Study on the Method of Drill Bit Selection based on Adaptive Neuro-Fuzzy Inference System

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Abstract

Drill bit selection has been playing an important role in improving drilling efficiency and reducing the cost of drilling. An adaptive neuro-fuzzy inference system (ANFIS) has been proposed for bit selection in oil drilling. Quantitative method is used to build the selection system. By analyzing the effects of the factors in drilling process, High quality using bit model and its corresponding influencing factors are selected to train the neural network to build the fuzzy rules and membership functions of the inference system. Finally the established inference system can be used to bit selection. It turns out that the correlation of predicting outputs and the actual values reached at 97.7%, by using a group of testing data to test the system. The ANFIS system integrates the advantages of neural network and fuzzy inference system getting over the problems of the demanding of expert experience for designing the fuzzy rules, the lacking of self-learning and poor accuracy. Finally, results obtained from the ANFIS approach we developed are compared with the results of the multiple regression method, demonstrating that the ANFIS method performed well.

Keywords

ANFIS, bit selection, drilling data, quantitative, drilling efficiency.

1. Introduction

A major concern is the realization of safe, efficient and high-quality drilling (Gao et al., 2004)[1]. The drill bit is an important tool that breaks the rock to form a borehole in drilling process. The performance of the borehole relates to formation characteristic, bit performance, well depth and the matching degree between the bit and the formation. To exploit the bit performance and obtain the high-performance borehole, some scientific methods are used for the bit type selection. These methods can be divided into two categories: qualitative and quantitative methods.

Rock is divided into different level according its rock mechanics as well as drill bits and the so called qualitative selection method is to match the level of both rock and bitThe quantitative selection method is based on a certain model which is quantified to determine the bit type, and its essential is to make good use of the existing practical drilling effects (such as the bit footage, drill life, average rate of penetration and drilling cost) as the reference for selecting an appropriate drill. In other word, the quantitative method possess the characteristic of strong comprehensiveness because of taking into account the known practical information including the statistics of bit type selection and the long-term field application effect.

ZHOU De-sheng, JIANG Ning-wen (1994) proposed the selection of drill bits on the basis of fuzzy clustering of strata and established dynamic clustering graphs according to the similarity between different the rock properties. Finally select the drill bit through combining with the manufacturer's instructions [3]. Chen Deguang, Tang Nianden (1995, 2000) used the gray-like whitening weight function clustering method to cluster rock according to hardness, drillability, compressive strength and other parameters[4]. Spaar JR, Ledgerwood LW (1995) has been proved that rock abrasive and internal friction angles have a good correlation and rock friction angle could determine the formation of grinding[5]. YANG Jin, GAO Deli (1999) clustered an integrated rock characteristic parameter using gray relational clustering method, thus provided a scientific basis for the drill selection[6].

Mason KL, ZHANG (1987, 1997) proposed the use of shear wave time difference for bit selection method[7-8]. Falcao , XING Xuesong (1993-2004) proposed a method for selecting PDC bit selection using the relationship between shear strength and unit footage drilling costs[9-11]. Fabian Robert T and Ronald Birch (1995) proposed a method for PDC bit selection based on the compressive strength at the bottom of the well[12-13]. Wilmot, Pan Qifeng (1999-2003) proposed a method to select the drill bit by taking the economic benefits of the drill bit and the various rock mechanics characteristics of the strata into account[14-15].

Nygaard, R., Hareland, G. (2007) Selected the PDC bits by a balanced scorecard,which is a management system for communicating Measuring performance and decision making among companies[16]. The method utilized improvement of the Sorting of decision criteria related to the penetration rate and bit wears by using drilling simulator based on the penetration rate to select bit. FENG Ding (1998) used the artificial neural network method for bit selection. Firstly, the error back propagation neural network method is used to qualitatively select the bit based on lithology and drilling methods. Using the used data of drill bits to calculate the composite index to quantitatively select the bit[17]. The limitations of using the above-mentioned drill bit selection methods which used the matching degree between rock and bit method are that there are a number of drill bits that match a formatiom, to choose which drill bit model will be another problem.

Bilgesu HI et al. (2000) proposed the use of a three-layer feedback neural network for drill bit optimization. The method used several different neural network models to determine the complex relationship among formation, drill performance and operating parameters. The input parameters are: drill bit size, total flow area of drill bit, drilling depth, footage, ROP, maximum and minimum bit pressure, maximum and minimum turntable speed and drilling fluid speed. The output are the type of drill bit. YAN Tie et al. (2002) proposed the use of adaptive resonant neural network for bit selection [19]. The neural network composed of 12 neurons, including area, well depth, drill ability coefficient, grinding coefficient, ROP, footage, bit pressure, speed, bottom water power, bottom hole pressure, drill bit tooth wear and Drill bearing wear. And the output layer is a drill bit model. In addition, the drill bit selection also has The cost per meter method, the ratio of power method, the economic benefit index method, the comprehensive index method, the attribute hierarchy analysis method [20-23].

In this paper, the adaptive neural fuzzy reasoning system is adopted, which uses the drill bit effect to evaluate the preferred drill bit similarly. Differently the reasoning system has the advantage of dealing with complex nonlinear problems. The fuzzy logic rules and membership function parameters of the method are determined by the self-learning of the neural network. The automatic rules of fuzzy rules and membership function solved the problem of requiring expert experience when uses simple fuzzy reasoning system rules, the lack of self-learning shortcomings, but also taking the advantages of accurate input and output. The input data are the formation, drilling depth, ROP, drill bit footage, drilling pressure, drill speed, The corresponding well used drill in the field are selected as output.

2. The Establishment of ANFIS

The adaptive neural fuzzy inference system is a fuzzy system with multi-layer neural networks[25,29].The network structure is shown in Figure 1. The whole system has a total of five layers, in which the first layer represents the input layer of the system, the fifth layer represents the response of the system as well as output of the system. The hidden layers are the node of membership functions and fuzzy rules. This architecture eliminates the drawbacks of the multi-layer feed forward network that is difficult for the observers to understand and modify. ANFIS simulates Takagi–Sugeno fuzzy rule of type-3, where the consequent part of the rule is a linear combination of input variables and a constant. Assuming that the ANFIS has two inputs x1 and x2 and one output, the following rules can be written for a first order Sugeno fuzzy model:

Rule 1:If x1 is A1 and x2 is B1; then

$$f_1 = p_1 x_1 + q_1 x_2 + r_1 \tag{1}$$

Rule 2:

If x1 is A_2 and x2 is B_2; then

$$f_2 = p_2 x_1 + q_2 x_2 + r_2 \tag{2}$$

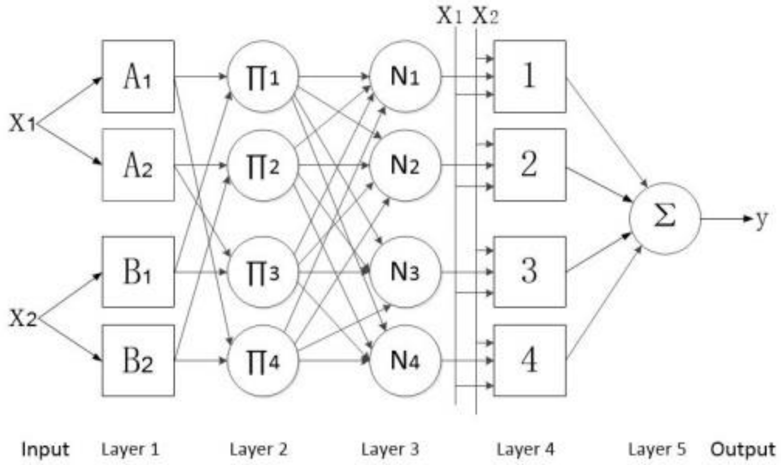


Fig.1: ANFIS with two-input Takagi–Sugeno model

Layer 1: This is the input layer where the input nodes, x1 and x2 enter the fuzzy network.

Layer 2: The fuzzy part of ANFIS is mathematically incorporated in the form of membership functions. A membership function $\mu_{Ai}(x)$ can be any continuous and piecewise differentiable function that transforms the input value x into a membership degree. Commonly Gaussian-based MF is the best choice because it leads to minimum training and testing errors as compared to the other shapes. Therefore, layer 2 is the fuzzification layer in which each node represents a membership according to the following three parameter Gaussian function:

$$\mu_{Ai}(x) = \exp\left[-\left(\left(\frac{x-c_i}{a_i}\right)^2\right)^{bi}\right] \tag{3}$$

Every node i in this layer is an adaptive node with a node function.

$$O_{2,i} = \mu_{Ai} \qquad i = 1,2 \tag{4}$$

$$O_{2,i} = \mu_{Bi-2} \qquad i = 3,4 \tag{5}$$

where x1 (or x2) is the input node i and A_i (or B_{i-2}) is a linguistic label associated with this node. Therefore O2,i is the membership grade of a fuzzy set (A_1, A_2, B_1, B_2).

As the values of the parameters a_i , b_i , c_i change, the bell-shaped functions vary accordingly, exhibiting various forms of membership functions on linguistic label Ai. Parameters in this layer are referred to as premise parameters.

Layer 3: Every node in this layer is a fixed node labeled as P, whose output is the product of all the incoming signals:

$$O_{3,i} = w_i = \mu_{Ai}(x_1) \cdot \mu_{Bi}(x_2) \tag{6}$$

Every node in this layer computes the multiplication of the input values and gives the product as the output [18]. The membership values represented by $\mu_{Ai}(x_1)$ and $\mu_{Bi}(x_2)$ are multiplied in order to find the firing strength of a rule where the variables x_1 and x_2 have the linguistic values A_i and B_i respectively.

Layer 4: This layer is the normalization layer which normalizes the strength of all rules according to the following equation:

$$O_{4,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2} \qquad i = 1,2 \tag{7}$$

where w_i is the firing strength of the ith rule which is computed in layer 3. Node i of this layer labeled as N computes the ratio of the ith rule's firing strength to the sum of all rules' firing strengths. For convenience, outputs of this layer are called normalized firing strengths[27].

Layer 5: Every node in this layer, labeled as an integer value, is an adaptive node with a node function[28]

$$O_{5,i} = \overline{w_i} f_i = \overline{w_i}\left(p_i x_1 + q_i x_2 + r_i \right) \tag{8}$$

$\overline{w_i}$ is the normalized firing strength from layer 4 and $\{p_i, q_1, r_i\}$ is the parameter set for this node. Parameters in this layer are referred to as consequent parameters.

Layer 6: The single node in this layer is a fixed node labeled as $\sum$ which computes the overall output as the summation of all incoming signals:

$$O_{6,i} = \sum_i w_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{9}$$

The ANFIS can be trained by a hybrid learning algorithm to identify the membership function parameters [21]. In the forward pass the algorithm uses least squares method to identify the consequent parameters $\{p_i, q_1, r_i\}$ on the layer 5. In the backward pass the errors are propagated backward and premise parameters $\{a_i, b_i, c_i\}$ are updated by gradient descent[29].

The condition of adaptive fuzzy inference system is

1. It must be a first order or zero order Sugeno system.
2. It's only for a single output system, and the use weight averaging method to solve the fuzzy.
3. All rules take the weight 1.

The system has a total of six inputs, which contains training data and test data. 450 sets of data has been selected from well drilling data from the well site, of which 400 of them are used for training of neural networks, and the remaining 50 sets of data are used to test the inference system. The workflow is shown in Figure 2. Through the traditional heuristic method, respectively, train the inference system with different types of membership function. The training errors for different types of membership functions are shown in Figure 3. It can be seen that the training error value of the Gaussian membership function is the smallest in the membership function of the bell-shaped and triangle-shaped, so the membership function of the Gaussian-shaped is chosen as the membership function of the fuzzy inference system. Similarly, the comparision of training error of Gaussian membership function in different number of inputs and outputs is shown in figure 4. It's difficult for the computer to train the network, because there are too much rules in five or more membership function. The training error is the minimum when the number of membership function is 4. So, four Gaussian membership functions are set for each input. The specific training parameters of the adaptive neural fuzzy inference system are shown in Table 1 [31]. As it can be seen from the training error in Fig. 5, the training error value converges to the minimum value at step 30. The membership functions of each input variable after training are shown in Figure 6.

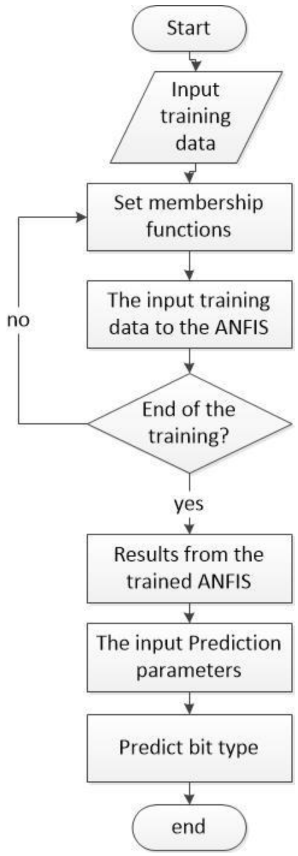


Fig.2 workflow

The comparison between the predicted output and the test data of the ANFIS based on the Gaussian membership function is shown in Fig 7. In order to ensure that the statistical distribution of input and output is roughly the same and speed up the convergence rate of training, the input and output data are normalized before training. The individual outliers of the predicted output and test data of the ANFIS shown in Fig. 7 are within the acceptable error range.

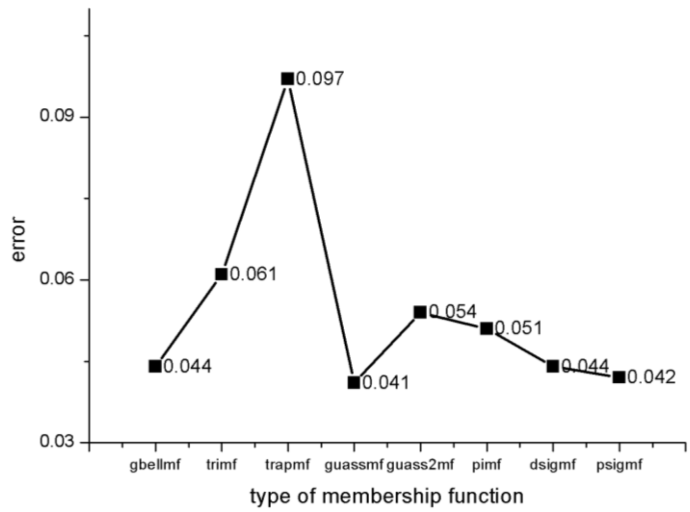


Fig. 3 Comparison of Training Error of Each Membership

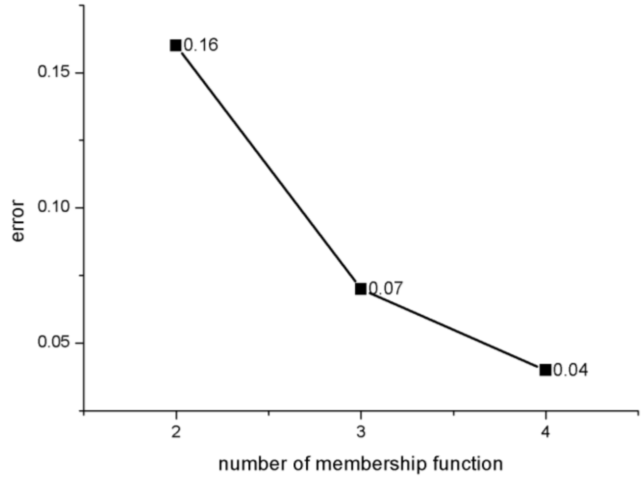


Fig.4 Comparison of training errors using different number of Gaussian membership function

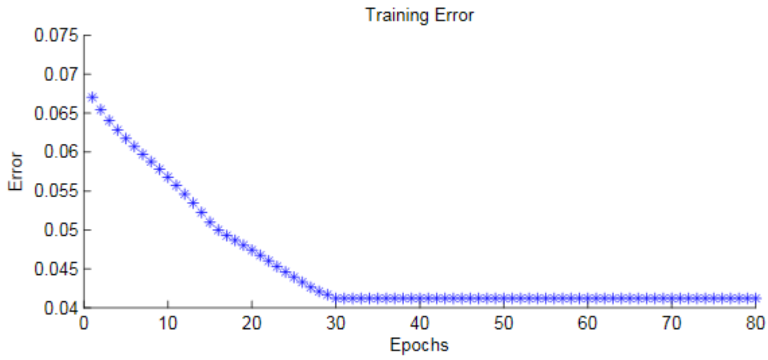
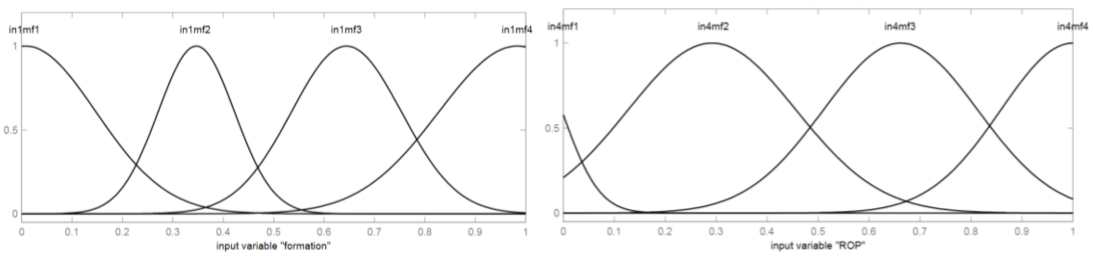


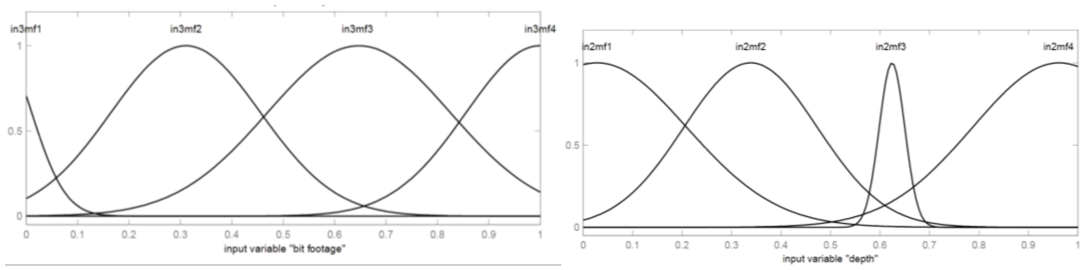
Fig.5 Training error plot for four Gaussian membership functions

Table 1. ANFIS training parameters

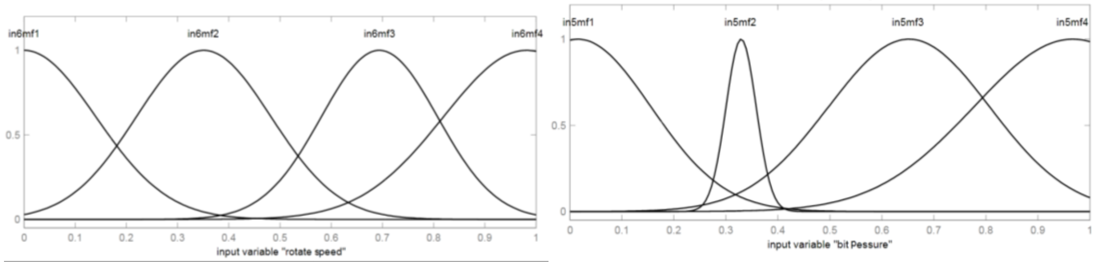
Number of nodes	8249
Linear parameters	4096
Non-linear parameters	48
Total number of parameter	4144
Training data	400
Test data	50
Fuzzy rules	4096



Formation ROP



Footage well depth



Rotate speed drill pressure

Fig.6 membership function image after training

3. Discussion

For the drill bit selection system based on the ANFIS, the drill bit model can be obtained by inputting the data of factors influencing the drilling. As the fuzzy system can get accurate output, the output of the selection results can be directly used for drill bit selection.

The training data are selected for the use of well-used cone bit data, so the bit selection system is based on the selection of roller cone bit selection applications. A total of 95 different types of drill bits were used in the 450 group of data. The RMSE of the prediction and test data is 0.079.

In order to demonstrate the accuracy of the system, a multiple linear regression model (MLR) was introduced to compare with ANFIS. The coefficients of the multiple regression model obtained by fitting the same training data as described above with the SPSS software are shown in table 2. Stepwise fitting method is taken during the fitting process, that is, the independent variables are in turn entered into the model in the fitting process, and some variables are eliminated according to the fitting situation. Finally, the fitting model of multiple linear regression is obtained. The comparision of the error values for both methods are shown in table 3. Root mean square error (RMSE) and mean absolute percentage error (MAPE) are the most commonly used errors to measure model accuracy. Their formulas are shown in formula (10), (11), in which n is the total number of sample data and At is the actual value, Ft is the predicted value of the model [32]. The root mean square error and the average percentage error of ANFIS predictions and real values were 0.079 and 0.17. They are significantly superior to the predictive results of multiple regression model. For the comparison of the correlation coefficient, the former model is also significantly higher than the latter. The fitting situation of ANFIS, multiple regression prediction results and the true value can be intuitively seen from figure 7. It can see that the values of ANFIS and real values fit well. The accuracy of the ANFIS is well by comparing the three kinds of data shown in Fig 8

$$RMSE=\sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(A_t-F_t\right)^2} \tag{10}$$

$$MAPE=\frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t-F_t}{A_t}\right| \tag{11}$$

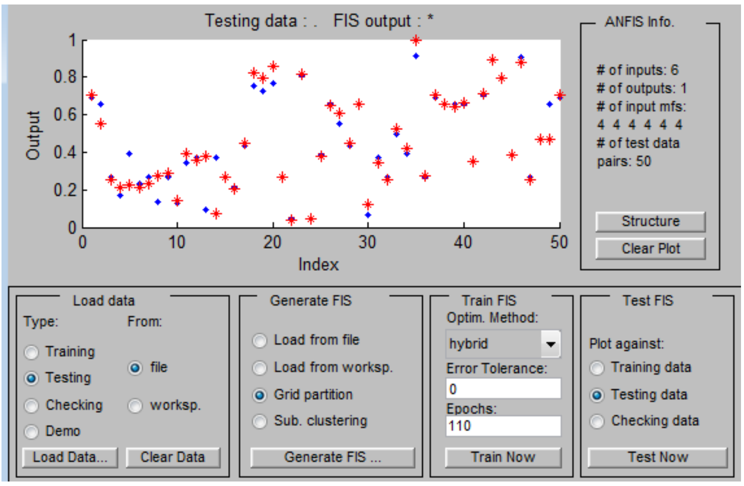


Fig.7 Comparison between test data and predicted

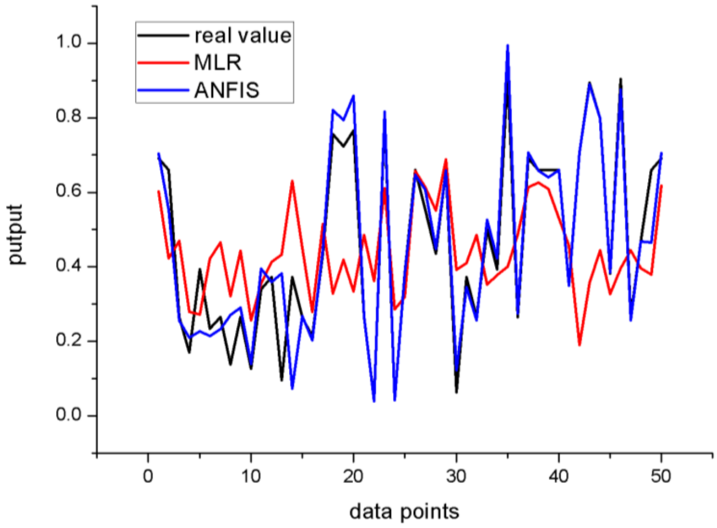


Fig.8 Comparison of Realistic value, MLR output, ANFIS output

Table 3. Comparison of ANFIS and MLR prediction results

	RMSE	MAPE	R^2
ANFIS	0.078443	0.171448	0.977314
MLR	0.2384	0.82316	0.790469

4. Summary

The current site drilling bit selection is still a question to be further explored. High quality selection results play an important role in reducing drilling costs and improving drilling efficiency. A new method of bit selection is proposed based on the adaptive fuzzy reasoning system. The system uses the method of quantitative drill bit selection. The selection system owns the advantages of adaptive and self-learning of neural network and the advantages of fuzzy inference system. Drill selection factors involving the formation, well depth and other parameters can effectively reflect the drilling conditions which can provide effective basis for the drill bit selection. The use of feature engineering in data mining method in the parameters, with which the data is discretized and normalized, can effectively speed up the data convergence rate and improve the operation rate. The system is applied to the selection of drill bits, the use of huge data on the drill bit selection, takes the advantages of comprehensive, strongly adaptive to the formation. By input the relevant parameters, the system recommends a drill type.

The predict result of ANFIS is better than the predict result of multiple regression model according to the mean square error , the average absolute percentage error and the correlation coefficient. The ANFIS proposed in this paper utilizes the ability of neural network learning to establish a useful analytical structure for drill bit selection. There is a huge research and use space in the current big data era. It can be wide used in a wider range of data.

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