Soft-Computation with Virtual Intelligence and Genetic Algorithms to Optimize Drilling Bit Selection

Emad Jamshidi[1*], Payam Alikhani[2]
1 Drilling Department, Exploration Directorate, National Iranian Oil Company, Tehran, Iran
2 Department of Petroleum Engineering, Petroleum University of Technology, Ahwaz, Iran
*Correspondence author: Tell: +98 913 381 0799 Email: emad.jamshidi@gmail.com

ABSTRACT

Drilling industry encounters various challenges during planning and drilling a new well. There are numerous parameters related to drilling operations that are planned and adjusted as drilling advances. Among them, bit selection is one of the most influential considerations for planning and constructing a new borehole. Conventional bit selections are mostly based on drillers' experiences in the field or mathematical equations, which stand more on recorded performances of similar bits from offset wells. It is evident that these sophisticated interrelations between parameters never can be stated in a single mathematical equation. In such intricate cases, utilizing virtual intelligence and Artificial Neural Networks (ANNs) is proven to be worthwhile in understanding complex relationships between variables. In this paper, two models are developed with high competence and utilizing ANNs. The first model provides appropriate drilling bit selection based on desired ROP to be obtained by applying specific drilling parameters. The second model uses proper drilling parameters obtained from optimizing procedure to select drilling bit, which provides maximum achievable ROP. Meanwhile, Genetic Algorithm (GA), as a class of optimizing methods for complex functions, is applied. The proposed methods assess the current conditions of drilling system to optimize the effectiveness of drilling, while reducing the probability of early wear of the drill bit. The correlation coefficients for predicted bit types and optimum drilling parameters in testing the obtained networks are 0.95 and 0.90, respectively. The proposed methodology opens new opportunities for real-time and in-field drilling optimization that can be efficiently implemented within the span of the existing drilling practice.

NOMENCLATURE

ANNs	Artificial Neural Networks
GAs	Genetic Algorithms
ROP	Rate of Penetration
RPM	Revolution Per Minute
TFA	Total Flow Area
UCS	Unconfined Compressive Stress
WOB	Weight on Bit
Δt	Travel Time, (μs/ft)
C_o	Formation average compressive strength, (Mpa)
D_{hole}	Hole Diameter, (Inch)
C_{ang}	Correction Factor for Angle (Dimensionless)
C_{size}	Correction Factor for Cutting Size (Dimensionless)
C_{MW}	Correction Factor for Mud Weight (Dimensionless)
$D_{50\ cut}$	Mean Cutting Size, (Inch)
ESV	Uncorrected Velocity, (ft/sec)
V_{slip}	Slip Velocity, (ft/sec)
F_k	Transfer Function in ANNs
B_{jk}	Bias in ANNs Structure
W_{ijk}	Weight in ANNs Structure

INTRODUCTION

The process of drilling a hole in the ground requires the use of drilling bits. Indeed, bits are the most basic tools used by the drilling engineers, and selection of the best bit is one of the most basic problems that he faces. Suitable bit selection as one of the main tool of drill string can play an important and significant rule in increase of ROP and consequently reduction of drilling cost. An extremely large variety of bits are manufactured for different situations encountered during drilling operation. It is important for the drilling engineers to learn fundamentals of bit design and different methods of bit selection, so he can understand fully the differences among various bits available. Drill-bit selection is one of the most important aspects of well planning. Bit optimization depends on several factors, including the type of formation drilled, directional requirements, drilling parameters and mud properties, etc. The efficiency of the bit should be measured in terms of cost/foot, taking into account the total operational costs. Comparing the sales price of two different bits is not a valid method of evaluation. One of the most sophisticated and popular bit selection methods is using Artificial Neural Networks (ANNs), because it accounts for all important drilling and formation parameters and can be used as a tool to select bits.

Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the network function is determined largely by the connections between elements. We can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements. Commonly neural networks are adjusted, or trained, so that a particular input leads to a specific target output. Therefore, the network is adjusted, based on a comparison of the output and the target, until the network output matches the target. Typically many such input/target pairs are needed to train a network. One of the most powerful features of neural networks is their ability to learn and generalize from a set of training data. They adapt the strengths/weights of the connections between neurons so that the final output activations are correct.

Meanwhile, Genetic Algorithms (GAs) is used for optimizing the parameters in the models proposed by ANNs. Genetic algorithms are a class of optimization methods, which are used in complex functions and have an extensive number of applications. GA is a stochastic search algorithm, which is applicable to multi-objectives optimization and can handle conflicts among objectives. In this study, it has been tried to develop two models by using Artificial Neural Networks and Genetic Algorithm. The first model predicts the optimum bit based on the drilling parameters, formation's property (unconfined compressive strength, UCS) and the desired rate of penetration (ROP). Moreover, in the second model the optimum drilling bit is predicted based on the optimizing the alterable drilling parameters (weight on bit, WOB, rotation per minute of drilling string, RPM, pump flow rate, GPM, total flow area of the bit, TFA and the stand pipe pressure, SPP) and maximum achievable ROP.

ANALYSIS AND MODELLING

Artificial neural networks (ANNs) are massively parallel distributed processing units known as neurons. These simple neurons have certain performance characteristics in common with biological neurons (Figure 1).

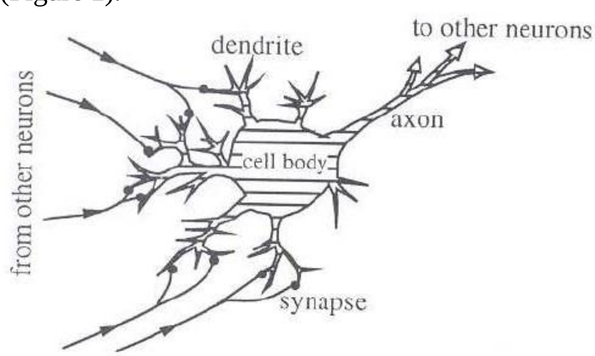

Figure 1
Simple Biological Neuron [1]

Neural networks are capable of learning in order to recognize, classify and generalize different systems. They are data-driven models, which learn by examples presented for them. A typical neural network consists of three layers of neurons called input, hidden and output layers, as shown by Figure 2.

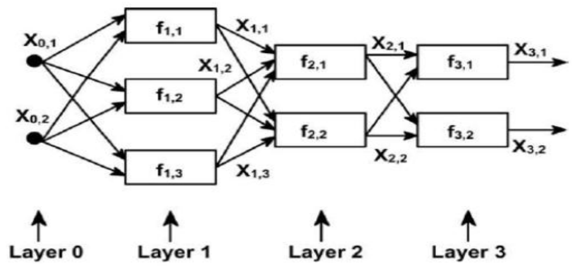

Figure 2
Typical Neural Network with Three layers of Neurons [1]

A neuron takes input values, which are multiplied by connection weights, from the proceeding neurons, adds them up them with a value called bias and feeds them to its transfer function to produce results. In general, the output from neuron j in layer k can be calculated by the following equation: [1].

$$x_{jk} = F_k(\sum_{i=1}^{N_{k-1}} W_{ijk} x_{i(k-1)} + b_{jk}) \quad (1)$$

In this formula W_{ijk} is the weight matrix, $x_{i(k-1)}$ is the input matrix, b_{jk} is bias and F_k is the transfer function. The weights and biases are adjusted by training process. The majority of ANN solutions have been trained with supervision. In this mode, the output of ANN is compared to the real output. Weights and biases, which are usually randomly set at the start, are then adjusted by learning function in a manner that the next iteration would result a closer match between the desired and actual output. The learning function works to minimize the current errors of all processing elements. During training process, modifying the weights and biases continues by applying the same training data set until acceptable network accuracy is reached [1].

Model Development: In the present study, a three-layered Feed-Forward Network is developed; including input, hidden, and output layers. Among the 2000 filtered available data sets which are gathered from nine different offset wells [2], 60 percent has been used for training, 20 percent was applied in validation process, and the remained 20 percent has been put to test the obtained results of the modeled bit and ROP functions. Drilling bits are introduced by International Association of Drilling Contractor's code (IADC) in the modeled functions for ANN [3].

For the first modeling process the proper bit is selected based on desired ROP to be achieved. In this model, size of bit, total flow area (TFA), depth in, depth out, drilling interval, weight on bit (WOB), rotation per minute of drilling string (RPM), ROP, mud circulation flow rate, pressure, Average compressive strength of formation (UCS) and mud weight (MW) have been feds inputs for ANN while IADC of bits are set to be outputs. Table 1 lists the applied range of parameters and Figures 3, shows the training cross-plot of real and ANN's predicted output by correlation coefficient of 0.96.

Table 1
Range of Parameters Used in ANN

Parameter	Range
Size(inch)	8.5-24
TFA(Total Flow Area)(inch^2)	0.745-1.834
Drill in(ft)	101-12015
Drilling interval(ft)	15-4967
WOB(1000lbs)	5.5-63
RPM(rev/min)	49-323
ROP(ft/hr)	6.8-57.2
Mud circulation rate(gal/min)	200-1072
Pressure(psi)	1205-3369
Compressive strength(Ucs)(mpa)	4.05-349.65
Mud Weight(MW)(PPG)	8.5-10

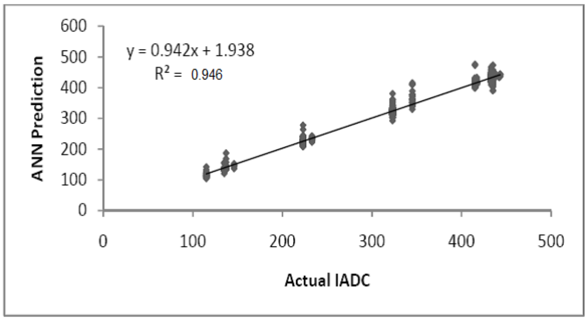

Figure 3
Training Cross-plot (Actual IADC vs. Predicted ANN IADC)

Then the testing data sets are implemented to ANN and the results are presented in Figure 4.

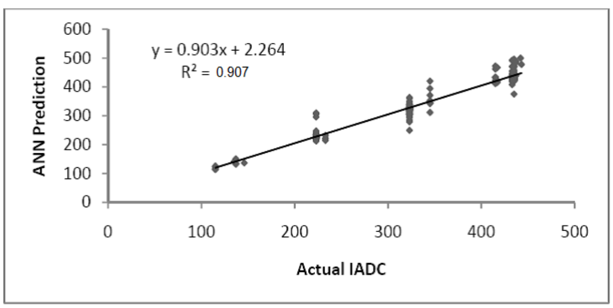

Figure 4
Testing Cross-plot (Actual IADC vs. Predicted ANN IADC)

Therefore, we can select a drilling bit which leads to desired ROP by applying specified drilling operation parameters. In this approach, all dominant parameters in bit performance have been considered for bit IADC function modeling to provide appropriate bit selection. The used drilling parameters are obtained from bit records, except that IKU correlation has been used to compute formation average compressive strength. IKU correlation in this work is defined as:

$$C_0 = 0.77 * (\frac{304.8}{\Delta t})^{2.93}$$

(2)

Where, C_0 is the formation average compressive strength, *Mpa*, and Δt, $\frac{\mu s}{ft}$, is travel time obtained by acoustic log.

In the following section, bit selection optimization is investigated based upon achieving maximum ROP. At the first step, an Artificial Neural Network which has similar structure and the same data sets with the previous model has been developed. The difference in this case is that bit IADC has been fed as an input for ANN, while ROP is targeted to be optimized. The figures related to training and testing of the network (Figures 5 and 6) are also provided.

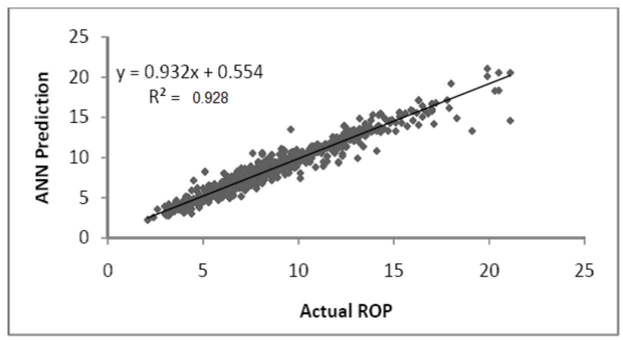

Figure 5
Training Cross-plot (Actual ROP vs. Predicted ANN ROP)

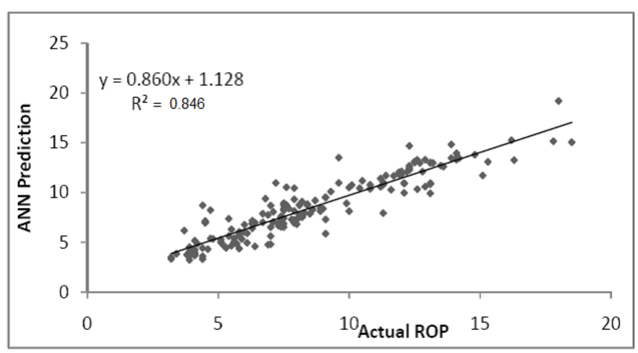

Figure 6
Testing Cross-plot (Actual ROP vs. Predicted ANN ROP)

As it is evident, fitting lines in the cross-plots of network outputs versus the targets of training and testing inputs confirm high accuracy of the resulted ROP function.

According to well profile bit selection optimization is done in four distinct hole sections. For optimization process, changes in the alterable parameters like WOB, RPM, TFA, mud circulation flow rate and pressure are permitted, while bit size and average compressive strength of formation should be kept constant. The ranges of alterable and the constant parameters values in different hole sections are presented in Table 2.

Table 2
Range of Parameters Used in Genetic Algorithm

Constant in Optimization	Variable in Optimizing
	All IADC Used
Size(inch)=22	TFA(Total Flow Area)(inch2)
Depth in(ft)=443	WOB(1000lbs)
Drilling interval(ft)=7134	RPM(rev/min)
Compressive strength (Mpa)=33.91	Mud circulation rate(gal/min)
	Pressure(psi)
	All IADC Used
Size(inch)=17.5	TFA(Total Flow Area)(inch2)
Depth in(ft)=7134	WOB(1000lbs)
Drilling interval(ft)=7931	RPM(rev/min)
Compressive strength (Mpa)=41.43	Mud circulation rate(gal/min)
	Pressure(psi)
	All IADC Used
Size(inch)=12.25	TFA(Total Flow Area)(inch2)
Depth in(ft)=7931	WOB(1000lbs)
Drilling interval(ft)=9689	RPM(rev/min)
Compressive strength (Mpa)=86.70	Mud circulation rate(gal/min)
	Pressure(psi)
	All IADC Used
Size(inch)=8.5	TFA(Total Flow Area)(inch2)
Depth in(ft)=9689	WOB(1000lbs)
Drilling interval(ft)=9827	RPM(rev/min)
Compressive strength (Mpa)=140.3	Mud circulation rate(gal/min)
	Pressure(psi)

Eventually, applying those maximum ROP obtained by genetic algorithm in optimization process may bring about bit floundering due to improper hole cleaning. Hole cleaning can be verified by computing minimum flow rate and velocity required to transfer cuttings to surface and comparing them with the values proposed by genetic algorithm in each hole section. This probability is discussed by using below formulas [4].

$$V_{\min} = V_{cut} + V_{slip}$$

(3)

Where,

$$V_{cut} \quad \frac{1}{[1-(\frac{D_{pipe}}{D_{hole}})^2 * (0.685 + \frac{17.82}{ROP})]}$$

(4)

$$V_{slip} = ESV * C_{angle} * C_{size} * C_{mw}$$

(5)

And where,

$$C_{angle} = 0.0365 * \theta_{angle} - 0.0002\theta_{angle}{}^2 - 0.2$$

(6)

$$C_{size} = -1.02 * D_{50cut} + 1.27$$

(7)

$$C_{mw} = 1 - 0.333 * (\rho_{mud} - 8.65)$$

(8)

$$ESV = 0.0052 * \mu_a + 3.1$$

$$\mu_a > 55cp \qquad (9)$$

$$ESV = 0.02 * \mu_a + 3.26$$

$$\mu_a < 55cp \qquad (10)$$

RESULTS AND DISCUSSION

The output tracks the targets very well and the R-value is over 0.95 and 0.93 in the first and second model respectively. If even more accurate results were required, we could

- Reset the initial network weights and biases to new values and train again
- Increase the number of hidden neurons
- Increase the number of training vectors

- Increase the number of input values, if more relevant information is available
- Try a different training algorithm

In this case, the network response is satisfactory and we can now use simulation to put the network to use on new inputs.

In developing an ANN model to produce reasonable results, training stopped when the validation error increases. Figure 7 confirm the results obtained by bit IADC model.

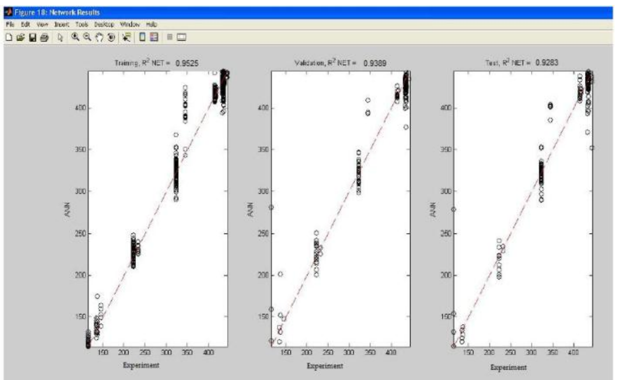

Figure 7
ANNs' Results for Bit IADC Function

Training and testing produce plots of the training errors, validation errors and testing errors, as shown in the Figure 8.

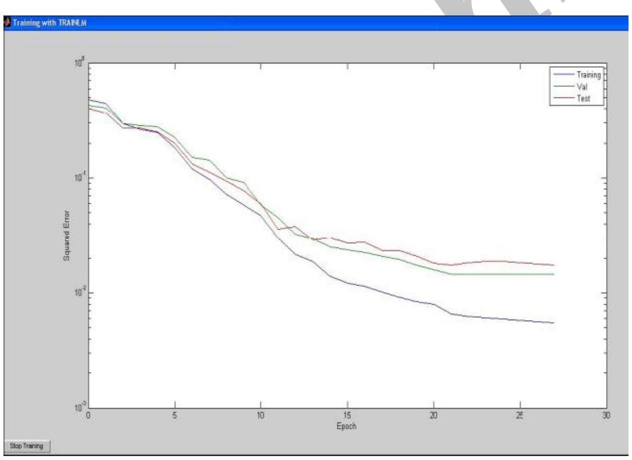

Figure 8
Results of Training with Trainlm for Bit IADC Function

Also, Figure 9 and Figure 10 show the processes of training, validating and testing of the ROP model and their related errors respectively.

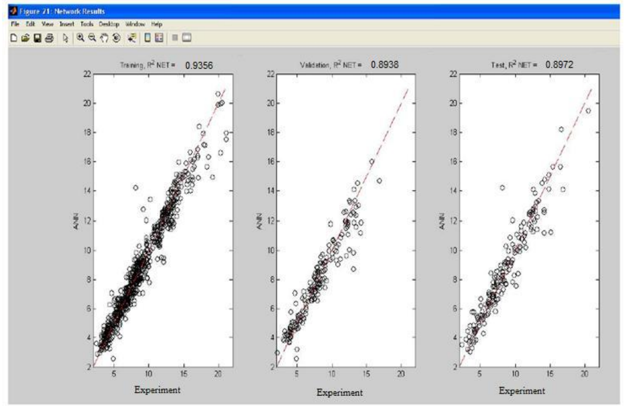

Figure 9
ANNs' Results for ROP Function

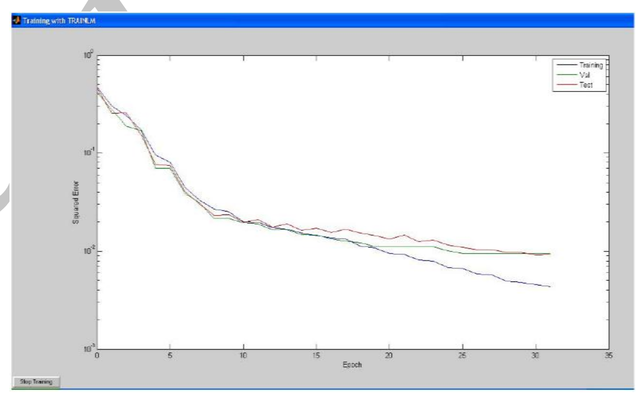

Figure 10
Results of Training with Trainlm for ROP Function

In these two models, the results are reasonable because the final mean square error is small, the test set error and the validations set error have similar characteristics, and no significant over fitting has occurred.

To check the obtained bit IADC's results of our ANN model, a sample set of input variables and the predicted bit IADC, consistent with this case, is tested (Table 3).

Table 3
Sample of Inputs and Output of Modeled Bit IADC Function
(Next page)

	Bit size	TFA	Depth in	Drilling Interval	WOB	RPM	Desired ROP	Flow rate	Pressure	UCS
Input	22	1.291	987	403	19.9	108	41	787	1025	45
Target	Bit IADC Code:4.3.5									

The results support the IADC model obtained by ANN. Verifying the obtained second model by ANNs (ROP function), the general observed trend of optimization processes in the four hole sections is a decrease in ROP by depth. This is due to the fact that the average compressive strength grows while depth increases. The concept that an increase in average compressive strength of fourth hole section leads in selection of harder bit is totally consistent with the optimization results generated by genetic algorithm.

In the some sections, optimization results provide low ROP comparing with other three sections, since the proper bit, consistent with average compressive strength of formation, has not been used in our offset wells. For reaching higher ROP the harder bits should be used. In this section according to the Table 4, we should use bit identified by IADC series seven or eight, because its uniaxial compressive strength is around 140.3 Mpa.

Table 4
Ucs of Formation and Consistent Bit, [5]

Unconfined Compressive Strength(Mpa)	Recommended Bit(IADC)
0-35	Series 1
35-40	Series 2
40-65	Series 3
65-85	Series 4
85-100	Series 5 and 6
100-150	Series 7 and 8

Moreover, it is worth to mention that, applying those drilling parameters for achieving maximum rate of penetration when specific drilling bit corresponding to this ROP is used may bring about some problems. In fact, checking the maximum allowable weight on bit, rotation per minute which can be applied on specific bit is essential. If optimum value of each drilling parameter does not locate in the interval of drill bit classifier table, the results are not valid and second choice should be verified.

Eventually, according to equations 3 to 10, hole-cleaning verification in the first hole section shows that the minimum velocity for proper hole cleaning should be around 2.7 ft/sec, while the velocity obtained by flow rate proposed by optimization procedure is around 3.8 ft/sec. As a result, there will not be bit floundering in the first section when using ROP and flow rate recommended by optimization results. Similar calculations confirm the validation of results in the other three sections.

Having used genetic algorithm as a powerful tool in optimizing process, the ROP has been optimized in each hole section for each bit separately. As it is shown before the input ranges of alterable and constant parameters values change in different hole sections.
These discrepancies are justified regarding differences in well geometry and limitations in mud circulation flow rate to consider hole cleaning and to avoid well kicking. Table 5 shows the results for all four holes sections.

Table 5
Result of Optimizing Bit Selection Based on ROP Using Genetic Algorithm

(Next page)

IADC	Depth in=443 ft Drilling interval=7134 ft Optimum ROP(ft/hr)	Depth in=7134 ft Drilling interval=7931 ft Optimum ROP(ft/hr)	Depth in=7931 ft Drilling interval=9689 ft Optimum ROP(ft/hr)	Depth in=9689 ft Drilling interval=9827 ft Optimum ROP(ft/hr)
1.1.5	37.3	Not Used	Not Used	Not Used
1.3.5	38.3	Not Used	Not Used	Not Used
1.3.7	37.9	34.3	29.7	25.7
1.4.6	40.6	37.4	34.4	29.5
2.2.3	61.2	48.7	41.7	32
2.3.3	61.3	51.7	41.8	31
3.2.3	60.6	57.2	42	30.8
3.4.5	56.7	57.7	42.6	32.9
4.1.5	55.4	55.7	48.4	35.8
4.1.7	56.4	54.8	49.3	25.7
4.3.3	52.5	55.7	47.4	40.7
5.1.7	53.9	57.5	50.1	40.8
5.2.7	51	57.5	49.6	39.3

Finally, the selected bit which provides the best ROP and other related parameters such as WOB, RPM, TFA, mud circulation flow rate and pressure are presented in Table 6.

Table 6
Recommended Bit and Drilling Bit Parameters Based on Optimizing ROP
Using Genetic Algorithm

Parameter	Depth in=443 ft Drilling interval=7134 ft	Depth in=7134 ft Drilling interval=7931 ft	Depth in=7931 ft Drilling interval=9689 ft	Depth in=7931 ft Drilling interval=9689 ft
IADC	2.3.3	3.4.5	5.1.7	5.1.7
ROP(ft/hr)	61.3	57.7	50.1	50.1
TFA(inch^2)	1.834	1.484	1.144	1.144
WOB(1000lbs)	36.5	44.05	50	50
RPM(rev/min)	120	210	135	135
Flow rate(gpm)	1072	979	871	871
Pressure(psi)	744	2057	2925	2925

But, when ROP expected to be obtained by using recommended bit fell in to value lower than the value of the second maximum ROP provides by the second bit recommended by optimization process, we should investigate the situation to make decision properly.

CONCLUSIONS

1. In the first model, by using the modeled bit IADC function and applying the corresponding drilling bit parameters, an appropriate bit was selected based on desired ROP to be achieved.

2. In the second model, by manipulating genetic algorithm in optimizing the modeled ROP function obtained by ANN, optimum ROP and other related parameters (i.e. TFA, WOB, RPM, mud circulation flow rate and pressure) for drilling different hole sections were determined. Finally, among all available bits, one with maximum predicted ROP was recommended.

KEYWORDS

Drilling Bit selection, soft computing, Virtual Intelligence, Artificial Neural Networks (ANNs), Provide max ROP, Genetic Algorithm (GAs)

REFERENCES

1. Beale M. H., Hagan M. T. and Demuth H. B., 2010, Neural Network Toolbox 7 User's Guide, The MathWorks Inc., 951 Pages.
2. N.I.S.O.C, 2010, Daily Report, Drilling Management.
3. Drill Bit Classifier, 2006, World Oil.
4. Mirhaj, S. A., Shadizadeh, S. R., Fazaelizadeh, M., 2007, Cutting removal simulation for deviatedand horizontal wellbores, SPE Middle Oil and Gas Show Paper 10544, Bahrain, 11-14, March.
5. Magarini, P., Lanzetta, C., Galletta, A., 1999, Overpressure Evaluation Manual, ENI Agip Division.