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Research on prediction of drilling energy consumption based on mechanism and data hybrid drive

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Abstract—Due to the harsh and changeable drilling environment and complex energy flow conditions, it is difficult to obtain an accurate and reliable energy consumption (EC) prediction model. To make up for the above shortcomings, taking into account the advantages of accurate and convenient power system measurement, an EC prediction model driven by a combination of mechanism and data is proposed. Based on the deviation between actual EC results and theoretical mechanism model calculation results, the least square support vector machine (LSSVM) data compensation model is established. And the whale optimization algorithm based on von Neumann topology is used to optimize the parameters of the LSSVM model. The experimental results show that the prediction error of the proposed method is 1.69%. Compared with the prediction results of the mechanism model and the data-driven model, the average prediction error of the proposed method is reduced by 0.27% and 2.9%.

Keywords: drilling; energy consumption prediction;data compensation;hybrid drive

I. INTRODUCTION

Electric energy resources are mainly generated by burning fossil fuels, and the consumption of electric energy in the process of rock drilling and coring will produce a certain carbon footprint [1-2]. How to reduce the carbon emission in the process of drilling and excavation, reduce the energy consumption (EC) of drilling, and improve the energy is important. Based on this, the concept of mechanical specific energy (MSE) has attracted extensive attention in drilling rock breaking efficiency. Lu et al. [3] analyzed the relationship between MSE and drilling rate in different formations, optimized drilling methods, and determined a reasonable range of drilling parameters for complex and variable formations. Xie et al. [4] used the MSE value as the evaluation index of drillability and combined the extreme learning machine to classify the drillability of coal and rock. The variation law of drilling speed and MSE of PDC bit was studied from three aspects: material type, rotational speed, and weight on bit (WOB). Guan et al. [5] found that when drilling soft to medium-hard rock, increasing WOB and rotational speed did not lead to a significant increase in MSE value. When drilling hard rock, increasing the WOB and rotational speed results in a significant decrease in mechanical specific energy, reducing drilling efficiency. Chen et al. [6] established an accurate MSE model for PDM rotary drilling by analyzing the performance of the positive displacement motor. The experimental results show that the minimum MSE is roughly equal to the confined compressive strength of the formation along with the depth of the well.

The above studies analyzed the influence of drilling rig working parameters on MSE but did not consider the influence degree of drilling rig working parameters on drilling energy. Li et al. [7] analyzed the influences of drilling rig impact power, rotational speed, propulsion force, and bit type on drilling SE by using the orthogonal test method, and the results showed that drilling rig SE was the lowest when drilling combination was 6.4kw, 240rpm and 3800N. Amjed Hassan et al. [8] collected the rotational speed, torque, WOB, and drilling rate in the process of drilling and coring, trained the artificial neural network model, and defined a new drilling efficiency evaluation index ROP/MSE, providing a fast and reliable evaluation for drilling operations. In the above research, the MSE value is used as an index to evaluate the efficiency of the drilling core. However, in practical engineering applications, the axial thrust and torque values of the drilling rig are not easy to control and measure, and the installation of the thrust and torque sensors indirectly affects the drilling efficiency. Considering the advantages of accurate, convenient, and cheap power parameter measurement, this paper uses drilling power as a bridge and uses a mechanism and data hybrid drive method to predict drilling EC and analyze drilling energy efficiency.

Ⅱ. DATA COMPENSATION MODEL BASED ON LSSVM

The mechanism model of EC during drilling and excavation is known, but the prediction results of EC are not accurate enough. Aiming at the problems existing in the mechanism model, to improve the accuracy of rig EC prediction during drilling and excavation, the data-driven model is used as an error compensator in parallel with the mechanism model to compensate and correct the mechanism model, as shown in Fig 1.

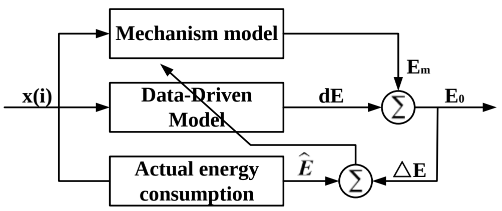

Fig. 1. Hybrid drive schematic

Among them, the data-driven model selects the least squares support vector machine (LSSVM) [9] and combines the whale optimization algorithm based on von Neumann topology to predict the drilling EC. Considering the length of the article, the optimization algorithm is not repeated here, see References 10 and 11 for details. Since LSSVM can convert traditional inequality constraints into equality constraints, nonlinear function mapping is used to realize the transformation of LSSVM input values into high-dimensional space. Therefore, this paper uses the LSSVM method to determine the error compensation model between the actual rig EC and the calculated energy consumption. Set the sample data set $\{x(i), y(i)\}_{i=1}^{N}$, input parameter $x(i) \in R^N$, and output parameter $y(i) \in \hat{E} \in R^N$. The LSSVM function of the EC bias model mapped to the high-dimensional space is as follows:

$$y(x) = \Delta E(x) = \omega^T \varphi(x) + b \tag{1}$$

Where, $\varphi(x)$ is the nonlinear mapping function, b is the bias and ω is the weight vector value. Through high-dimensional space transformation, the function optimization problem of LSSVM can be transformed into the following form.

$$\min_{\omega,b,e} J_p(\omega, e) = \frac{\|\omega\|^2}{2} + \frac{\gamma}{2}\sum_{k=1}^{N} e_k^{\ 2} \tag{2}$$

The constraint condition for transformation is

$$y_k = \omega^T \varphi(x_k) + b + e_k \quad \text{k=1,2,}\cdots\text{,N} \tag{3}$$

Among them, γ is a penalty factor, which satisfies $\gamma > 0$, and is used to control the balance between training error and model complexity; e_k is a slack variable.

The Lagrangian transformation function L is

$$L(\omega, b, e, a) = J(\omega, e) - \sum_{k=1}^{N} a_k [\omega^T \varphi(x_k) + b + e_k - y_k] \tag{4}$$

Where, a_k is the Lagrange multiplier. It can be calculated by the KKT optimization condition.

$$\begin{cases} \dfrac{\partial L}{\partial \omega} = 0 \Rightarrow \omega = \sum\limits_{k=1}^{N} a_k \varphi(x_k) \\ \dfrac{\partial L}{\partial b} = 0 \Rightarrow \sum\limits_{k=1}^{N} a_k = 0 \\ \dfrac{\partial L}{\partial e_k} = 0 \Rightarrow a_k = \gamma e_k, k = 1, 2, \cdots, N \\ \dfrac{\partial L}{\partial a_k} = 0 \Rightarrow \omega^T \varphi(x_k) + b + e_k - y_k, k = 1, 2, \cdots, N \end{cases} \tag{5}$$

Through calculation, the following formula is obtained:

$$\begin{bmatrix} 0 & I^T \\ I & \Omega + \gamma^{-1} I \end{bmatrix} \begin{bmatrix} b \\ a \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix} \tag{6}$$

Where $a = [a_1, a_2, \cdots, a_N]$, $y = [y_1, y_2, \cdots, y_N]$, $\Omega_{ki} = \varphi(x_k)^T \varphi(x_i)$, k,i=1,2,$\cdots$,N 。

Through the Mercer conditional calculation, the high-dimensional mapping function φ and the kernel function $k(x_k, x_i)$ can be calculated by the formula (7).

$$k(x_k, x_i) = \varphi(x_k)^T \varphi(x_i) \tag{7}$$

Finally, the LSSVM regression function can be established as follows:

$$y(x) = \Delta E(x) = \sum_{k=1}^{N} a_k k(x, x_k) + b \tag{8}$$

Among them, the values of a and b are calculated by the formula (6).

In this paper, the radial basis function with good generalization ability and wide convergence domain is selected as the kernel function of the LSSVM regression model, and its expression is as follows:

$$K(x_k, x_i) = \exp\left(-\frac{\|x_k - x_i\|^2}{2\sigma^2}\right) \tag{9}$$

Among them, σ is the width of the kernel function. Considering that the parameters σ and γ seriously affect the learning ability and generalization ability of the LSSVM model, this paper uses the whale optimization algorithm based on von Neumann topology to optimize and analyze σ and γ .

III. EXPERIMENTAL VERIFICATION

To verify the feasibility and advanced nature of the proposed method, in this section, the drilling test is carried out through the coal mine tunnel drilling rig. The experimental device is shown in Fig 2. The EC in the drilling process is mainly determined by the working parameters of the drilling rig (rotation speed, ROP value). The rotation speed and ROP value of the drilling tool are controlled by adjusting the gear of the drilling rig and the opening of the throttle valve. During the test, the ROP value was indirectly measured by the displacement sensor, and the data acquisition equipment was used in combination with DEWESOFTV7.1 software for data processing, the data acquisition instrument is shown in Fig 2b; the power signal is measured by FLUKE435-II power quality analyzer, as shown in Fig 2c. The energy efficiency of drilling and coring is determined by the ratio of the energy consumed by cutting the rock to the load energy.

$$\eta = \frac{E_{md}}{E} \tag{10}$$

Among them, η represents the energy efficiency of cutting the rock, and the energy consumed by cutting the rock and the total load energy are denoted by E_{md} and E .

During drilling and coring, ROP values were averaged 10 times in [1,2], [2,3], [3,4], [4,5], and [5,6] respectively, and energy parameters under 10 groups of test data were calculated, as shown in table 1. It was observed that at the same rotational speed, the larger the ROP value, the greater the power consumed by rock cutting, but the drilling time was greatly reduced, resulting in a reduction in the final EC, improved drilling energy efficiency, and achieved the purpose of energy saving. The average ROP value and the load power curve were fitted to obtain the EC mechanism model of the drilling rig. The details are as follows: the fitting curves of the drilling rig at 123 rpm and 220 rpm are $y = 225.23x + 3216.6, R^2$=0.97 and $y = 236.69x + 3544, R^2$=0.98 , respectively. Among them, the R^2 value is approximately equal to 1, indicating that the ROP value fits well with the drilling load power, and the magnitude of the load power value can be indirectly reflected by the ROP value during the drilling process. The lower the speed and ROP value, the smaller the load power value; the lower the load EC obtained under the parameter combination of low speed and high ROP value; the greater the rig rotational speed and ROP value, the greater the energy efficiency value. The results show that the optimal parameter combinations for low power, low EC, and high energy efficiency are: the rotational speed is 123rpm, and the ROP value is 1.58m/h (corresponding to the first group of experiments in Table 1); the rotational speed is 123 rpm, and the ROP value is 5.64 m/h (corresponding to the fifth group of experiments in Table 1); the rotational speed is 220rpm, and the ROP value is 5.37 m/h (corresponding to the tenth group of experiments in Table 1). To more intuitively express the optimal parameter combination under different energy parameters, a line graph as shown in Fig 3 is drawn.

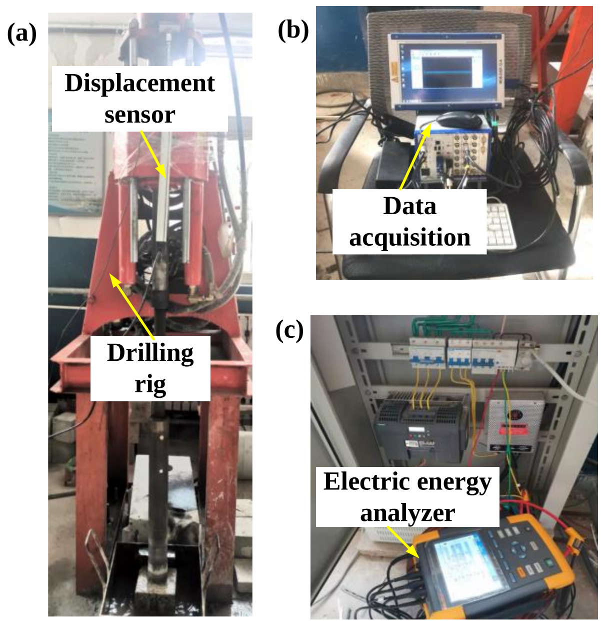

Fig. 2. Experimental platform and equipment

TABLE 1. Effect of drilling parameters on energy parameters

Drilling depth (m)	Rotating speed	ROP value (m/h)	Load power (w)	Cutting rock power(w)	Time (s)	EC for cutting rock (kJ)	Load EC (kJ)	Efficiency (%)
0.1	123	1.58	3609.83	683.83	228.38	156.17	824.40	18.94
0.1	123	2.49	3772.30	846.30	144.76	122.51	546.08	22.43
0.1	123	3.77	4035.70	1109.70	95.51	105.99	385.46	27.50
0.1	123	4.58	4166.19	1240.19	78.69	97.59	327.83	29.77
0.1	123	5.64	4563.12	1637.12	63.85	104.53	291.36	35.88
0.1	220	1.50	3865.60	844.60	240.00	202.70	927.74	21.85
0.1	220	2.49	4171.80	1150.80	144.79	166.62	604.02	27.59
0.1	220	3.46	4355.56	1334.56	104.07	138.89	453.30	30.64
0.1	220	4.36	4606.76	1585.76	82.52	130.85	380.14	34.42
0.1	220	5.37	4786.38	1765.38	67.05	118.36	320.91	36.88

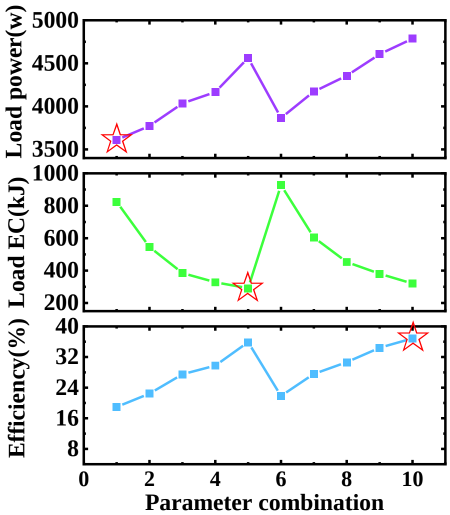

Fig. 3. Energy parameter values under different parameter combinations

To verify the superiority of the hybrid model in predicting EC, 30 groups of random experiments were carried out with the variables of rotational speed and ROP. Among them, the mechanism model is obtained by fitting the experimental data; the nonlinear mapping relationship in the data-driven model is obtained through the LSSVM model, where the number of whales is 15 and the maximum number of iterations is 25. Next, the mechanism model, the data-driven model, and the hybrid model are used to predict and analyze the EC under the 30 sets of parameter combinations, and some of the prediction results and their errors are shown in Table 2.

TABLE 2. Comparison of predicted values of various models

number	Rotating speed	ROP value (m/h)	EC(kJ)				Error (%)		
			Actual value	Mechanism model	Data model	Hybrid model	Mechanism model	Data model	Hybrid model
1	123	1.35	970.88	937.16	868.82	959.38	3.47	10.51	1.18
2	123	1.51	868.82	846.60	825.05	862.18	2.56	5.04	0.76
3	123	1.59	825.05	809.46	868.82	831.69	1.89	5.31	0.80
4	123	2.24	596.36	599.17	680.45	600.30	0.47	14.10	0.66
5	123	3.65	394.44	398.55	377.03	396.89	1.04	4.41	0.62
6	123	3.89	377.03	378.70	394.44	374.35	0.44	4.62	0.71
7	123	4.11	358.52	362.87	377.03	361.21	1.21	5.16	0.75
8	123	4.73	325.50	325.84	304.26	321.49	0.10	6.53	1.23
9	123	4.88	304.26	318.15	325.50	317.81	4.57	6.98	4.45
10	123	5.64	291.36	286.47	304.26	272.58	1.68	4.43	6.45
				……					
21	220	3.69	436.20	430.95	431.87	434.63	1.20	0.99	0.36
22	220	3.72	431.87	428.19	436.20	433.44	0.85	1.00	0.36

23	220	3.85	417.64	416.27	431.87	419.95	0.33	3.41	0.55
24	220	4.17	394.32	391.40	382.23	392.77	0.74	3.07	0.39
25	220	4.18	382.23	390.27	394.32	391.64	2.10	3.16	2.46
26	220	4.27	380.33	383.77	382.23	375.73	0.90	0.50	1.21
27	220	4.57	368.26	364.42	380.33	363.83	1.04	3.28	1.20
28	220	4.95	342.46	343.05	326.21	341.06	0.17	4.75	0.41
29	220	5.25	326.21	328.21	315.83	326.38	0.61	3.18	0.05
30	220	5.49	315.83	317.66	326.21	315.66	0.58	3.29	0.05

To more intuitively display the EC prediction results of each model, the EC prediction line graph shown in Fig 4 and the error histogram shown in Fig 5 are drawn. It is observed that, compared with the mechanism model and the data-driven prediction model, the EC prediction value of the hybrid model is closer to the real value. Fig 5 shows that the prediction results of the data-driven model have the largest error relative to the actual value. The average relative errors of the EC mechanism model, the data-driven model, and the actual value are 1.96% and 4.59%, respectively. Compared with this, the average error of the EC prediction accuracy of the proposed hybrid model is 1.69%, which is reduced by 0.27% and 2.9%, respectively. The above results show that the data error compensation model based on LSSVM makes up for the deficiency of the mechanism model in predicting EC and improves the prediction accuracy. Therefore, the hybrid model can reflect the EC characteristics of the drilling rig to some extent.

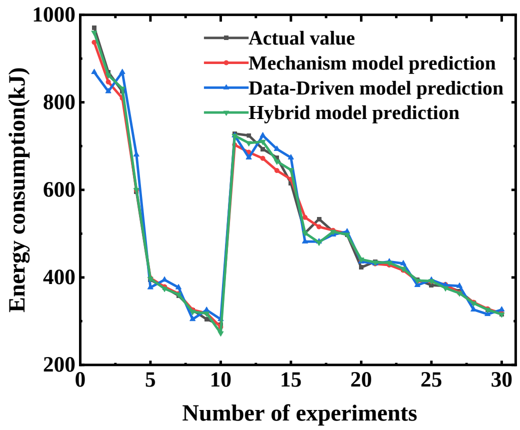

Fig. 4. Comparison results of different EC prediction models

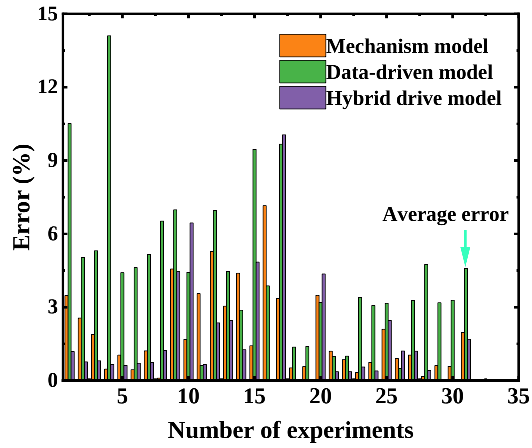

Fig. 5. EC prediction errors of different models

Ⅳ.CONCLUSION

In this paper, a comprehensive load EC prediction method combining data modeling and mechanism analysis is proposed. The feasibility and practicability of the model are verified by drilling tests. The following conclusions are drawn:

(1)The average error between the EC prediction results of the hybrid model and the actual results is only 1.69% when the artificial rock is drilled and cored. Compared with the prediction results of the mechanism model and the data-driven model, the average prediction error is reduced by 0.27% and 2.9%, which verifies the high efficiency of the hybrid-driven model.

(2)On the premise of meeting the drilling requirements, with the increase of the ROP value, the EC of drilling and coring is significantly reduced, because the drilling time is shortened with the increase of the ROP value. Therefore, by adjusting the working parameters of the drilling rig, the drilling energy efficiency can be effectively improved and the EC can be reduced.

(3)The method integrates data and mechanism models, and is suitable for other drilling rigs in the field of drilling and excavation. In addition, to achieve energy saving and emission reduction of drilling rigs, while improving the accuracy and speed of the algorithm, the hybrid drive method is used to predict drilling EC.

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