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FULL LENGTH ARTICLE

Estimation of lost circulation amount occurs during under balanced drilling using drilling data and neural network

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KEYWORDS

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Abstract Lost circulation can cause an increase in time and cost of operation. Pipe sticking, formation damage and uncontrolled flow of oil and gas may be consequences of lost circulation. Dealing with this problem is a key factor to conduct a successful drilling operation. Estimation of lost circulation amount is necessary to find a solution. Lost circulation is influenced by different parameters such as mud weight, pump pressure, depth etc. Mud weight, pump pressure and flow rate of mud should be designed to prevent induced fractures and have the least amount of lost circulation. Artificial neural network is useful to find the relations of parameters with lost circulation. Genetic algorithm is applied on the achieved relations to determine the optimum mud weight, pump pressure, and flow rate. In an Iranian oil field, daily drilling reports of wells which are drilled using UBD technique are studied. Asmari formation is the most important oil reservoir of the studied field and UBD is used only in this interval. Three wells with the most, moderate and without lost circulation are chosen. In this article, the effect of mud weight, depth, pump pressure and flow rate of pump on lost circulation in UBD of Asmari formation in one of the Southwest Iranian fields is studied using drilling data and artificial neural network. In addition, the amount of lost circulation is predicted precisely with respect to two of the studied parameters using the presented correlations and the optimum mud weight, pump pressure and flow rate are calculated to minimize the lost circulation amount.

1. Introduction

The range of mud-pressure gradients that secures safe drilling of formations is known as the mud-gradient window; the lower and upper limits are usually determined by the pore-fluid pressure and fracture gradients of the formation. This range may become too narrow in certain operational scenarios, however,

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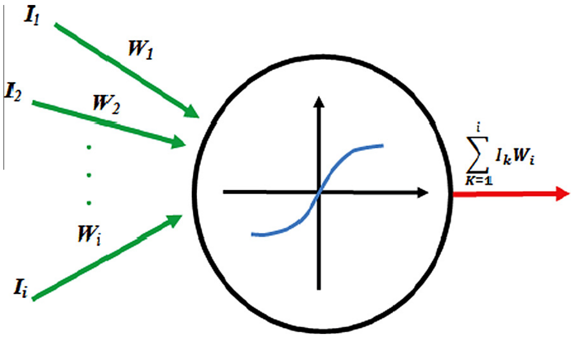

Figure 1 Schematic illustration of AN N.

such as when drilling deep water or highly deviated wells, or through depleted zones [1].

Lost circulation is a common problem that occurs in drilling operations. This problem may happen in formations having high permeability or fractures. In addition, lost circulation can occur due to induced fractures. The possibility of lost circulation increases by drilling at high depth or at depleted reservoirs with low pore pressure [2].

Lost circulation can cause many different problems such as: increase in time and cost of operation, pipe sticking, formation damage and uncontrolled flow of oil and gas [3]. Estimation of the amount of lost circulation is useful in dealing with these problems. Different parameters have an influence on lost circulation and its amount. Some of these parameters are mud weight, pump pressure, depth, etc. [4].

In this article, the effect of mud weight, depth, pump pressure and flow rate of pump on lost circulation amount in UBD of Asmari formation in one of the Southwest Iranian field is studied using artificial neural network. In additional, the amount of lost circulation in Asmari formation of this field is predicted precisely with respect to two of studied parameters using the presented correlations. Genetic algorithm is also used to minimize the amount of lost circulation.

As Asmari formation is the most important oil reservoir of the studied field, UBD is the best choice to prevent fracturing. Conventional drilling may cause some problems such as induced fracturing and lost circulation. It is important to have a good estimation on lost circulation due to the high cost of UBD. To attempt this, three wells are selected among all drilled wells in this reservoir. These wells have the most, moderate and no lost circulation. Then, the amount of lost circulation is predicted with respect to different factors using artificial neural network.

Human neural network is the origin idea of artificial neural network which is a parallel system and a mathematical model and can find the complex relations between different parameters [5]. ANN has been used in different fields since 1960 and was announced as a new science in 1965 [6].

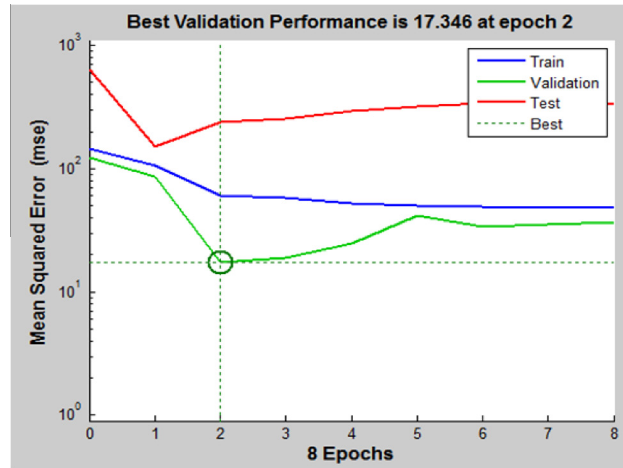

Figure 3 Performance of designed neural network.

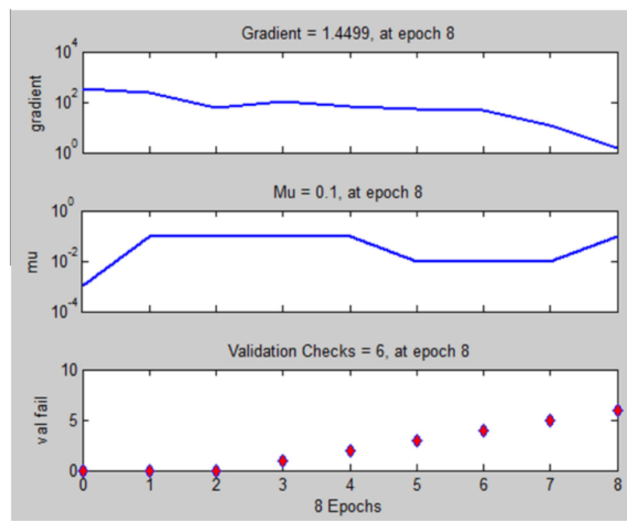

Figure 4 Training state of designed neural network.

2. Neural network and genetic algorithm

Neural networks are computational systems which are capable of learning and using their learning to predict outputs of a complex system. They consist of a large number of processing elements called neuron. These elements are connected to each

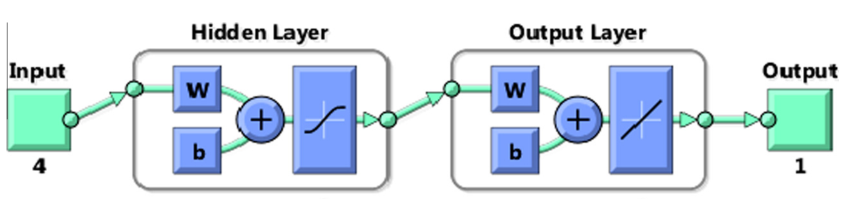

Figure 2 Designed neural network to estimate the amount of lost circulation.

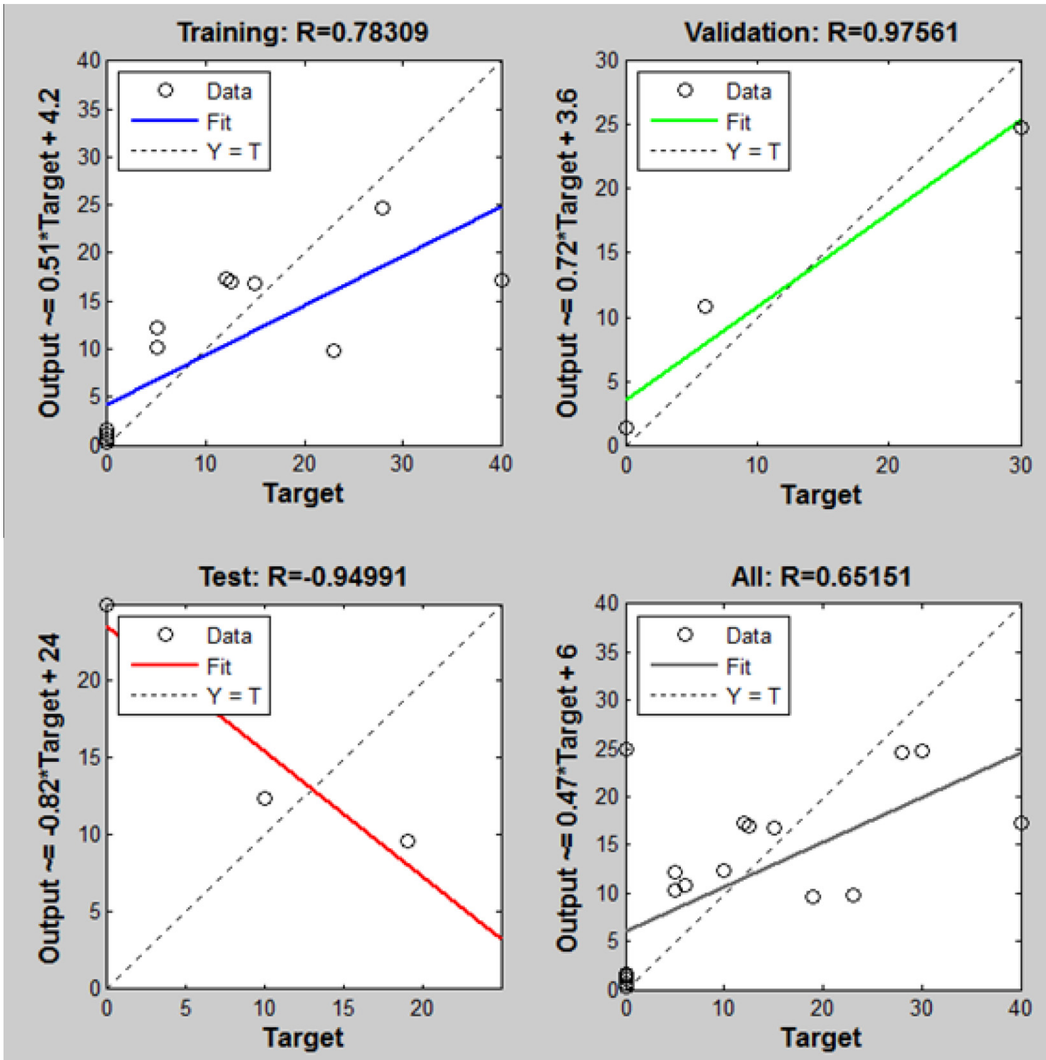

Figure 5 Comparison the outputs of neural network and observed data.

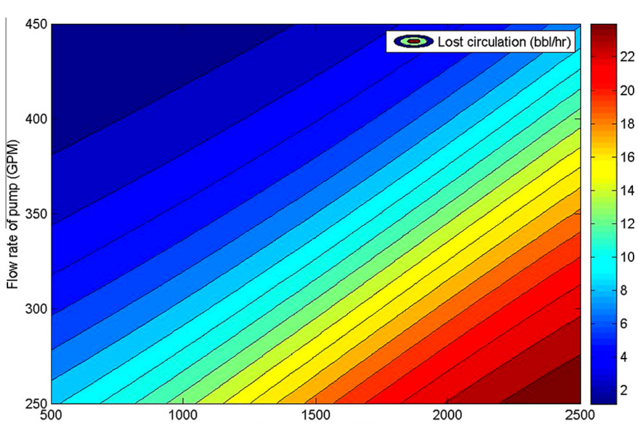

Figure 6 The effect of pump pressure and flow rate of pump on the amount of lost circulation in mud weight of 50 pcf.

Table 1 Coefficients used in Eq. (5).

P_{00}	22.79	P_{10}	0.005942
P_{01}	−0.03318	P_{20}	$-1.791 * 10^{-6}$
P_{11}	$4.821 * 10^{-5}$	P_{02}	−0.0003272
P_{30}	$-7.8 * 10^{-10}$	P_{21}	$2.038 * 10^{-8}$
P_{12}	$-2.054 * 10^{-7}$	P_{03}	$7.377 * 10^{-7}$

Table 2 Regression quality of Eq. (5).

SSE	431.5
R-Square	0.996
RMSE	0.4081

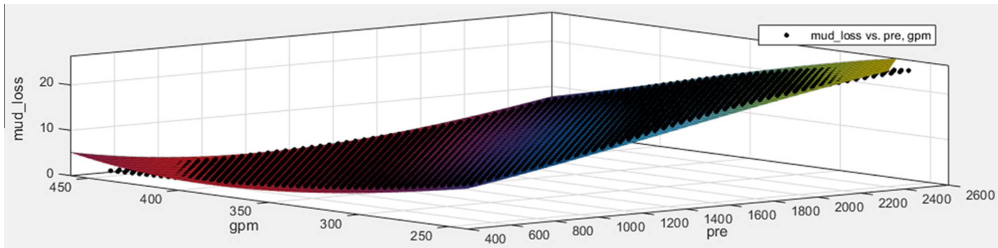

Figure 7 Comparison Eq. (7) and the outputs of neural network.

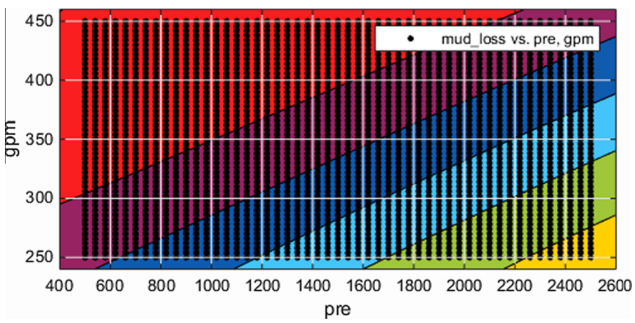

Figure 8 Contours obtained from model proposed by Eq. (7).

other work together to solve a problem [7]. ANN is a trustworthy tool which can predict and estimate between the parameters of complex relations very fast and accurately. Fig. 1 shows the schematic of an ANN [8].

Genetic algorithm is a tool to optimize and reach the optimum value of a function. The procedure of this algorithm is to select randomly initial solutions (initial populations) from the possible solution space. The fitness function is determined for each solution, and the solutions are consequently ranked. The population then evolves through several operations, such as reproduction, crossover, and mutation to optimize the fitness function and obtain the final optimal solution. The process is repeated until a termination criterion is satisfied [9].

This evolutionary algorithm is preferred to classical optimization approaches because it can handle the nonlinear, non-convex, and non-smooth optimization problem of the component sizing for the hybrid system. The non-convexity of the problem makes it difficult for classical optimization methods to obtain a global optimum. GAs, on the other hand, globally search the domain of possible solutions for an optimal solution [10,11].

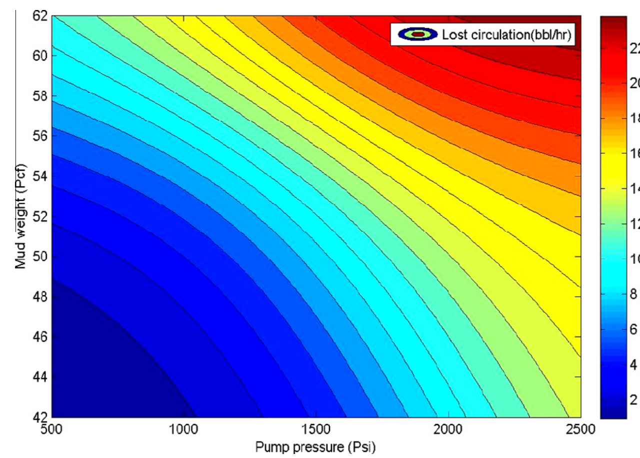

Figure 10 The effect of pump pressure and mud weight on the amount of lost circulation with a pump flow rate of 350 GPM.

Table 3 Coefficients used in Eq. (7).

I_{00}	10.25	I_{10}	4.977
I_{01}	5.67	I_{20}	0.8676
I_{11}	0.1059	I_{02}	0.1321
I_{30}	−0.1206	I_{21}	−0.1578
I_{12}	−0.5879	I_{03}	−0.5234

3. Methodology

The amount of lost circulation in UBD of Asmari formation is estimated by a two-layer feed-forward neural network which has 3 neuron in its hidden layer. Inputs of ANN are mud weight, pump pressure, depth and pump flow rate. In this

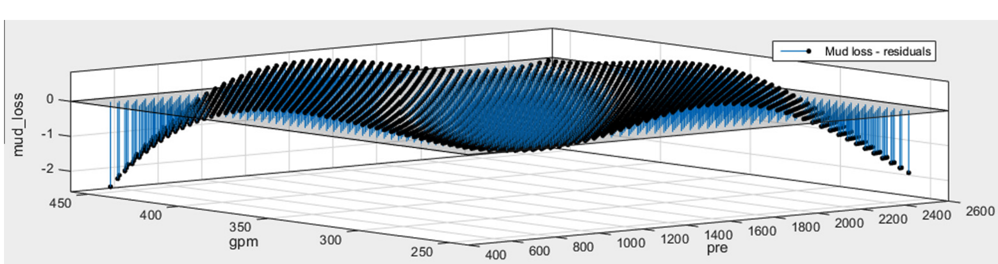

Figure 9 Residual plot (Eq. (7) and neural network).

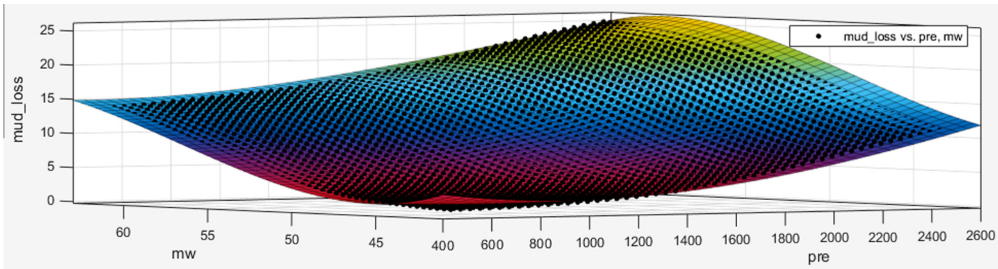

Figure 11 Comparison of Eq. (9) and the outputs of neural network.

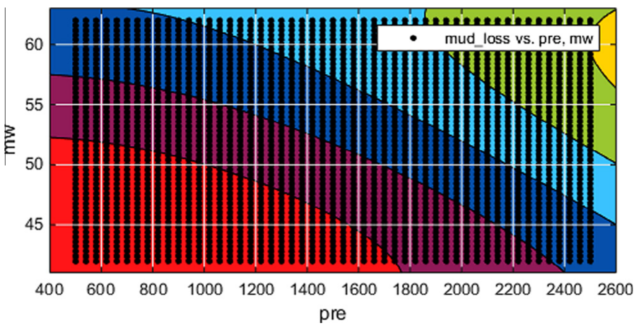

Figure 12 Contours obtained from the model proposed by Eq. (9).

ANN 70% of data belongs to learning, 15% to validation and 15% is used to test. Amount of lost circulation is the only output of the network. This ANN is shown in Fig. 2. Transform function is sigmoid. Using the Levenberg–Marquardt algorithm and mean square error, the following figures achieved. These figures illustrate the performance of ANN.

Fig. 3 shows the trend of error decrease in learning, validation and testing data. According to this figure, the best state of neural network is in the second epoch. This part is clarified using a circle and showing the least amount of error in validation data. Fig. 4 illustrates the different states during the learning of the ANN. For example, validation fail diagram shows the number of times that validation data fail. In validation states, neural network tries to decrease the error between learning and validation using a trial manner. In the created ANN, the operation of training is stopped after trend of error decrease is changed for the sixth time.

Fig. 5 examines the regression of data individually. The horizontal axis is for target and the vertical axis is designed for output of the created neural network. Designed neural network

Table 4 Regression quality of Eq. (7).

SSE	91.48
R-Square	0.9991
RMSE	0.1879

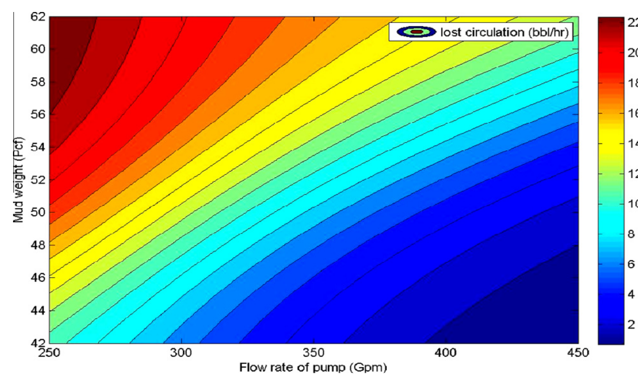

Figure 14 The effect of pump flow rate and mud weight on the amount of lost circulation with a pump pressure of 1500 psi.

Table 5 Coefficients used in Eq. (8).

K_{00}	10.18	K_{10}	−5.142
K_{01}	5.479	K_{20}	0.599
K_{11}	−0.1109	K_{02}	0.1081
K_{30}	0.05675	K_{21}	−0.3618
K_{12}	0.7632	K_{03}	−0.4217

Table 6 Regression quality of Eq. (8).

SSE	116.2
R-Square	0.9988
RMSE	0.2118

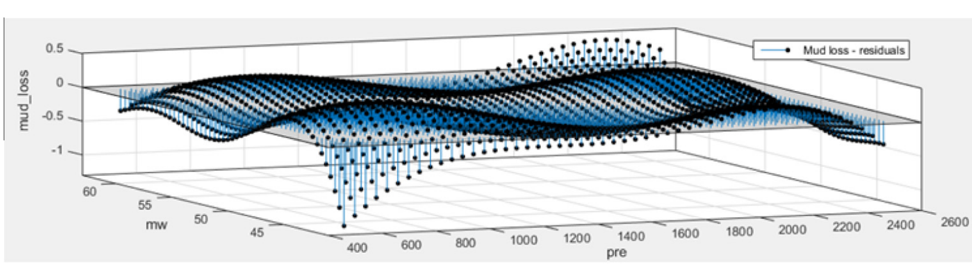

Figure 13 Residual plot (Eq. (9) and neural network).

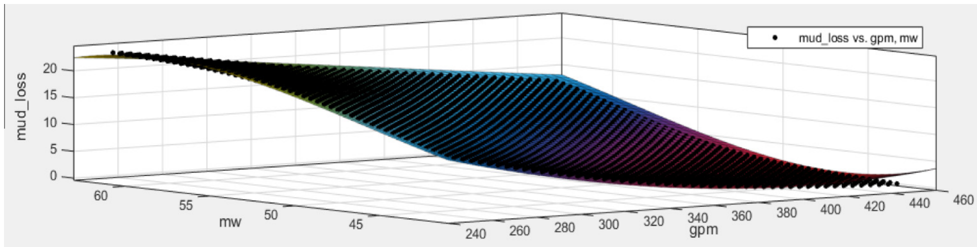

Figure 15 Comparison of Eq. (10) and the outputs of neural network.

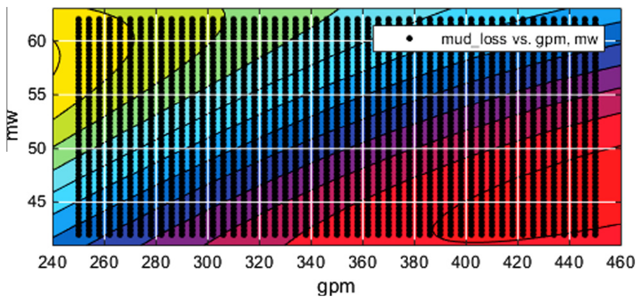

Figure 16 Contours obtained from model proposed by Eq. (10).

works accurate according to the discussed figures. Hence, in order to proposed correlations between the effective parameters and the amount of lost circulation, regression can be done on the outputs of created neural network. The depth of drilling in Asmari formation can be ignored according to its low thickness. In each step, mud weight, pump pressure or flow rate of pump is constant and a correlation is proposed which relates the amount of lost circulation with two other parameters.

The quality of regression can be examined using R-Square, sum of squared errors of prediction (SSE) and root mean square error (RMSE) [5]. SSE is the sum of squared difference between observed data and model data and is obtained from Eq. (1). R-Squared shows the quality of similarity between observed and model data. As this number approaches 1, the model can predict more precisely. R-Square is calculated from Eq. (2). RMSE is a factor which is obtained from Eq. (3) [7]. In each case, the residual plot is plotted. The vertical axis of this plot shows the difference of data and the created model using neural network [12].

$$\mathrm{SSE} = \sum_{i=1}^{n}(z_i - f)^2 = \sum_{i=1}^{n}(\epsilon)^2 \tag{1}$$

$$\text{R-Square} = 1 - \frac{\mathrm{SSE}}{\sum_i (z_i - \bar{z})^2} \tag{2}$$

$$\mathrm{RMES} = \sqrt{\frac{\sum_{i=1}^{n}(z_i - f)}{n}} \tag{3}$$

Here, z_i is data and f is data obtained from model. Also n is the number of data.

4. Evaluating the amount of lost circulation

Using the designed neural network, the effect of parameters on the amount of lost circulation is estimated. Fig. 6 illustrates the effect of pump pressure and pump flow rate in depth of 2350 m. and mud weight of 50 Pcf. According to the data obtained from three wells, 50 Pcf. is the average weight of used drilling fluid in UBD of Asmari formation. Cantors show the amount of lost circulation in barrel per hour. Increasing the pump pressure leads to an increase in lost circulation. It is obvious that fractures may be created due to high pump pressure and lost circulation happens. Lost circulation can be decreased by an increase of pump flow rate. Its reason is related to hole cleaning and cutting transportation. In high flow rates, cuttings transport better. In poor hole cleaning, downhole pressure will be increased due to accumulation of cuttings. This matter shows the critical role of hole cleaning in UBD.

Correlations able to calculate lost circulation amount can be very helpful tools in UBD of Asmari in this field. For this purpose, parameters affecting the lost circulation should be determined. The stress analysis of a crack involves Navier's static-equilibrium equations as the problem is treated by the linear theory of elasticity. These equations can be stated as follows:

$$\frac{\partial \sigma_{rr}}{\partial r} + \frac{1}{r}\frac{\partial_{r\theta}}{\partial \theta} + \frac{\sigma_{rr} - \sigma_{\theta\theta}}{r} = 0 \tag{4}$$

$$\frac{1}{r}\frac{\partial \sigma_{\theta\theta}}{\partial \theta} + \frac{\partial_{r\theta}}{\partial r} + \frac{2\sigma_{r\theta}}{r} = 0 \tag{5}$$

in which, σ is stress in cylindrical coordinates. According to the equations, the hoop stress applied on wellbore has an

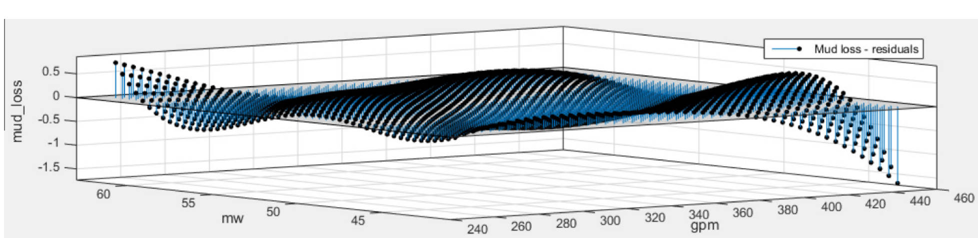

Figure 17 Residual plot (Eq. (10) and neural network).

important role in fracturing and lost circulation [1]. To improve hoop stress, wellbore pressure should be considered as the main parameter [13]. Wellbore pressure is a function of mud weight, pressure of pump, and flow rate [14,15]. Hence, Eqs (4) and (6) are defined. For simplicity, one of the parameters are assumed to be constant in each of the equations.

In order to relate pump pressure and flow rate of pump to amount of lost circulation, Eq. (6) can be defined. This equation will change to Eq. (7) using the regression of ANN outputs.

$$mud\ loss = f(pre.gpm) \tag{6}$$

$$\begin{aligned} f(pre, gpm) = {} & P_{00} + P_{10} * pre + P_{01} * gpm + P_{20} * pre^2 \\ & + P_{11} * pre * gpm + P_{02} * gpm^2 + P_{30} * pre^3 \\ & + P_{21} * pre^2 * gpm + P_{12} * pre * gpm^2 \\ & + P_{03} * gpm^3 \end{aligned} \tag{7}$$

The coefficients used in Eq. (7) are shown in Table 1. In addition, Table 2 is included of regression quality factors. As R-Square is very close to 1, Eq. (7) is very accurate. Fig. 7 is the residual plot which compares the outputs of ANN and Eq. (7).A very good fitness can be seen and all the points are the same except in the corners which belong to regions with high pressure and low flow rate pump or low pressure and high flow rate pump. Difference between ANN outputs and Eq. (7) can be observed by comparing Figs. 6 and 8. Contours in Fig. 8 are obtained from Eq. (7). It is obvious that the differences can be easily ignored due to their very small value (see Fig. 9).

The effect of pump pressure and mud weight on amount of lost circulation is shown in Fig. 10 using the design neural network. Pump flow rate is assumed constant to be 350 GPM which is the average of used flow rate during the drilling of three wells. It is clear that an increase of pump pressure and mud weight leads to lost circulation and increase in its amount.

Using the regression of ANN outputs, Eq. (8) can be changed to Eq. (9). Eq. (9) is used to calculate the amount of lost circulation in barrel per hour.

$$mud\ loss = g(pre.Mw) \tag{8}$$

$$\begin{aligned} g(pre, Mw) = {} & I_{00} + I_{10} * pre + I_{01} * Mw + I_{20} * pre^2 \\ & + I_{11} * pre * Mw + I_{02} * Mw^2 + I_{30} * pre^3 \\ & + I_{21} * pre^2 * Mw + I_{12} * pre * Mw^2 + I_{03} * Mw^3 \end{aligned} \tag{9}$$

Coefficient of Eq. (9) can be found in Table 3. Also Table 4 included the regression quality factors. Eq. (9) has a good accuracy as R-Square is close to 1 and RMSE is small. Fig. 11 compares the outputs of ANN and outputs of Eq. (9). Fig. 12 is plotted according to Eq. (9). Fig. 13 illustrates the differences between outputs of neural network and Eq. (9). This difference is at its high value at high pump pressures

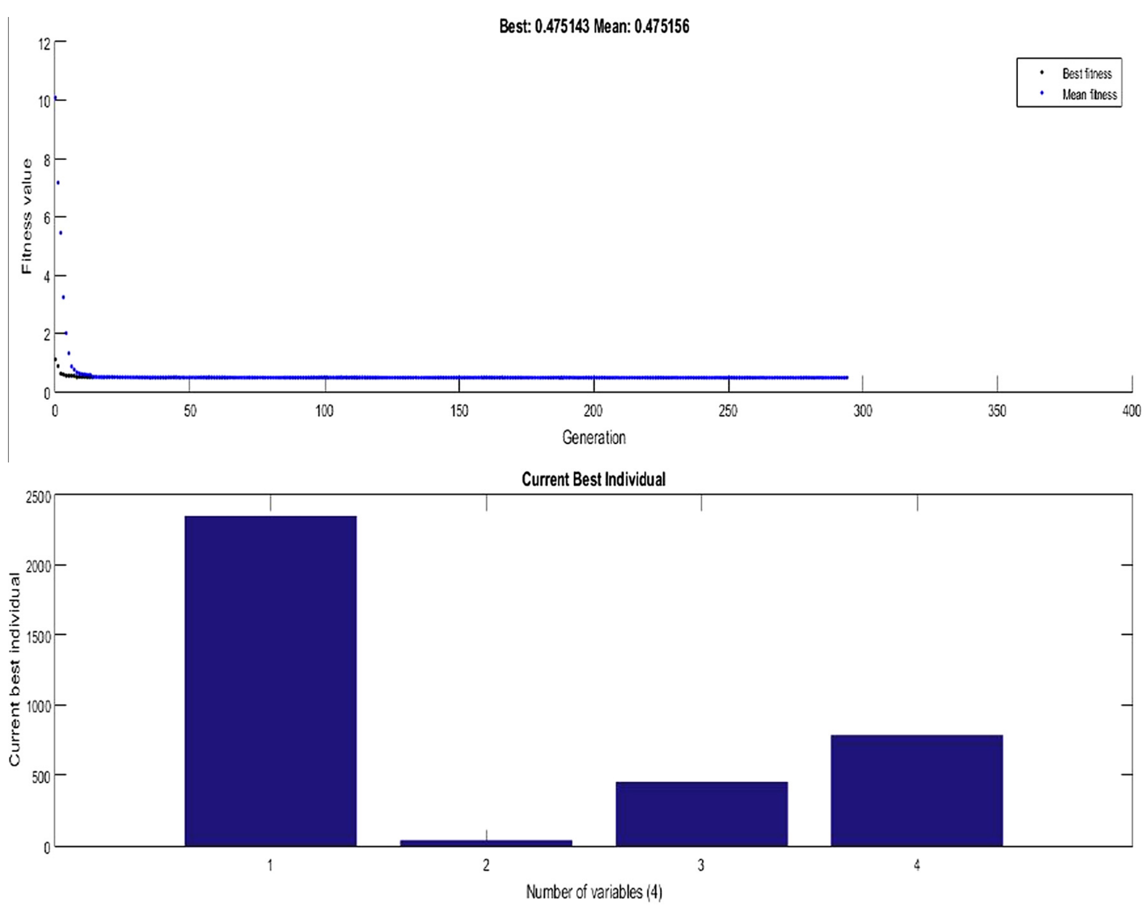

Figure 18 Fitness of GA (upper figure) and value of parameters at the last generation (bottom figure).

and high mud weights. The biggest difference of calculated lost circulation using Eq. (9) and the designed ANN is about 1 bbl/h which can be ignored.

In the last step, the effect of mud weight and flow rate of pump is shown in Fig. 14 using the design neural network. The amount of lost circulation can be decreased by increasing the pump flow rate or decreasing the mud weight. Eq. (10) is proposed to calculate the amount of lost circulation by regression of ANN outputs.

$$\begin{aligned} h(gpm, Mw) = {} & K_{00} + K_{10} * gpm + K_{01} * Mw + K_{20} * gpm^2 \\ & + K_{11} * gpm * Mw + K_{02} * Mw^2 + K_{30} * gpm^3 \\ & + K_{21} * gpm^2 * Mw + K_{12} * gpm * Mw^2 \\ & + K_{03} * Mw^3 \end{aligned} \tag{10}$$

The coefficients of Eq. (10) are in Table 5. Table 6 shows the factors of regression quality. In addition, Figs. 15–17 are corresponding to the design model.

The genetic algorithm is used to optimize the discussed parameters on the amount of lost circulation. The inputs of GA are amounts of lost circulation obtained from the created ANN model. Lost circulation is predicted for a flow rate of 250–450 GPM, mud weight of 42–62 Pcf and a pump pressure of 500–2500 Psi. Fig. 18 illustrates the fitness of algorithm during about 300 generations. This figure also shows the amount of optimized parameters in the final generation. These values for flow rate, mud weight, and pump pressure are 42 Pcf, 450 GPM, and 784 Psi, respectively.

5. Conclusion

1. The amount of lost circulation can be estimated using the created neural network.
2. It is possible to calculate the lost circulation in different situations of UBD of Asmari formation in the studied field with a very good accuracy using the proposed correlations.
3. The amount of lost circulation has a direct relation to pump pressure and a reverse relation to flow rate. By managing one of these factors, the unfavorable effects of the other can be reduced.
4. It is practical to keep one of the factors pump pressure, mud weight or flow rate constant and choose the other two parameters according to the proposed correlations to have the least amount of lost circulation.
5. Hole cleaning is very important in UBD to prevent lost circulation.
6. The parameters are optimized using a combination of GA and ANN.

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