[Regular Paper]

Artificial Neural Networks Approach for Estimating Filtration Properties of Drilling Fluids

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Filtrate volume and permeability of filtercake are two main properties of drilling fluids. During this decade, various ways for estimating of them are proposed. In this study, a new approach based on artificial neural networks (ANNs) has been designed to estimate filtrate volume and permeability of filtercake using the static filtration data. In this speeding up approach 75% of experimental data have been used to train the neural network and the remaining data have been applied to test the performance of the network. Finally, the estimated results of filtrate volume and permeability of filtercake obtained from the network have been compared against the values obtained by empirical correlations used for calculation of these parameters.

Keywords

Static filtration, Filtrate volume, Permeability, Artificial neural network

1. Introduction

Pressure difference between the hydrostatic pressure of the mud column and the pressure of the fluids in the pore of the formation causes mud to invade the permeable formation. This phenomenon which is called as fluid loss is an undesirable happening which drilling industry is encountered. As the mud solids are filtered out onto the walls of the hole, they remain to make a low permeable cake through which only filtrate can pass. Two types of static filtration and dynamic filtration may occur in drilling an oil well. Static filtration takes place when the mud is not being circulated. On the contrary, dynamic filtration happens when the mud is being circulated. The rate of dynamic filtration is higher than the static one because the growth of the filtercake is confined by the erosive force of the mud[1)].

Fluid loss through this filtercake is often measured in the laboratory. For decades, various laboratory attempts under both static and dynamic filtration are accomplished on the investigations of mudcake buildup and invasion rates[2)~5)]. The result of these experiments indicated that at constant rate and pressure of circulation, the filtration rate into the mudcake was at first high, but as time passed, this rate would decrease to an equilibrium value. Moreover, the data of these literatures show the dependency of this equilibrium rate on circulation rate, differential pressure, mud composition, temperature. Furthermore, it was implied that after a period of static filtration by resuming the circulation, the mudcake thickness would change or not.

The theory of this phenomenon was first presented by Outmans (1963)[6)]. Later, other works are done[7)~9)]. However, as yet no sufficiently comprehensive theory of mud filtration has been presented to allow prediction of the filtration properties of drilling fluids.

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. In the filtration fields, not a notable work was done based on ANNs. In this study, a new approach has been developed to predict filtrate volume and permeability of filtercake. The approach is based on artificial neural net technology.

2. Neural Networks

Computerized artificial neural network model tries to imitate simplified biological learning processes and simulate some functions of human nervous system. This adaptive and the most popular intelligent technique has parallel information processing system that can develop associations, transformations or mapping between objects or data. A neural network consists of simple processing units called neurons. It should be notified that the neural network approach does not use a pre-described algorithm for solving a problem. However, it learns the solution model automatically by training on some inputs and their expected outputs[10)].

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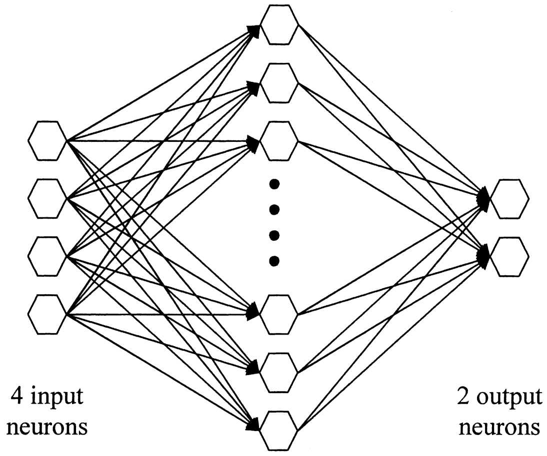

Fig. 1 The Design of ANN

A back propagation network is multi-layered and information flows from the input to the output through at least one hidden/middle layer. Each layer contains neurons that are connected to all neurons in the neighboring layers. The connections have numerical values (weights) associated with them. During the training phase, the weights are adjusted according to the generalized delta rule. Training is completed when the network is able to predict the given output. Although the training process may take maximum 5 min to be finished, the simulation process is too fast. When a network is trained, it can be used easily to simulate other independent data in a higher speed. Therefore, ANN is a method that speeds up the calculations of simulation.

3. The Identification of the Network

A three-layer back propagation neural network was used in all cases due to its success in solving other petroleum engineering problems[11] and its ability to generalize with good accuracy. Consequently, this neural network was developed using three layers. The three-layer back propagation neural network was designed with four input, thirty hidden, and two output neurons. The design of ANN is shown in **Fig. 1**. As it is shown, the hidden layer joining the input and the output layers is itself connected to these both layers by linkers known as weights. The value of these weights can be varied from zero to one. The ANN learns by repeatedly adjusting these weights until the results produced are similar to the correct outputs in the training set. The number of neurons in the hidden layer is determined by try and error method of solution. Applying this method, it is found that 30 neurons is the best number that causes the best convergence between the produced results and the training data. 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 backpropagation 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.

Time, pressure drop, water and sodium chloride weight percents were used as input. The output layer was consisted of filtrate volume and permeability. This network was trained using 154 data sets. The remaining 51 data, which were not seen by the network during training, were reserved to test the performance of the network. A robust back propagation gradient descent-learning algorithm was used to train the network. This algorithm utilizes adaptable learning rates and momentums that adapt themselves during learning.

Table 1 Composition of Various Mud (Ghorbani, 2004)

Mud name	Weight percent		
	Water	Bentonite	Sodium chloride
A	97	3	0
B	94	6	0
C	91	9	0
D	89	9	2
E	86	9	5
F	81	9	10

4. Methodology

In this approach, ANNs are devoted to the computation of the filtrate volume and permeability of the mudcake. This is accomplished by means of Matlab[14] toolbox on Pentium 4 PC with 256 MB of RAM. A number of sets of real static filtration data[12] are used to evaluate the effectiveness of the approach. The experiments done by Ghorbani (2004) were performed in the standard API filtration test[13] which is mainly used in static filtration.

Table 1 shows the composition of various drilling mud used in this work. Drilling mud is a mixture of clay minerals, and other additives that enhance properties such as density, viscosity, gelation, etc., and a fluid which may be either water or oil.

As a result of pressure difference, the fluid portion of the mud (the mud filtrate) filtered into the formation ahead of the bit and into the wall of the borehole. The penetration of the mud filtrate which happens radially can cause the displacement of the formation fluids ahead of it. This mud fluid invasion is investigated in this work. In fact, the neural network is applied to es-

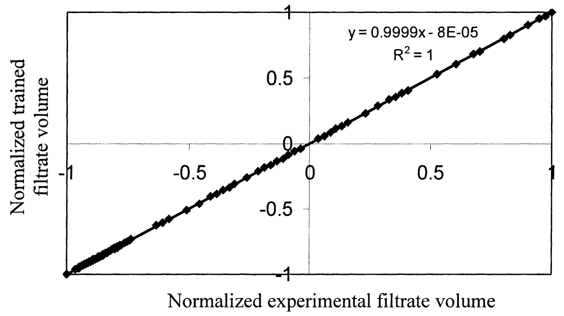

Fig. 2 The ANN Training Results for Filtrate Volume

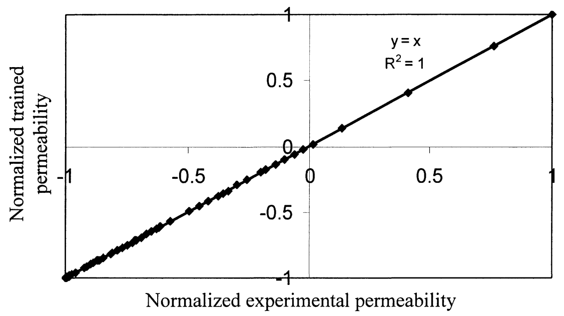

Fig. 3 The ANN Training Results for Mud Cake Permeability

timate Filtrate volume and the permeability of the mudcake.

5. Results and Discussions

As mentioned above, the network using 154 data sets is trained in such a way that it can simulate 51 data sets accurately. The network is able to predict filtrate volume and permeability of mudcake simultaneously. The training results are shown in **Figs. 2** and **3**. As can be seen in these figures, there is a very good agreement between the experimental data and the trained ones. This illustrates that the networks trained very well and now can be used to simulate independent data for filtrate volume and permeability of mudcake. **Figures 4** and **5** illustrate the simulated results of these parameters. The equations of the form $y = f(x)$ in the **Figs. 2**-**5** are the equations of the regression lines. When all the points fall exactly on the line of 45°, the regression line is $y = x$. In this case, the network is trained or simulated very well. Otherwise, the regression line has the form of $y = ax + b$. The regression constants (R^2-value) which are also appeared in these figures show the agreement of trained and simulated data with experimental data. In the ideal situation, when these parameters are exactly similar, $R^2 = 1$.

In addition, Ghorbani (2004) suggested some correlations due to his own experimental data to predict filtrate volume and permeability of mudcake[12]:

For mud A, B, and C

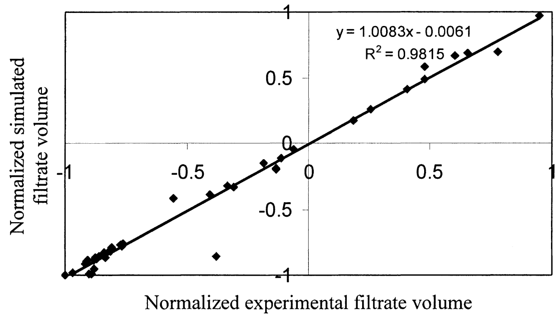

Fig. 4 The ANN Simulated Results for Filtrate Volume

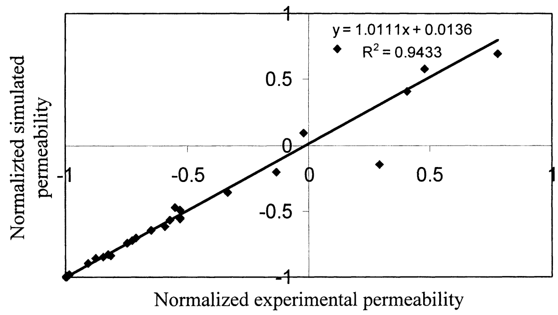

Fig. 5 The ANN Simulated Results for Mud Cake Permeability

$$Q_w = 1.92 w_b^{-0.45} \cdot \Delta P^{0.25} \cdot t^{0.5} \qquad R^2 = 0.85 \tag{1}$$

$$k = 3 w_b^{-0.35} \cdot \Delta P^{-0.73} \cdot t^{-0.5} \qquad R^2 = 0.93 \tag{2}$$

For mud D, E, and F

$$Q_w = 8.3 w_n^{0.57} \cdot \Delta P^{0.1} \cdot t^{0.5} \qquad R^2 = 0.95 \tag{3}$$

$$k = 15.42 w_n^{0.55} \cdot \Delta P^{-0.9} \cdot t^{-0.5} \qquad R^2 = 0.95 \tag{4}$$

In the next step, the simulated results of the network are compared with the results of these correlations and the experimental data. The comparisons of filtrate volume and mudcake permeability are shown in **Tables 2** and **3** for mud A and D, respectively. These results are represented in **Figs. 6** through **9**. In these figures, simulated data are compared with the experimental and correlated data. As can be seen, an excellent agreement exists between simulated and experimental data rather than correlated data. The error percent of these parameters due to their experimental values are demonstrated in **Tables 4** and **5**. Also, in these tables, one can see the relationship between the magnitude of error and variation of the parameters. The main conclusion that can be derived from these tables is the less error percent of the ANN results in comparison of the correlated results. This shows the capability and precision of the network trained and used to simulate. Therefore, ANN is a useful tool for calculating the filtration properties than empirical correlations.

Table 2 The Comparison of Simulated Filtrate Volume with Experimental and Correlated Results

Mud	Bentonite weight percent	Sodium chloride weight percent	Pressure drop [10^5 Pa]	Square root of time [$\mathrm{min}^{1/2}$]	Filtrate volume [m*l*] Exp.	Filtrate volume [m*l*] Sim.	Filtrate volume [m*l*] Corr.
A	3	0	1	3.8	5.2	4.9182	4.4502
A	3	0	1	5.8	7.5	7.5180	6.7924
A	3	0	1	7.5	9.2	9.3254	8.7833
A	3	0	2	3.2	5	5.4008	4.4566
A	3	0	2	5.5	7.8	7.9110	7.6598
A	3	0	2	7.2	9.4	8.8924	10.0274
A	3	0	3	2.25	4	0.2449	3.4678
A	3	0	3	5	7.6	7.3640	7.7063
A	3	0	3	6.75	9.6	9.5297	10.4035
D	9	2	1	1.4	18	23.5972	17.2502
D	9	2	1	2.45	28	27.0248	30.1878
D	9	2	1	3.2	35	32.9553	39.4289
D	9	2	2	1.75	24	24.8103	23.1103
D	9	2	2	2.65	33	34.4689	34.9956
D	9	2	3	0	0	0.0000	0
D	9	2	3	2	27	27.3539	27.5047
D	9	2	3	2.85	36	35.7747	39.1942

Table 3 The Comparison of Simulated Permeability with Experimental and Correlated Results

Mud	Bentonite weight percent	Sodium chloride weight percent	Pressure drop [10^5 Pa]	Time [min]	Permeability [10^{-15} m^2] Exp.	Permeability [10^{-15} m^2] Sim.	Permeability [10^{-15} m^2] Corr.
A	3	0	1	20	0.54	0.5973	0.4567
A	3	0	1	40	0.36	0.2489	0.3229
A	3	0	1	60	0.28	0.2962	0.2637
A	3	0	2	20	0.3	0.2197	0.2753
A	3	0	2	40	0.19	0.1814	0.1947
A	3	0	2	60	0.15	0.1306	0.159
A	3	0	3	20	0.2	0.2036	0.2048
A	3	0	3	40	0.13	0.1352	0.1448
A	3	0	3	60	0.1	0.09	0.1182
D	9	2	1	4	11	10.9404	11.2881
D	9	2	1	8	7	7.1583	7.9819
D	9	2	2	2	9	9.059	8.5548
D	9	2	2	6	4.5	4.4071	4.9391
D	9	2	2	10	3.2	3.6544	3.8258
D	9	2	3	4	4	4.0036	4.1996
D	9	2	3	8	2.5	2.6654	2.9696

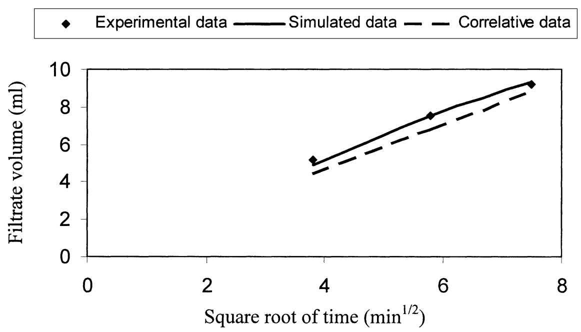

Fig. 6 The Comparison of Simulated Filtrate Volume with Experimental and Correlated Results for Mud A at $\Delta P = 1 \times 10^5$ Pa

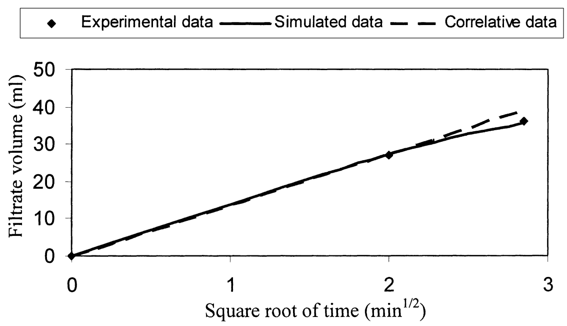

Fig. 7 The Comparison of Simulated Filtrate Volume with Experimental and Correlated Results for Mud D at $\Delta P = 3 \times 10^5$ Pa

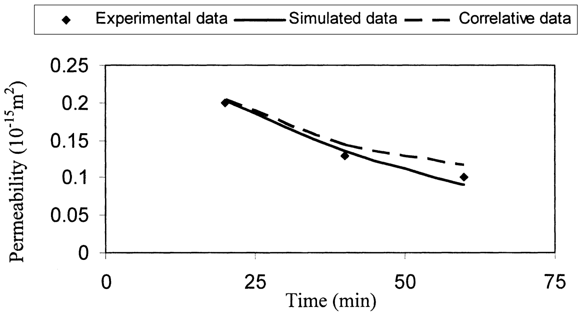

Fig. 8 The Comparison of Simulated Permeability with Experimental and Correlated Results for Mud A at ΔP = 3 × 10^5 Pa

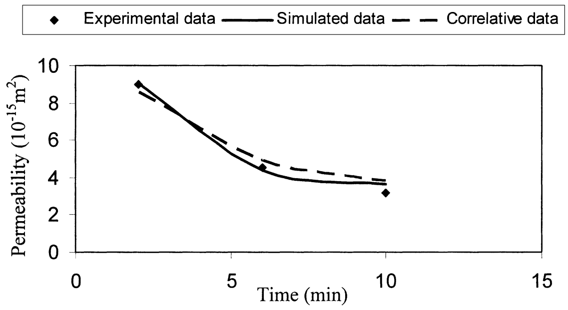

Fig. 9 The Comparison of Simulated Permeability with Experimental and Correlated Results for Mud D at ΔP = 2 × 10^5 Pa

Table 4 The Comparison of the Error Percents of the Filtrate Volume Results

Mud	Pressure drop [10^5 Pa]	Square root of time [min$^{1/2}$]	Experimental filtrate volume [m*l*]	Simulated filtrate volume [m*l*]	Correlated filtrate volume [m*l*]	% Error of simulated filtrate volume	% Error of correlated filtrate volume
A	1	3.8	5.2	4.9182	4.4502	−5.2	−14.4
A	1	5.8	7.5	7.5180	6.7924	0.24	−9.43
A	1	7.5	9.2	9.3254	8.7833	1.36	−4.53
D	3	0	0	0	0	0	0
D	3	2	27	27.3539	27.5047	1.31	1.87
D	3	2.85	36	35.7747	39.1942	−0.62	8.87

Table 5 The Comparison of the Error Percents of the Permeability Results

Mud	Pressure drop [10^5 Pa]	Time [min]	Experimental permeability [10^{-15} m^2]	Simulated permeability [10^{-15} m^2]	Correlated permeability [10^{-15} m^2]	% Error of simulated permeability	% Error of correlated permeability
A	3	20	0.2	0.2036	0.2048	1.8	2.4
A	3	40	0.13	0.1352	0.1448	4	11.4
A	3	60	0.1	0.09	0.1182	−10	18.2
D	2	2	9	9.059	8.5548	0.65	−4.95
D	2	6	4.5	4.4071	4.9391	−2.06	−34.7
D	2	10	3.2	3.6544	3.8258	14.2	19.5

6. Conclusions

Filtrate volume and permeability of mudcake are two main parameters of filtration properties which are investigated in this paper and a new method for calculating them is recommended. The approach presented in this study automates the process of predicting these parameters. This new approach is based on artificial neural networks which not only speed up calculations of simulating but also increase the accuracy of estimating. In the first glance, it may seem that using the algebraic equations is speedier than ANN method, but as it is mentioned before, when a network is trained, simulating process may take a few minutes to be accomplished.

The consuming time of simulating in ANN is much less than the empirical correlations. It can be trained very well and simulate data precisely. Furthermore, it is shown that the results of the network are in good agreement with experimental data. Therefore, this approach can be replacement of correlations because the developed model provides better predictions and higher accuracy than the empirical correlations developed specifically for these data groups.

Nomenclatures

k	: permeability	[md (10^{-15} m^2)]
Q_w	: filtrate volume	[m*l*]
ΔP	: pressure drop	[Pa]
t	: time	[min]
w_b	: bentonite weight percent	[—]
w_n	: sodium chloride weight percent	[—]
R^2	: regression constant	[—]

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要　　旨

人工ニューラルネットワーク手法を用いた掘削泥水の沪過特性の評価

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マッドケーキの沪過量ならびに浸透率は掘削流体の特性を評価するための重要なパラメーターである。過去十年の研究において，その評価手法としては種々の方法が提案されてきている。本報告においては，スタティックな泥水沪過実験データを使用し，人工ニューラルネットワーク（ANN）手法に基づいた上記の二つの泥水特性（マッドケーキ沪過量ならびに浸透率）の評価方法に関しその適用可能性を検討している。本手法においては，泥水沪過実験データの75％がニューラルネットワーク学習に供され，残りの25％の実験データが同ネットワークのパフォーマンスチェックに利用された。その結果，高い精度で実験データを評価することが可能であることが判明した。さらに，実験データに基づいたGhorbaniの関係式により推定されたマッドケーキ沪過量，浸透率値とも比較され，その整合性についても確認された。