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A comprehensive evaluation method for states adjustment priority of drilling process ⋆

Yang Zhou [*,**] **Xin Chen** [*,**,†] **Min Wu** [*,**] **Weihua Cao** [*,**]

[*] *School of Automation, China University of Geosciences, Wuhan, 430074, China (e-mail: wumin@cug.edu.cn)*
[**] *Hubei key Laboratory of Advanced Control and Intelligent Automation for Complex Systems, Wuhan, 430074, China (e-mail: weihuacao@cug.edu.cn)*

Abstract: Drilling is an important means of obtaining resources. It is important to determine appropriate drilling states adjustment priority to guide operation of the drilling. However, the priority of drilling states adjustment is difficult to determine because of the influence of multiple parameters. In this paper, a priority comprehensive evaluation method is developed to solve this problem. Firstly, support vector regression (SVR) method and long short-term memory (LSTM) neural network are introduced to build rate of penetration (ROP) prediction model and mud pit volume (MPV) prediction model, respectively. Then, the comprehensive evaluation vector is obtained by fuzzy comprehensive evaluation method based on analysis of formation drillability, rock characteristic, pump pressure variation, ROP and MPV fluctuations. Finally, the drilling states adjustment priority is determined by the principle of maximum membership and comprehensive analysis method. The simulation based on actual drilling data indicates that the proposed method can determine the adjustment priority and guide the operation of the drilling process.

Keywords: Drilling process, adjustment priority, fuzzy comprehensive evaluation

1. INTRODUCTION

Drilling is an important means of obtaining resources and energy. During the drilling process, proper operation is of great significance to increase the drilling speed and maintain safety. Before conducting operation, the adjustment priority of drilling states needs to be determined to provide a reference for the operation. The adjustment priority means the adjustment order of drilling states, that is, improve rate of penetration or maintain mud pit volume at first.

The priority of the drilling states adjustment is mainly determined by the encountered formation. For example, if the encountered formation is relatively stable, the ROP can be improved by increasing the weight on bit (WOB), and the fluctuation of the bottom hole pressure caused by the high WOB can be tolerated, that is, the efficiency can be improved within a certain safety variation. However, the encountered formation is variable, when a complex and fractured formation is encountered, the adjustment priority of the drilling states is difficult to determine. In addition, variation of drilling parameters can also affect the adjustment of the drilling states, such as pump pressure variation and MPV fluctuation. How to integrate various parameters to determine the drilling state adjustment priority is an important issue.

In the recent research, the evaluation of the drilling states adjustment priority transform into separate evaluations of efficiency and safety. In the aspect of drilling safety, it is mainly focused on analyzing the kick and the mud lose. A new hydrate formation region (HFR) prediction model was established to evaluate the wellbore blockage risk in different drilling stages based on mass, momentum and energy balance equations (Liu et al., (2019)). Based on second order Taylor series expansion and Rosenbluthe method, two analytical methods were proposed to calculate collapse and fracture pressures in the form of the probability distribution (Ma et al., (2019)). A PSO-SVR algorithm was developed to obtain the risk evaluation results and realize the real-time dynamic risk evaluation (Liang et al., (2019)). A fuzzy synthetic evaluation method was developed to reduce the drilling risk and applied to the real project (Liu et al., (2013)).

Although drilling safety is important, more scholars pay attention to drilling efficiency evaluations to analyze how to improve ROP. The improvement of ROP can reduce drilling time and bring economic benefits.

In terms of efficiency evaluation, the drilling rate index and ROP are used to evaluate the efficiency. Five artificial neural network methods were used to build drilling rate

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† Corresponding author: Xin Chen (chenxin@cug.edu.cn)

index prediction models to analysis the drilling efficiency (Fattahi et al., (2017)). Rock mechanics experiments were conducted to show that rate of penetration has high relationship with drilling rate index and quantify hardness (Moein et al., (2014)). A data-driven model was built to predict ROP and drilling efficiency can be improved based on the formation information (Hegde et al., (2017)).

The above independent evaluation of efficiency and safety can guide the drilling process to some extent. Separate analysis of efficiency or safety is not comprehensive, and determination of adjustment priority needs to consider multiple parameters. Fuzzy comprehensive analysis can be used to solve such multi-parameter decision-making problems (Hu et al., (2018)). However, the determination of the drilling state adjustment priority needs to consider the trend of some parameters, such as ROP and MPV. Fuzzy comprehensive analysis method can not predict the trend of ROP and MPV. Therefore, it is necessary to introduce prediction models to predict ROP and MPV. In addition, the decision vector generated by the fuzzy comprehensive evaluation method cannot determine the adjustment priority directly. For these reason, a two-level evaluation method is developed to determine the priority of the drilling state adjustment. The SVR method and the LSTM method are introduced to construct the ROP and MPV prediction models, respectively. After that, Based on analysis of drilling parameters, the fuzzy comprehensive evaluation method and the comprehensive analysis method are used to determine the priority of the states adjustment of the drilling system.

The structure of this paper is listed below. Section 2 describes the drilling process and its characteristics. Section 3 introduces the basic framework of evaluation method. Section 4 and section 5 detail the prediction models and fuzzy comprehensive evaluation method. Section 6 verifies the proposed method by using the actual drilling data. Section 7 concludes the paper.

2. DRILLING PROCESS DESCRIPTION AND ANALYSIS

This section briefly describes and explains the characteristics of the drilling process.

2.1 Introduction of the drilling process

As shown in Fig. 1, the drilling system consists of two subsystems, the drill string system and the circulation system, which is referred from Gan et al., (2019). The drill string system is mainly composed of derrick, rotary table, drill string and drill bit. It provides sufficient pressure and power to the drill bit to achieve continuous rock breaking. The circulation system is mainly composed of drilling fluid, mud pump and mud pit. The mud pump pushes the drilling fluid into the hollow drill string, which ejects from the bottom hole, and returns to the ground through the annulus. In this process, the drilling fluid is used to maintain stable bottom hole pressure, carry the cuttings back to the ground and lubricate the drill bit. The drilling system parameters are shown in the Table 1.

Table 1. List of parameters in the drilling system

Drilling process variables	Abbrevation	Unit
Weight on bit	WOB	kN
Rotation Speed	RPM	r/min
Pump pressure	SPP	Mpa
Flow rate	Q	m^3/min
Mud Weight	MW	g/cm^3
Depth	/	m
Formation drillability	FD	/
Rock characteristics	RC	/
Rate of Penetration	ROP	m/hr
Mud Pit Volume	MPV	m^3

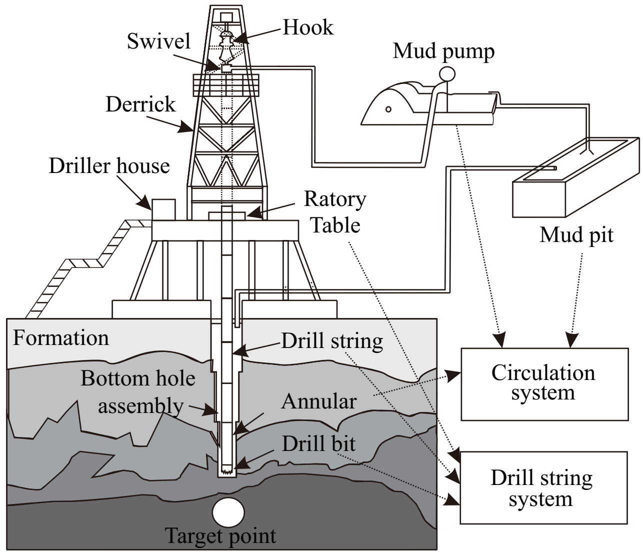

Fig. 1. The structure of the drilling system

2.2 Description of the drilling process characteristics

There are a large number of physical reactions in the drilling process, and the entire drilling system is very complicated. However, the drilling system still provides information to evaluate the priority of drilling states adjustments.

(1)Nonlinearity and complex: There are strong fluid-solid relational reaction between the drill string, drill bit, mud, and formation rocks. As a result, the relationships among the drilling parameters and ROP are complex and nonlinear. In addition, although the MPV also has a complex nonlinear relationship with the drilling parameters, the trends of MPV has time series characteristics, and the time series prediction method can well fit the trends.

(2)Multi-parameter effects: Drilling states adjustment priority are subject to numerous factors. It is difficult to determine by observing changes in one or two parameters, and it is necessary to consider variations of multiple parameters. In addition, the variations of some parameters have fuzziness in the determination of priority. The fuzzy comprehensive evaluation method can solve such multi-parameter fuzzy decision problem, which is introduced to determine adjustment priority in our research.

(3)Decision making difficulties: During the drilling process, the MPV is maintained by adjusting the MW and Q of the circulation system, the ROP is improved by adjusting the WOB and RPM of the drill string system. The adjustment of MW can also improve ROP to some extent, but it may also cause fluctuations in MPV. Moreover, when drill bit contacts with the bottom rock, the vibration often appears due to unstable formation at bottom hole (Kamel et al., (2014)), which will cause fluctuation of bottom hole pressure (Zhao et al., (2016)) and mud pit volume (MPV). These vibrations can be mitigated by adjusting WOB and RPM. In other words, the MPV is also affected by WOB and RPM. The variations of the MPV is also related to the operating parameters of the drill string system. Therefore, the coupling relationships make the determination of the priority of drilling state adjustment more difficult.

These characteristics, such as nonlinearity, multi-parameter effects, decision making difficulties make it difficult to determine the adjustment priority of drilling process. In addition, the one step ahead values of some parameters also affects the adjustment priority. Therefore, a reliable evaluation method needs to be developed that can predict drilling parameters and determine adjustment priority.

3. THE MAIN STRUCTURE OF THE PRIORITY EVALUATION METHOD

In order to determine the adjustment priority, we develop a comprehensive evaluation method, which includes modeling and comprehensive evaluation. The framework of evaluation method is shown in Fig. 2. In the modeling process, two prediction models are built to predict the ROP and MPV. Then, the fuzzy comprehensive evaluation method and comprehensive analysis are combined to determine the adjustment priority. ΔP in Fig. 2 denotes the fluctuation of SPP.

For modeling process, the ROP prediction model is constructed by SVR method and MPV prediction model is constructed by LSTM neural network. The SVR method is a regression method based on support vector machine, which is often used to establish nonlinear models to solve prediction problems (Chen et al., (2015); Xiang et al., (2018)) and suitable for ROP modeling. The LSTM neural network is adopted to build the MPV prediction models. The LSTM neural network has a good effect in solving time series prediction problems (Yang et al., (2019); Wang et al., (2018)) and suitable for MPV modeling. The output of the ROP and MPV prediction models are served as the inputs of the comprehensive evaluation.

In terms of comprehensive evaluation, FD, RC, ΔP, MPV and the output of prediction models are used as evaluation inputs. The membership functions evaluate the influences of various factors. The comprehensive analysis method determines the final adjustment priority by analyzing the evaluation results based on maximum membership principle and drilling requirements.

4. ROP AND MPV PREDICTION MODEL

In this section, the support vector regression (SVR) method is employed to establish the ROP prediction model and the long short term memory (LSTM) neural network method is used to build the MPV prediction model.

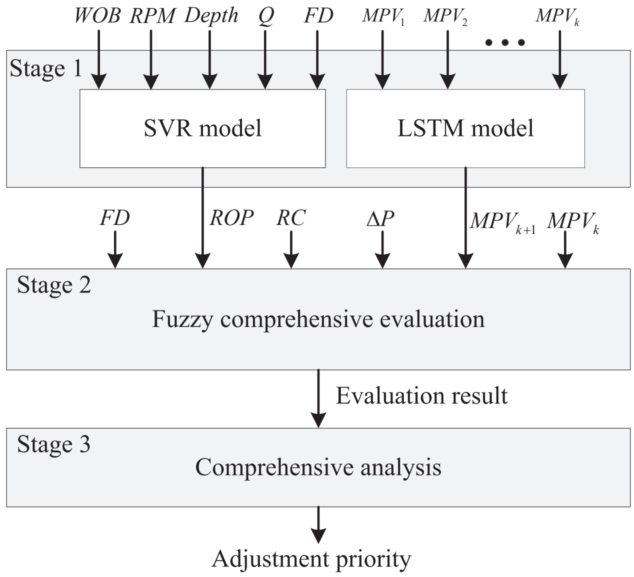

Fig. 2. The framework of the evaluation method

4.1 The SVR prediction model

For ROP prediction model, the support vector regression (SVR) method is adopted to build prediction model. SVR is a regression method based on support vector machine (Shevade et al., (2000)), which has been applied in the drilling process.

There are n sets of data for building prediction model. The input data $U_{in,i}=\left(x_{wob,i}^k, x_{rpm,i}^k, x_{Depth,i}^k, x_{q,i}^k, x_{fd,i}^k\right)$ and output data $H_{out,i} = x_{ROP,i}^{k+1}$, in which the i denotes the sample sequence and k denotes the time sequence. The $U_{in,i}$ is composed of current parameters, WOB, RPM, Depth, Q, FD, while the $H_{out,i}$ corresponds to one step ahead ROP. For SVR prediction model, it has certain causal relation:

$$f(x) = \omega\phi(U_{in,i}) + b \tag{1}$$

where $\phi(\cdot)$ is a nonlinear mapping function, then the slack variable ξ_i and ξ_i^* are introduced. The problem of fitting ω and b can be transformed into a quadratic programming problem

$$\begin{aligned} &\min : \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*), \\ &\text{s.t.} \begin{cases} H_{out,i} - \omega\phi\left(U_{in,i}\right) - b \le \varepsilon + \xi_i \\ -H_{out,i} + \omega\phi\left(U_{in,i}\right) + b \le \varepsilon + \xi_i^* \\ \xi_i \ge 0, \xi_i^* \ge 0 \end{cases} \end{aligned} \tag{2}$$

where C denotes the penalty factor and $\varepsilon > 0$ is a small number. Further, some basis function has to be used to approximate the nonlinear function $\phi(x)$. In this paper, the widely used radial basis function

$$K(x, x') = \exp\left(\frac{-\|x - x'\|^2}{2\sigma^2}\right) \tag{3}$$

is selected. Then, by using the Lagrange function, the fitted function becomes

$$\hat{H}_{out,i} = \sum_{i=1}^{n}\left(a_i - a_i^*\right)K\left({U'}_{in,i}, U_{in,i}\right) + b \tag{4}$$

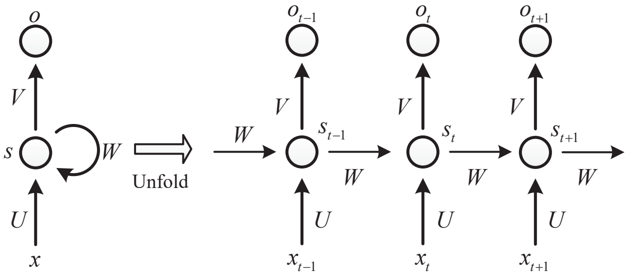

Fig. 3. The structure of the RNN

where a_i and a_i^* are the Lagrange multipliers arising in the the dual problem to this optimization problem.

Two hyper-parameter, C and σ, need to be carefully designed in the SVR prediction model. The grid search method and k-fold cross validation (k-FCV) are combined to obtain them. Two hyper-parameter are searched in the range of $C = 2^{sc}$, $sc = -10, -9.5, ..., 10$ and $\sigma = 2^{sg}$, $sg = -10, -9.5, ..., 10$. Parameters C and σ are updated according to the size of the grid. When C and σ are given, the average error is computed as

$$e_{(C,\sigma)} = \frac{1}{k} \sum_{u=1}^{k} e_u \tag{5}$$

where e_u is the uth error in k-fold cross-validation method. The optimal parameters C and σ are obtained with minimal $e_{(C,\sigma)}$.

4.2 The LSTM neural network prediction model

Accurate prediction of MPV change trend can provide a reference role drilling process decision-making. The change of MPV has obvious characteristics on the long and short time scale. On the long time scale, it gradually decreases. On the short time scale, the trend of MPV is similar to a sine wave. Therefore, LSTM neural network is introduced to build MPV prediction model.

For the LSTMNN prediction model, suppose there is a time series of MPV as follow:

$$s = (s_{t-1}, s_{t-2}, ..., s_{t-h}) \tag{6}$$

The h consecutive lags from s to forecast the future MPV, s_t. The origin data sets for predicting $P = \{s_{t_1}, s_{t_2}, s_{t_3}, ..., s_{t_k}\}$ are

$$\begin{array}{l} S_1 = \{s_{t_1-1}, s_{t_1-2}, ..., s_{t_1-d}\}, \\ S_2 = \{s_{t_2-1}, s_{t_2-2}, ..., s_{t_2-d}\}, \\ ..., \\ S_{t_k} = \{s_{t_k-1}, s_{t_k-2}, ..., s_{t_k-d}\} \end{array} \tag{7}$$

where P is the MPV to be predicted at time $t_1, t_2, ..., t_k$, s_i is the corresponding consecutive lags. The time series s_i is selected as the input of the LSTMNN, and P is the output of the LSTMNN. The length of the time series data d is 36 in our research.

LSTM neural network is a modified recurrent neural network (RNN), which is shown in Fig. 3.

The output layer and hidden layer can be calculated as

$$\hat{y}_t = g(Vs_t) \tag{8}$$

$$s_t = f(Ux_t + Ws_{t-1}) \tag{9}$$

RNN is difficult to solve long-term sequence problems due to gradient disappearance or gradient explosion. Therefore, the LSTM neural network was developed to solve this problem (Hochreiter et al., (1997)). The LSTM neural network retains long-term time sequence cell states C_t by introducing forgetting gate, input gate, and output gate.

The cell state C_t can record long-term sequence information, which can be calculated as

$$C_t = f_t \circ C_{t-1} + i_t \circ \tilde{C}_t \tag{10}$$

where f_t is the output of forget gate, i_t is the output of input gate, $\circ$ denotes multiply by element. $\tilde{C}_t$ denotes a vector of new candidate values of cell states.

The output gate is calculated as

$$out_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{11}$$

The final output of hidden layer is determined by the output gate and cell state, which can be calculated as

$$h_t = out_t \circ \tanh(C_t) \tag{12}$$

A back propagation trough time (BPTT) method is used to adjust weights and biases of the LSTM neural network with the objective function being

$$L(t) = \min \frac{1}{2} \sum_{i=1}^{R} (y_i - \hat{y}_i)^2 \tag{13}$$

5. DRILL STATE ADJUSTMENT PRIORITY EVALUATION

The fuzzy comprehensive evaluation method is used to determine the priority of the drilling state adjustment. First, the evaluation set $U = [\,FD\ ROP\ RC\ \Delta P\ \Delta V\,]$ is determined. The evaluation set contains five evaluation factors, namely FD, ROP, RC, ΔP and ΔV. ΔP and ΔV denote fluctuation of SPP and MPV. The weight vector A of evaluation factors is set to $A = [\,0.1\ 0.3\ 0.1\ 0.3\ 0.2\,]$. The comment set for the evaluation factor is set to $V = [\,0\ 1\ 2\,]$. For each evaluation factor, if the comment value is large, the drilling efficiency can be adjusted at first. On the contrary, the drilling safety can be adjusted at first.

For each comment value, the membership functions of evaluation factors (e_{va}) are set as

$$\begin{array}{l} C_{V=0}(e_{va}) = \begin{cases} \dfrac{e_{va} - pa_{V=0}^{lb}}{pa_{V=0}^{mb} - pa_{V=0}^{lb}}, pa_{V=0}^{lb} < e_{va} < pa_{V=0}^{mb} \\ \dfrac{pa_{V=0}^{ub} - e_{va}}{pa_{V=0}^{ub} - pa_{V=0}^{mb}}, pa_{V=0}^{mb} \le e_{va} < pa_{V=0}^{ub} \end{cases} \\ C_{V=1}(e_{va}) = \begin{cases} \dfrac{e_{va} - pa_{V=1}^{lb}}{pa_{V=1}^{mb} - pa_{V=1}^{lb}}, pa_{V=1}^{lb} < e_{va} < pa_{V=1}^{mb} \\ \dfrac{pa_{V=1}^{ub} - e_{va}}{pa_{V=1}^{ub} - pa_{V=1}^{mb}}, pa_{V=1}^{mb} \le e_{va} < pa_{V=1}^{ub} \end{cases} \\ C_{V=2}(e_{va}) = \begin{cases} \dfrac{e_{va} - pa_{V=2}^{lb}}{pa_{V=2}^{mb} - pa_{V=2}^{lb}}, pa_{V=2}^{lb} < e_{va} < pa_{V=2}^{mb} \\ \dfrac{pa_{V=2}^{ub} - e_{va}}{pa_{V=2}^{ub} - pa_{V=2}^{mb}}, pa_{V=2}^{mb} \le e_{va} < pa_{V=2}^{ub} \end{cases} \end{array} \tag{14}$$

The e_{va} denotes the evaluation factors FD, ROP, ΔP and ΔV. The value of membership functions parameters $pa_{V=0}^{lb}$, $pa_{V=0}^{mb}$, $pa_{V=0}^{ub}$, $pa_{V=1}^{lb}$, $pa_{V=1}^{mb}$, $pa_{V=1}^{ub}$, $pa_{V=2}^{lb}$,

$pa^{mb}_{V=2}$, $pa^{ub}_{V=2}$ are shown in Table 2. These parameters are not fixed in the drilling process, which can be modified according to the operation requirements.

Table 2. Model performance indicators

e_{va}	FD	ROP	ΔP	ΔV
$pa^{lb}_{V=0}$	7	0	0.2	0.14
$pa^{mb}_{V=0}$	10	1	0.3	0.20
$pa^{ub}_{V=0}$	12	2	0.4	/
$pa^{lb}_{V=1}$	4	1	0.05	0.08
$pa^{mb}_{V=1}$	6	2.5	0.15	0.12
$pa^{ub}_{V=1}$	8	4	0.25	0.16
$pa^{lb}_{V=2}$	0	3	0	0
$pa^{mb}_{V=2}$	2.5	4.5	0.05	0.05
$pa^{ub}_{V=2}$	5	6	0.1	0.1

These membership functions are set according to the actual drilling needs. The RC indicates the completeness or fracture of the rock, which can be determined by the operator. The RC can be divided into frauture, semi-complete, complete and corresponding to 0, 1, and 2 of the comment set.

Therefore the fuzzy evaluation matrix is constructed as

$$R = \begin{bmatrix} C_{V=0}(FD) & C_{V=1}(FD) & C_{V=2}(FD) \\ C_{V=0}(ROP) & C_{V=1}(ROP) & C_{V=2}(ROP) \\ C_{V=0}(RC) & C_{V=1}(RC) & C_{V=2}(RC) \\ C_{V=0}(\Delta P) & C_{V=1}(\Delta P) & C_{V=2}(\Delta P) \\ C_{V=0}(\Delta V) & C_{V=1}(\Delta V) & C_{V=2}(\Delta V) \end{bmatrix} \quad (15)$$

The comprehensive evaluation vector can be calculated as

$$S = A \cdot R \quad (16)$$

The priority of the drilling state adjustment is determined by comprehensive analysis of S based on the maximum membership principle and actual drilling requirements.

6. SIMULATION RESULTS

The validity of the evaluation method is verified by the actual drilling data. The best parameters C and σ for ROP prediction model are 1.41 and 1.00, respectively. A total of 336 sets of data are used for modeling, with 298 sets of data for training and 38 sets of data for testing. For the prediction models, five criteria are used to for verification:

(1) Root-mean-squared error:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \quad (17)$$

(2) Maximum absolute error (MAE):

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|\hat{y}_i - y_i| \quad (18)$$

(3) Mean absolute percentage error (MAPE):

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \times 100\% \quad (19)$$

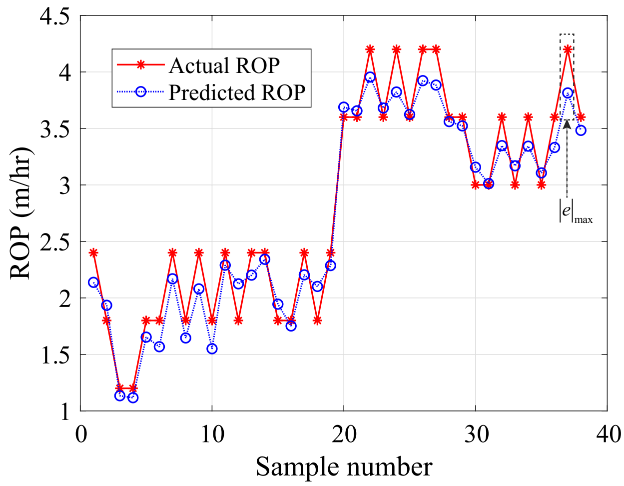

Fig. 4. Prediction result of ROP

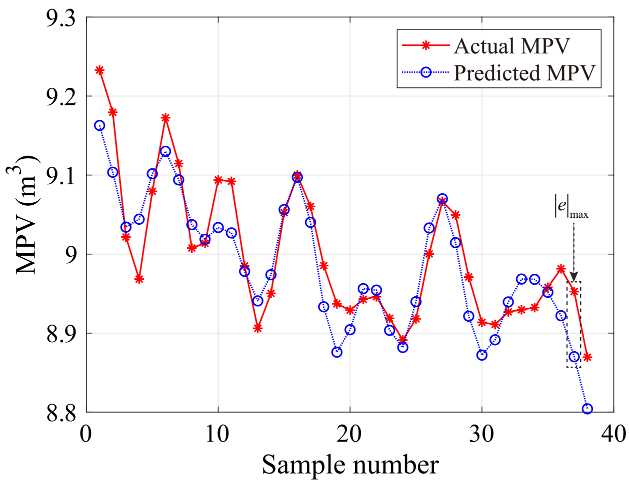

Fig. 5. Prediction result of MPV

(4) Maximum absolute error:

$$e_{\max} = \max(|\hat{y}_i - y_i|) \quad (20)$$

The prediction results are shown in the Fig. 4 and Fig. 5. The performance indicators of the two prediction models are shown in Table 2.

Table 3. Model performance indicators

	RMSE	MAE	MAPE	$e_{\max}$
ROP model	0.2036	0.1759	6.816%	0.3808
MPV model	0.0407	0.0331	0.3679%	0.0824

It can be seen from Fig. 4, Fig. 5 and Table 3, the prediction values of ROP and MPV are close to the actual value. For the ROP prediction model, the value of the membership function hardly changes even at the point of maximum absolute error. In addition, there is a clear upward trend in ROP because the formation becomes stable and it is easy to increase the ROP. For the MPV prediction model, the prediction model can follow the downward trend of MPV, and at the maximum absolute error point, the prediction error has no affect on the value of the membership function. Although the prediction values have some errors with the actual value, these errors are acceptable for the practical application.

In terms of comprehensive evaluation, three different depths of drilling data are used to evaluate the priority of the drilling state adjustment.

$$\begin{array}{l} U_1 = [7, 4.2, complete, 0.07, 0.06] \\ U_2 = [8, 2.4, semi-complete, 0.17, 0.10] \\ U_3 = [7, 1.2, fracture, 0.27, 0.18] \end{array} \quad (21)$$

The fuzzy evaluation matrix of S_1, S_2, and S_3 are

$$R_1 = \begin{bmatrix} 0 & 0.50 & 0 \\ 0 & 0 & 0.80 \\ 0 & 0 & 1 \\ 0 & 0.20 & 0.60 \\ 0 & 0 & 0.80 \end{bmatrix}, R_2 = \begin{bmatrix} 0.33 & 0 & 0 \\ 0 & 0.93 & 0 \\ 0 & 1 & 0 \\ 0 & 0.80 & 0 \\ 0 & 0.50 & 0 \end{bmatrix}, R_3 = \begin{bmatrix} 0 & 0.50 & 0 \\ 0.80 & 0.13 & 0 \\ 1 & 0 & 0 \\ 0.70 & 0 & 0 \\ 0.67 & 0 & 0 \end{bmatrix} \quad (22)$$

The comprehensive evaluation vector of U_1, U_2, and U_3 are

$$\begin{array}{l} S_1 = [\,0 \;\; 0.11 \;\; 0.68\,] \\ S_2 = [\,0.03 \;\; 0.72 \;\; 0\,] \\ S_3 = [\,0.68 \;\; 0.09 \;\; 0\,] \end{array} \quad (23)$$

For S_1, drilling efficiency will be prioritized based on the principle of maximum membership. For S_3, the fluctuations of MPV and SPP are relatively large, and according to the principle of maximum membership, drilling safety will be adjusted first. For S_2, the priority is difficult to determine by maximum membership function. However, from the perspective of RC, and ΔP and ΔV, the current drilling process is in a low safety state. Therefore, in order to ensure stable operation of the drilling process, drilling safety will be adjusted first.

7. CONCLUSION

In this paper, a comprehensive evaluation method is developed to determine drilling states adjustment priority. This method can make multi-parameter decisions by analysing RC, ΔP, ΔV, FD and MPV. The adjustment priority can guide the drilling operation. Before evaluation, the SVR method and LSTM neural network are used to build ROP and MPV prediction models, and the output of the prediction models are served as part of the evaluation factors. Simulation results based on actual drilling data show that the accuracy of the prediction model can meet the actual needs and the determined priority can guide drilling process operations. In addition, we also focus on building a comprehensive control systems for the drilling process, one of which will run our method. The priority of drilling states adjustment will provide an important reference for drilling process control.

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