An integrated prediction and optimization method for drilling rate of penetration

Zhong Li¹, Yi Wu¹, Zhaoyu Pang¹, Jiaxuan Gao², Jie Cao²,³, *
¹CNOOC Research Institute Co., Ltd., Beijing, 100028, China
²College of Petroleum Engineering, Xi’an Shiyou University, Xi’an, Shaanxi, 710065, China
³State Key Laboratory of Petroleum Resources and Prospecting, China University of Petroleum (Beijing), Beijing 102249, China
*Corresponding author’s e-mail: jie.cao@xsyu.edu.cn

Abstract. The rate of penetration (ROP) is a crucial indicator in drilling engineering and has been the focus of interest for decades. Previous researches established many models in terms of rock physical and mechanical properties, drilling technology and equipment capabilities, drilling fluid rheological properties, and drilling engineering parameters. However, most of the above models are based on engineering experience and logical reasoning. In this paper, we investigate drilling modeling and optimization based on machine learning and intelligent optimization algorithms. The ROP modeling is achieved using a BP neural network model, which is further applied in the optimization of weight on bit (WOB) and revolution rate (RPM). The results demonstrated that the optimized operational parameters, as recommended by WOB and RPM, can increase the drilling efficiency by 12.3%. This methodology can be further applied in actual field operations as suggested parameters to the drilling efficiency further.

1. Introduction
The rate of penetration (ROP) is a crucial indicator in drilling engineering, and it is one of the critical factors affecting the drilling cycle and operating cost. Over the decades, researchers and engineers in drilling engineering have been committed to the improvement of ROP [1]. They have established many models in terms of rock physical and mechanical properties, drilling technology and equipment capabilities, drilling fluid rheological properties, and drilling engineering parameters. However, most of the above models are based on engineering experience and logical reasoning. The drilling modeling and solving process are relatively complicated, and the considerations of influencing factors are also limited. In recent years, with the development of big data and artificial intelligence technology, drilling operation decision-making has shown a trend from experience-driven and logic-driven to data-driven [2], bringing new technical ideas for comprehensively considering multiple factors to increase ROP. Therefore, following this development trend, we investigate drilling modeling and optimization based on machine learning and intelligent optimization algorithms.

The BP neural network is called the feedforward network model. It is a nonlinear mathematical model with a continuous transfer function. It is a neural network that guides learning through continuous error back propagation. It uses a gradient descent method to minimize the mean square error. BP neural network has two learning methods. One is forward propagation, which is to input external information through each neuron of the input layer and pass it to the hidden layer. Then the hidden layer will carry
out further processing and then pass the information through Output layer output. When the error between the actual output and the expected output is large, another learning method is used-error back propagation, the output result is back propagated to the output layer in a specific way, and each neuron is redistributed according to the feedback of the error signal The weights and thresholds are recalculated, and so on, until the specific range of error reduction or the expected number of learning. In the prediction of the ROP, we first need to collect, select and process the drilling data that affects the ROP from side wells or wells in the same area, and then input the data into the created BP network model for training and get trained[3]. The model only applies to this well, and then inputs the relevant data of the drilling belt into the trained model for processing to obtain the predicted value. BP neural network also has certain limitations, such as slow training speed, easy to fall into local minima, and other shortcomings [4].

Collect and process the drilling information and logging data of other wells in the block, and select applicable methods for modeling. Then use the processed data to train the established model and the trained model. Finally, input the relevant data to be drilled into the trained model and output the predicted value. Through the comparative analysis of actual drilling speed and predicted drilling speed during drilling, the occurrence of drilling accidents can be predicted and prevented in advance. In addition, the mechanical drilling speed can be changed to the maximum by adjusting and setting drilling parameters[5]. In this way, the purpose of increasing oil production and reducing costs can be achieved, and the risk of drilling can be effectively reduced.

Research on drilling speed-up methods is divided into three categories, namely, physical model methods, statistical model methods, and machine learning methods. The physical model method mainly speeds up by describing the impact of critical parameters on ROP. The fitting method can establish the ROP model of a specific area to optimize the drilling speed. The method of using the statistical model in ROP prediction has some similarities with the method of the traditional model. The main similarity between the two is that the ROP model must be selected in advance based on the drilling variables. The main difference is that the statistical model usually does not try to represent the physical properties of the bit and the interaction between the rock formation and the bit like traditional models. Both the physical model and the statistical model method start from the pre-selection of a specific model. The machine learning method can learn complex patterns in the training phase and determine the ROP model in advance. After the learning phase, the trained model can make predictions for new inputs. The current methods of using machine learning for ROP prediction can be roughly divided into five methods: artificial neural networks (ANN), support vector machines (SVM), fuzzy inference systems, neuro-fuzzy and integrated models[6], [7]. [8].

2. ROP modeling
In order to increase drilling speed, it is first necessary to establish a mechanical rate of penetration model and then to optimize the controllable engineering parameters in real time within the safe operation interval. Here, we use the widely used BP neural networks models to build out the ROP prediction model[9]. The results of the BP prediction model are shown in Figure 1 for training, validation, testing, and overall performance. Given a complete set of data points, the model performed very well. Here, the data set is 70% for training and 15% each for training and validation. The final model using all data points is regenerated for further application.
The actual ROP and predict ROP using the model is shown in Figure 2, along the depth of drilling. It is obvious the prediction model is solid in catching the trend and details of drilling efficiency. Therefore, we can deploy it for further optimization.

Figure 2. Actual ROP and predicted ROP along with the depth, in a normalized scale
3. ROP optimization
To improve drilling efficiency, there are mainly two steps. First, use the BP neural network prediction model to generate the initial weights and thresholds randomly. Secondly, use the GA algorithm to calculate the fitness of the result, and output GA when the evaluated objective function or iteration requirements are met. GA algorithm is inspired by Darwin’s theory of evolution. The algorithm is a simulation of the evolutionary mechanism of biological genetics and has gradually developed into an optimization algorithm that searches for extreme values at random. Here, we choose the maximum average ROP as our objective function to optimize the operational controlled parameters, i.e., the WOB and RPM. Since the data is normalized initially, the results shown in the following are mainly in the range of [0,1].

The results after optimization is that \([\text{WOB}, \text{RPM}] = [0.4741, 0.4553]\). These are the optimum values that deliver the highest average ROP. Here, we treated the WOB and RPM as constant for simplicity, which can be further freed in the following research. The average ROP increased from 0.2853 to 0.3204 with the above optimum operation parameters by 12.3%. This is a significant improvement in real case practice.

4. Conclusion
In this research, we presented a combined methodology of ROP prediction and optimization. The results demonstrated that optimizing the operational parameters, WOP and RPM, can increase the drilling efficiency by 12.3%. This methodology can be further applied in actual field operations as suggested parameters to the drilling efficiency further. The study in this article has specific reference significance for the realization of drilling operation-driven intelligent decision-making in the context of big data. In addition, further research can be focused on more sophisticated optimizations of the ROP, for example, with more detailed values as suggestions for each drilling formation and interval.

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