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The prediction and optimization of ROP based on MLP-PSO

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Abstract—**In an effort to reduce production costs in the oil and gas industry, this paper addresses the prediction and optimization of the Rate of Penetration (ROP), a critical factor in increasing drilling speed. The study first establishes an ROP prediction model using Multi-Layer Perceptron (MLP) to capture the relationships between real-time ROP and various influencing factors. The model considers adjustable drilling parameters such as weight on bit and drilling rate to establish an ROP maximization objective function, which is subsequently solved using the Particle Swarm Optimization (PSO) method. Results indicate that the MLP model effectively captures the relationship between drilling engineering parameters and ROP, achieving a relative error rate of 2.8%. Furthermore, by employing the optimization algorithm, the actual ROP value increases by 162%, significantly enhancing drilling efficiency. Both theoretical and practical case tests demonstrate that the MLP-PSO model proposed in this paper exhibits superior accuracy, reliability, and interpretability, providing a more dependable foundation for parameter optimization in production.**

Keywords-rate of penetration; MLP; PSO; Drill speed increase

I. INTRODUCTION

As oil and gas exploration tends to develop in deep, offshore, and unconventional directions, the difficulty, and cost of drilling are increasing which is an essential issue for drilling optimization. To solve this problem, the rate of penetration (ROP) in drilling engineers attracts more and more attention, because the cost of drilling is mainly determined by the time it takes [1].

ROP is divided into the forward prediction model and the inverse optimization problems of two steps, in which, The prediction model of ROP is the key to improving ROP and reducing drilling time [2]. Many researchers have attempted to build the prediction model based on mathematical methods [3], geological information [4] or machine learning [5] et al., and have obtained a large number of good experimental results. However, understanding the correlation between ROP and many complex factors in the practical drilling process remains an unsolved problem.

In recent years, with the combination of new technologies in the formation field and the petroleum industry, a variety of intelligent prediction and optimization models for ROP have been established [6, 7]. However, a single algorithm can easily fall into local optimum and the stability of prediction results is poor. Therefore, it is necessary to develop a prediction and optimization model of ROP based on hybrid algorithms.

Therefore, this paper proposes a prediction and optimization model of ROP based on MLP-PSO. To build such a model, we first adopt Multi-Layer Perception (MLP) as a forward model to predict ROP. The role of the model is to find out how various factors (such as weight on bit, drilling rate, mud density, and other engineering factors, as well as geological factors such as formation lithology and mechanical properties) affect the drilling efficiency. Then, based on the prediction model, it is necessary to solve the optimization problem with PSO. According to the actual stratum, lithology, mechanical properties, and other actual conditions, by constantly adjusting drilling weight, drilling rate, and other engineering parameters to obtain a higher ROP. We confirmed the usefulness and advantages of the MLP-PSO model in ROP prediction and optimization through experiments on real oilfield data.

II. BACKGROUND

A. *Multi-Layer Perception(MLP)*

Multi-layer Perceptron (MLP) is a forward neural network, which maps a set of input vectors to a set of output vectors. It consists of multiple node layers, each of which is fully connected to the next layer. Except for the input node, each node is a neuron with a nonlinear activation function. A typical MLP neural network consists of three basic neural units, as shown in Fig. 1, which are the input layer, the hidden layer, and the output layer, respectively. The input layer receives the input signals to be processed, the output layer performs the tasks required for prediction and classification, and the hidden layer is the real computing engine of MLP.

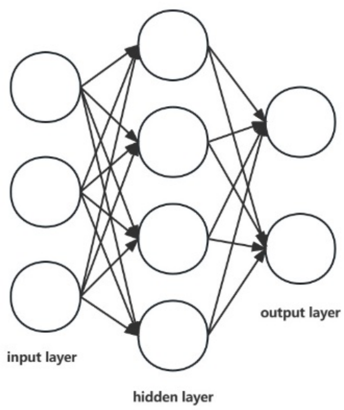

Figure 1. Typical MLP neural network

B. Particle Swarm Optimization(PSO)

Particle Swarm Optimization (PSO) was first proposed by Eberhart and Kennedy in 1995. Its basic concept stems from the study of bird foraging behavior. PSO uses a particle to simulate the bird individuals, each particle can be considered as a search individual in an N-dimensional search space. The current position of the particle is a candidate solution for the corresponding optimization problem, and the flight process of the particle is the search process of the individual. The flight speed of the particle can be dynamically adjusted based on the particle's historical optimal position and the population's historical optimal position. The formula for the update speed and position of each particle is as follows.

$$dV_i^d = \omega V_i^d + c_1 r_1 \left(P_i^d - X_i^d \right) + c_2 r_2 \left(P_g^d - X_i^d \right) \tag{1}$$

$$X_i^d = X_i^d + \alpha V_i^d \tag{2}$$

In which, i = 1, 2, …, M; d = 1, 2, …, N. V_i^d denotes the velocity of each particle, X_i^d denotes the current position of the particle, P_i^d denotes the individual optimal position of the particle, and P_g^d denotes the global optimal position of the particle swarm. ω is a non-negative number indicating the inertia factor, which the larger the value, the wider the range of the particle leap. c_1 and c_2 denote the acceleration factors of the particle swarm. r_1, r_2 are arbitrary numbers in the range of [0, 1]. α is a constraint factor to control the weight of the velocity.

The standard PSO algorithm flows as shown in Fig. 2.

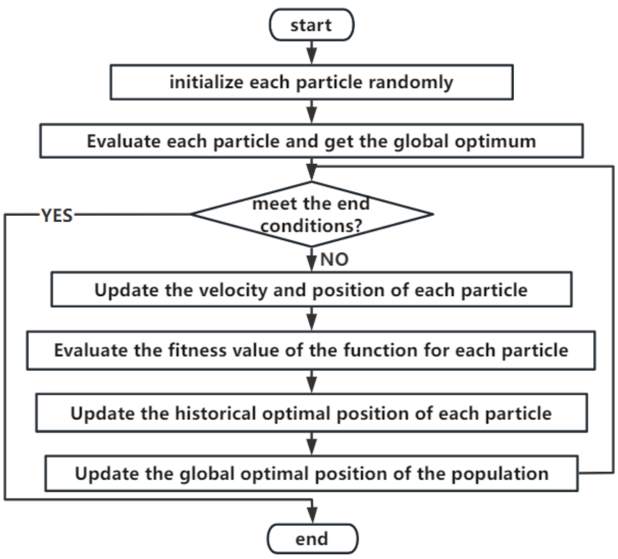

Figure 2. Standard PSO algorithm flows

1). Initialize the particle swarm, including the population size N, the position Xi and velocity Vi of each particle randomly;

2) Calculate the fitness value of each particle;

3) Update the velocity Vi and position Xi of each particle;

4) Evaluate the fitness value of the function for each particle;

5) Update the historical optimal position Xi of each particle and the corresponding fitness value;

6) Update the global optimal position Xi of the population and the corresponding fitness value

7) If the end condition of the algorithm is met, then end, otherwise return to step 3).

III. ROP PREDICTION

Fig. 3 is the sequence flow of our research. The input is the data of drilling engineering, and the data has removed the repeat and invalid values. Then feature engineering analysis is carried out, and the correlation between input parameters and output is briefly calculated to understand the feature background and facilitate the establishment of prediction model. Then, MLP ROP prediction model was built on the basis of the above research, and this process was a combination of training and testing. When the prediction model is established, it can be used for ROP optimization. This process starts with parameter initialization, which continuously calculates and evaluates the prediction model through an iterative process, continuously selects the parameters through PSO optimization method, and finally obtains the best project parameter recommendation.

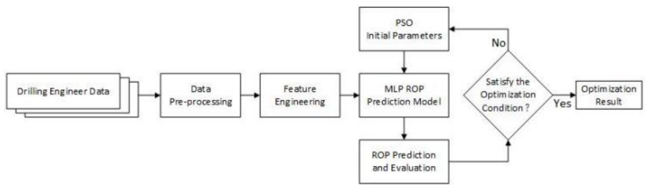

Figure 3. the methodological sequence of ROP prediction and optimization

A. Feature Engineering

The current research direction of ROP prediction tends to adopt machine learning methods, which can be achieved through data-driven methods. This paper uses the actual data of a domestic oil field to design the method and verify its reliability and accuracy of the method. The dataset contains 5950 rows of data from a well depth of 3156 to 4346 meters. Each row contains 12 parameters, whose names and units are shown in Table 1.

TABLE 1. THE PARAMETERS OF ROP PREDICTION.

	Abbreviation	Property Name	Units
The Import Parameters of ROP Prediction Model		Depth	m
	RPMA	Rotary Speed (surf,avg)	r/min
	WOBA	Weight-on-Bit (surf,avg)	tonne
	MFIA	Mud Flow In (avg)	L/min
	MDIA	Mud Density In (avg)	g/cm^3

HKLA	Hookload(avg)	tonne
TQA	Rotary Torque (surf,avg)	KN.m
SPPA	Standpipe Pressure (avg)	MPa
MFOA	Mud Flow Out (avg)	L/min
BDTI	BitTime	h
TVA	Tank Volume (active)	m^3
ROP	Rate of Penetration (avg)	m/h

We briefly analyzed the relationship between these engineering parameters and ROP through the Pearson coefficient thermal diagram in Fig. 4. It can be seen from the figure that these engineering parameters and geological parameters have an obvious correlation with ROP. The complexity of ROP prediction can also be expressed in the thermal map, which is correlated with many factors, making the physical model powerless in the face of ROP prediction. Referring to the results of feature engineering, this model selects all 12 parameters as inputs to establish the ROP prediction model.

Figure 4. Correlation coefficient heat map(Pearson Correlation Coefficient)

B. *ROP prediction model*

This paper establishes a 4-layer MLP model, and the specific parameters of the model are shown in Table 2.

TABLE 2. PARAMETERS OF ROP PREDICTION MODEL.

Layer	Output Shape	Parameters
Linear-1	[-1,32,5950,1024]	12288
ReLU-2	[-1,32,5950,1024]	0
Linear-3	[-1,32,5950,512]	524800
ReLU-4	[-1,32,5950,512]	0
Linear-5	[-1,32,5950,256]	131328
ReLU-6	[-1,32,5950,256]	0
Linear-7	[-1,32,5950,256]	65792
ReLU-8	[-1,32,5950,256]	0
Linear-9	[-1,32,5950,128]	32896
ReLU-10	[-1,32,5950,128]	0
Linear-11	[-1,32,5950,1]	129
Total node parameters: 767233		
Trainable node parameters: 767233		
Untrainable node parameters: 0		

C. *ROP prediction experiment*

The ROP prediction model of X well was established by 2000 times epoch training. The prediction results of the model are shown in the Fig. 5. It can be seen from the figure that the prediction accuracy is high. Compared with the actual ROP, its R2 is 0.91, MSE is 11.78, and the relative error is only 2.8%. The results show that MLP used in this paper can well characterize the internal relationship between engineering parameters and ROP.

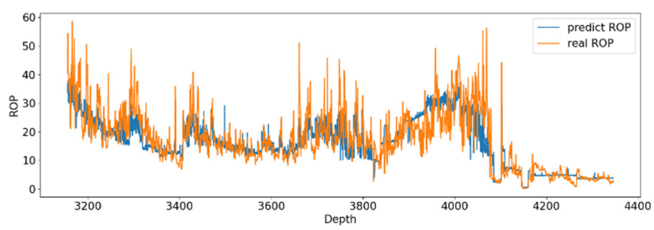

Figure 5. The ROP prediction result.

IV. ROP OPTIMATION

A. *Optimation object function*

The optimization problem in drilling engineering is a typical multi-objective optimization, in which ROP is the most important KPI indicator in drilling engineering, so it becomes the most frequently used optimization target. In this paper, an optimization model F is established in ROP optimization, and constraint conditions are added to ensure that the optimization results are in line with the actual conditions, and can make the drill string vibration in a low range. In this problem, we reduce the whole optimization problem to a goal equation F to maximize ROP.

$$F(WOB, RPM, Q) = \max_{WOB,RPM,Q} \left\{ \frac{1}{N} \sum_{i}^{N} ROP_i \right\} \tag{3}$$

The constraint condition is

$$WOB_l \leq WOB \leq WOB_u \tag{4}$$

$$RPM_l \leq RPM \leq RPM_u \tag{5}$$

$$Q_l \leq Q \leq Q_u \tag{6}$$

The optimization is constraint by WOB, RPM, and Q drilling fluid flow rate, and N is the total number of all measurement parameters. Each of these three parameters will have a constraint condition at the same time to conform to the actual conditions, and the optimized parameters can be achieved in practice. After determining the objective function and constraints, we use the PSO algorithm to optimize the solution to obtain the optimal value of ROP.

B. Experiment result and discussion

In this section, an adjustment period of 100m is used to optimize the entire section of the test data for the adjustable parameters such as weight on bit, rate of penetration, and fluid flow in the above equation. The optimized result is shown in Fig. 6, which shows that the optimized ROP increased by more than 162% over the previous ROP in all test sections, while the optimized result was achieved with the constraints of the parameter range.

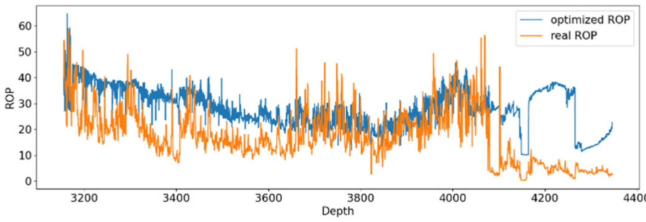

Figure. 6. The ROP optimization result.

From the final test results, this method has achieved very significant results, but we can not ignore the deficiencies contained in it. The first disadvantage of this method is that generalization is not tested and the prediction model achieves high accuracy, but its application to other Wells in the same area has not been compared in detail. The second disadvantage is that although the constraint range of optimization parameters is given in the optimization process, it is not connected with the real conditions of the equipment, but is only given by the technical personnel according to their own understanding. Therefore, the follow-up of this part also needs to make in-depth docking with the actual situation, and further advance the theoretical research method to practical application.

V. Conclusion

In this study, utilizing actual drilling data from an oil field, a Rate of Penetration (ROP) prediction model was constructed using the Multi-Layer Perceptron (MLP) approach, while the Particle Swarm Optimization (PSO) algorithm was employed to optimize the engineering parameters of the well. Evaluating the model from a prediction accuracy standpoint, the MLP model demonstrates a relatively precise prediction performance, with a minimal relative error of only 2.8%. In terms of ROP optimization, the application of the PSO optimization algorithm leads to a substantial increase in the average ROP value by 162%, indicating a considerable improvement in efficiency.

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