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Estimating the initial pressure, permeability and skin factor of oil reservoirs using artificial neural networks

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Abstract

Artificial neural network, a biologically inspired computing method which has an ability to learn, self-adjust, and be trained, provides a powerful tool in solving pattern recognition problems. In this study, a new approach based on artificial neural networks (ANNs) has been designed to estimate the initial pressure, permeability and skin factor of oil reservoir using the pressure build up test data. Five sets of actual field data in conventional and dual porosity reservoirs have been used to test the results of the neural network. The results from the network are in good agreement with the results from Horner plot. Finally, it is shown that the application of artificial neural networks in a pressure build up test reduces the cost of the test and it is also a valuable tool for well testing.

Keywords: Artificial neural networks; Initial pressure; Permeability; Skin factor; Pressure build up test; Well test

1. Introduction

For a long time, petroleum engineers have attempted to determine the effective permeability and the initial pressure of a reservoir. At first, permeabilities were found from direct analysis of the cores taken from the well and next completed by productivity index data. However, these methods do not calculate the actual permeability of the formation and cause significant deviation from the actual values. As the rate of build up in a shut-in well is affected by the permeability of the producing formation, the build up pressure tests may be necessary for a direct estimation of the effective permeability based on actual performance of a well (Coats et al., 1967).

Pressure build up testing which is the most familiar transient well testing technique has been extensively used. For the accomplishment of this test, a producing well is shut-in, so the pressure begins to increase. The most common and simplest analysis techniques require a constant rate producing well. In that case, the pressure is measured immediately before shut-in and is recorded as a function of time during the shut-in period.

The ancient usage of the pressure build up data was done by Muskat (1937). He presents an extrapolation theory and relates the change in pressure with time to the parameters of the reservoir. His method which had only a qualitative application can be used to extrapolate the measured well pressure to a true static pressure. As it did not take into account the fluid compressibility, his method was an approximate way. Later, another method was proposed by Miller et al. (1950) that includes the effects of compressibility on the treatment of pressure

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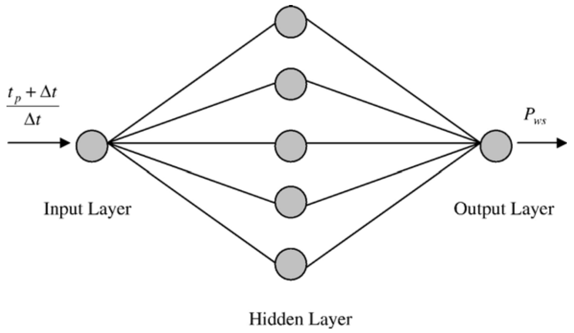

Fig. 1. Different layers of the nueral networks.

behaviour in oil wells. In the next year, a somewhat different treatment was presented by Horner (1951). He deduced the basic equation for pressure build up analysis. His proposed equation applies quite well without modification to newly completed wells in oil reservoirs above the bubble point. The equation mentioned that if we plot the pressure (P_w) observed during a closed-in period as a function of the logarithm of $\left(\frac{t_p+\Delta t}{\Delta t}\right)$, a straight line should be obtained, where t_P and Δt are the producing time and the shut-in period, respectively. This plot is commonly called the Horner plot. It was popular to use the slope and the intercept of the Horner plot to calculate the values of permeability and skin factor. The assumptions of Horner method are infinite reservoir, single-phase liquid flow and homogeneous reservoir. From principles of well test interpretation, the infinite acting flow regime typically occurs about one and a half cycles after the end of wellbore storage.

Petroleum engineers have shown a high degree of open-mindedness in utilizing new technologies from different disciplines to solve old and new petroleum engineering problems. Using CT-Scan, MRI, Microwave, and even expert systems are good examples. The modern and recently used method for the parametric modeling is the artificial neural networks (ANNs). Today, ANNs have emerged as powerful tool in modeling of the complex systems. First, a syntactic pattern of recognition and a ruled-based system was used by Allain and Horne (1990) to determine the reservoir model and its parameters (Allain and Horne, 1990). Despite this fact, it was required a preprocessing of the derivative data and a complex definition of rules to adjust the nonideal behaviour. The ANNs were used by Al-Kaabi et al. (1990), Al-Kaabi and Lee (1993) to improve the well test interpretation model from pressure derivative data (Al-Kaabi et al., 1990; Al-Kaabi and Lee, 1993). Indeed, their work was a qualitative description of the reservoir and did not compute the reservoir parameters. Some techniques for model recognition were reviewed by Horn (1992). A new approach was illustrated by Anraku and Horne (1993) to discriminate between reservoir models in well test analysis by the sequential predictive probability method. However, before this process some parameters of the models should be estimated. Mohaghegh and Ameri (1995) have shown that neural networks can predict formation permeability using geophysical well log data. A simultaneous regression with Genetic Algorithm (Holland, 1975) was used by Güyagüler et al. (2001) to select the most probable reservoir model among a set of candidate models, consistent with a given set of pressure transient data. However, their method needed additional computational time compared to conventional analysis techniques.

In this study, a new approach has been designed to predict initial pressure, permeability and skin factor of oil reservoirs. The approach is based on artificial neural net technology by using the pressure build up test data. The present study automates Hornar method for calculating initial pressure, permeability and skin factor.

2. Back propagation neural network

ANNs are computing systems based on the belief that intelligence is achieved by means of the interaction of large numbers of simple processing units which are

Table 1
Well and reservoir parameters

Parameter	Test 1	Test 2	Test 3	Test 4	Test 5
r_w (ft)	0.354	0.35	0.29	0.198	0.3
ϕ	0.09	0.28	0.07	0.039	0.1
B (RB/STB)	1.55	1.25	1.28	1.136	1.2
q (STB/D)	4900	1449.6	750	250	4500
h (ft)	482	100	36	69	100
μ (cp)	0.2	0.6	1.0	0.80	0.5
c_t (psi^{-1})	22.6×10^{-6}	12×10^{-6}	18.05×10^{-6}	17×10^{-6}	0.1×10^{-4}
P_i (psig)	3365	2218.46	92.32	4410.8	4269.9
t_p (h)	310	204.47	50.75	13630	21
$P_{wf}(\Delta t=0)$ (psig)	2761	1759.1822	0	3534	3420

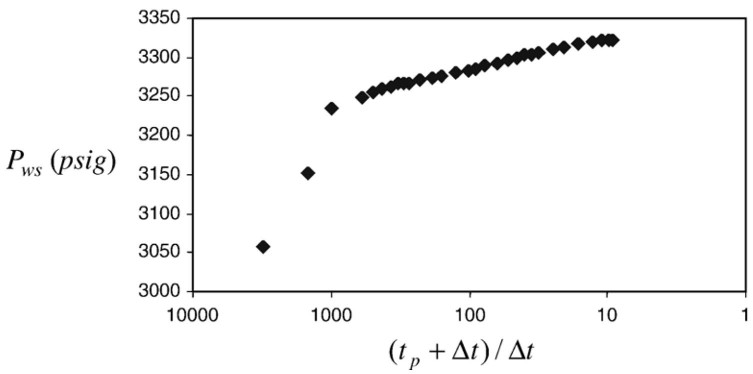

Fig. 2. The Horner plot of pressure build up data for well No. 1.

called nodes. A multilayer ANN consists of different layer of nodes as shown in Fig. 1. The first and the last layers are the input and output layers, respectively. Due to the number of the inputs and outputs, these layers have nodes. The intermediate layer which is exact between these two layers, connect them indirectly. This layer is called the hidden layer. The number of the nodes in the hidden layer may vary from one to the optimum one. The optimum number of nodes required in the hidden layer is problem dependent, being related to the complexity of the input and output mapping, the amount of noise in the data and the amount of training data available. If the number of nodes in the hidden layer is too small the back propagation algorithm will fail to converge to a minimum during training. Conversely, too many nodes will result in the network overfitting the training data resulting in poor generalization performance.

Learning is the main process in neural net operation because the simulation process depends on that. Mathematically, learning is the process by which a set of weights are found that produces the expected output when a net is presented within an input. Therefore, ANNs learn tasks by changing the weight of links between nodes (Bean and Jutten, 2000; Bhatt and Helle, 2002; Helle et al., 2001; Mohaghegh et al., 1994).

In the training process of a Back Propagation Artificial Neural Network (BP-ANN), the error between the network output with the desired one is propagated through the network. According to this, the weights are adjusted. This process continues until the network output reaches an acceptable value. This training process leads to the learning of ANN. When this process has finished, the ANN is ready to simulate other inputs (Bean and Jutten, 2000; Bhatt and Helle, 2002; Helle et al., 2001; Mohaghegh et al., 1994). BP-ANNs have already been used to model and simulate various chemical processes (Shaw et al., 1997).

3. Utilization of Matlab neural network toolbox

The field of neural networks has a history of some five decades, but has found recent applications only in the past fifteen years, and the field is still developing rapidly. Today, neural networks can be trained to solve problems that are difficult for conventional computers or human beings. Meanwhile, Matlab (2001) provides a powerful toolbox and greatly facilitates this procedure.

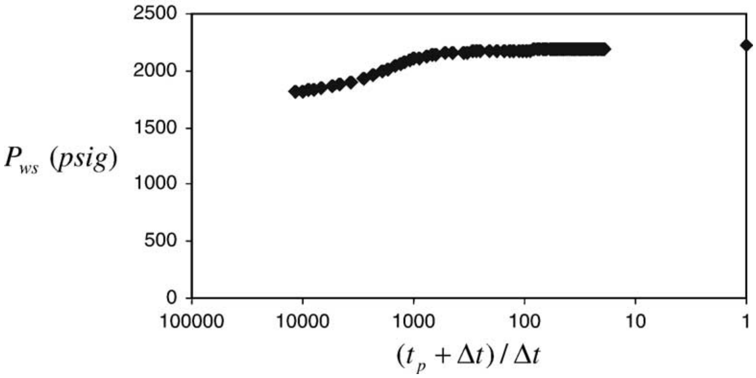

Fig. 3. The Horner plot of pressure build up data for well No. 2.

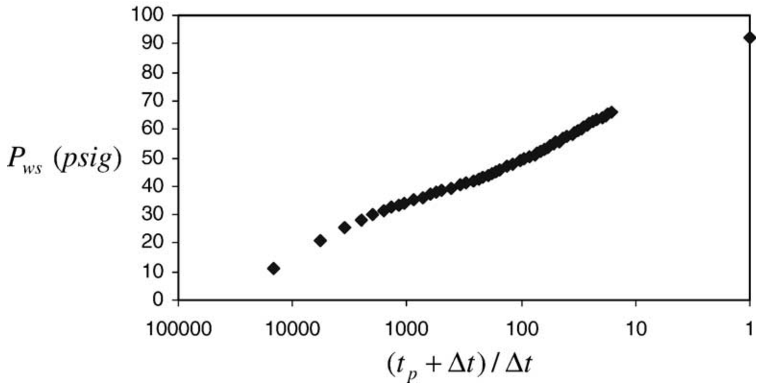

Fig. 4. The Horner plot of pressure build up data for well No. 3.

To create and train a network using this toolbox, following items should be considered:

1– Enter the input and target vectors in its suitable format in the workspace of Matlab.
2– Normalize these vectors independently to assign a number between −1 and 1 to each element of vectors.
3– Type "nntool" to open the Matlab neural networks toolbar.
4– Import these two data as the input and target of the network using "Import" button.
5– To create a new network press its button and enter the required information such as its name, type, input range, number of neurons and etc. Clicking on "Create", you can actually make the network and return to the "Network/data Manager" window.
6– Click on "View" to check the characterization of the network you made.
7– In its "Initialize" part, introduce the input and press the "Initialize Weights" button.
8– To train the network, specify the input and output by clicking on the left tab "Training Info" and selecting these parameters. Choosing "Training Parameters" tab gives you ability to change parameters such as the epochs and error goal.
9– Clicking on "Train Network", the specified network tries to be trained gradually. This process finishes when the defined error is reached.

4. Methodology

The methodology of the approach used in this work is considered in two categories.

4.1. Calculation of the initial pressure

In this approach, ANNs are devoted to the computation of the initial pressure of reservoirs. This is accomplished by means of Matlab toolbox. Consequently, the neural model (See Fig. 1) are devoted to the computation of the shut-in bottom-hole pressure (P_{ws}) (the output neuron), in function of $\left(\frac{t_p+\Delta t}{\Delta t}\right)$ (the input neuron of the input layer).

The manner of training the ANNs is the same as the procedure mentioned before. Initial pressures of reservoirs are the simulating results of these trained networks.

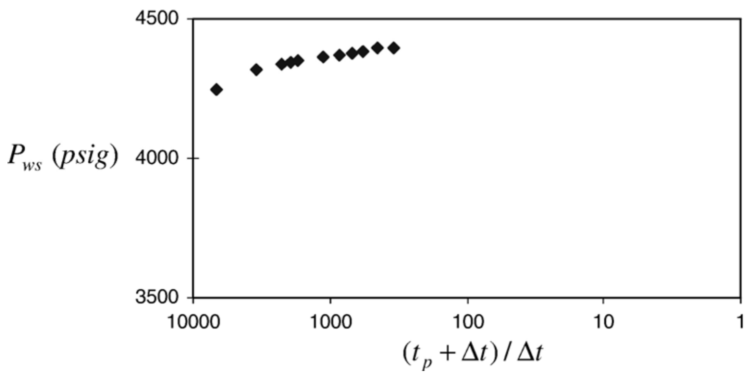

Fig. 5. The Horner plot of pressure build up data for well No. 4.

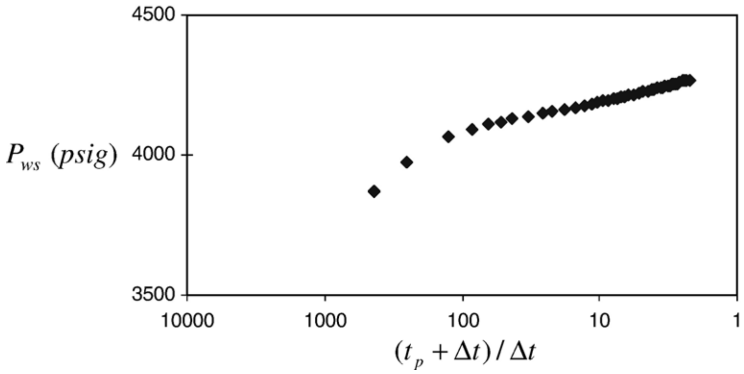

Fig. 6. The Horner plot of pressure build up data for well No. 5.

A number of sets of real well test data are used to evaluate the effectiveness of the approach. Five sets of actual field data during the infinite acting period were selected to illustrate the behaviour of the method. The data for these build up tests were obtained from books by Earlougher (1977), Horne (1995), and Sabet (1991).

Table 1 shows the value of the well and reservoir parameters for these tests. The Horner plots for five build up tests are shown in Figs. 2–6.

It is mentioned that Test 1, 2, and 4 are in conventional reservoirs and Tests 3 and 5 are in dual porosity reservoirs.

Five independent ANNs are trained related to the five sets of pressure build up data. As can be seen in Fig. 1, the output layer (P_{ws}) is a function of the input layer $\left(\frac{t_p+\Delta t}{\Delta t}\right)$. Only one hidden layer for each network has been considered. The optimized number of hidden nodes (neurons) has been determined during the learning and training processes by trial and error tests. After training of the three-layer, feed-forward, back propagation network, the initial pressure of the reservoir can be found from the simulation of this network due to the suitable inputs (i.e., $(t_p+\Delta t)/\Delta t=1$, see Eq. (2)).

4.2. Calculation of permeability

Permeability is the most important rock parameter in the flow of reservoir fluids. From reservoir engineering, reservoir management and enhanced recovery design point of view, knowledge of rock permeability and its spatial distribution throughout the reservoir is of utmost importance. Conventionally core analysis and well test data interpretations are the most reliable way of acquiring permeability values of a formation (Mohaghegh et al., 1994; Earlougher, 1977).

During the infinite acting period, the pressure is a logarithmic function of the Horner time in a build up test. The values of permeability can be estimated from the slope of the semi log straight line. In this work, ANNs are used to estimate the permeability. In that case, it is not necessary to plot the mentioned line and find its slope. For selecting straight line, we choose Δt_D a constant more than 100 (Earlougher, 1977).

After training of the ANN and computing the initial pressure as described in the previous section, the pro-

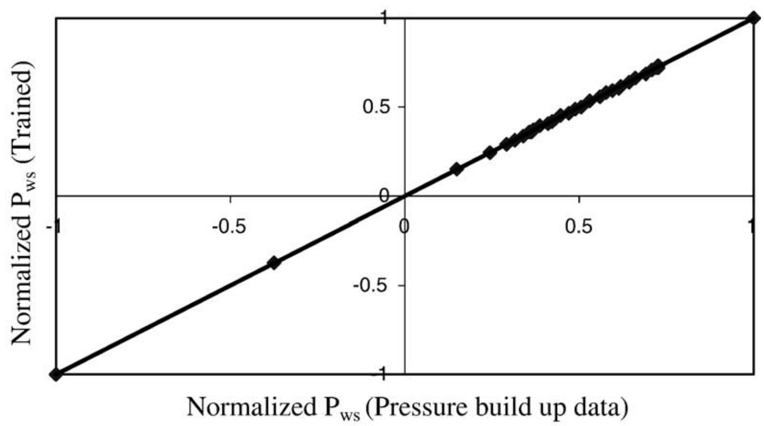

Fig. 7. The ANNs training results for well No. 1.

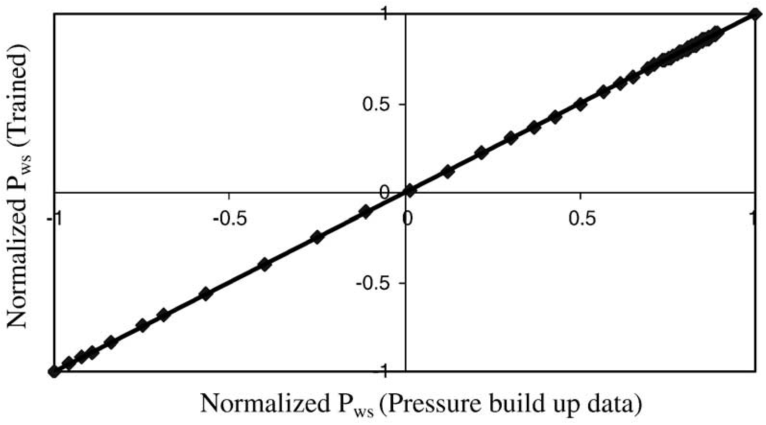

Fig. 8. The ANNs training results for well No. 2.

cedure for calculating the permeability by using ANNs is as follows:

1– Initialize Δt_D a constant more than 100.
2– Make initial guess for k.
3– Calculate Δt from the following equation:

$$\Delta t_D = \frac{0.0002637 k \Delta t}{\phi \mu c_t r_w^2}. \quad (1)$$

4– Calculate $\left(\frac{t_p+\Delta t}{\Delta t}\right)$ as input of the network.
5– Run the trained network and simulate the above input to find P_{ws} from trained network.
6– Find the slope of the Horner plot (m) from the following equation (Horner, 1951):

$$P_{ws} = P_i - m \log\left(\frac{t_p + \Delta t}{\Delta t}\right) \quad (2)$$

It should be noted that P_i is the initial pressure which is estimated previously by the network.

7– Calculate a new value for the permeability (k) by using the following equation (Horner, 1951):

$$m = \frac{162.6 qB\mu}{kh}. \quad (3)$$

8– Until this k converges the previous k goes to step 3 else stop.

4.3. Calculation of skin factor

The pressure drop in a well per unit rate of flow is controlled by various parameters. One of these parameters existing beside the resistance of the formation and the viscosity of the fluid is the additional resistance concentrated around the wellbore. This resistance which is defined as the skin effect detracts the capacity of a well production. The degree of damage (or improvement) is expressed in terms of a skin factor which can be either positive or negative. In the next step of this work, ANNs are used to calculate skin factor of the wells.

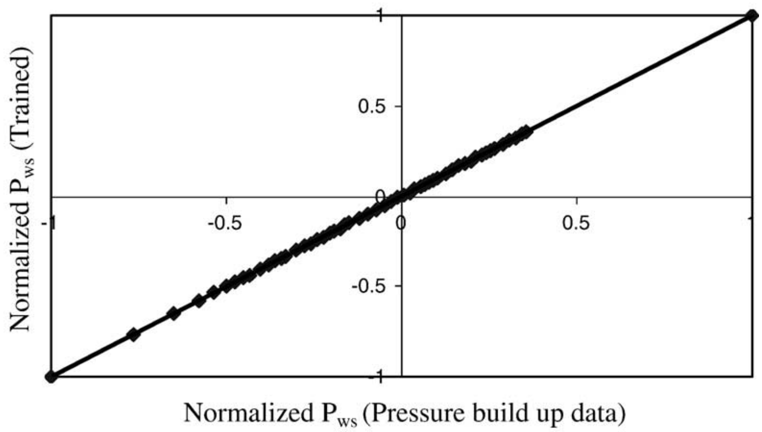

Fig. 9. The ANNs training results for well No. 3.

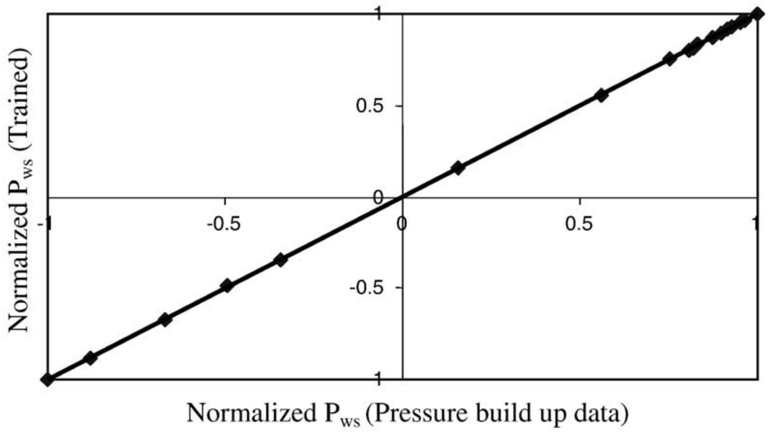

Fig. 10. The ANNs training results for well No. 4.

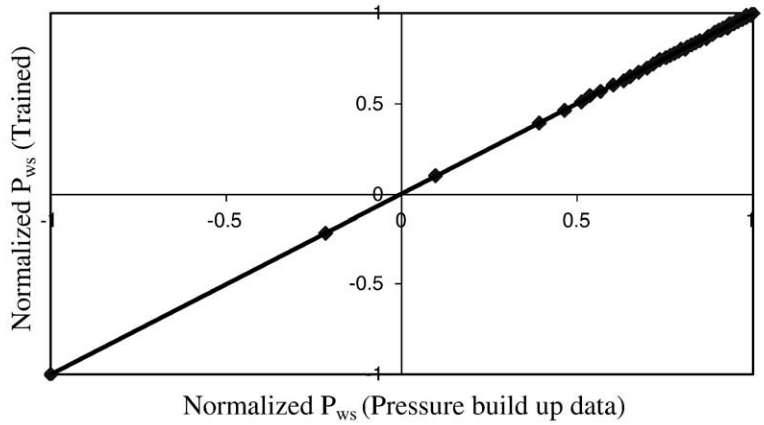

Fig. 11. The ANNs training results for well No. 5.

For achieving this purpose, the following steps should be accomplished:

1– Choose a Δt in the intermediate of the pressure build up data. This parameter should be selected in such a way that the point of $\left(\frac{t_p+\Delta t}{\Delta t}, P_{ws}\right)$ is located in the straight-line portion of the Horner plot.
2– Calculate $\frac{t_p+\Delta t}{\Delta t}$ as input of the network.
3– Run the trained network and simulate the above input to find P_{ws}.
4– Obtain the false pressure (P^*) from the following equation using the input and output of the network (Earlougher, 1977).

$$P^* = P_{ws} - m\log\left(\frac{t_p + \Delta t}{\Delta t}\right) \tag{4}$$

The amount of m is estimated in the latest loop of permeability calculations.

5– Determine the skin factor from the following equation (Earlougher, 1977):

$$s = 1.1513\left[\frac{P_{wf}(\Delta t = 0) - P^*}{m} - \log\left(\frac{kt_p}{\phi\mu c_t r_w^2}\right) + 3.2275\right] \tag{5}$$

In this equation the permeability estimated in the previous part of calculation is applied. In fact, ANNs

Table 2
The initial pressure for each reservoir

Well no.	Kind of the reservoir	Initial pressure from the Horner plot (psig)	Initial pressure from the neural network (psig)	% Error
1	Conventional	3365	3362.7	0.07
2	Conventional	2218.46	2208.7	0.44
3	Dual porosity	92.32	92.078	0.26
4	Conventional	4410.8	4405.9	−0.11
5	Dual porosity	4269.9	4269.9	0.00

Table 3
The calculated permeability from the Horner plot and neural network

Well no.	Kind of the reservoir	Permeability from the Horner plot (md)	Permeability from the neural network (md)	% Error
1	Conventional	12.8	13.43	4.9
2	Conventional	128.12	135.18	5.5
3	Dual porosity	255.33	272.15	6.6
4	Conventional	7.65	8.05	5.2
5	Dual porosity	3100	3258	5.1

Table 4
The calculated skin factor from the Horner plot and neural network

Well no.	Kind of the reservoir	Skin factor from the Horner plot	Skin factor from the neural network	% Error
1	Conventional	8.60	9.22	7.2
2	Conventional	18.37	19.14	4.2
3	Dual porosity	−4.12	−3.98	3.4
4	Conventional	6.37	6.81	6.9
5	Dual porosity	−1.20	−1.26	5.0

have implicit role in the calculation of skin factor. In other words, ANNs emerged itself in the calculations of parameters needed in above equation.

5. Results and discussions

Five sets of pressure build up data as shown in Figs. 2–6, are used to train the ANNs. The training results are shown in Figs. 7–11. As can be seen in these figures, there is a very good agreement between the pressure build up data (normalized P_{ws}) and the trained data. This illustrates that the networks trained very well and now can be used to simulate the initial pressure, permeability and skin factor of each reservoirs. In Table 2 the initial pressure from the Horner plot and the neural network are compared with each other. The close agreement between them is more obvious in the error percent given in that table. Calculated values of permeability from Horner plot and neural network are shown in Table 3. It was shown that neural networks can predict formation permeability using pressure build up data with good accuracy. Table 4 presented the results of skin factor calculations from either Horner plot or neural network.

Table 5
The reservoir properties calculated from different method for well No. 1

Properties	From the Horner plot	From the neural network using all data	From the neural network using some data
Initial pressure (psig)	3365	3362.7	3365
Permeability (md)	12.8	13.43	12.77

In the next step, the effect of the ANNs on the reduction of costs for pressure build up test is investigated. Providing several data for an experiment required a large amount of money. These data are nothing else than shut-in bottom-hole pressure as a function of shut-in period. An ANN is trained with 28 sets of pressure build up data for well No. 1 by 15 neurons. 75% of these data are utilized for training and the remainder are used in simulating. The shut-in bottom-hole pressure results are represented in Figs. 12 and 13. In these figures, trained and simulated data are compared with the pressure build up data, respectively. An excellent agreement can be seen in between them. Therefore, this shows that providing numerous data for a pressure build up test is not necessary a lot and data

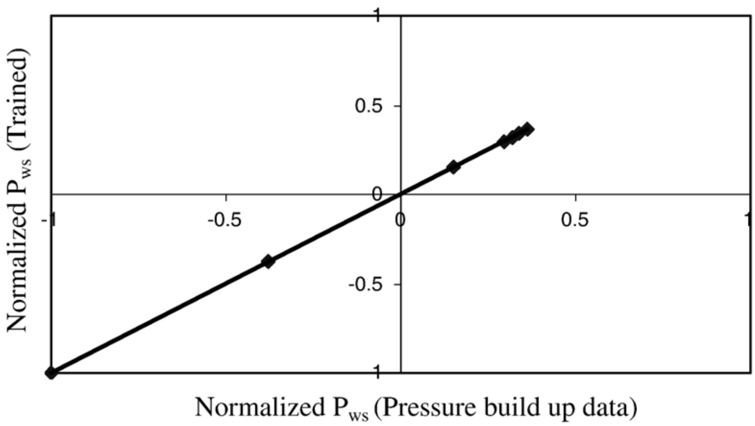

Fig. 12. The ANNs training shut-in bottom-hole pressure results for well No. 1 using some data.

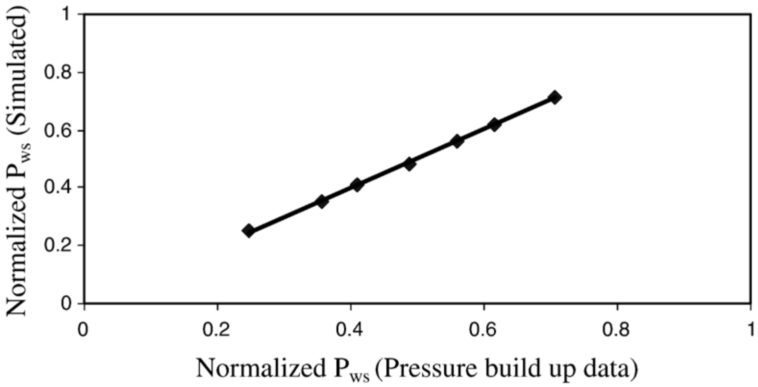

Fig. 13. The ANNs simulating shut-in bottom-hole pressure results for well No. 1 using some data.

can be increased by helping ANNs. In other words, a limited data can be taken from the field and extended by ANNs. As a result, the cost of a pressure build up test is decreased. The calculated initial pressure and permeability from this method is compared with the results of the previous method and the results of the Horner plot in Table 5. With this method not only we can reduce the costs but also we can predict the reservoir properties more accurately.

6. Conclusions

The approach presented in this study automates the process of pressure build up test analysis. Human involvement occurs only at the initial poor guess for permeability. This new approach is based on artificial neural networks to calculate the initial pressure, permeability and skin factor of reservoirs. This method is capable of predicting these parameters for different kinds of reservoirs. Furthermore, this approach provides a new way to speed up the calculations and not use tedious and time-consuming plots. A pressure build up test has high cost (the cost of performing the test in addition to loss of production during the test). The present study shows the use of artificial neural networks in a pressure build up test which may reduce the cost of the test. Indeed, a pressure build up test together with ANNs needs less than data points for calculating reservoir parameters.

7. Nomenclature

Δt_D	Dimensionless shut-in time
k	Permeability, md
Δt	Shut-in period, h
ϕ	Porosity, fraction
μ	Viscosity, cp
c_t	Total compressibility, psi^{-1}
r_w	Wellbore radius, ft
t_p	Producing time, h
P_{ws}	Shut-in bottom-hole pressure, psi
m	Slope of linear portion of the Horner plot, psi/cycle
h	Formation thickness, ft
q	Flow rate, STB/D
B	Formation volume factor, RB/STB
P_i	Initial pressure, psig
s	Skin factor
$P_{wf}(\Delta t=0)$	The flowing pressure just prior to shut-in, psi
$P*$	False pressure, psi

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