md)	170–230
Permeability in Layer 3 Z direction (md)	15.83–25.83
Production rate (STB/D)	4,000–7,000

rocks' pores and permeability of each rock depends on the nature of the reservoir. *Sw* and *So* from Fig. 4 represents the initial water and oil saturation of the reservoir before the production come out from the reservoir. The value of initial water and oil saturation is considered as constant in the whole reservoir, that are 0.12 and 0.88 respectively. There is a one gas injection well in LAYER 1 at this first grid block of the reservoir with injection rate of 100,000 MMscf/D. While there is another well which is known as the production well of the reservoir and it is perforated in the LAYER 3 at the opposite corner of the gas injection well. The production well can produce a maximum production rate of 20,000 STB/D and minimum production rate of 1,000 STB/D. The minimum bottom-hole flowing pressure of production well is 1,000 psi. The middle layer is considered as empty because there is no oil, gas and water in this layer. The aquifer value of the reservoir is zero, therefore there is no flow at the boundaries of the reservoir grid system. Whereas the reservoir has an initial pressure of 4,800 psia and temperature is considered as 200 °K. This paper contains the porosity, permeability and production rate as the key input parameters to build the dynamic well SRM for multiphase flow simulation. Table 1 represents the base case study values and their range, which are considered to build the database for the proposed study. The mean value of input parameters such as porosity and permeability range is the same as the value of the base case study.

5 Results and Discussion

This section explains the results of the developed dynamic well SRM for bottom-hole flowing pressure (BHFP) with reservoir characteristics such as, porosity, permeability and production rate constraint values as input parameters. 100 training cases were generated from BOAST and 5-fold cross validated was conducted

Table 2 Quantitative measurements of 5-fold cross validation from 100 training cases using BPNN and RBNN

Model	RMSE	MAPE	σ	Accuracy (%)
BPNN	0.2283	3.5767	0.0135	87
RBNN	0.2059	3.2271	0.0136	**96**

Best result is indicated in bold

Table 3 Quantitative error measurement of 15 testing cases using RBNN

Algorithm	RMSE	MAPE	Accuracy (%)
BPNN	2786.4	695.5	63
RBNN	**7.9**	**14.66**	**64.5**

Best result is indicated in bold

towards the developed BPNN and RBNN. Table 2 shows the average results from the 5-fold cross validation training data. The statistical results such as root mean square error (RMSE), mean absolute percentage error (MAPE), standard deviation (σ) and accuracy were presented in the table. It is shown that RBNN performs better with 96 % accuracy as compared with BPNN only can achieve 87 % accuracy.

Once the training is conducted to build a static well SRM, 15 series of test cases were generated randomly to test the dynamic well SRM. Table 3 show the results of dynamic well SRM. The error values such as RMSE, MAPE and accuracy are calculated to measure the error between the target and predicted output. It again shows that RBNN outperforms BPNN with slight better accuracy of 65 %, however, there is quite a huge gap between on the error rates between the two techniques as shown in the table, albeit RBFF still performs better than the other. The time that the BOAST simulator takes to calculate one simulation run (test case) is about 1 min and for 15 simulation runs, it took a total of 15 min on the Intel (R) Core (TM) i5-3470 CPU @ 3.2 GHz CPU, whereas SRM using ANN only took a maximum of 1 s to compute the results for the all simulation runs (15 test cases) on the same CPU with a good approximation.

Once the dynamic well SRM is built according to the specified condition such as with production rate constraint. Then it is used to test developed SRM according to the end user requirement. To test the dynamic well SRM by changing the production rate constraint of a well at any time. Table 4 represents the arbitrary test cases values to test the dynamic well SRM by switching the constraint values.

Case 1 from Table 4 is used to predict the results of bottom-hole flowing pressure (BHFP) using BPNN and RBNN approaches. Figure 5 represents the results of dynamic well SRM by giving the production rate constraint value as input parameter to calculate the BHFP for year 1, 2, 4, 6, 8, 9 and 10. And for year 3, 5, 7 the BHFP value is already prescribed. However, RBNN and BOAST results matches with each other by accuracy of 63 %. Whereas, BPNN and BOAST results matches with each other by accuracy of 47 %.

Case 2 from Table 4 is used to produce the results of BHFP for year 1, 2, 5, 6, 9 and 10 by giving the value production rate as input parameter using dynamic well SRM, but for year 3, 4, 7 and 8 the BHFP is already prescribed as shown in the Fig. 6. However, RBNN and BOAST matches with each other by accuracy of 98.9 % and BPNN and BOAST results matches with each other by accuracy of 97.8 %.

Table 4 Reservoir characteristics used to build well SRM with production rate constraint

Input parameters	Case 1	Case 2
Porosity in Layer 1 (%)	4	4
Porosity in Layer 2 (%)	4	3
Porosity in Layer 3 (%)	2	3
Permeability in Layer 1 X direction (md)	511	524
Permeability in Layer 1 Y direction (md)	511	519
Permeability in Layer 1 Z direction (md)	114	72
Permeability in Layer 2 X direction (md)	42	43
Permeability in Layer 2 Y direction (md)	57	42
Permeability in Layer 2 Z direction (md)	37	31
Permeability in Layer 3 X direction (md)	185	206
Permeability in Layer 3 Y direction (md)	218	177
Permeability in Layer 3 Z direction (md)	20	23
Production rate (STB/D)	5,546	5,854

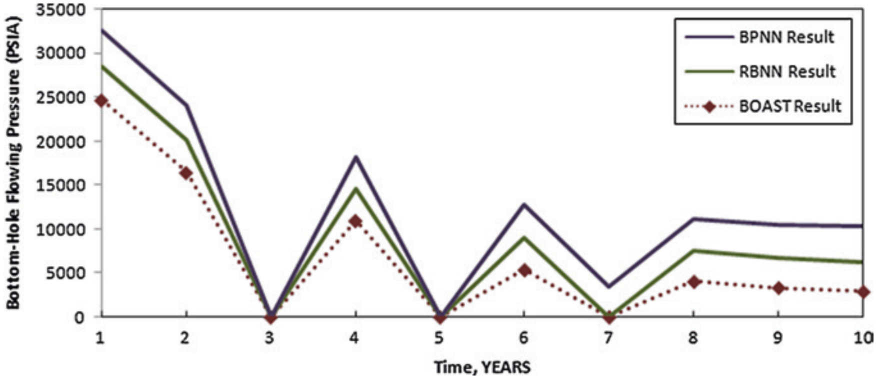

Fig. 5 Testing results of well SRM with production rate (Case 1)

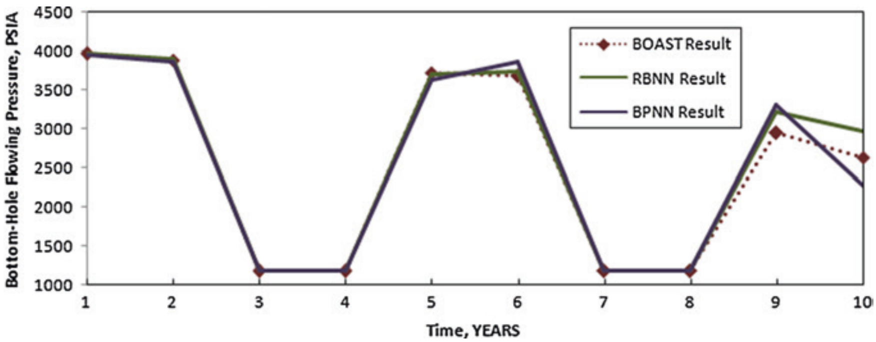

Fig. 6 Testing results of well SRM with production rate (Case 2)

From the stated cases, case 1 represents a case performed at the lower tile whereas case 2 shows a case with performance at the higher tile.

6 Conclusion

In this paper, results of dynamic well SRM with production rate constraint have been presented with two different types of ANN, i.e. RBNN and BPNN. From the case study conducted, RBNN outperforms BPNN in building the dynamic SRM. Also, two statistical error measurements have been conducted to see the absolute error of target and predicted output of the trained network. The study have carried with both BPNN and RBNN to build the SRM in order to predict the future results in less amount of time. It is also obvious dynamic well SRM has a capability of fast and accurate replication of numerical simulation models results at different time steps. The future work and challenge will involve complex reservoir with larger numbers of grid blocks in its geological structure with many number of injection and production wells to optimize the production of reservoir.

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