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Drilling Rate Optimization by Automatic Lithology Prediction Using Hybrid Machine Learning

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ABSTRACT

It is essential to obtain valuable information during drilling from the formation that is being drilled for rate optimization. In the drilling operation, the process of lithology and formation determination is extremely obscurant and it seems machine learning, as a novel prediction method that can model complicated situations having a high degree of uncertainty, could be beneficial. In this work, the real-time drilling data was applied to predict the formation type and lithology while drilling that formation using a genetic algorithm and Taguchi design of experiment optimized artificial neural network. Drilling data of twelve wells in one of Iranian gas fields were applied for this work. 47500 sets of data were selected, and after data control, 31200 data sets were selected as valid data and imported to artificial neural networks. For performing this research, by changing the network features and optimizing the structure of the network using the Taguchi method and optimizing the weight and biases of the network using the genetic algorithm, a unique artificial neural network was designed. The results show that the developed hybrid machine learning method can predict formation and lithology with a high degree of accuracy.

Keywords: : Real-Time Drilling Data, Formation Lithology, Virtual Intelligence, genetic algorithm, design of experiment

INTRODUCTION

A formation is the basic unit of lithostratigraphy. A formation is composed of some layers or strata with some similar or comparable properties such as lithology or color. The lithology of a rock unit is representative of physical features of this rock such as color, texture, grain size, and composition [1, 2]. Having enough information of the formation under the bit, is very significant for bit selection optimization [3], lost circulation prediction [4] shale swelling inhibition, wellbore instability and other important drilling issues [5]. One of the most critical and costly problems that may be experienced during drilling operation is loss of circulation. This problem imposes considerable expenses to the drilling companies due to the drilling fluid that is lost to the formation or subsequence problems like wellbore instability or stuck pipe [6]. Also, when

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active shales are existing in the wellbore, shale swelling and wellbore instability can be a common problem.

Onyia in 1988 [6] shows that a close relation between log data and lithology of a formation is existing; however, getting a good relation between log data and geological properties of the rock is impossible due to the high nonlinearity of the rock properties. Some conventional statistical methods such as box and whisker plots, histograms, the analysis of average and variance and cross plots, were used by Reed et al. in 1997 [7], Killeen in 1997 [8], McDowell et al in 1988 and 2004 [9, 10], and Vella and Emerson in 2009 [11] to find out the physical properties of the rock and relate them to the geology of the formation. These methods do not provide accurate means to predict lithology [5, 6, 12-14].

Because of conventional techniques limitation on solving complicated issues, in recent years, several researchers started to use the multi-variable pattern recognition methods for predicting properties of a formation [15-19].

The neural network successfully applied to downhole logging data [16-26]. At the newest attempt, Corina and Hovda in 2018 [27] tried to predict lithology from log data using the kernel density estimation method. Although their work was satisfactory, it needs measurement while drilling (MWD) tools during drilling operations. Benaouda et al. in 1999 [17] and Ojha and Maiti in 2013 [21] applied the first time the artificial neural network in ocean drilling to predict lithology in a situation where drilling core recovery is not suitable.

For finding the relation between real-time drilling data and formation lithology, a feed-forward back propagation neural network with high ability of learning can be applied. In this work at the first trial, we tried to predict the formation type and lithology of one of the Iranian gas fields using the back-propagation neural network. Although the results were kind to some extent, they were not satisfactory. Therefore, in the next attempt, we designed a Genetic algorithm optimized the neural network in conjunction with the Taguchi experiment design method to improve the results.

EXPERIMENTAL PROCEDURE

Approach

Many techniques and procedures can be found in the literature for forecasting lithology and formation type during or after drilling. Collecting cuttings from the shale shaker and analyzing them by the geologists is the most common method. Although in this method, lithology can be specified precisely, but there is a considerable lag time in this determination and can cause some severe problems. For example, formation change can cause a blowout or loss of circulation if it is not diagnosed quickly. One of the other important methods of lithology determination is logging, but previously mentioned problems still exist. Other technique is employing adjacent well data. Although it can be accompanied by some significant uncertainties but it is more applicable [28].

In this work, it is wanted by us to forecast formation and lithology while drilling, not after drilling. Obviously, formation type may affect drilling rate, that is, in all of the drilling rate equations such as Garnier and van Lingen in 1959 [29], Galle and Woods in 1963 [30] and Bourgoyne and Young in 1974 [31], formation strength or formation constant will be introduced as an essential input, although there are some other inputs such as drilling fluid properties [32], weight on bit and rpm of bit. Therefore, in this work, first, all variables affecting the rate of penetration (ROP) will be determined by us, and then the formation constant will be replaced with ROP.

The Bourgoyne and Young Method [30] (Figure 1) is one of the important Rete of penetration methods since it is based the past drilling parameters. Equation 1 gives the common form of relation of rate of penetration introduced by Bourgoyne and Young in 1974 [31]:

$$ROP = f_1 f_2 f_3 f_4 f_5 f_6 f_7 f_8 \quad (1)$$

Equation 1 can be rearranged as follows:

$$f_1 = \frac{ROP}{f_2 f_3 f_4 f_5 f_6 f_7 f_8} \quad (2)$$

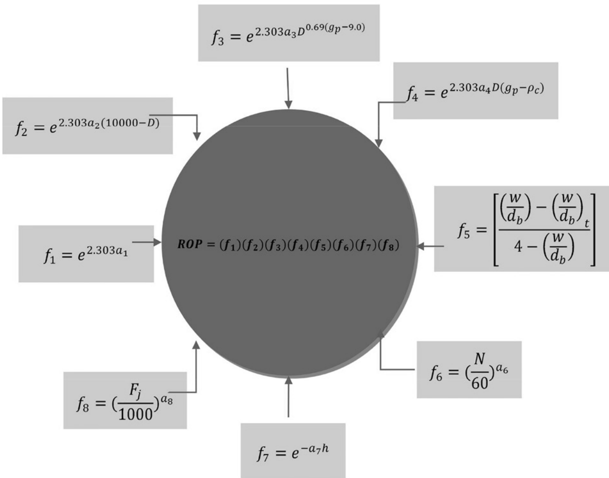

Figure 1: drilling parameter items considered to affect the rate of penetration (equations from Bourgoyne and Young in 1974 [31])

Moreover, solving this equation is not easy due to the lack of constants a_1- a_8, so the artificial neural network (ANN) will be used for the approach. In this method, ROP and also effective parameters on functions f_2 to f_8 would be introduced to ANN, and effective parameters on f_1 are calculated.

In this work, the current well real-time drilling data and adjacent well were introduced to the optimized ANN to detecting lithology and formation exactly while drilling. Input parameters to the ANN and output parameters are shown in Figure 2.

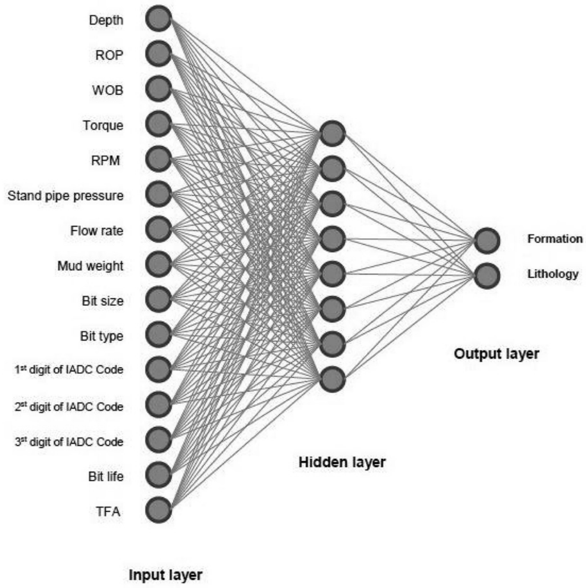

Figure 2: Feed-forward back-propagation artificial neural network used in this work.

Optimizing ANN using GA

The complexity and non-continuity of geological problems make the genetic algorithm a more useful and preferable tool over the traditional backpropagation method for finding weight and bias of an ANN. The researches by Van Rooij et al. in 1996 [33] and Vonk et al. in 1997 [34] have proposed using metaheuristic methods such as genetic algorithm or ant colony algorithm to regenerate ANN structure as well as its weights and bias.

The previous studies did not optimize ANN parameters and structure using Search algorithms. Saemi et al. in 2007 [35], developed a method for optimizing ANN structure and parameters using GA. They show that their model could estimate the reservoir permeability with good precision. In this work, real GA was employed to optimize weights and the threshold of ANN to find the best solution for the fitness function for the first time. In addition, the required code for solving the problem was developed by MATLAB R2015B software.

Input Parameters of the Neural Network

Burgoyne at 1991 [36] showed that some parameters such as bit rotating speed, weight on bit, pump flow rate and pump pressure as well as formation type and lithology can affect the drilling rate. This idea will be used for finding lithology and type of formation. This means that when drilling a particular formation, the drilling rate would be constant when drilling parameters are constant. In other words, drilling rate change shows lithology change during drilling with constant drilling parameters. Therefore, drilling parameters and ROP would be introduced to the GA-ANN network as the input and lithology and formation would be considered as the output of the network.

In this work, 47000 sets of data from twelve wells in the South Pars gas field (Figure 3) were selected (Figure 2). After the effective parameters on Equation 1 were considered, some parameters were chosen as the most effective parameters on the drilling rate. Selected parameters which can also use as an indicator for formation and lithology change are: bit depth, drilling rate, torque on bit, WOB, rotating speed (RPM) of bit, pressure of pump, flow rate of pump, size of bit, and type of bit.

Output Parameters of the Neural Network

This network was designed for formation type and lithology prediction. Therefor a two-digit code representing formation type and lithology can be used as the output. First, a code to all encountered formation was assigned by us as South Pars gas field wells were being drilled. Moreover Table 1 shows Name of formations and assigned codes to each formation.

Figure 3: South Pars Gas Field, South of Iran [28].

Table 1: Encountered formation in the South Pars gas field and assigned codes to these formations.

Formation	Code	Formation	Code	Formation	Code	Formation	Code
Gachsaran	1	Mishrif	7	Fahlyan	13	Neyriz	19
Asmari	2	Hamadi	8	Hith	14	Dashtak	20
Jahrom	3	Mauddud	9	Arab	15	Kangan	21
Sachun	4	Kazhdomi	10	Daran	16	Dalan	22
Halul	5	Darian	11	Dyiab	17	Nar	23
Lafan	6	Gadvan	12	Surmeh	18		

For generating code for the lithologies, encountered lithologies in the drilled formation in this field was studied precisely. It was noted that there are ten primary lithologies in the encountered formations. So, a number between 1 and 6 was allocated to lithology. In Table 2, the encountered lithology and assigned codes are shown to each one.

Therefore as it can be seen in Table 3, a number between 1 and 24 would be representative of the formation type and a number between 1 and 6 would shows the lithology.

Table 2: Encountered lithology in the South Pars gas field and assigned codes to these lithologies.

lithology	code	Lithology	Code
Limestone	1	Argillaceous limestone	1.5
Dolomite	2	Dolomite/limestone	2.5
Anhydrite	3	Anhydrite/Dolomite	3.5
Shale	4	Shale/limestone	4.5
Marl	5	Clay	6

Table 3: Generated output code for determining formation type and lithology.

Formation type (1 to 24)	Lithology type (1 or 6)

Optimizing Network Parameters Using Taguchi Method

Taguchi method is one of important procedures of design of experiment introduced by the Japanese engineer Genichi Taguchi [39, 40]. Using this method relation between input and output parameters can be obtained with fewer energy, try or experiments. For this purpose, there are also other methods, such as full factorial design, fractional factorial design, etc. [38].

Moreover, tables of orthogonal arrays were provided by Taguchi to be used as statistical designs that were well suited for estimating the main effects. In Table 4, the Taguchi method flowchart and an example of L27 orthogonal array are shown.

Table 4: Taguchi L27 arrays with seven factors, each one in 3 levels.

Experiment number	Level of factor 1	Level of factor 2	Level of factor 3	Level of factor 4	Level of factor 5	Level of factor 6	Level of factor 7
1	1	1	1	1	1	1	1
2	1	1	1	1	2	2	2
3	1	1	1	1	3	3	3
4	1	2	2	2	1	1	1
5	1	2	2	2	2	2	2
6	1	2	2	2	3	3	3
7	1	3	3	3	1	1	1
8	1	3	3	3	2	2	2
9	1	3	3	3	3	3	3
10	2	1	2	3	1	2	3
11	2	1	2	3	2	3	1
12	2	1	2	3	3	1	2
13	2	2	3	1	1	2	3
14	2	2	3	1	2	3	1
15	2	2	3	1	3	1	2
16	2	3	1	2	1	2	3
17	2	3	1	2	2	3	1
18	2	3	1	2	3	1	2
19	3	1	3	2	1	3	2
20	3	1	3	2	2	1	3
21	3	1	3	2	3	2	1
22	3	2	1	3	1	3	2
23	3	2	1	3	2	1	3
24	3	2	1	3	3	2	1
25	3	3	2	1	1	3	2
26	3	3	2	1	2	1	3
27	3	3	2	1	3	2	1

RESULTS AND DISCUSSION

In the first attempt, a conventional feed-forward back-propagation artificial neural network was designed to solve the problem.

For solving the model, it is common to divide input data into three parts of training, validation and test. For training the network, the group of training data would be used, but the group of validation data would be used to prevent over-fitting. For this purpose, training will be continued until the MSE related to the data group of validation continue to decrease. In other words, when MSE of validation data starts to increase, training of the network stops, since overfitting and memorization begin to grow in the network [40].

For data modeling the neural network toolbox of Matlab R2015b software was applied.

At the first trial, as published in 2015 [28], all 47500 available set data were introduced to various ANNs. By changing parameters of the network's output, results were changed and in the best conditions (selecting a 3 layer network with 15 neuron and Tansig activation function in first layer, 8 neuron and Tansig activation function in second layer and 2 neurons and Purelin activation function in third layer), results for R-value for training, testing, and validation data were 0.88, 0.87 and 0.87 respectively. Also, the best value of the MSE was 0.012.

Designed ANN was not satisfactory, so data refining and data quality control performed. Therefore, from the 47500 data set, 31200 data sets were selected as valid data for which 20800 data were selected for training, 5200 for validation, and 5200 for testing. Furthermore, a GA optimized ANN was designed to find weights and biases of the selected ANN. Fitness function of the designed network is the average difference between predicted and expected values for the lithology and formation. The cost of the fitness function of a chromosome in the GA can be calculated using equation 3:

$$U = \frac{1}{N \times M} \sum_{k=1}^{N} \sum_{j=1}^{M} \left(Target\left(j,k\right) - Output\left(j,k\right) \right)^2 \quad (3)$$

where e is the sum of the MSE, b is the number of output nodes, a is the number of training samples, Target (j, k) is the expected output, and Output (j, k) is the actual output. Thus minimization of the sum of MSE (e) can lead to the fitness function value be closer to zero. Every time that fitness value of all chromosomes is calculated, a new population of new chromosomes might be reproduced through one of these operators: selection, crossover, and mutation.

The action of selection in the genetic algorithm can be performed using roulette-wheel selection, tournament selection, or random selection. In the crossover process, two chromosomes would randomly exchange part of their information. In the mutation process, information of one gen would be changed randomly. Aim of the mutation is giving local random search ability to the genetic algorithm.

It should be persisted that for optimizing an ANN, in addition to optimizing weights and biases, the structure of the network should also be optimized. For this purpose, the number of hidden layers, the number of nodes in hidden layers, and the activation functions of various layers can be changed separately by us. As it can be seen, it is almost impossible to test all of these scenarios, because if it is just wanted by us to test scenarios with 1 to 3 hidden layers, with 3 levels of nodes in hidden layers and 3 previous mentioned activation functions (as it is shown in Table 5), 2187 types of networks should be tested. As it is impossible to simulate all of these scenarios, the Taguchi experiment design approach can be employed to reduce the number of experiments from 2187 to just 27, as it is shown in Table 6.

For considering the effect of each factor on the obtained results from the network, an analysis of Taguchi designed experiments was performed with Minitab software. Also, the obtained results are shown in Figure 4. As can be seen, the last three factors have a drastic effect on the network design, and on the contrary, the first four factors have a negligible effect.

Table 5: Selected factors for Optimizing the structure of ANN and various levels for each factor.

	Number of hidden layers	Number of neurons in hidden layers	Activation factor in the first layer	Activation factor in the second layer	Activation factor in the third layer	Activation factor in the fourth layer	Activation factor in the fifth layer
Level 1	1	5	Tansig (T)	Tansig (T)	Tansig (T)	Tansig (T)	Tansig (T)
Level 2	2	8	Logsig (L)	Logsig (L)	Logsig (L)	Logsig (L)	Logsig (L)
Level 3	3	12	Purelin (P)	Purelin (P)	Purelin (P)	Purelin (P)	Purelin (P)

Table 6: Various selected scenarios and obtained results from ANN.

Number of scenarios	Number of layers	Number of neurons	Activation functions	MSE	Training data R-value	Validation data R-value	Test data R-value	All data R-value
1	3	15-5-2	T-T-T*	0.00212	0.9908	0.9905	0.9891	0.9905
2	3	15-5-2	T-T-L*	0.0819	0.8064	0.8108	0.8076	0.8072
3	3	15-5-2	T-T-P*	0.00171	0.9925	0.9916	0.9904	0.9921
4	3	15-8-2	L-L-T	0.00158	0.9931	0.9922	0.9921	0.9928
5	3	15-8-2	L-L-L	0.0815	0.8065	0.8054	0.8122	0.8072
6	3	15-8-2	L-L-P	0.00178	0.9922	0.9914	0.9912	0.9920
7	3	15-12-2	P-P-T	0.0193	0.9128	0.9180	09151	0.9140
8	3	15-12-2	P-P-L	0.0794	0.8505	0.8485	0.8468	0.8497
9	3	15-12-2	P-P-P	0.0199	0.9101	0.9075	0.9178	0.9109
10	4	15-5-5-2	L-P-T-L	0.0816	0.8045	0.8130	0.8137	0.8072
11	4	15-5-5-2	L-P-L-P	0.00319	0.9861	0.9844	0.9843	9856.
12	4	15-5-5-2	L-P-P-T	0.00426	0.9809	0.9800	0.9790	0.9805
13	4	15-8-5-2	P-T-T-L	0.0819	0.8068	0.8043	0.8095	0.8068
14	4	15-8-5-2	P-T-L-P	0.00652	0.9714	0.9691	0.9683	0.9706
15	4	15-8-5-2	P-T-P-T	0.00505	0.9780	0.9794	0.9734	0.9775
16	4	15-12-5-2	T-L-T-L	0.0815	0.8075	0.8073	0.8074	0.8075
17	4	15-12-5-2	T-L-L-P	0.00087	0.9969	0.9951	0.9947	0.9958
18	4	15-12-5-2	T-L-P-T	0.00134	0.9935	0.9910	0.9915	0.9928
19	5	15-12-5-5-2	T-L-T-P-L	0.0816	0.8063	0.8097	0.8082	0.8071
20	5	15-12-5-5-2	P-L-L-T-P	0.00250	0.9892	0.9872	0.9871	0.9885
21	5	15-12-5-5-2	P-L-P-L-T	0.00508	0.9779	0.9757	0.9774	0.9775
22	5	15-12-8-5-2	T-P-T-P-L	0.0796	0.8346	0.8394	0.8330	0.8351
23	5	15-12-8-5-2	T-P-L-T-P	0.00143	0.9937	0.9925	0.9926	0.9934
24	5	15-12-8-5-2	T-P-P-L-P	0.00357	0.9844	0.9836	0.9821	0.9839
25	5	15-12-12-5-2	L-T-T-P-L	0.0813	0.8076	0.8012	0.8105	0.8071
26	5	15-12-12-5-2	L-T-L-T-P	0.0006	0.9966	0.9965	0.9967	0.9966
27	5	15-12-12-5-2	L-T-P-L-T	0.00147	0.9936	0.9914	0.9930	0.9932

*: P=PURELIN, T=TANSIG, L=LOGSIG

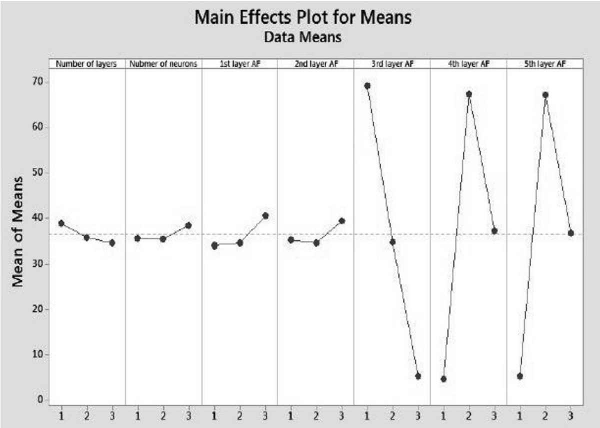

Figure 4: Main effect plot for means of each factor.

Therefore, a feed-forward backpropagation network with five layers was selected as the solution to this problem. In this network, the number of neurons in layers 1 to 5 is 15, 12, 12, 5, and 2, respectively with activation functions of Logsig, Tansig, Logsig, Tansig, and Purelin, respectively (Figure 5). This network (that is shown in Table 6 by scenario 25 in detail) was solved after 500 iterations by the designed GA-ANN algorithm. In this case, MSE was 0.0006, which was completely acceptable.

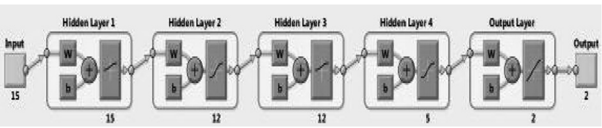

Figure 5: structure of constructed artificial neural network and details of network training.

Moreover, network results for training, testing, validation, and total data are respectively shown in Figure 6. R-value for all of these four groups is more than 99 percent, as can be seen in Figure 6. Furthermore, after data refining and network optimization, 13% improvement in R-value was achieved.

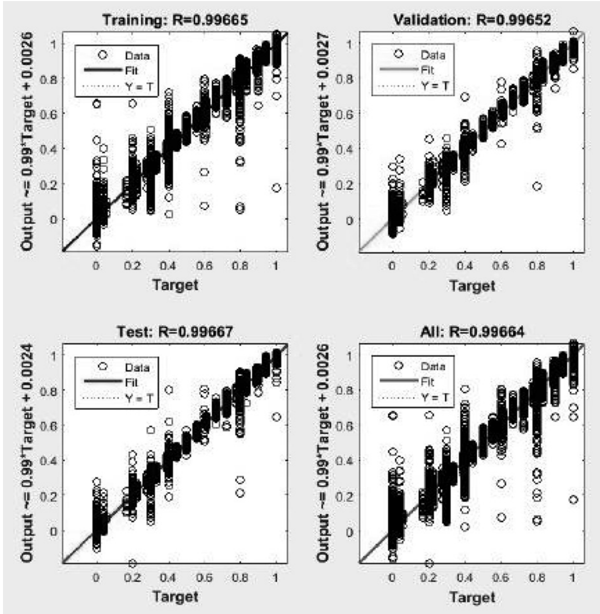

Figure 6: training result of training, validation, test, and all data of the trained neural network.

CONCLUSIONS

In this work, an approach for rock and formation classification based on real-time drilling data was developed. Moreover, the developed method gives the ability of quick determination of formation and lithology while drilling to the geologist and driller. Furthermore, the proposed methodology helps the drilling engineer to recognize the drilling problems quickly and making correct decisions.

Many researchers attempted to predict formation type and lithology with various methods such as using log data or seismic data before, during or after drilling, but many times, the results were not satisfactory [7,8,10,11,16,21,23-26]. In this work, real-time drilling data was refined and introduced to a genetic algorithm, and the Taguchi experiment design optimized the artificial neural network. Moreover, a proper network was selected by optimizing the properties of the network using the genetic algorithm and the Taguchi DOE method. Obtained results can be classified as follows:

• Real-time formation and lithology prediction are useful because of controlling numerous drilling problems such as stuck pipe, blow out or loss of circulation before accruing, reducing drilling costs, optimizing drilling operations, determining drilling parameters, and increasing drilling rate.

• A quick, accurate, and not expensive method was developed for diagnosing the formation and lithology change precisely when drilling a rock.

• The selected methodology is based on virtual intelligence, specifically artificial neural networks, and the genetic algorithm searching method. They are proven to be able to solve severe, complicated problems containing high degrees of uncertainty.

• Moreover, data refinement and quality control of data and optimizing ANN improved the output results by 13%.

• A methodology was explained for network type selection and adjusting the network features using the Taguchi method of DOE.

• The introduced method for finding the best weights and biases of ANN using GA could reduce simulation time and cost and increase the accuracy of the simulation.

• It seems a GA optimized artificial neural network with five layers, in which the number of neurons in layers 1 to 5 are 15, 12, 12, 5, and 2 respectively, and activation functions are Logsig, Tansig, Logsig, Tansig, and Purelin respectively is the best solution. This network was solved after 500 iterations, and its MSE was 0.0006, which is quite acceptable.

• Finally, it is recommended to optimize the structure of the ANN using other optimization methods like particle swarm or the artificial bee colony algorithm.

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NOMENCLATURES

ANN	*: Artificial Neural Network*
BP	*: Back-propagation*
DOE	*: Design of Experiments*
MSE	*: Mean Squared Error*
MWD	: Measurement While Drilling
ROP	: Rate of Penetration (ft/h)
RPM	: Round per Minute

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