Journal of Simulation and Analysis of Novel Technologies in Mechanical Engineering
16 (3) (2024) 0005~0017
DOI 10.71939/jsme.2024. 1092079

Research article

Optimization of drilling penetration rate through the optimal design of drilling leg and mechanical and hydraulic parameters of drilling using energy characteristic method (case study: South Pars gas field)

Mohammad Reza Nouri[1], Mojtaba Rahimi[1,2*], Ali Mokhtarian[3]
[1] *Department of Petroleum Engineering, Khomeinishahr Branch, Islamic Azad University, Khomeinishahr/Isfahan, Iran*
[2] *Stone Research Center, Khomeinishahr Branch, Islamic Azad University, Isfahan, Iran*
[3] *Department of Mechanical Engineering, Khomeinishahr Branch, Islamic Azad University, Khomeinishahr/Isfahan, Iran*

[*] rahimi@iaukhsh.ac.ir; rahimi2726@gmail.com

(Manuscript Received --- 08 Jan. 2024; Revised --- 00, 0000; Accepted --- 15 May 2024)

Abstract

Since the first well was drilled to discover underground formations, oil industry professionals have explored many methods to increase the length and stability of the well and hence to achieve higher efficiency. The development of the drilling industry accelerated in the past decades to increase oil production and reduce related costs. The purpose of this study is to describe the existing drilling techniques and to deal with the optimization method for drilling a new well in the South Pars gas field. The South Pars gas field is a common offshore gas condensate field known as the largest gas field in the world, approximately 38% of which is located on the Iranian side. In this research, first a well plan was presented to start the optimization, and then, its final three holes (including 16, 12 ¼, and 8 ½-inch holes) were modeled in Landmark software. During modeling in Landmark, the well profile, BHA (Bottom Hole Assembly), drilling fluid properties, drilling hydraulics, effective drag, and surface torque were simulated and then optimized based on operational constraints (such as pump capacity) and mechanical constraints. Furthermore, the mechanical energy characteristic method was used to study the correlations between the actual rate of penetration (ROP) obtained based on field data and theory, and the artificial neural network was used to optimize the drilling process. Landmark results indicated that the drilling of 16, 12 ¼, and 8 ½-inch holes was limited by the selection of mud characteristics, so the optimal values of plastic viscosity (PV), yield point (YP), revolutions per minute (RPM), and mud pumping volume per minute (GPM) were calculated. For each hole, the results from the modeling and optimization of the artificial neural network showed an excellent correlation between drilling parameters and ROP for the 12 ¼ and 8 ½-inch sections (R-Train, R-Test, R-Validation, and R-All were all larger than 0.99 for these sections), while the correlation was very good for the 16-inch section (the above parameters were all around 0.92 for this section). The results of this study can be applied to a real drilling process to maximize drilling efficiency.

Keywords: Rate of penetration (ROP), Optimal design, Mechanical and hydraulic parameters, Energy characteristic method, South Pars gas field.

1- Introduction

So far, many studies have been carried out on maximizing the drilling speed using optimization of mechanical parameters, drilling hydraulics, analysis of the well path, and drilling leg. By considering the high complexity of drilling different intervals that are placed in series, Wilson and Bentsen proposed three steps for optimization: First, minimizing the cost of drilling per meter (foot) in a "bit-run". The second step is to minimize the drilling cost of a specific interval, and the final step is to minimize the drilling cost of all intervals by considering a general drilling program for all intervals [1]. Burgoyne and Young presented one of the most important optimization studies, in which a linear drilling model with eight functions was proposed to predict the drilling speed, which can be called the most complete drilling model [2]. Operating companies developed specific techniques in which operating personnel could perform on-site optimization by referring to pre-determined diagrams and relationships [3]. Tammy and Warren put forward a drilling model in which the drilling speed was expressed as a function of bit size, rock strength, weight on the drill bit, and rotational speed [4]. By examining the factors affecting the "cutting removal" from the bottom of the well, Bizanti and Blick proposed some curves to optimize the "bottom hole cleaning" [5].

Warren achieved the proof of a drilling equation by assuming that while drilling, the bottom of the well is completely cleaned and the cuttings are completely transported. Warren's equation, which became known as the two-term equation, becomes a three-term equation in the case that the well is not completely cleaned [6]. Using the drilling information of the previous wells, Maidla and Ohara initially obtained the necessary coefficients of Burgoyne and Young’s model, and then predicted the drilling speed in that field using this model and presented graphs to optimize the costs in that field [7]. Taking into account the influence of factors such as the "abrasion effect of the bit tooth", Hareland and Hoberock presented Warren's modified drilling model [8]. The results of their study demonstrated that the prediction accuracy of the drilling penetration rate increases significantly by considering the aforementioned parameter. Samuel and Miska investigated the optimization of drilling with a positive displacement motor [9]. According to their study, the optimization of the drilling operation with the motor inside the well is highly dependent on the initial angle of drilling with the motor. Pereira determined the optimization parameters in horizontal wells and showed their effect on reducing costs [10]. This study revealed that despite a more than two-time increase in the cost of horizontal drilling compared to drilling vertical wells in some fields, the cost of drilling horizontal wells can be greatly reduced by optimizing the drilling parameters.

Yibing and Ergun at the University of Alberta used foam to optimize the cleaning of vertical wells in a laboratory model [11]. According to the results of their investigation, cleaning the bottom of the well from drilling debris increases the life of the drill bit and substantially increases the drilling speed. Ogunrinde and Dosunmu investigated the critical parameters for cleaning the bottom of the well and presented a model by which the appropriate parameters of drilling and specifications of drilling fluid for obtaining optimal hydraulics were specified. This study investigated horizontal and deviated wells with an angle of more than 45 degrees [12]. Through an artificial neural network and with the assumption of having optimal hydraulics and cleaning the bottom of the well, Wang and Salehi presented an intelligent system to predict drilling fluid rheology, flow rate, pump pressure, and other drilling parameters [13].

Alsubaih and his colleagues conducted investigations to optimize the penetration rate of drilling in the wells of the Mishrif Formation in one of Iraq's fields using the energy characteristic method. By collecting information from 25 wells from the studied field, they optimized parameters such as drilling fluid pumping flow rate, weight on the drill bit, drill torque, rotary table circumference, and drilling fluid weight and increased the drilling speed in this field. [14] Robinson and his colleagues modeled a function to optimize the drilling speed in different holes using artificial intelligence and energy characteristic methods as well as information collected from drilling operations in land and sea wells. Despite the generality of the used database, the function provided by them predicted the penetration rate of drilling in different fields with acceptable accuracy [15]. Through the experience obtained from drilling operations in 12 wells in the Middle East, using the information collected from them, and with the help of the energy characteristic method, Abdelaal and his colleagues optimized the drilling penetration rate in the future wells of the studied field. The selection of optimal drilling parameters led to an increase in the penetration rate of drilling by an average of 10.5% [16].

Hashemizadeh et al. used five artificial intelligence models, including Bayesian ridge regression (BRR), K-nearest neighbor (KNN), support vector machine (SVM), decision tree (DT), and adaptive boosting regression with decision tree (ABR-DT), for mud weight estimation based on a data bank in five southern gas points. In these points, the variables affecting mud weight were as follows: true vertical depth (TVD), hole size, slope, viscosity, yield point (YP), plastic viscosity (PV), gel strength (measured at 10 min, 10 min, and 30 min), and API fluid loss. Finally, it was observed that the accuracy of the models was ranked as: ABR-DT > DT > SVM > KNN > BRR. Moreover, sensitivity analysis showed that the predicted mud density is strongly influenced by the values of plastic viscosity and real vertical depth [17].

In summary, many studies have been conducted on maximizing drilling speed by optimizing mechanical parameters, drilling hydraulics, well path analysis, and drilling leg. However, none of them investigated all the issues raised at the same time and studied their effects on each other. The most important difference between the present study and the previous works is that the above-mentioned cases are investigated for the first time in the South Pars gas field in a detailed and comprehensive manner which will eliminate the weakness of the previous models. In other words, this study does not have similar precedents in Iran. Because, in addition to being poorly adapted to Iran's fields, the previous models did not examine all the effective parameters of the drilling penetration rate, thus, they are incomplete models. In our proposed model, all the important and effective parameters in the drilling penetration rate are examined. Therefore, while observing the appropriate accuracy for the presented model, the model is considered both comprehensive and complete.

2- Methods

2-1- Energy characteristic relation

The characteristic relation of the energy regarding the drilling penetration rate (equation 1) is the basis of the present study:

$$ROP = \frac{13.33\,\mu N}{DB\left(\frac{CCS}{EFFM.WOB} - \frac{1}{A}\right)} \tag{1}$$

where ROP is the drilling speed (ft/h), μ is the specific coefficient of sliding friction of the bit, N is the number of bit cutters, CCS is the compressive strength of the formation (psi), WOB is the weight on the bit (lbs), EFFM is the mechanical efficiency (percent), DB is the diameter of the drill (inches), A is the cross-sectional area of the hole being drilled (square inches). It should be noted that among the above variables, only the compressive strength of the formation is independent of the well design, and the rest of the parameters are dependent on the type of well design and other mechanical and hydraulic parameters and well conditions. That is, the drilling speed depends on the mechanical parameters of drilling, such as the weight on the bit and around the rotary table, and the hydraulic parameters of drilling, including the pumping flow rate of the drilling fluid, the rheology of the drilling fluid, and the design of the drill nozzles. Therefore, in this study, by applying the energy characteristic method and simulating drilling operations in South Pars gas field wells in Landmark software, the mechanical and hydraulic parameters of drilling will be optimized to maximize the drilling speed. In other words, after simulating the drilling operation in different holes of a well in the South Pars field by Landmark software, the optimal design of drilling hydraulics, drilling leg, and mechanical parameters is carried out and the optimal parameters obtained from the simulation are placed in the energy characteristic relationship, which leads to optimized drilling speed.

2-2- South Pars gas field

The South Pars gas field is the largest in the world and is located in the Persian Gulf and in the territorial waters of Iran and Qatar. This gas field is shared between Iran and Qatar and is called the North Dome gas field in Qatar. Iran and Qatar have always been competing for superiority in exploiting the hydrocarbon resources of this field since the beginning of production from this common field. Fig. 1 shows the geographical location of this field [18].

Fig. 1 Geographical location of the South Pars gas field [18]

The area of this field is 9,700 square kilometers, of which 3,700 square kilometers are in the territorial waters of Iran and 6,000 square kilometers are in the territorial waters of Qatar. The reserves of the Iranian sector contain 50% of Iran's gas reserves and 8% of the world's gas reserves. The well drilling route of the

South Pars field mainly includes drilling the following five holes:

A) 32-inch hole

This hole is dug from the bottom of the sea (at a depth of about 60 meters) to about 200 meters. The mud used in drilling this hole is seawater and viscose pile. Fars group formations are the most important formations that are excavated in this hole. Due to the large diameter of this hole, it is difficult to clean the bottom of the well from drilling debris. To solve this problem, viscose gel is utilized, which consists of PHG and Guar Gum. It is worth mentioning that this hole is drilled with "26" and "32" Hole Openers. Then the guide tube "26" is driven into this hole and cemented.

B) 23 ½-inch hole

This hole is drilled with a toothed bit 23 ½-inch and seawater along with a viscous pile as drilling fluid to the depth of installation of surface wall pipe. This hole, like the previous one, has the problem of cleaning the bottom of the well from drilling debris, for which PHG and Guar Gum are used. The formations that are drilled in this hole are Asmari, Jahrom, and Ilam. During the drilling of each of these formations, certain problems appear and necessary predictions must be made to solve these problems. For example, while drilling the hole, the appearance of H_2S gas up to 18 ppm has been reported in the previous wells. H_2S Scavenger is used to reduce the corrosive effect of H_2S gas on the wall pipes and the drill string. Among other problems of this hole can be complete leakage of the drilling fluid, sticking of the wall string, and drilling in the Jahrom Formation. Finally, after the drilling of this hole, the wall pipe 18 5/8" is driven and then it is cemented. Of course, due to the complete absence of fluid in the Jahrom Formation, cement return is not observed on the surface.

C) 16-inch hole

This hole is drilled with a button bit or PDC and polymer mud along with viscose pile up to the Hith Formation and a depth of about 1700 meters. The formations that are excavated in this hole are Lafan, Saruk, Kazhdomi, Darian, Gadvan, Fahlian, and finally a few meters of Hith Formation. Due to the angulation rate in this hole and its curved shape, many problems appear during drilling. Because of the presence of Gadvan Formation in this hole, polymer mud or oil base mud should be employed to prevent the activity and swelling of this formation during drilling. Flowing of formation fluid (water and oil) from the Kazhdomi Formation has been reported in previous wells. Partial and total leakages of drilling fluid in the Fahlian formation, as well as the presence of H_2S gas in the two Darian and Hith formations, are other problems of drilling a 16" hole in the South Pars gas field. Finally, the operation of this hole is completed by driving and cementing the wall string 13 3/8".

D) 12 ¼-inch hole

This hole in the South Pars gas field is very important because of reaching the final angle of the well. The mentioned hole is drilled with a PDC bit owing to the drilling of hard and anhydride formations. The drilling fluid used in this hole is polymer mud. Hith, Sormeh, Niriz, Dashtak, and Aghar shale formations, and finally a few meters of Kangan can be seen in the excavation of this hole. Drilling in this hole continues to a depth of about 2900 meters and up to the Kangan Formation. The eruption of salt water in the Dashtak Formation and the collapse of the well wall in the Shili Aghar Formation are among the most important challenges of drilling in this hole. This hole is finished by driving and cementing the wall string 9 5/8". Besides, due to the placement of the underground safety valve (3SV) inside this wall line, the wall pipe 10 3/4" is used instead of 9 5/8" in the first 160 meters.

E) 8 ½-inch hole

Due to the drilling in the reservoir, the drilling operation of this hole has a special sensitivity. The aforementioned hole is drilled with a PDC bit to the head of the Nar evaporite formation (about 3400 meters deep). Polymeric drilling fluid is utilized in this hole as in the previous holes. Kangan and Dalan field formations and several meters of Nar evaporite formation are excavated in this hole.

The pressure difference trap in the Dalan Formation, the presence of drilling mud, and the presence of H2S gas in the Kangan Formation are among the problems of drilling in this hole. At the end of the operation of this hole, the lining string 7" is driven and cemented. Note that the well completion operation in the South Pars field is in the form of a Mono Bore. In this way, the core pipes 7" are connected to the hanger of the lining pipe 7", and they continue as a completion string up to the surface [18].

3- Artificial neural network

An artificial neural network is a data processing system that takes ideas from the human brain and entrusts data processing to many small processors that act in a parallel network to solve a problem. In these networks, with the help of programming knowledge, a data structure is designed that can act like a neuron. This data structure is called a neuron. Then by creating a network between these neurons and applying a training algorithm to it, they train the network [19].

In this memory or neural network, neurons have two active states (on or 1) and inactive (off or 0) and each edge (synapse or connection between nodes) has a weight. Positively weighted edges are stimulated or activated in the next inactive node, and edges with negative weight make the next connected node inactive or inhibited (if it was active) [20-22].

After training the neural network, applying a specific input to it leads to a specific response. The network adapts based on matching and symmetry between the input and the target until the output of the network and the target match (Fig. 2). Generally, a large number of these input and output pairs are used to train the network in this process, which is referred to as supervised learning. Input and training data in petroleum engineering can be laboratory data, data obtained in the field, data obtained from field simulation, or a combination of these [23-25].

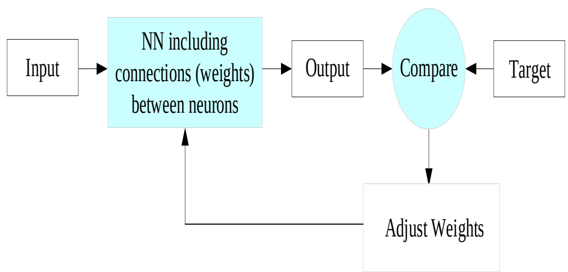

Fig. 2 The training process of a neural network [26]

4- Simulation of the path of the studied well

First, a real well drilled in the South Pars gas field was selected as a case study. Fig. 3 exhibits the route designed in the drilling program of the studied well. It should be noted that all the limitations mentioned above have been observed in this design. The final angle of the well is 45.11 degrees, the final depth of the well is 15204 drilling feet, and the actual vertical depth is 11480.5 feet. This route has been obtained after trial and error and designing different routes and comparing the results. In the designed path, the amount of drilling and the length of the driven wall string are optimal. Attention has also been paid to the operational limitations of the region.

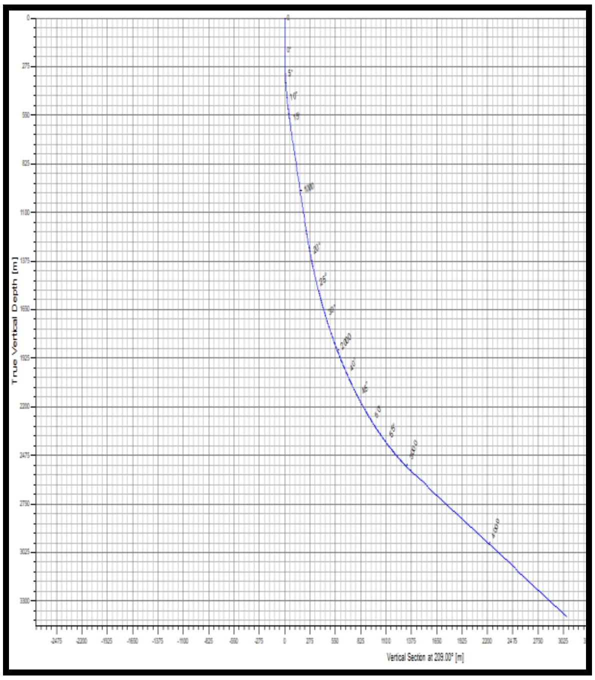

Fig. 3 The route designed for the studied well

5- Results and analysis

To drill a 16-inch hole, the BHA in Table 1 was used, which was optimized through the input data to the software.

Table 1: BHA required for drilling the 16-inch hole

Section Type	Length (m)	MD (m)	OD (in)	ID (in)
Bit	0.500	1,970.00	16.000	
Mud Motor	9.327	1,969.50	9.625	3.000
MWD	6.492	1,955.55	8.250	2.250
NMDC	9.460	1,949.06	9.500	2.500
Drill Collar	68.000	1,939.60	9.500	2.500
Jar	10.241	1,871.60	9.500	2.500
Drill Collar	9.600	1,861.36	9.500	2.500
Heavy Weight	203.000	1,851.76	5.000	3.000
Drill Pipe	1,648.760	1,648.76	5.000	4.276

For drilling in the 12 ¼-inch hole, the BHA in Table 2 was used, which was optimized according to the data entered into the software.

Table 2: BHA required for drilling the 12 ¼-inch hole

Section Type	Length (m)	MD (m)	OD (in)	ID (in)
Drill Pipe	2,920.345	2,920.34	5.000	4.276
Heavy Weight	203.000	3,123.34	5.000	3.000
Drill Collar	9.600	3,132.94	8.500	2.250
Jar	10.241	3,143.19	8.000	2.500
Drill Collar	68.000	3,211.19	8.500	2.250
NMDC	9.460	3,220.65	8.500	2.250
MWD	6.492	3,227.14	8.250	2.250
Mud Motor	7.742	3,239.50	8.000	3.000
Bit	0.500	3,240.00	12.250	

To drill in the 8 ½-inch hole, the BHA in Table 3 was utilized, which was optimized according to the data entered into the software.

The specifications of mud required for drilling the 16-inch, 12 ¼-inch, and 8 ½-inch holes are given in Table 4, and the assumptions used to calculate the carrying capacity of drilling fragments are presented in Table 5.

Table 3: BHA required for drilling the 8 ½-inch hole

Section Type	Length (m)	MD (m)	OD (in)	ID (in)
Drill Pipe	4,649.849	4,649.85	5.000	4.276
Heavy Weight	27.000	4,676.85	5.000	3.000
Jar	10.058	4,686.91	6.500	2.750
Heavy Weight	218.000	4,904.91	5.000	3.000
M/LWD	8.500	4,922.55	6.750	1.920
Mud Motor	9.144	4,931.70	6.750	3.000
Bit	0.305	4,932.00	8.500	

Table 4: Specifications of the mud used for drilling the 16-inch, 12 ¼-inch, and 8 ½-inch holes

	Base Density (lbm/ft^3)	PV (Mulnf) (cp)	YP (Tau0) ($lbf/100ft^2$)
16-inch Hole	69	18	24
12 ¼-inch Hole	93	2	22
8 ½-inch Hole	81	20	22

Table 5: Excavation assumptions in the 16-inch, 12 ¼-inch, and 8 ½-inch holes

	Rate of Penetration (m/hr)	Cuttings Diameter (in)	Bed Porosity (%)
16-inch hole	10	0.240	36
12 ¼-inch hole	8	0.24	36
8 ½-inch hole	6	0.24	36

According to the selected parameters, Tables 6-8 present the optimal hydraulic specifications of the drilling bit for these three holes. Therefore, the optimal drilling conditions were selected according to Table 9.

Table 6: Hydraulic parameters of the drill bit for drilling in the 16-inch hole

Pump Rate (GPM)	850	800	780
Stand Pipe Pressure (Psi)	2950	2870	2950
HSI (hhp/in2)	0.5	0.8	1.2
JIF (Jet Impact Force)-lb	630	798	938
Bit Nozzle (in/32)	9x16	3x14 + 6x13	9x12

Table 7: Hydraulic parameters of the drill bit for drilling in the 12 ¼-inch hole

Pump Rate (GPM)	530	510	510	510
Stand Pipe Pressure (Psi)	2970	2960	3176	3361
HSI (hhp/in2)	0.4	0.7	1.2	1.7
JIF (Jet Impact Force) (lb)	389	516	691	811
Bit Nozzle (in/32)	6x16	3x16 + 3x14	6x13	6x12

Table 8: Hydraulic parameters of the drill bit for drilling in the 8 ½-inch hole

Pump Rate (GPM)	400	380	380
Stand Pipe Pressure (Psi)	2880	2807	2958
HSI (hhp/in2)	0.5	0.7	1.3
JIF (Jet Impact Force) (lb)	244	288	392
Bit Nozzle (in/32)	6x16	6x14	6x12

Table 9: Optimal drilling conditions for the 16-inch, 12 ¼-inch, and 8 ½-inch holes

	GPM	RPM	PV	YP
16-inch hole	780	70	5	20
12 ¼-inch hole	510	70	10	22
8 ½-inch hole	250	70	10	25

6- ROP optimization using neural network

By using the refined data in the Landmark software as well as the energy characteristic method, logical connections between inputs (μ, CCS, EFFM, WOB, DB, and A) and ROP as output can be understood. In this case, for each hole, it is possible to check the drilling speed and optimize it easily at any time using the trained neural network. In this part, for each hole, 400 data were extracted from wells drilled in the studied field, and the results are reported below. Note that in all parts, the diagram in Fig. 4 is used as a neural network. For this purpose, the first 70% of the data was allocated for training, 15% of the data for testing, and 15% of the data for validating the artificial neural network. In addition to the test, the validation of the artificial neural network is performed to measure the sensitivity of the artificial neural network to the change process of individual data. To find the best neural network architecture for this problem, a trial and error method was used. First, starting with a hidden layer that included one neuron, and adding the number of hidden layers and neurons to the layers, the network error was checked. The optimal number of neurons in the hidden layer must be found because if the number of neurons in the hidden layer is more than the limit, the generality of the artificial neural network will decrease. Furthermore, if they are less than the optimal limit, the network error will increase. After software analysis and trial and error, the best network with the least possible error was selected. The best neural network model was obtained with a hidden layer with 10 neurons. Therefore, the artificial neural network that was finally designed contained 10 neurons (flow rate, μ, CCS, EFFM, WOB, DB, A, RPM, torque, and area of rotary table) in the first/input layer, 10 neurons in the hidden layer, and 1 neuron (ROP) in the output layer. Moreover, the transfer functions for the hidden layer were selected as tangent sigmoid and for the output layer as linear. Choosing a combination of the sigmoid tangent transfer function and linear transfer function for the designed artificial neural network causes the network to have an acceptable efficiency for estimating any type of linear and non-linear functions.

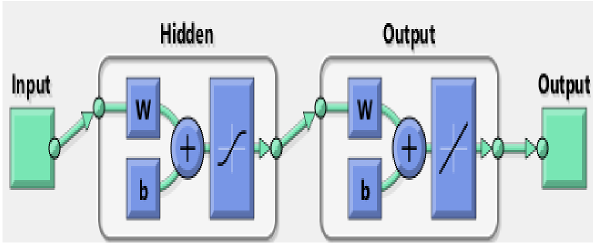

Fig. 4 Neural network employed to optimize and simulate penetration rate

A) 16-inch hole

The results of optimization and adaptation of the neural network model to the field data are shown in Figs. 5-6.

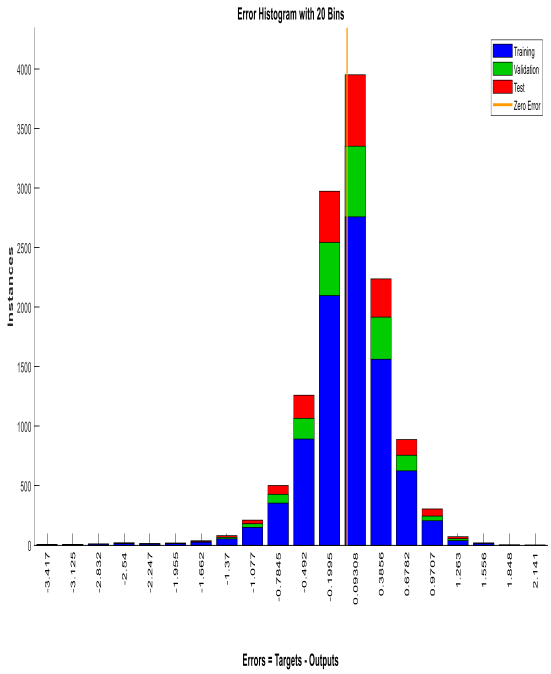

Fig. 5 Histogram of neural network error in ROP prediction for the 16-inch hole

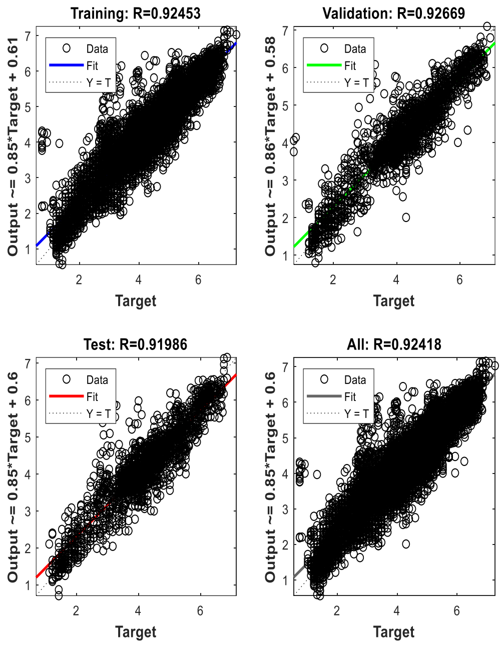

Fig. 6 Regression of neural network error in ROP prediction for the 16-inch hole

As it is clear from Figs. 5-6, the designed neural network predicts the drilling penetration rate in the 16-inch hole with a negligible error.

B) 12 ¼-inch hole

The results of optimization and matching of the neural network model to the real data are given in Figs. 7-8.

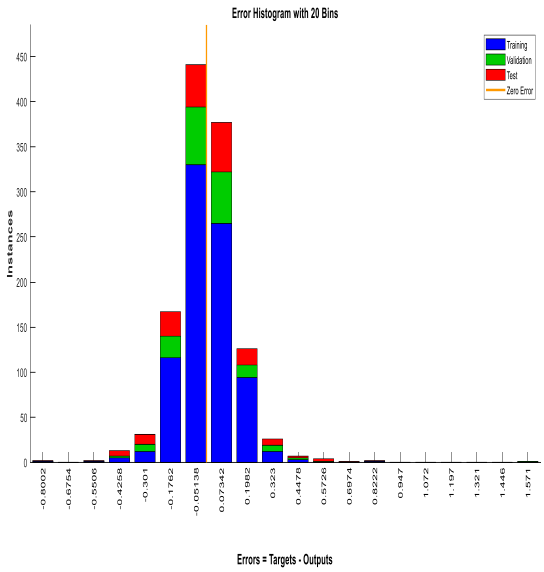

Fig. 7 Histogram of neural network error in ROP prediction for the 12 ¼-inch hole

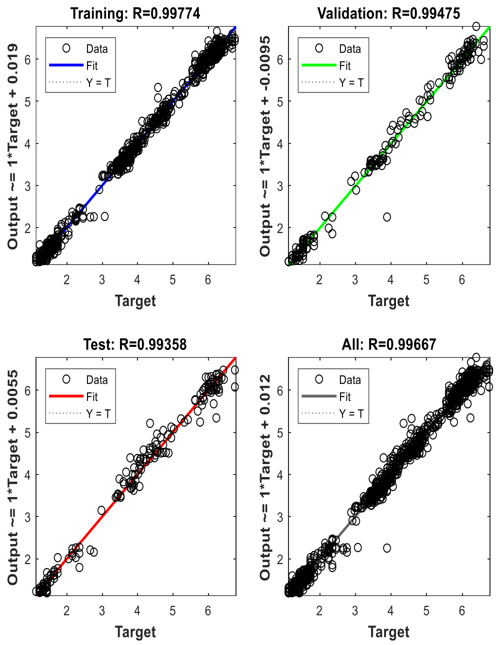

Fig. 8 Regression of neural network error in ROP prediction for the 12 ¼-inch hole

As it is evident from Figs. 7-8, the designed neural network predicts the drilling penetration rate in the 12 ¼-inch hole with a negligible error.

C) 8 ½- inch hole

The results of optimization and adaptation of the neural network model to the field data are shown in Figs. 9-10.

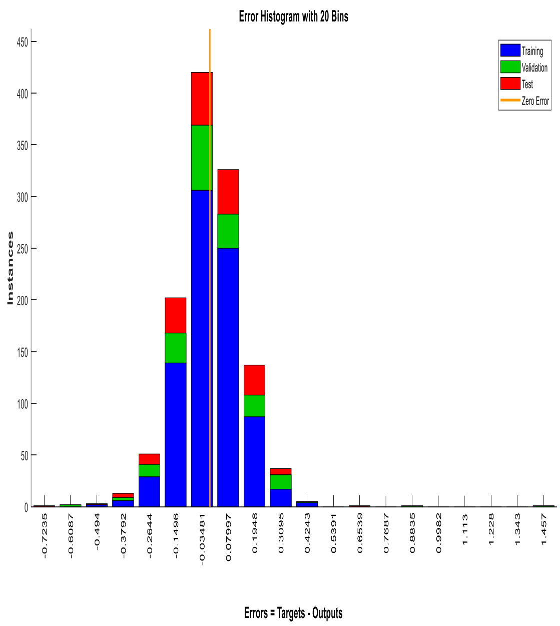

Fig. 9 Histogram of neural network error in ROP prediction for the 8 ½-inch hole

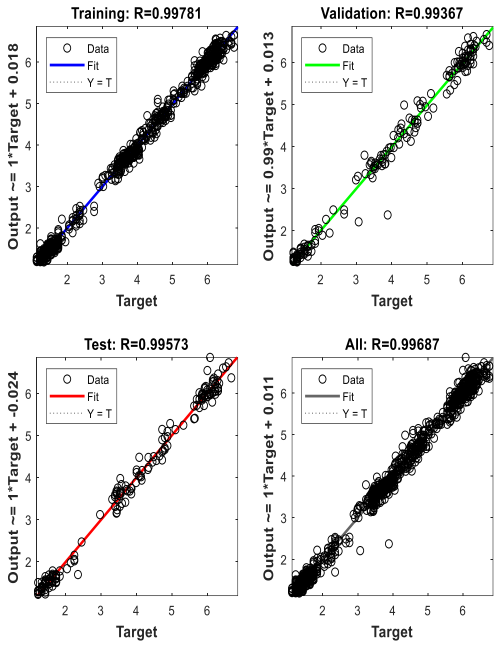

Fig. 10 Regression of neural network error in ROP prediction for the 8 ½-inch hole

As it is clear from Figs. 9-10, the designed neural network predicts the drilling penetration rate in the 8 ½-inch hole with a negligible error.

7- Examining the results and comparing neural networks

Examining the results and comparing them with the neural networks reflect the performance of the artificial neural network in predicting the penetration rate. They are compiled in Table 10.

Table 10: Checking the results and comparing the neural networks

	R-Train	R-Test	R-Validation	R-All
16-inch hole	0.924	0.926	0.919	0.924
12 ¼-inch hole	0.997	0.994	0.993	0.996
8 ½-inch hole	0.997	0.993	0.995	0.996

Therefore, by examining the data obtained from the curve fitting on the drilling speed, it is clear that the use of the neural network method can lead to the correct prediction of the data with an R-value of more than 0.92. The power of neural network analysis and the accuracy of the resulting data in the 16-inch hole are less in the holes with smaller sizes (i.e., 12 ¼- and 8 ½ holes). The reason for this phenomenon can be found in the characteristics of the neural network, and it can be expected that better results will be obtained by changing its characteristics. The high power of the neural network in predicting data for holes smaller than 16 inches can lead to the improvement of drilling operations in the South Pars field.

8- Conclusion

Based on the recorded data from the previous wells drilled in a field and with the help of appropriate models, the drilling penetration rate can be predicted. In this regard, the use of a suitable model to estimate the penetration rate allows accurate and usable results to be obtained. One of the ways to reduce the drilling cost is to optimize the drilling parameters to obtain the highest penetration rate. Many parameters affect the penetration rate of the drill, which can generally be divided into four categories of operating parameters, parameters related to construction characteristics, parameters related to the type and design of the drill, and parameters describing the amount of drill wear.

In this study, with a case study of the process of drilling wells in the South Pars gas field, first, the different steps of drilling were discussed. Then the design of a well in the strategic field of South Pars was carried out with the help of Landmark software and was reviewed according to operational limitations. Finally, the penetration rate in the formation was checked using the energy characteristic method. The output data from the drilling operations in the South Pars gas field were reused and an attempt was made to determine the relationship between operational data and theoretical data using an artificial neural network. Final results were also presented. In summary, the main outputs of this study are as follows:

1. The drilling program of three basic holes in the South Pars gas field was studied and the drilling line was designed and reviewed in terms of mechanical characteristics.
2. Drilling hydraulics were designed for the final three holes of the well and then were optimized according to the field conditions.
3. Histogram and regression of neural network error in ROP prediction for the three holes were investigated which all demonstrated that the designed neural network predicts the drilling penetration rate in all three holes with a negligible error.
4. Operational data were utilized along with energy characteristic theory and were optimized using artificial intelligence.
5. For each hole, the results from the modeling and optimization of the artificial neural network indicated an excellent correlation between drilling parameters and ROP for the 12 ¼ and 8 ½-inch sections (R-Train, R-Test, R-Validation, and R-All were all greater than 0.99 for these sections), while the correlation was very good for the 16-inch section (the above parameters were all around 0.92 for this section). Hence, the results of this study can be applied to a real drilling process to maximize drilling efficiency.

References

[1] Wilson, D. C., & Bentsen, R. G. (1972, October). Optimization techniques for minimizing drilling costs. In *SPE Annual Technical Conference and Exhibition?* (pp. SPE-3983). SPE.

[2] Bourgoyne Jr, A. T., & Young Jr, F. S. (1974). A multiple regression approach to optimal drilling and abnormal pressure detection. Society of Petroleum Engineers Journal, 14(04), 371-384.

[3] Eren, T., & Ozbayoglu, M. E. (2010, January). Real time optimization of drilling parameters during drilling operations. In SPE Oil and Gas India Conference and Exhibition (pp. SPE-129126). SPE.

[4] Warren, T. M. (1981). Drilling model for soft-formation bits. Journal of Petroleum Technology, 33(06), 963-970.

[5] Bizanti, M. S., & Blick, E. F. (1986, March). Fluid dynamics of wellbore bottomhole cleaning. In SPE Permian Basin Oil and Gas Recovery Conference (pp. SPE-15010). SPE.

[6] Warren, T. M. (1987). Penetration-rate performance of roller-cone bits. SPE Drilling Engineering, 2(01), 9-18.

[7] Maidla, E. E., & Ohara, S. (1991). Field Verification of Drilling Models and Computerized Selection off Drill Bit, WOB, and Drillstring Rotation. SPE Drilling Engineering, 6(03), 189-195.

[8] Hareland, G., & Hoberock, L. L. (1993, February). Use of drilling parameters to predict in-situ stress bounds. In SPE/IADC Drilling Conference and Exhibition (pp. SPE-25727). SPE.

[9] Samuel, G. R., & Miska, S. (1998, September). Optimization of drilling parameters with the performance of multilobe positive displacement motor (PDM). In IADC/SPE Asia Pacific Drilling Technology Conference and Exhibition (pp. SPE-47791). SPE.

[10] Pereira, J. J. (1999). Comprehensive optimization of drilling parameters for horizontal wells. The University of Tulsa.

[11] Li, Y., & Kuru, E. (2004, March). Optimization of hole cleaning in vertical wells using foam. In SPE Western Regional Meeting (pp. SPE-86927). SPE.

[12] Ogunrinde, J. O., & Dosunmu, A. (2012, August). Hydraulics optimization for efficient hole cleaning in deviated and horizontal wells. In SPE Nigeria Annual International Conference and Exhibition (pp. SPE-162970). SPE.

[13] Wang, Y. (2014). Drilling Hydraulics Optimization Using Neural Networks. University of Louisiana at Lafayette.

[14] Alsubaih, A., Albadran, F., & Alkanaani, N. (2018, January). Mechanical specific energy and statistical techniques to maximizing the drilling rates for production section of mishrif wells in southern Iraq fields. In SPE/IADC Middle East Drilling Technology Conference and Exhibition (p. D031S002R003). SPE.

[15] Robinson, T. S., Batruny, P., Gomes, D., Hashim, M. M. H. M., Yusoff, M. H., Arriffin, M. F., & Mohamad, A. (2022, March). Successful Development and Deployment of a Global ROP Optimization Machine Learning Model. In Offshore Technology Conference Asia (p. D021S009R001). OTC.

[16] Abdelaal, K., Atere, K., LeRoy, K., Eddy, A., & Smith, R. (2022, March). Holistic Real-Time Drilling Parameters Optimization Delivers Best-in-Class Drilling Performance and Preserves Bit Condition-A Case History from an Integrated Project in the Middle East. In SPE Canadian Energy Technology Conference. OnePetro.

[17] Hashemizadeh, A., Bahonar, E., Chahardowli, M., Kheirollahi, H., & Simjoo, M. (2022). A data-driven approach to estimate the rate of penetration in drilling of hydrocarbon reservoirs.

[18] South Pars Drilling Program, Pars Oil and Gas Company.

[19] Galle, E. M., & Woods, H. B. (1963). Best Constant Weight And Potary Speed For Rotary Rock Bits.

[20] Hareland, G., & Rampersad, P. R. (1994, April). Drag-bit model including wear. In SPE Latin America and Caribbean Petroleum Engineering Conference (pp. SPE-26957). SPE.

[21] Hareland, G., Nygaard, R., Virginillo, B., & Munro, H. (2007, April). Drilling Simulation vs. Actual Performance in Western Canada. In SPE Rocky Mountain Petroleum Technology Conference/Low-Permeability Reservoirs Symposium (pp. SPE-106570). SPE.

[22] Salehi, S., & Nygaard, R. (2015). Full fluid–solid cohesive finite-element model to simulate near wellbore fractures. Journal of Energy Resources Technology, 137(1), 012903.

[23] Gjelstad, G., Hareland, G., Nikolaisen, K. N., & Bratli, R. K. (1998, July). The method of reducing drilling costs more than 50 percent. In SPE/ISRM Rock Mechanics in Petroleum Engineering (pp. SPE-47342). SPE.

[24] Rostami, H., & Khaksar Manshad, A. (2014). A new support vector machine and artificial neural networks for prediction of stuck pipe in drilling of oil fields. Journal of Energy Resources Technology, 136(2), 024502.

[25] Salehi, S., Hareland, G., Dehkordi, K. K., Ganji, M., & Abdollahi, M. (2009). Casing collapse risk assessment and depth prediction with a neural network system approach. Journal of Petroleum Science and Engineering, 69(1-2), 156-162.

[26] Samuel, R. (2013). Modeling and Analysis of Drillstring Vibration in Riserless Environment. Journal of Energy Resources Technology, 135(1), 013101.