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A Developed Model Based on Particle Swarm Algorithm for Optimization of Drilling Penetration Rate in Petroleum Field

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Abstract

In this research, geological and drilling data of petroleum field have been used to optimize the drill penetration rate. Drill depth parameters, drill weights, drill speed, drilling fluid flow, tube pressure and torque have been selected as effective and inertial parameters for obtaining a relationship for predicting drill penetration rates. The RBF neural network has been used to achieve this relationship. Finally, using the particle swarm optimization algorithm, variable parameters including drill weight, drill speed, drilling fluid flow and pipe pressure have been adjusted to obtain the optimum drill penetration rate. The results show that drill speed and depth have the greatest and least impact on drilling speed. Due to the combination of different states, it can be concluded that with increasing depth, if the weight on the drill and the speed of rotation of the drill less are used, increasing the hydraulic parameters can achieve the highest rate of drilling. Also, it can be concluded that drill speed and depth have the greatest and least impact on drilling speed. Due to the combination of different states, it can be seen that with increasing depth, if the weight on the drill and the speed of rotation of the drill less are used, increasing the hydraulic parameters can achieve the highest rate of drilling. Of course, the condition of this matter is more difficult to formations with increasing depth.

Keywords: *Optimization; Neural network; Swarm optimization algorithm; Drilling; Drill speed.*

1. Introduction

The drilling of oil and gas wells is one of the most complexes, difficult, costly and challenging obstacles to the development of a field due to the high risk of operations and hazards. Drilling a well is done by drilling rig. This drilling rig like a small town solves all its needs. For drilling a well, a rotational system is used with towers with different powers for different depths. In drilling a well, several important factors such as drilling rigs, drill design, drilling mud design, drilling pipe design, construction of casted and lined pipes, cementing and well safety are effective [1]. The rapid progress of the industry, the advent of oil as a source of energy and the increasing demand for it, and the need for more oil wells, led to the development of a blunt drill that began in 1800, to gradually accelerate the song so that better equipment was made, Steam was used and the technical skills of the dredges went up [2]. At the beginning of the drilling industry, superfluous and scarce supplies of oil were being exploited, but now, by digging very deep wells, it is possible to exploit the layers of oil associated with earlier geological periods [3]. The characteristics of deep oil and gas resources are their increasing pressure, which is one of the major issues of drilling. Today, drilling equipment and oil wells are constructed to withstand pressures between 200 and 1,000 atmospheres, and only the rotational technique allows drilling in such reservoirs. In addition to dry drill rigs operating in plains, mountains and deserts, marine drilling machines operate in the water and drill their drills to the bottom of the sea and drill [4]. These devices are built or floating. Floating devices can now be excavated in waters up to a depth of 1500 meters. Electric motors boost this ability to use the power available gradually and to the desired extent. Therefore, there is less shock and vibration in these towers. Most of the ductile power is used by pump pumps and Draw works. One of the most important early studies on optimal drilling was done [5]. A linear penetration rate model and performed a multiple regression analysis of drill data in order to select drill weights, drill speed and hydraulic speed by Silva, *et al.* [6]. They found that the regression analysis method could be systematically used to evaluate many of the constants in the penetration rate equation. They stated that multiple well data sources are needed to evaluate regression constants. They concluded that the use of relatively simple drilling optimization equations could reduce drilling costs by about 10%. They proposed a comprehensive method for determining optimal drilling techniques. In this study, the experimental relations of penetration rate, weight at drill, hydrostatic strength and drilling were shown. They combine five relationships in a single diagram to determine the optimal drilling method of the minimum field test data. They, based on laboratory results, achieved a reduction in penetration rate due to increased rock strength, controlled by differences between the flowers and the pore pressure. They also noted that the rock digging capability was inferior to the surface, due to the pressure caused by excavations at ground depths. Graham and Monch is one of the first researchers to evaluate drilling data to determine the optimum weight in drill and rotational speed [7]. They used a mathematical analysis method for the cost of drilling in optimal conditions. Proposed mathematical relations included the constant of the region's formation. Their results led to calculating the drill and the speed of rotation using calculations in any drilling conditions in order to minimize the total cost of drilling. They showed the relationship between the drilling efficiency and penetration rate controlled by the speed or weight of the drill. He showed that these two parameters are adjustable with differential pressure depth, flower characteristics, speed, jet speed and drill design. In his studies, the graphs were presented showing the relationship between the degree of penetration and the various parameters of the drilling. These diagrams were used to determine the optimal drilling parameters. As in previous studies, the new model was also designed to determine the proper flow rate for cleaning drilling logs [8]. Using the concept of mechanical energy, Dupriest and Koederitz evaluated the efficiency of drilling drills in real time. Their system allows the digger to continuously monitor the calculated MSE through the surface of measurements and charts related to conventional mechanical drilling. The type of drill is easily identifiable using the results of the system [9]. They have conducted a case study on drilling in a closed hydraulic system. The data obtained during the drilling on the basis of real time was obtained through satellite communication.

The PSO (Particle swarm optimization algorithm) method is a global optimization method that can be used to solve problems that answer a point or surface in an n-dimensional space. In this space, assumptions are made, and an initial velocity is allocated to particles, and communication channels between particles are considered. These particles then move in the response space, and the results are calculated based on a "merit criterion" after each time frame. Over time, particles tend to accelerate towards particles that meet a higher standard of competence and are in the same communication group. The main advantage of this approach to other optimization strategies is that the large number of overcurrent particles makes the method more flexible than the local optimal response problem.

Artificial neural networks (ANNs) can be used to construct a precision estimator. Artificial neural networks are very similar to the usual statistical methods. The reason for this is that they are optimized in both unknown parameters in order to achieve the best model between input data and corresponding output data. Artificial neural networks have been used in various oil engineering fields such as reservoir characterization, fluid properties research and well analysis analysis. The most important thing in achieving the best performance for artificial neural networks is the size of the data or sample, the proper geometry of the network and the estimated parameters [10]. Ezz El-Deen *et al.* investigated drilling Vibration Modes and Penetration Rate Modeling using Artificial Neural Network and Multiple Linear Regression Analysis in Khoman Formation at the Egyptian Western Desert [11].

2. Research method: modeling

2.1. Well formation data used in this study

In this research, complete geological data of one well has been used to optimize the drill penetration rate. Formations data, along with the depth of each, are presented in Table 1.

Table 1. Well formation information used in this research work.

Formation	Depth (MD)		Metrage (MD)	Metrage (TVD)
	From	To		
1	1447	1450	3	3
	1450	1612	162	162
2	1612	1640	28	28
3	1640	1756	116	116
4	1756	1774.50	18.5	18.5
	1774.50	1790	15.5	15.5
	1790	1900	110	110
	1900	1973	73	73
	1973	1989	16	16
	1989	2073	84	84
	2073	2160	87	87
5	2160	2199	39	39
	2199	2199	0	0
	2199	2269	70	70
6	2269	2353.80	84.8	84.8
7	2353.80	2358	4.2	4.2
	2358	2371	13	13
	2371	2383	12	12
8	2383	2402	19	19
9	2402	2570	168	168
10	2570	2656	86	86
11	2656	2796	140	140
	2796	2933	137	137
	2933	3021	88	88
	3021	3030	9	9
	3030	3090	60	60
	3090	3117	27	27
	3117	3170	53	53
	3170	3240	70	70
	3240	3257	17	17
12	3257	3327	70	70
	3327	3398	71	71
	3398	3490	92	92
13	3490	3564	74	74
	3564	3625	61	61
14	3625	3705	80	80

2.2. Development modeling using neural networks of RBF (Radial Basis Function) model and particle swarm algorithm

Radial base neural networks are considered as one of the special method of artificial neural networks. Their simple structure, along with fast learning algorithms and good estimation capabilities, can be used among other artificial neural networks and has been widely used in many branches, including engineering. The neural networks of the radial base function are referred to a three-layer grid network that is fully interconnected. In this network, the hidden units run the radial function, and the output units execute the weighted mass of the hidden units. The hidden layer in the neural network is considered to be the radial base function as the only place where non-linearity exists in neurons. This is while there is no non-linearity in the output layer. However, there are no weight connections from the input layer to the hidden layer, and only the output layer has weighted connections. In order to train this network, a two-step approach is usually used. Initially, hidden layers and centers are predicted by branching algorithms such as decision trees. In addition, particle and genetic swarm algorithms are also considered in branching algorithms. Then the hidden layer connects to the output layer and so the weights are set using the least squared mean algorithms. In this study, particle swarm optimization algorithm was used to increase the accuracy of the learning process. The neural network of the radial base function is characterized by two categories of data, including inputs and outputs. Its structure consists of three layers: entrance, hidden and output. The network is connected to the nodes in the input layer to the surrounding area. A nonlinear converter is applied between the input layer and the output layer by the hidden layer. The nodes in the hidden layer are connected to the centers that specify the grid structure. The neural network uses the radial base function of the Gaussian function or other functions to activate the response from the hidden unit. Network responsiveness is provided by activating the template by the output layer used as a unit of aggregation. The neural network model of the radial base function is given by the equation (1) for the output j:

$$y_j^{(i)} = \sum_{k=1}^{K} \omega_{jk} \varphi_k \left[x(i), c_k, \sigma_k \right] \tag{1}$$

$$j = 1,2,\cdots,n \qquad i = 1,2,\cdots,N$$

where:

$$c_k = \left[c_{k1}\ c_{k2}\ \cdots\ c_{km} \right]^T \in R^m \qquad \sigma_k = \left[\sigma_{k1}\ \sigma_{k2}\ \cdots\ \sigma_{km} \right]^T \in R^m$$

$$k = 1,2,\cdots,K \qquad k = 1,2,\cdots,K$$

In equation (1) wjk, the neural network weights are the radial base function associated with the output j, ck is the vector value of the central value and σk is the vector of the width value in the radial base function of the neural network

It should be noted that the RBF model consists of two layers, the first layer of the radial base and the second layer, the linear output. Characteristics of the network structure for each of the formations are presented in Table2.

Table 2. Structural characteristics of the RBF network for the studied formation.

Formation	Maximum number of neurons	Spread
1	40	1.1
2	10	1.1
3	40	1.1
4	45	1.1
5	30	1.1
6	40	1.1
7	10	1.1
8	10	1.1
9	45	1.1
10	50	1.1
11	55	1.1
12	45	1.1
13	45	1.1
14	35	1.1

In this research work, firstly, 2464 data extracted from well information were classified according to the geological data of wells and for each of the formations were divided into two categories: educational data (80%) and evaluation data (20%). Also, before applying the neural network, all input and output data were normalized and their values were reduced to -1 to +1. In order to normalize the following formula was used:

$$XN=2(X-Min\ X)/\ (MaxX-MinX)-1 \qquad (2)$$

In the formula above x is the amount of data required, minX is the minimum value of the data, MaxX is the maximum value of the data, and XN is the normalized value of the data x. This will make all the data in a range, and it will be easier and faster to find the network connection between the input and output data. Also, when outputting from the network to get the output value from the normalized state, just the XN, MinX, and MaxX are pasted in the above equation and the value of x is computed.

The RBF models was designed to predict the drill penetration rate in different formations using 6 input parameters, the main goal of this study is to optimize the drill penetration rate. Before starting the optimization, two important issues were to be identified. Firstly, what is the optimal rate in each of the formations and, secondly, which of the parameters affecting the drill penetration rate can be changed. The first case is to determine the optimum penetration rate in each of the formations using the available data as well as the query of those employed and experienced in well drilling. Modifiable parameters were also determined by the information available in the resources and persons employed in the drilling industry. Selected parameters include weight on drill, rotation per minute, flow of drilling fluid and pipe pressure. Therefore, in this optimization, the amount used for other parameters that cannot be changed is the same as reported information. To optimize the drill penetration rate, the particle swarm optimization algorithm was used. The particle swarm optimization algorithm performs optimization by minimizing the mean least squared error [12]. The description of this algorithm and how it functions is presented in Chapter 3. The structure of the algorithm used for all formations is identical and is presented in Table 3.

Table 3. The structure of the particle optimization algorithm used in this research.

Particle swarm optimization (PSO)	Swarm size	30
	Maximum number of iterations	25
	Cognition coefficient	2
	Social coefficient	6

3. Results and discussion

In this section, after modeling using the RBF neural network, the accuracy of the presented model was compared with the real well data.

3.1. RBF neural network model validation

The results of the comparison for each of the formations are given in Figures 1 to 13. Part A of the figure shows the output of the model against the reported drill penetration rate data of the studied well. As it can be seen from the figures, the drill penetration rate values are close to the X=Y line, which indicates the accuracy of the model and the low degree of uncertainty in predicting the drill penetration rate in different formations. In part b, the reported and predicted drill penetration rate data shapes by the RBF model are plotted against each data number simultaneously. As can be seen from the figure, the predicted values are very close to the values extracted from the well data, which means the accuracy and power of the model in estimating the penetration rate of the drill. Part C shows the bar graph of error frequency, as can be seen, a significant number of data have an error close to zero, and as a result, they have the highest frequency. Part d of the figure shows the relative error for the presented model. As shown in the figure, almost all predicted values of the drill penetration rate are close to the zero line for the relative error, which confirms the claim of the accuracy of the RBF model.

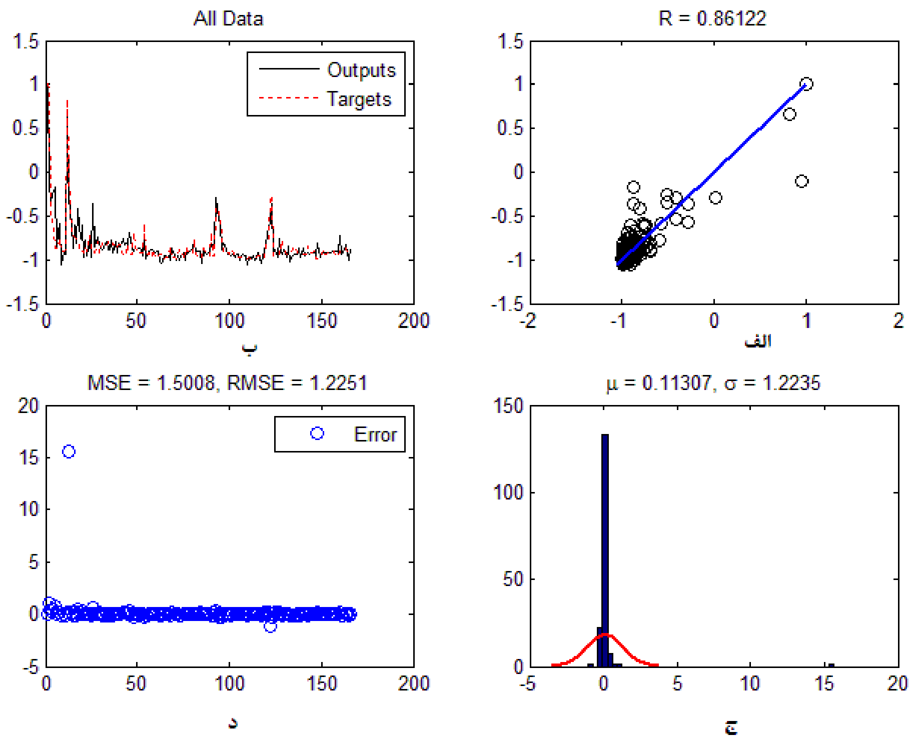

Figure 1. Comparison between the results of the RBF model and actual well data for Formation (1).

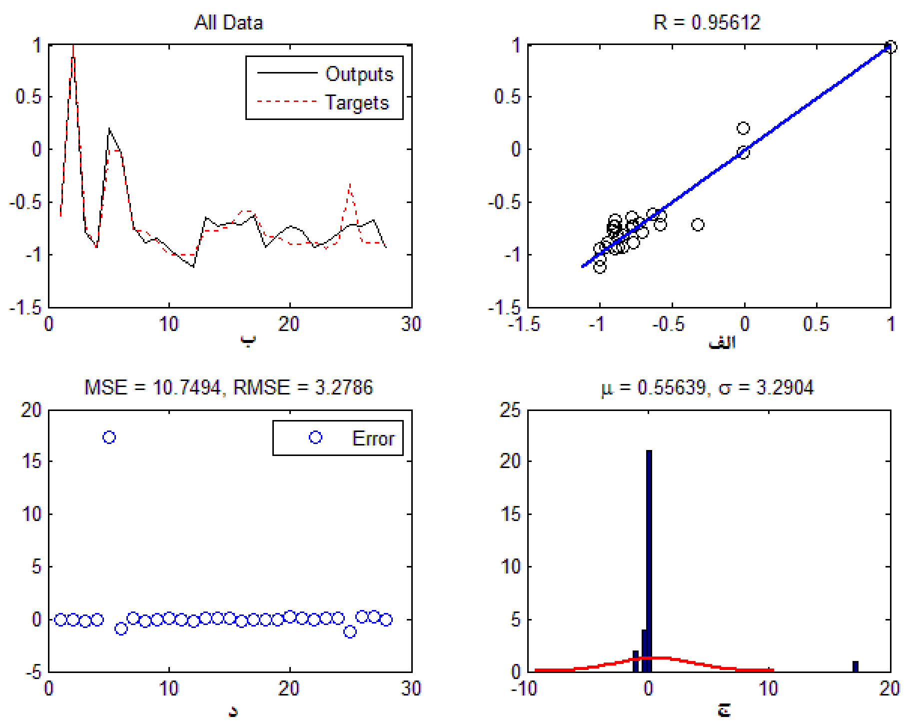

Figure 2. Comparison between the results of the RBF model and actual well data for Formation (2).

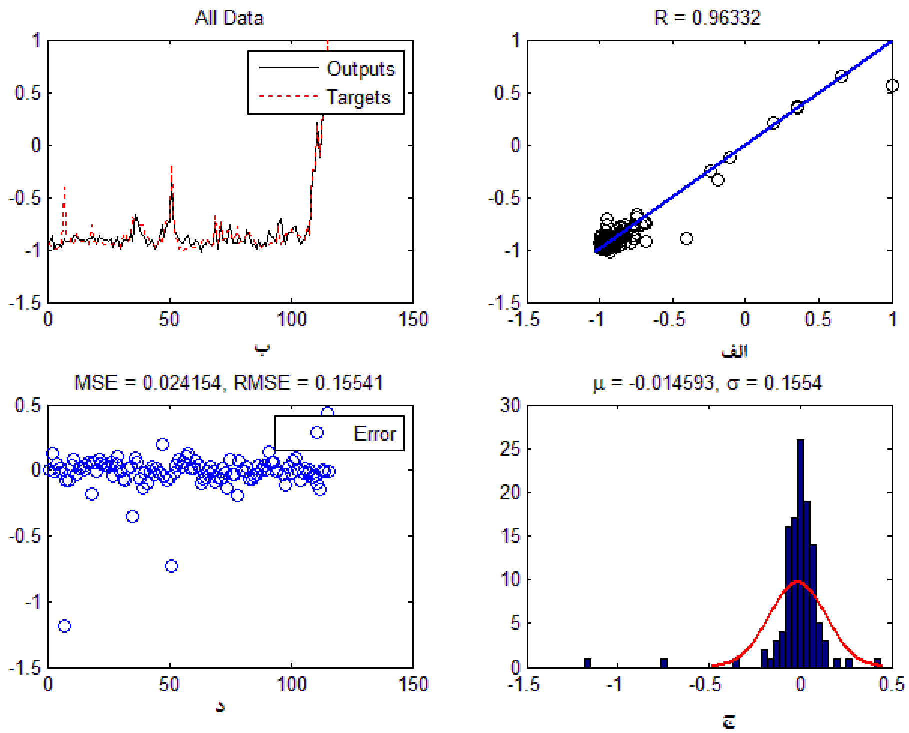

Figure 3. Comparison between the results of the RBF model and actual well data for Formation (3).

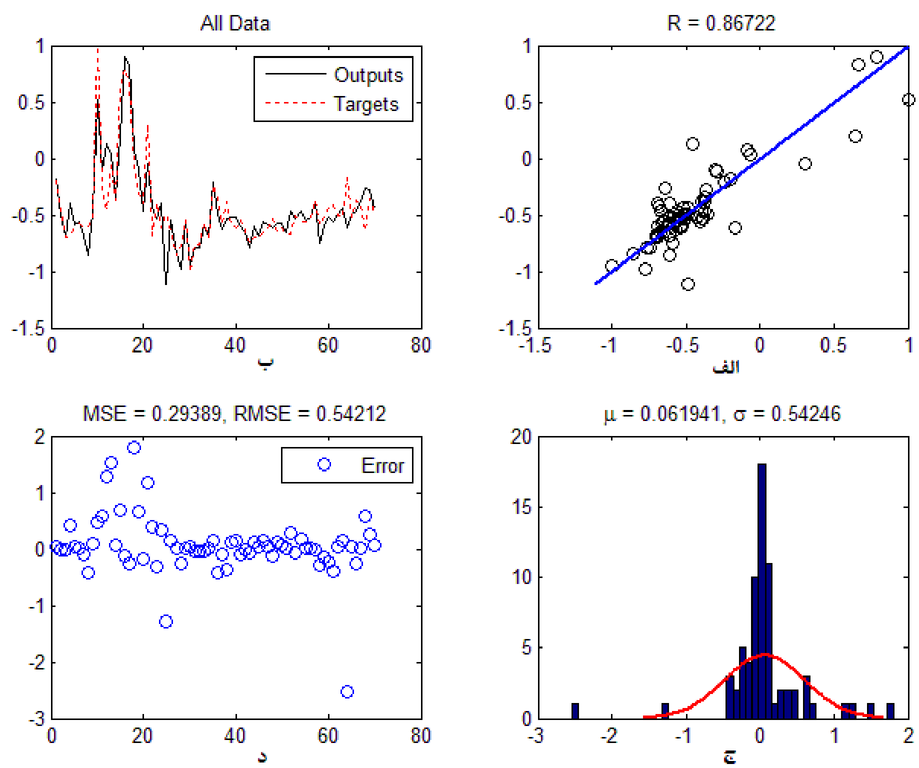

Figure 4. Comparison between the results of the RBF model and actual well data for Formation (4).

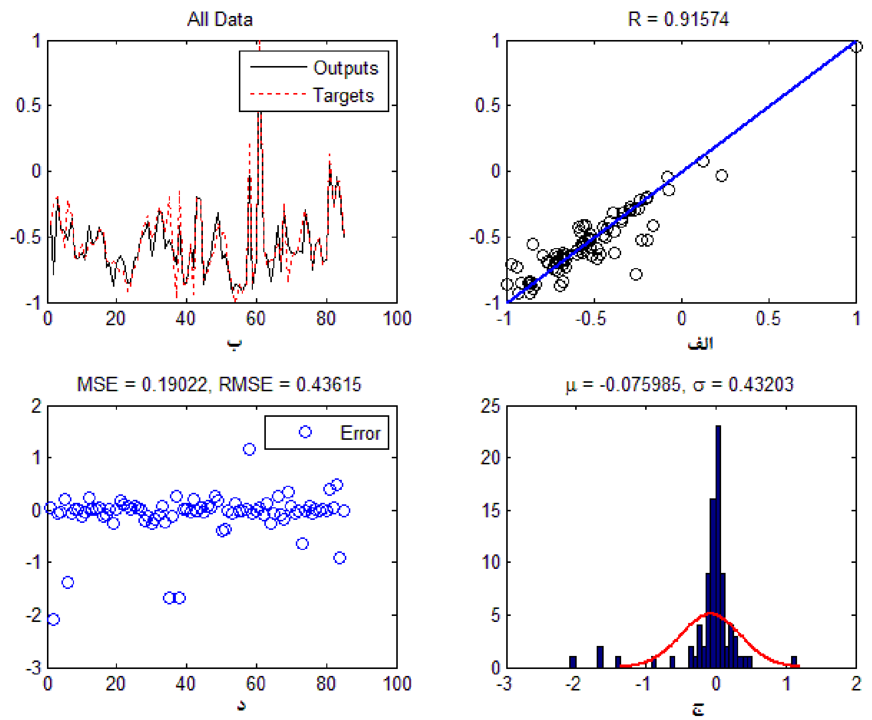

Figure 5. Comparison between the results of the RBF model and actual well data for Formation (5).

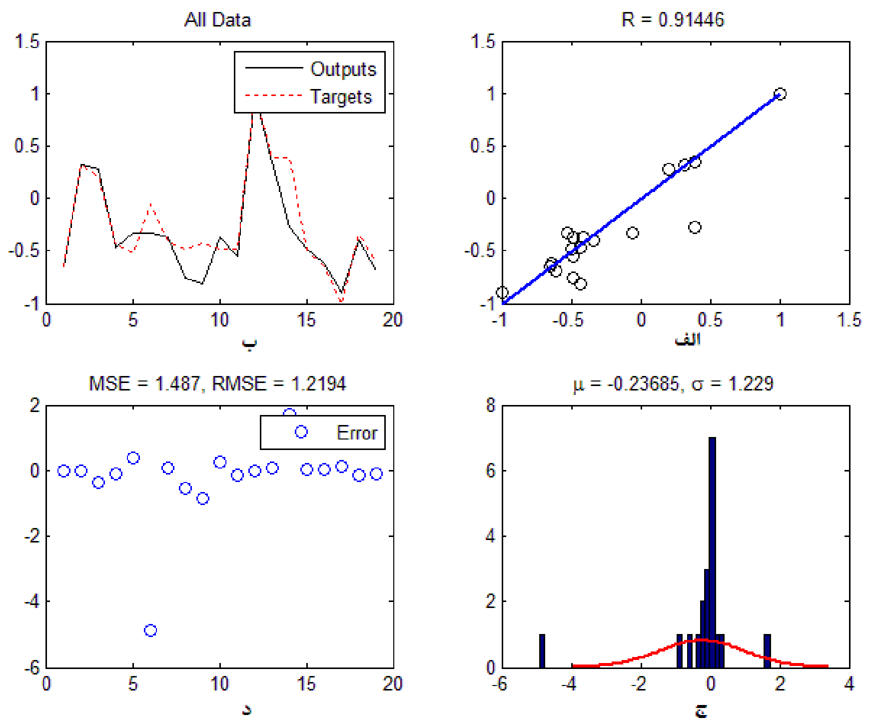

Figure 6. Comparison between the results of the RBF model and actual well data for Formation (6).

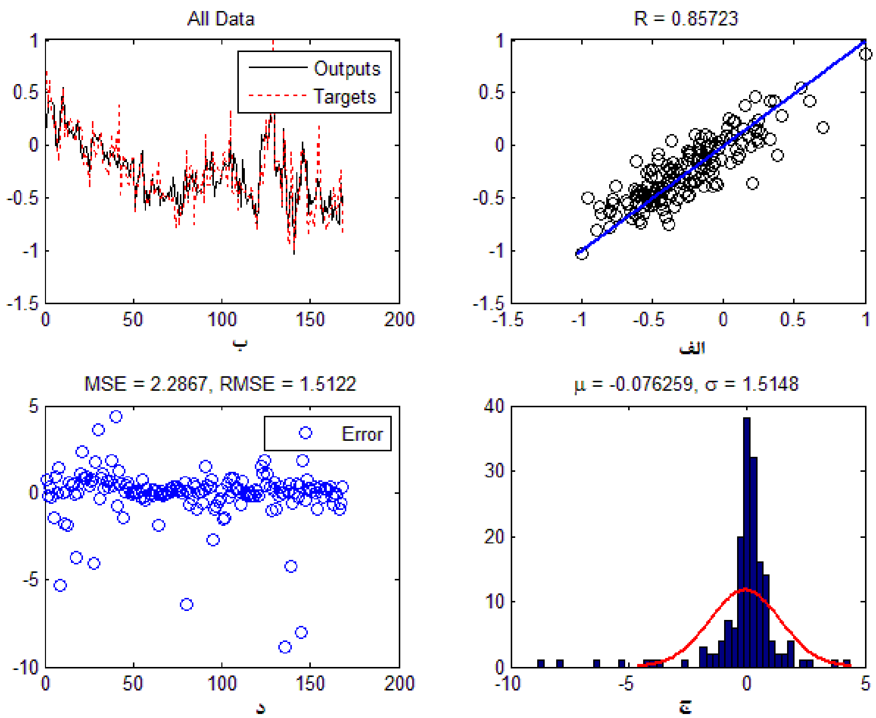

Figure 7. Comparison between the results of the RBF model and actual well data for Formation (7).

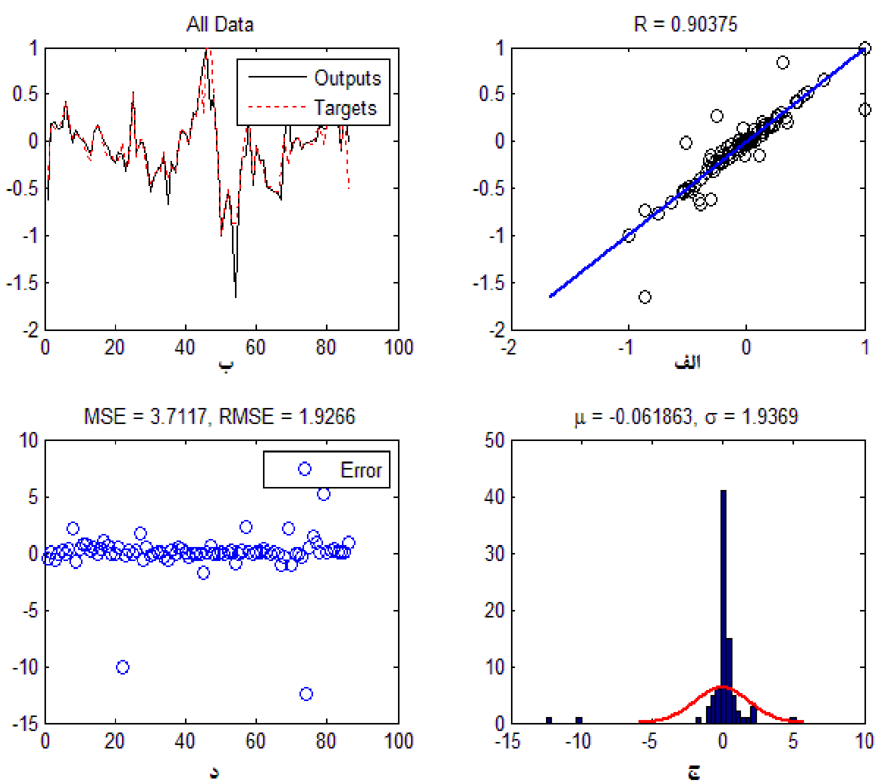

Figure 8. Comparison between the results of the RBF model and actual well data for Formation (8).

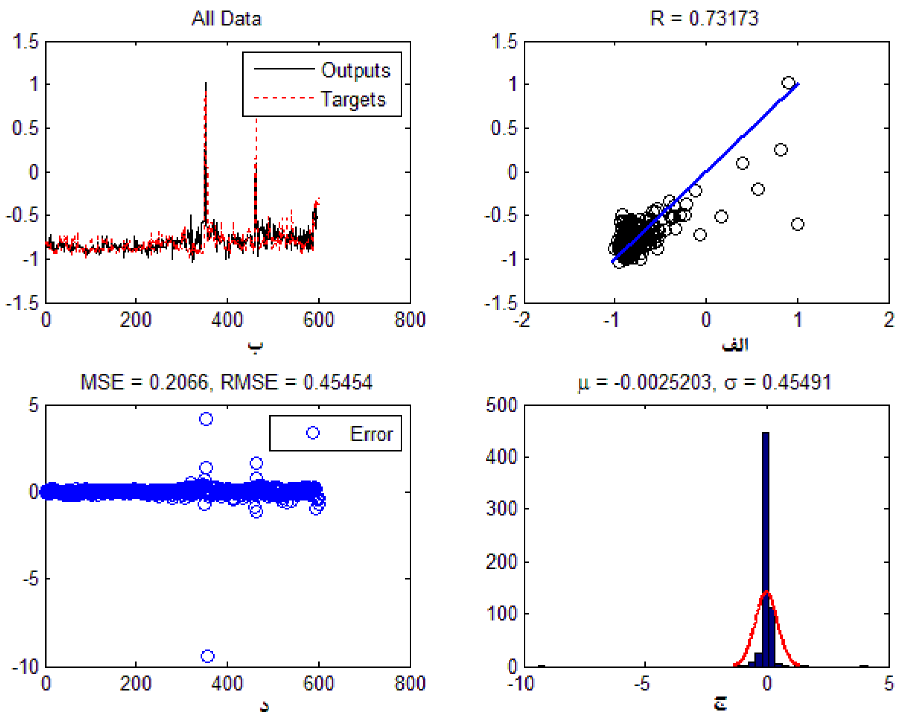

Figure 9. Comparison between the results of the RBF model and actual well data for Formation (9).

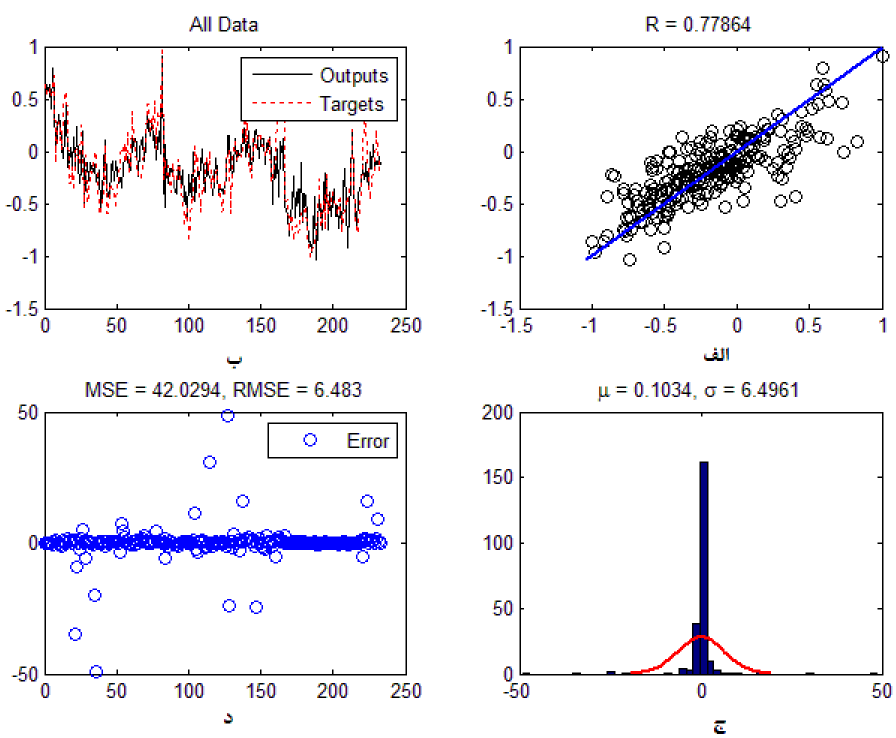

Figure 10. Comparison between the results of the RBF model and actual well data for Formation (10).

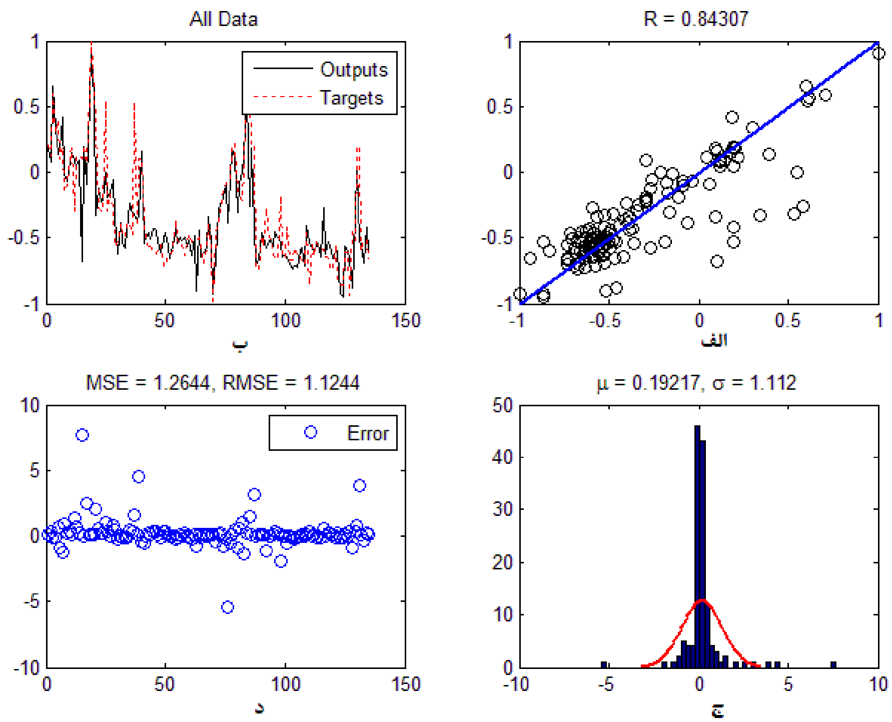

Figure 11. Comparison between the results of the RBF model and actual well data for Formation (11).

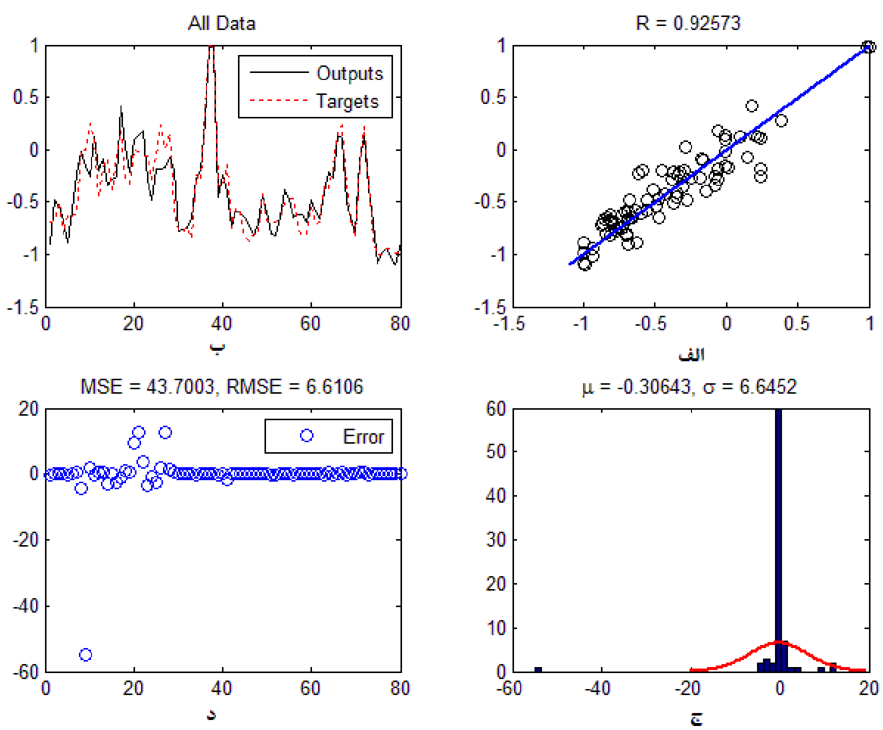

Figure 12. Comparison between the results of the RBF model and actual well data for Formation (12).

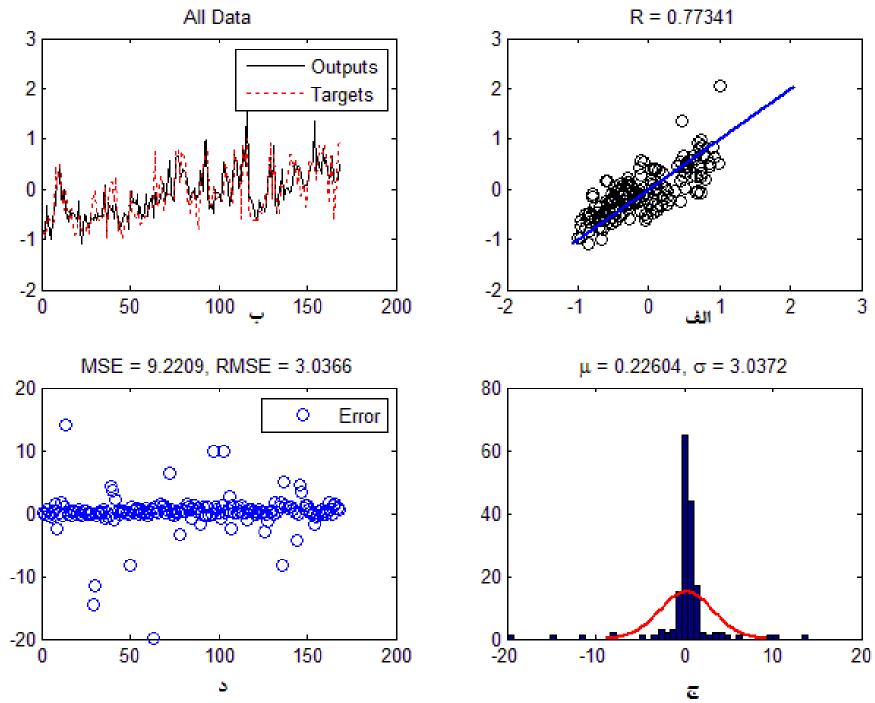

Figure 13. Comparison between the results of the RBF model and actual well data for Formation (13).

3.2. Optimization of rate of penetration

In this section, optimization of rate of penetration has been studied. The statistical characteristics the input and output parameters of the RBF model for each of the formations are presented in Table 4.

Table 4. Statistical characteristics of input and output parameters for formations.

Formation (1)				
Parameter	Minimum	maximum	Average	Standard deviation
Bit Depth (m)	1447.0000	1612.0000	1529.5000	48.0642
Rot Torque (kflb)	0.3500	8.4300	4.0823	1.3142
WOB (kIbs)	0.1100	15.6530	5.6434	3.5245
RPM (RPM)	26.0000	108.0000	57.3313	10.9248
Flow (gpm)	595.5290	698.7530	657.1877	42.6137
SPP (psi)	1361.5650	2612.2140	2226.3376	254.3455
ROP (min/m)	0.1100	15.6530	5.6434	3.5245
Formation (2)				
Parameter	Minimum	Maximum	Average	Standard deviation
Bit Depth (m)	1613.0000	1640.0000	1626.5000	8.2260
Rot Torque (kflb)	2.5300	5.5600	4.0832	0.7324
WOB (kIbs)	0.4030	16.8650	6.1801	3.7806
RPM (RPM)	43.0000	65.0000	63.1429	3.9695
Flow (gpm)	595.5290	688.3600	652.9635	18.2464
SPP (psi)	2373.1760	2874.2890	2599.2637	120.5607
ROP (min/m)	2.0300	39.5300	7.8057	7.8645
Formation (3)				
Parameter	Minimum	Maximum	Average	Standard deviation
Bit Depth (m)	1641.0000	1756.0000	1698.5000	33.6303
Rot Torque (kflb)	2.1800	8.2600	3.9393	0.8993
WOB (kIbs)	0.1260	38.3160	5.9467	6.7648
RPM (RPM)	53.0000	66.0000	63.1379	2.5940
Flow (gpm)	453.7360	698.7530	647.7340	24.7294
SPP (psi)	2333.3600	2962.7370	2565.6362	102.6069
ROP (min/m)	0.9800	80.8700	8.6116	13.0571

Formation (4)				
Parameter	Minimum	Maximum	Average	Standard deviation
Bit Depth (m)	2403.0000	2570.0000	2486.5000	48.6415
Rot Torque (kflb)	1.0000	7.8100	5.2388	1.0256
WOB (kIbs)	0.4190	40.7410	11.7087	10.5490
RPM (RPM)	0.0000	139.0000	75.3391	31.7818
Flow (gpm)	555.8270	754.3360	667.6855	38.6444
SPP (psi)	1936.3370	2990.3240	2487.3411	305.0935
ROP (min/m)	1.4200	162.6700	17.8048	27.1145
Formation (5)				
Parameter	Minimum	Maximum	Average	Standard deviation
Bit Depth (m)	2200.0000	2269.0000	2234.5000	20.3511
Rot Torque (kflb)	1.1200	8.9600	4.8189	1.6820
WOB (kIbs)	10.4650	26.3740	16.4714	3.0214
RPM (RPM)	20.0000	59.0000	46.0571	9.1285
Flow (gpm)	588.2480	683.1370	602.4220	12.5877
SPP (psi)	2359.0980	2891.4950	2679.0745	106.5171
ROP (min/m)	3.2500	20.1200	7.9096	3.0638
Formation (6)				
Parameter	Minimum	Maximum	Average	Standard deviation
Bit Depth (m)	2270.0000	2354.0000	2312.0000	24.6813
Rot Torque (kflb)	1.0000	9.1100	5.0751	1.7761
WOB (kIbs)	0.3590	26.2790	11.5436	4.4570
RPM (RPM)	29.0000	59.0000	48.8000	3.3338
Flow (gpm)	595.5290	619.9830	601.0347	6.3993
SPP (psi)	2293.5440	3011.2270	2745.4906	132.3396
ROP (min/m)	3.6300	16.0200	6.4989	1.8631
Formation (8)				
Parameter	Minimum	Maximum	Average	Standard deviation
Bit Depth (m)	2355.0000	2383.0000	2369.0000	8.5147
Rot Torque (kflb)	1.8000	5.2200	3.3966	0.9533
WOB (kIbs)	2.7380	30.9240	13.3136	6.5454
RPM (RPM)	40.0000	130.0000	72.1034	33.5882
Flow (gpm)	584.1850	725.9780	652.0499	47.3676
SPP (psi)	2103.7070	2819.2570	2686.8151	145.7902
ROP (min/m)	8.6700	75.7200	32.3210	18.0177
Formation (9)				
Parameter	Minimum	Maximum	Average	Standard deviation
Bit Depth (m)	2384.0000	2402.0000	2393.0000	5.6273
Rot Torque (kflb)	1.2000	5.2100	3.2089	1.0239
WOB (kIbs)	4.9980	18.5690	13.7951	3.5919
RPM (RPM)	25.0000	49.0000	38.6842	6.5069
Flow (gpm)	527.4150	663.5230	638.3958	42.8414
SPP (psi)	1820.4440	2775.3170	2552.4488	291.9339
ROP (min/m)	6.7000	40.0700	19.2074	8.2042
Formation (10)				
Parameter	Minimum	Maximum	Average	Standard deviation
Bit Depth (m)	2403.0000	2570.0000	2486.5000	48.6415
Rot Torque (kflb)	1.0000	7.8100	5.2388	1.0256
WOB (kIbs)	3.2690	31.9120	14.9636	3.4418
RPM (RPM)	30.0000	61.0000	55.0595	6.6366
Flow (gpm)	595.4680	718.8890	621.9242	24.3320
SPP (psi)	2277.9020	2863.7660	2566.4663	113.6429
ROP (min/m)	2.7800	14.7500	7.2171	2.0339
Formation (11)				
Parameter	Minimum	Maximum	Average	Standard deviation
Bit Depth (m)	2571.0000	2656.0000	2613.5000	24.9700
Rot Torque (kflb)	3.2500	7.5900	5.4183	0.8609
WOB (kIbs)	4.9780	17.9500	11.9739	2.6271
RPM (RPM)	54.0000	60.0000	57.8023	2.4050
Flow (gpm)	595.4680	639.5460	614.8513	11.1041
SPP (psi)	2383.8410	2785.8400	2576.0456	94.7325
ROP (min/m)	2.8300	13.8800	7.9899	1.9922

Formation (12)				
Parameter	Minimum	Maximum	Average	Standard deviation
Bit Depth (m)	2657.0000	3257.0000	2957.0000	173.6380
Rot Torque (kflb)	2.1000	8.0600	4.8900	0.9596
WOB (kIbs)	1.4970	30.1850	10.7723	3.9425
RPM (RPM)	29.0000	151.0000	71.4659	34.1351
Flow (gpm)	493.3880	714.5630	619.3673	52.6785
SPP (psi)	2029.4790	2942.8290	2633.5524	169.3806
ROP (min/m)	2.5000	84.5700	10.7206	7.7097
Formation (13)				
Parameter	Minimum	Maximum	Average	Standard deviation
Bit Depth (m)	3258.0000	3490.0000	3374.0000	67.4055
Rot Torque (kflb)	3.6600	6.3400	4.9852	0.4047
WOB (kIbs)	3.4720	30.1850	14.9530	4.2462
RPM (RPM)	120.0000	151.0000	148.5365	5.0283
Flow (gpm)	544.4280	714.5630	665.6446	39.7075
SPP (psi)	47.6370	2780.8630	2489.9228	243.6634
ROP (min/m)	2.6000	31.7300	14.5551	5.6152
Formation (14)				
Parameter	Minimum	Maximum	Average	Standard deviation
Bit Depth (m)	3491.0000	3625.0000	3558.0000	39.1152
Rot Torque (kflb)	3.4900	6.4800	5.2070	0.4819
WOB (kIbs)	0.1940	15.9940	7.9474	3.5593
RPM (RPM)	129.0000	151.0000	144.1333	9.1560
Flow (gpm)	359.6280	663.5230	652.9748	25.7324
SPP (psi)	939.9420	2667.6720	2471.6235	200.6583
ROP (min/m)	4.2300	29.7200	12.7772	5.0850

In order to optimize the drill penetration rate, a model based on the radial base function's neural network was used to predict the drill penetration rate. The proposed model (RBF) predicts the drill penetration rate as a function of drill depth, drill weight (WOB), rotational minutes (RPM), flow (GPM), standing pipe pressure (SPP) and torque. Due to the huge impact of formation on drilling rate and the different behavior of this parameter in different formations, the RBF model was created for each formation individually.

The results of the optimization of the drill penetration rate in each of the formations are presented in Table 5.

Table 5. Statistical properties of input and output parameters after optimization for formations.

Formation (1)				
Parameter	Minimum	Maximum	Average	Standard deviation
WOB (kIbs)	0.1100	15.6530	5.5052	5.0223
RPM (RPM)	26.0000	108.0000	57.6707	23.9681
Flow (gpm)	595.5290	698.7530	654.0017	37.0971
SPP (psi)	1361.5650	2612.2140	2162.3322	368.9227
ROP (min/m)	3.9615	4.1192	4.0002	0.0105

Formation (2)				
Parameter	Minimum	Maximum	Average	Standard deviation
WOB (kIbs)	0.4030	13.5251	5.4013	4.3485
RPM (RPM)	48.9751	65.0000	60.4356	4.8404
Flow (gpm)	632.7046	688.3600	678.0733	15.2245
SPP (psi)	2373.1760	2874.2890	2601.5993	195.9171
ROP (min/m)	3.8709	5.7093	4.0730	0.3335
Formation (3)				
Parameter	Minimum	Maximum	Average	Standard deviation
WOB (kIbs)	0.1260	38.3160	9.2277	12.6357
RPM (RPM)	53.0000	66.0000	61.6124	4.3897
Flow (gpm)	453.7360	698.7530	612.6712	87.3227
SPP (psi)	2333.3600	2962.7370	2507.3290	200.3573
ROP (min/m)	3.2883	10.1656	4.0884	0.7321

Formation (4)				
Parameter	Minimum	Maximum	Average	Standard deviation
WOB (kIbs)	0.4190	40.7410	17.0360	14.6865
RPM (RPM)	0.0000	139.0000	71.6460	49.3939
Flow (gpm)	555.8270	754.3360	643.4455	65.6618
SPP (psi)	1936.3370	2990.3240	2472.0373	362.5273
ROP (min/m)	2.2589	9.8054	5.9995	0.2847
Formation (5)				
Parameter	Minimum	Maximum	Average	Standard deviation
WOB (kIbs)	10.4650	26.3740	19.1517	6.1747
RPM (RPM)	20.0000	59.0000	50.9023	8.8006
Flow (gpm)	588.2480	683.1370	621.4238	36.5919
SPP (psi)	2359.0980	2891.4950	2674.9196	180.6402
ROP (min/m)	5.9507	6.0039	5.9993	0.0060
Formation (6)				
Parameter	Minimum	Maximum	Average	Standard deviation
WOB (kIbs)	0.3590	26.2790	16.7756	8.0664
RPM (RPM)	29.0000	59.0000	40.8503	9.9488
Flow (gpm)	595.5290	619.9830	608.9025	7.8866
SPP (psi)	2293.5440	3011.2270	2611.0864	246.6416
ROP (min/m)	4.9984	5.0162	5.0003	0.0019
Formation (7)				
Parameter	Minimum	Maximum	Average	Standard deviation
WOB (kIbs)	2.7380	16.2221	7.2384	4.4089
RPM (RPM)	40.0000	115.4084	69.3578	25.7183
Flow (gpm)	584.1850	691.4313	631.7674	30.8411
SPP (psi)	2103.7070	2819.2570	2376.4624	178.0402
ROP (min/m)	19.9314	24.7049	20.3383	1.0297
Formation (8)				
Parameter	Minimum	Maximum	Average	Standard deviation
WOB (kIbs)	10.0262	18.5690	16.9014	2.5859
RPM (RPM)	28.8551	49.0000	39.1726	6.6022
Flow (gpm)	545.5376	663.5230	653.5124	26.7393
SPP (psi)	2206.7444	2775.3170	2624.7501	191.3081
ROP (min/m)	14.9993	20.0102	15.5249	1.2407
Formation (9)				
Parameter	Minimum	Maximum	Average	Standard deviation
WOB (kIbs)	3.2690	31.9120	22.3472	9.3363
RPM (RPM)	30.0000	61.0000	45.3073	11.1517
Flow (gpm)	595.4680	718.8890	662.3358	44.3952
SPP (psi)	2277.9020	2863.7660	2532.3399	200.2868
ROP (min/m)	6.6004	6.6936	6.6594	0.0065
Formation (10)				
Parameter	Minimum	Maximum	Average	Standard deviation
WOB (kIbs)	4.9780	17.9500	11.5408	4.7580
RPM (RPM)	54.0000	60.0000	55.6553	1.8749
Flow (gpm)	595.4680	639.5460	613.9494	16.2400
SPP (psi)	2383.8410	2785.8400	2601.9839	140.8986
ROP (min/m)	6.6588	6.6746	6.6604	0.0021
Formation (11)				
Parameter	Minimum	Maximum	Average	Standard deviation
WOB (kIbs)	1.4970	30.1850	15.6715	10.2138
RPM (RPM)	29.0000	151.0000	78.8628	43.1987
Flow (gpm)	493.3880	714.5630	633.7300	73.8496
SPP (psi)	2029.4790	2942.8290	2639.3688	293.7473
ROP (min/m)	5.0459	8.0996	6.0021	0.0971
Formation (12)				
Parameter	Minimum	Maximum	Average	Standard deviation
WOB (kIbs)	3.4720	30.1850	18.7423	10.3812
RPM (RPM)	120.0000	151.0000	137.0029	10.7793
Flow (gpm)	544.4280	714.5630	619.3930	64.7511
SPP (psi)	47.6370	2780.8630	1406.1989	1028.8606
ROP (min/m)	5.8271	7.0027	6.6547	0.0835

Formation (13)				
Parameter	Minimum	Maximum	Average	Standard deviation
WOB (kIbs)	0.1940	15.9940	4.9322	5.0336
RPM (RPM)	129.0000	151.0000	143.0018	7.7092
Flow (gpm)	359.6280	663.5230	453.1697	92.4788
SPP (psi)	939.9420	2667.6720	1772.3211	683.3598
ROP (min/m)	11.9190	13.0370	12.0069	0.0896
Formation (14)				
Parameter	Minimum	Maximum	Average	Standard deviation
WOB (kIbs)	2.9590	17.2950	9.9044	5.1242
RPM (RPM)	129.0000	150.0000	138.6476	8.0286
Flow (gpm)	644.4530	661.4650	655.2844	5.5279
SPP (psi)	2179.0730	2680.8970	2389.7825	183.0540
ROP (min/m)	11.7363	12.2334	12.0012	0.0416

The results show that the parameters used in drilling can be changed in such a way that the amount of drill penetration rate approaches its optimum value. However, by examining the reported wells as well as the information after optimization, it can generally be concluded that drill speed and depth have the greatest and least impact on drilling speed. Due to the combination of different states it can be concluded that with increasing depth, if the weight on the drill and the speed of rotation of the drill less are used, increasing the hydraulic parameters can achieve the highest rate of drilling. However, this is not always the case, and among the optimized tables for some formations a different composition has been seen. Also, it can be concluded that drill speed and depth have the greatest and least impact on drilling speed. Due to the combination of different states it can be seen that with increasing depth, if the weight on the drill and the speed of rotation of the drill less are used, increasing the hydraulic parameters can achieve the highest rate of drilling. Of course, the condition of this matter is more difficult to formations with increasing depth. Also, using the obtained relationship to predict the drill penetration rate in certain formations, it can be used in other wells that have crossed the formations used in this study and easily calculate the optimal parameters.

4. Conclusion

In this study, complete geological and drilling data from one of the wells of Iran were used to optimize the drill penetration rate. Drill depth parameters, drill weights, drill speed, drilling fluid flow, tube pressure and torque were selected as effective and inertial parameters for obtaining a relationship for predicting drill penetration rates. The RBF neural network was used to achieve this relationship. Finally, using the particle swarm optimization algorithm, variable parameters including drill weight, drill speed, drilling fluid flow and pipe pressure were changed to obtain the optimum drill penetration rate. In order to optimize the drill penetration rate due to the different geological characteristics of each of the formations and as a result of different drill behavior, well information is classified based on the formations that passed through the well, and thus obtaining the relationship as well as optimization. For each formation, it was done separately. After careful examination of all geological information and drilling wells and several other wells (which were not confidential due to the information provided in the dissertation), it was concluded that, in general, it is not possible to determine the exact influence of the parameters on the penetration rate Digging comments and depending on multiple conditions, the effect of parameters varies. In general, it can be concluded:

1. The drill speed and depth have the greatest and least impact on drilling speed.
2. Due to the combination of different states it can be seen that with increasing depth, if the weight on the drill and the speed of rotation of the drill less are used, increasing the hydraulic parameters can achieve the highest rate of drilling.
3. The condition of this matter is more difficult to formations with increasing depth.

Symbols and abbreviations

ANNs	*Artificial neural networks*
MSE	*Mean square error*
PSO	*Particle swarm optimization*
RBF	*Radial basis function*
ROP	*Rate of penetration*
RPM	*Rotation per minute*
SPP	*Stand pipe pressure*
WOB	*Weight on bit*

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