ROP Interval Prediction Model According to Iterative Reweighted Regularization LS-SVM

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Abstract

We propose using iterative reweighted regularization LS-SVM classification algorithm to predict the rate of penetration (ROP). The existing drilling data are used as the input and output of the training model. First normalization of input data and division of the output data intervals, then used the data as training data. The data are trained by SVM classification algorithm, and drilling speed prediction model could be build. The model is adopted to make a simulation prediction of the ROP of impending drilling well in the same area. The results show that when the numbers of ROP classification intervals are 4, the prediction accuracy rate is 97%, and when the numbers are 8, the accuracy rate is more than 90%. In this way the drilling state can be assessed and the auxiliary decision support is provided for optimizing drilling parameters and bit types as well as drilling optimization.

Keywords

Support vector machine, Classification, ROP, Interval, Prediction.

1. Introduction

As one of the main means and key links of oil and gas exploration and development, drilling engineering has the characteristics of capital, technology intensive, high investment and high risk.Reasonable drilling design has a very significant impact on oil and gas exploration and development benefits[1-3].Drilling mechanical drilling speed and wellbore size, bit structure, characteristics of rock formation (such as rock strength, formation drillability, etc.), drilling parameters (such as drilling pressure, rotational speed, hydraulic parameters, etc.), drilling fluid performance and drilling tools Related factors such as combination.Accurate prediction of the ROP can effectively calculate drilling costs and drilling time, thereby guiding drilling process parameter design, arranging rigs and drilling crews, and providing a basis for drilling designers[4].

The current rate of drilling is mainly based on the experience of field engineers and their judgment of existing drilling data.How to combine existing data with the experience of drilling engineers to form a reliable prediction model of drilling rate has become an urgent problem to be solved in drilling engineering[5-7].Machine learning technology and big data technology provide new ideas for solving this problem[8-15].Machine learning, as the core technology of artificial intelligence, is fundamentally based on inductive learning of mathematics and computer technology.The machine learning process is first of all to supervise the process of learning to build a model. There are many ways to build a model, algebraic expressions, decision trees, neural networks, etc. This process requires a large amount of correct data to train the ideal model. more precise.Because of its high technical accuracy, machine learning has been widely used in many fields such as economic forecasting, disease monitoring, population control, etc. By using multiple features as input variables and correspondingly corresponding output results, the results of different features are analyzed. The degree of influence, the establishment of mathematical models.In terms of drilling rate prediction of drilling, machine learning technology can help provide more accurate prediction results by: matrix theory method and statistical processing method for initial processing of existing drilling data, and then drilling The parameter data is understood as a large matrix form. The strength of the rock inside the different strata of the target block and its drillability and the characteristics of the drilling fluid used need to be processed by laboratory experiments to form a training sample of the drilling rate classification template.Then, the sampled samples are subjected to sample selection processing, feature selection processing, feature estimation, principal component analysis, etc., so as to obtain the correlation between different drilling parameters and the mechanical drilling speed.

According to the drilling data that has been obtained in the target block, the wells that need to predict the drilling rate are divided into different drilling speed intervals.The initial processed drilling data is taken as an input parameter, and the existing drilling data of the target block is trained through the supervised learning classification method to obtain the drilling rate classification prediction method.Different supervised learning classification algorithms (such as support vector machine, artificial neural network, etc.) are used to process the data, compare the accuracy of the training results, and select the classification prediction method with higher accuracy and higher stability.Based on the existing well logging data, the data is processed and statistically analyzed, and the mechanical drilling rate is divided into different classification intervals. The iterative re-regular regularized LS-SVM algorithm is used to train the mechanical drilling rate prediction model.This method is expected to accurately predict the rate of penetration and accurately plan the drilling before drilling, and provide auxiliary decision support for the preferred drilling parameters, drill bit model and drilling optimization.

2. Iterative re-weighting regularization of LS-SVM

2.1 Theoretical derivation

LS-SVM is an improved version of the standard support vector machine (SVM), which can solve the problem of linear kkt system. LS-SVM is closely related to Gaussian process and normalized network, but pays more attention to the interpretation of the original dual specification.The LS-SVM transforms the inequality constraint of the original method into an equality constraint, which simplifies the solution of the Lagrange multiplier α. The original problem is the QP problem, and in the LS-SVM it becomes the problem of solving the linear equations.
The objective function of the iterative re-weighting regularization LS-SVM algorithm is:

$$\min \mathrm{P}(w,\delta)=\min\ \frac{1}{2}\sum_{i=1}^{m}\delta_i^2+\frac{c}{q}\|w\|_q^q \tag{1}$$

The constraints are:

$$\text{s.t. } y(x_i\cdot w)=1-\delta_i, i=1,2,3\cdots n \tag{2}$$

Substituting constraints into the objective function, eliminating the slack variable δ_i:

$$\mathrm{P}(w,\delta)=\min\ \frac{1}{2}\sum_{i=1}^{m}(1\text{-}y_i\cdot(x_i\cdot w))^2+\frac{c}{q}\|w\|_q^q \tag{3}$$

make $k(x)=\|w\|_q^q=\sum_{i=1}^{n}|w_i|^q$,when $0<q<\infty$ When it comes to:

$$\frac{\partial k(x)}{\partial w_i}=qw_i^{q-1}sign(w_i)=qw_i^{q-2}\cdot w_i \tag{4}$$

The function P(w) finds the derivative of the coefficient wi and makes the derivative equal to 0:

$$w_i=\left[\text{-}\frac{1}{c}|w_i|^{2-q}\right]\sum_{j=1}^{m}y_j\cdot x_{j,i}\cdot(y_j\cdot(x_j\cdot w)-1) \tag{5}$$

Using the iterative re-weighting method to solve the value of wi, the initial setting wi=1, the value of the kth iteration is given by:

$$w_i^k=\left[\text{-}\frac{1}{c}|w_i^{k-1}|^{2-q}\right]\sum_{j=1}^{m}y_jx_{j,i}(y_j\cdot(x_j\cdot w)-1) \tag{6}$$

2.2 Oil drilling machinery drilling rate data set

The data set is the field data and is used as the training sample in machine learning, this design first makes a simple processing on it, and then calculates the correlation coefficient matrix before establishing the model.

Relevant calculation results and model establishment results:

Correlation coefficient matrix:

1. R = weight on bit

1.0000 0.2626

0.2626 1.0000

2. R = hook load

1.0000 0.0948

0.0948 1.0000

3. R = pump pressure

1.0000-0.2826

0.2826 1.0000

4. R = drilling speed of rotary table

1.0000-0.1096

0.1096 1.0000

5. R = drilling fluid displacement

1.0000-0.3197

0.3197 1.0000

6. R = internal temperature of drilling fluid

1.0000 0.3142

0.3142 1.0000

7. R = external temperature of drilling fluid

1.0000 0.3300

0.3300 1.0000

8. R = density in drilling fluid

1.0000-0.1753

0.1753 1.0000

9. R = external density of drilling fluid

1.0000-0.1543

0.1543 1.0000

10. R = torque

1.0000-0.4366

0.4366 1.0000

Model establishment results when binary classification

Theta =

0.6983

8.7010

0.4945

3.8604

1.1735

3.1236
1.1826
6.2243
0.7436
0.2530
3.7445
Accuracy results:
Accuracy =
0.7374
Tetrad, when dichotomies are 1
Theta =
0.1124
7.1429
1.6330
1.8289
1.7956
1.6055
1.1153
1.1300
1.6582
0.0279
2.6893
The accuracy of
Accuracy =
0.7210
When the dichotomies are 0
Theta =
2.3415
4.9014
5.4617
3.0591
1.6503
0.5498
0.3730
3.3853
0.6137
3.5013
2.6874
The accuracy of
Accuracy =
0.7705

As can be seen from the results, its accuracy rate is even lower than the previous model. From the analysis of the correlation coefficient matrix, we can find that some of the features we selected have little correlation coefficient with the results. Is not large, we did not abandon the matrix with low correlation coefficient. However, the feature with the highest correlation coefficient is not more than 50%, so the accuracy rate of our model is not very high and can be explained. It is field data, the accuracy rate of over 70% still indicates that this algorithm can be applied in such problems.

In order to make the mutual influence between the characteristics of the sample is small, we conducted the normalized processing, improve the accuracy, but the complex data in oil drilling formation influencing factors is more, and there will be a bit change in the process of Drilling tool or the rate of penetration and engineering drilling rate does not match the best case, there is the accuracy of the lead to establish the model of training sample not guaranteed.

This design takes the same stratum as far as possible, 2500 to 3000 vertical depth data for training. In addition, a relatively average classification method is selected based on previous experience. More than 70% accuracy model can be obtained through field data training. Indicate that this algorithm can be used in the prediction of drilling rate of petroleum machinery, but it needs more correct data and more rigorous modeling process to be popularized.

2.2 Case Analysis.

Taking a block in the Middle East as an example, the drilling speed prediction model is verified.According to the analysis of the data that has been drilled in the target layer, if the mechanical drilling rate is divided into four sections, the interval of the mechanical drilling rate is set to 0-6 m/h, 6-8 m/h, 8-10 m. /hour, above 10 m / h, as the output of the model.Due to the many influencing factors of the mechanical drilling speed, in order to control the variables, the formation depth of 3390-3520m is selected as the reference data.Because in the 3390-3520m formation, the drill bit used is similar to the geological structure, which will reduce the error of the drilling rate prediction.The input factors of the model are selected: drilling pressure (WOB), Hookload, SPP, RPM, and FlowIn.At the same time, by measuring the correlation between various factors and the rate of penetration, the process of affecting the rate of penetration of these factors can be better understood.In the process of drilling, combined with various factors to improve the drilling parameters and reasonable debugging, the drilling speed can be effectively maintained, and the drilling efficiency can be improved.Using the drilling data training model of more than 50 wells in the block, the model was validated using one well data.The technical route established by the model is shown in Figure 1.

The input data is normalized, and the processed input data is a 0-1 interval number.Since the support vector machine algorithm can only deal with the two-class problem, the mechanical drilling rate that needs to be predicted is first divided into two categories with a classification boundary of 8 m/hour, and the class label with a mechanical drilling speed of less than 8 m/h is defined as -1, mechanical The class label with a drilling speed greater than 8 m/h is 1, for classification training.Then, the labels of the four drilling rate prediction intervals are again defined as -2, -1, 1, 2, and the svm algorithm is used to classify the training to obtain the ROP prediction model.

The verification horizon is 3390-3520 meters and the well depth is 130 meters. Figure 1 shows the model verification when the mechanical drilling speed is divided into four prediction intervals.As can be seen from Figure 1, the number of predicted error labels is 4, which are 3411, 3428, 3442, and 3454, respectively, and the accuracy of the drilling rate prediction is 97%.

The interval prediction mechanical drilling speed is used, and the more the classification interval is divided, the smaller the error with the actual mechanical drilling speed.Since the support vector machine algorithm can only be used to deal with the two-class problem, the partitioning interval must be 2n.When the number of prediction intervals is set to 8, the interval for setting the penetration rate is 0-5 m/h, 5-6 m/h, 6-7 m/h, 7-8 m/h, 8-9 m/ The algorithm is used to train the prediction model by hour, 9-10 m/hr, 10-11 m/h, and above 11 m/hr.

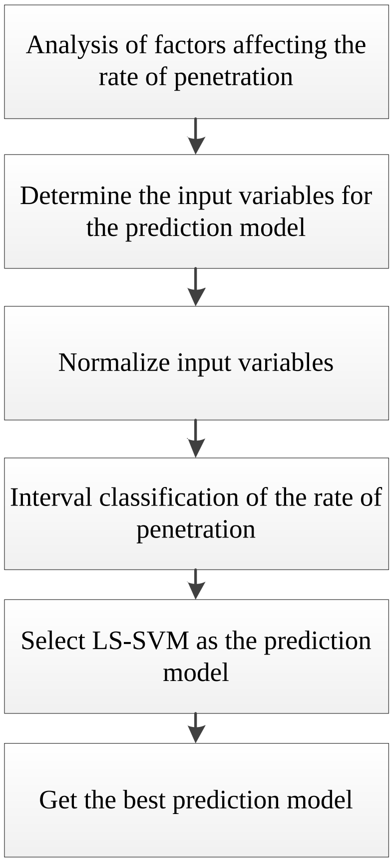

Figure 1. Technical route

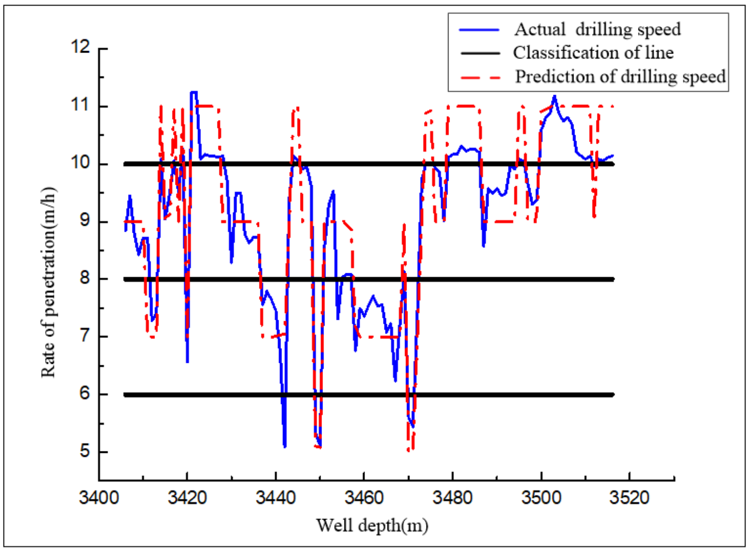

Figure 1: Comparison of predicted drilling speed and actual drilling speed in four intervals

It can be seen from Fig. 2 that, due to the increase of the prediction interval, the drilling speed division is more similar to the actual situation. The prediction error number of the model is 10, which are well depths 3411, 3413, 3428, 3430, 3442, 3454, 3467, 3475, respectively. At 3487 and 3496 meters, the accuracy of the prediction at this time was 92%.

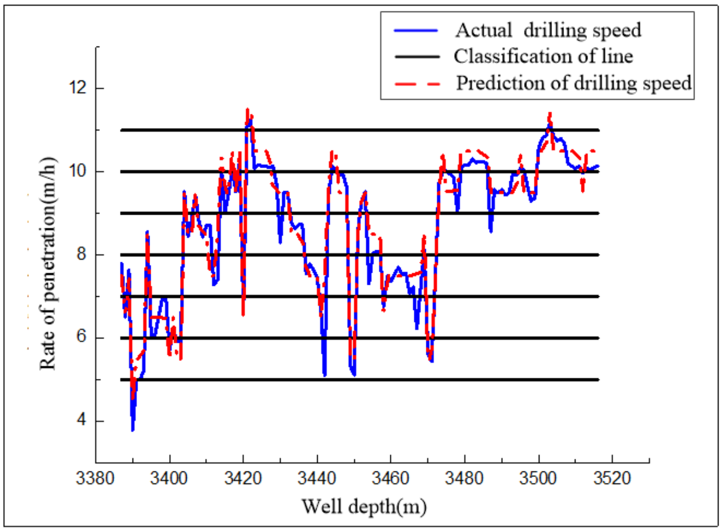

Figure 2 shows the model verification when the mechanical drilling rate is divided into eight prediction intervals.

3. Conclusion

In this paper, the improved support vector machine algorithm-iterative re-regular regularization LS-SVM algorithm is used to analyze the existing drilling data, logging data and the drilling data collected in real time during the drilling process, and the internal relationship between it and the mechanical drilling rate is obtained. A new way to train the drilling rate prediction equation through machine learning method is proposed. An interval mechanical drilling speed model is proposed and simulated according to the actual drilling data. The results show that with the refinement of the drilling speed interval, the drilling speed The prediction effect is gradually improved; the data mining technology is used to simulate and predict the drilling speed, and compared with the actual drilling value, the drilling status can be evaluated to provide auxiliary decision support for the preferred drilling parameters, drill bit model and drilling optimization; The limitation of the vector machine algorithm, the number of classification intervals must be 2n, and may not be applicable in some cases. Therefore, further combining with other machine learning methods for drilling rate prediction is the next research direction for future work.

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