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Research on the Adaptive Prediction Model for Drilling Accidents Based on PSO-SVM

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Abstract: Drilling accidents, complex and diverse, occur dynamically uncertain, as the traditional prediction methods are generally of low prediction accuracy and poor adaptability. In order to improve the accuracy of drilling accidents prediction, an adaptive prediction model for drilling accidents based on support vector machine with particle swarm optimization (PSO-SVM) is proposed. The model optimizes SVM parameters by means of the strong global search ability of PSO algorithm to reduce the blindness of SVM parameters selection; it retrain, re-optimize and regenerate the new prediction model after the misclassification accidents have been added to the sample set in order to correctly identify the similar misclassified accidents. The innovation of this model is the adaptive mechanism introduced on the basis of the traditional PSO-SVM model which can be initiative to re-generate prediction model for complex drilling accidents to improve the accuracy of drilling accidents prediction and adapt with different drilling conditions. Finally, verification of the model is completed through predicting the actual accident instances and comparing with the traditional PSO-SVM model. The results show that this model has stronger adaptive ability and higher prediction accuracy, so it will be of great significance for accurately predicting drilling accidents and reducing the cost of drilling.

Key words: Drilling accident, prediction, adaptive, SVM, PSO

INTRODUCTION

Oil drilling is a complex underground engineering influenced by many vague, random and dynamic uncertain factors. Accidents might occur at any time in the process of drilling which seriously threatens the safety of drilling; therefore, real-time monitoring of the state of drilling and accurately predicting drilling accident will be of great significance for improving the drilling efficiency and reducing the cost of drilling. The current methods of predicting the drilling accidents have artificial judgment, expert system, neural network and D-S evidence theory, etc. however, their instantaneity and accuracy of accident prediction are lower with the qualitative judgment by the human experience due to the strong concealment of drilling process and the down-hole situation that cannot directly be obtained. The method of expert system can solve many of the problems of accident prediction but it needs a large amount of production rules and computations for the requirements of complex system. It is difficult to obtain the evidence for the method of D-S evidence theory and the amount of information would sharply increase when there are increasing abnormal patterns. The method of neural network requires many training samples, the speed of training is very slow and the choice of model parameters is based on experience. In addition, the occurrence of drilling accident has dynamic uncertainty and different drilling environments or conditions (such as strata, drilling condition, drilling rig, etc) could cause different accidents that have different omens, so the model of accident prediction should be of higher adaptability and prediction accuracy, yet the existing prediction methods are difficult to meet the requirements.

Support Vector Machine (SVM) (Shen *et al*., 2010) is a learning algorithm based on statistical theory which can primely solve the problems of small sample size, nonlinear and high-dimensional pattern recognition but it is difficult to choose the SVM parameters. The Particle Swarm Optimization (PSO) (Li and Wang, 2009) is an optimization algorithm based on swarm intelligence which can faster converge to the global optimum and thus it can be used to optimize SVM parameters. Traditional prediction model based on PSO-SVM has higher prediction accuracy by PSO optimizing SVM parameters but it is lack of adaptability and is low in prediction accuracy for the new or abnormal accident samples. Consequently, this study proposes an adaptive prediction model for drilling accident based on PSO-SVM to better adapt with the complex drilling conditions and improve the accuracy of accident prediction.

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SUPPORT VECTOR MACHINE AND PARTICLE SWARM OPTIMIZATION

Support vector machine (SVM): Given a training set:

$$T = \{(x_1, y_1), (x_2, y_2), \cdots, (x_l, y_l)\} \tag{1}$$

where, i = 1, 2,..., l, $x_i \in R^N$ is the N-dimensional vector; $y_i \in \{1,-1\}$ is the category value. If there were a separating hyperplane: w·x+b = 0 to make all x_i meet Eq. 2:

$$y_i(w \cdot x_i + b) \geq 1, \quad i = 1, 2, \cdots, l \tag{2}$$

where, w is the N-dimensional vector; b is a real number, then the training set would be linearly separable. By statistical learning theory, we know that if the training set can be completely separated by the hyper-plane and the distance between the hyper-plane and recent sample data is maximum, then the hyper-plane is the optimal hyper-plane (Fig. 1).

If the training set were not linearly separable, meaning that some samples can't be correctly separated by the hyper-plane; we would need to introduce the non-negative slack variable $\xi \geq 0$, i = 1,..., l and then convert the Eq. 2-3:

$$y_i(w \cdot x_i + b) \geq 1 - \xi_i \quad i = 1, 2, \cdots, l \tag{3}$$

The problem becomes to seek the optimization problem under the constraint of Eq. 3 and is expressed as:

$$\min_{\omega, b, \xi} \ \frac{1}{2} w^T w + C \cdot \sum_{i=1}^{l} \xi_i \tag{4}$$

where, C is the penalty factor and the greater C, the greater punishment for the misclassified samples. Use the Lagrange multiplier method to solve Eq. 4 and introduce the Lagrange function (Zhang, 2004), then Eq. 4 becomes to:

$$\begin{aligned} L(w, b, a, \xi, \gamma) = \frac{1}{2} w^T w + C \sum_{i=1}^{l} \xi_i - \\ \sum_{i=1}^{l} a_i \left| y_i (w^T x_i + b) - 1 + \xi_i \right| - \sum_{i=1}^{l} \gamma_i \xi_i \end{aligned} \tag{5}$$

where, $a_i \geq 0$, $\gamma_i \geq 0$ are Lagrange multipliers. Seek the partial differential of w, b and ξ_i and make them equal to zero, then obtain the dual problem of Eq. 5:

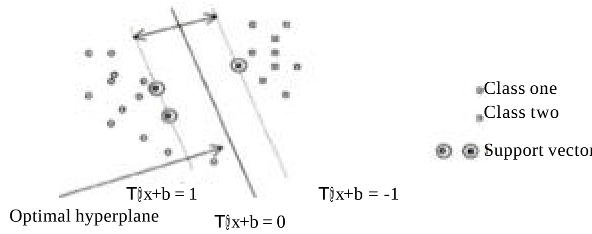

Fig. 1: Optimal hyper-plane schematic diagram

$$\begin{aligned} &\min_{a} \ \frac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} y_i y_j a_i a_j x_i \cdot x_j - \sum_{j=1}^{l} a_j \\ &\text{s.t} \ \sum_{i=1}^{l} y_i a_i = 0, \qquad 0 \leq a_i \leq C, \quad i = 1, \cdots, l \end{aligned} \tag{6}$$

Solve Eq. 6 to get $a^* = (a_1^*, a_2^*, \ldots, a_l^*)$ and calculate:

$$b^* = y_j - \sum_{i=1}^{l} y_i a_i^* x_i \cdot x_j$$

The final decision function is expressed as:

$$f(x) = \text{sgn}\left(\sum_{i=1}^{l} y_i a_i^* x_i \cdot x + b^*\right) \tag{7}$$

For nonlinear problems, the inner product $x_i \cdot x_j$ is replaced by the kernel function $K(x_i, x_j) \equiv \phi(x_i)^T \phi(x_j)$ which maps the vector X into a high dimensional space by the function ϕ. Common kernel functions have a variety of forms; in this study, the kernel function is selected as the Radial Basis Function (RBF) which can preferably solve the complex nonlinear problems. The RBF is expressed as:

$$K(x, x_i) = \exp\left\{-\sigma \|x - x_i\|^2\right\} \quad \sigma > 0 \tag{8}$$

where, σ is the width coefficient of RBF.

Particle swarm optimization (PSO): PSO guides the whole population to move toward the possible solution with the information transfer and cooperation mechanism between the inter-groups which could gradually increase the possibility of founding the better solution in the solving process.

Set a population composed by m particles. In the D-dimensional space, each particle's position is expressed as $x_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$ and their speed is expressed as $v_i = (v_{i1}, v_{i2}, \ldots, v_{iD})$. Then x_i and v_i change according to the following Eq. 9 and 10:

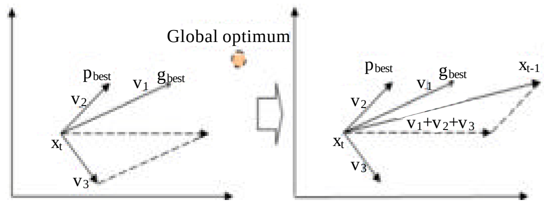

Fig. 2: Particle speed and position adjustment diagram

$$v_{id} = \omega \cdot v_{id} + c_1 \cdot rand() \cdot (p_{id} - x_{id}) + c_2 \cdot rand() \cdot (p_{gd} - x_{id}) \quad (9)$$

$$x_{id} = x_{id} + v_{id} \qquad i = 1, 2, \cdots, m \quad (10)$$

where, c_1, c_2 are learning factors which make the particle has the ability of self-summary and learning from the outstanding individual to be more close to the global optimum (Fig. 2); rand () is the random function in the range of 0 and l; ω is the inertia weight which plays the role of balancing the global search and the local search in PSO algorithm.

Constructing the fitness function f(x) is used to evaluate each particle's performance and setting the stop condition such as the maximum number of iterations is used to determine the convergence of f(x). Let $p_{ibest} = (p_{i1}, p_{i2}, \ldots, p_{iD})$ represents the individual best position, $g_{best} = (g_{i1}, g_{i2}, \ldots, g_{iD})$ represents the global best position. The current position x_i would be evaluated when searching in the problem domain. If $f(x_i)$ is better than p_{ibest}, then p_{best} is equal to x_i; if $f(x_i)$ is better than $f(g_{best})$, then g_{best} is equal to x_i; update all particles by Eq. 8 and 9, iterating like this until the stop condition is met.

The choice of inertia weight ω has a great influence on the performance of PSO, the larger ω, the stronger global search capability; the smaller ω, the stronger local search capability. This study uses the adaptive strategy of ω which makes the weight value decrease linearly with the iteration.

Setting ω_{max} is the maximum weight, ω_{min} is the minimum weight and t_{max} is the maximum number of iterations, so the weight ω is expressed as:

$$\omega = \omega_{max} - \frac{t}{t_{max}}(\omega_{max} - \omega_{min}) \quad (11)$$

Y.shi and R.Ebethart point out that the PSO optimizes better, when the weight ω changes linearly from 1.4 to 0.4 by experiments (Shi and Eberhart, 1998).

ESTABLISH THE ADAPTIVE PREDICTION MODEL FOR DRILLING ACCIDENT BASED ON PSO-SVM

Select characteristic parameters: Using the method of PSO-SVM to establish the adaptive prediction model for drilling accident, first the characteristic parameters that characterize the drilling state should be extracted from many drilling parameters. Analyzing comprehensively the impact of the various drilling accident factors and referring the diagnostic methods of drilling accident which are concluded by drilling experts (Jiang, 2001), six characteristic parameters is selected to compose the feature vector X which include drilling pressure, pump pressure, pump volume, rotation speed, drilling speed and torque.

Establish adaptive model: The process of establishing the adaptive prediction model is divided into the following three stages as shown in Fig. 3:

- **Build the data set:** The sub-module of data reads the drilling accident instance and generates accident sample set by the form of feature vector X, randomly select half of the samples to compose the training set, the rest of samples as the testing set to optimize SVM parameters
- **Generate prediction model:** Use SVM to read the training set, train it with the initial SVM parameters delivered by PSO algorithm and get the initial prediction model. Then predict the test sample and calculate prediction accuracy with the fitness function F of PSO algorithm. If the F's stop condition is met, then this prediction model is the optimal prediction model, otherwise, the PSO algorithm iterates and passes the updated training parameters to SVM, SVM retrains and regenerates the optimal prediction model, such iteration is repeated until the stop condition is met
- **Predict accident:** Real-time drilling data is converted into the feature vector x after the pretreatment, then the optimal prediction model predicts x and outputs the result. Comparing the prediction result with the actual accident category, if prediction result is error, then the category of misclassification accident would be amended and added to the training set, the model will retrain and regenerate the optimal prediction model to correctly identify such misclassification accident and adapt different drilling conditions

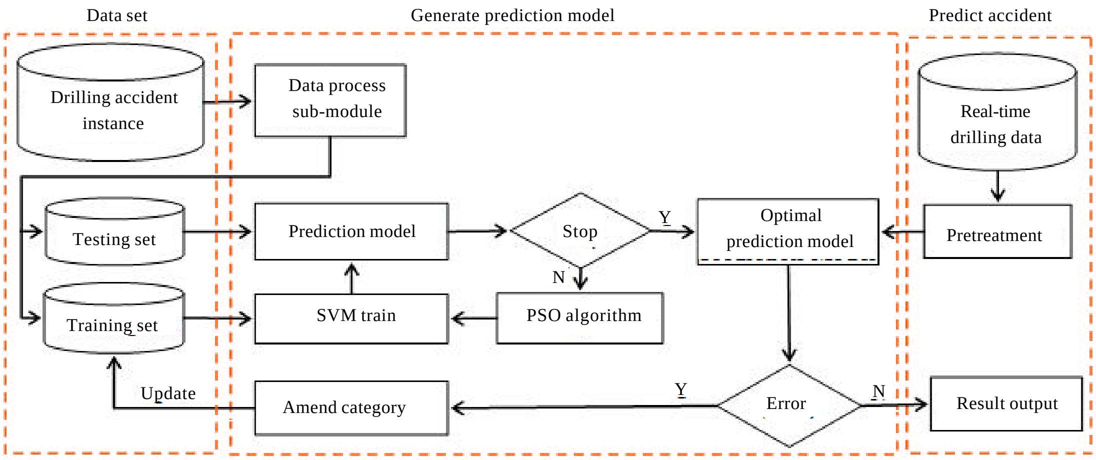

Fig. 3: Adaptive prediction model based on PSO-SVM

The core part of the adaptive prediction model based on PSO-SVM is optimizing the SVM parameters. Radial basis function is selected as the kernel function of SVM model, therefore, the parameters needed to optimize include the penalty factor C, the error å and the width coefficient σ, so the particle variable is expressed as x_i = (c, ε, σ). The fitness function is used to evaluate the performance of each particle. Consider too many variables will increase the complexity of accident prediction, we need to remove unnecessary variations to reduce the variable dimensions and improve the efficiency and the accuracy of accident prediction (Shao *et al*., 2006). In this study, the fitness function is expressed as $\beta = n_p/N$, where, β is the accident prediction accuracy; n_p is the number of samples predicted correctly; N is the total of samples predicted.

The main steps of core algorithm in the adaptive prediction model based on PSO-SVM are as follows:

- Define the particle size m, the maximum number of iterations t_{max}, inertia weight ω and learning factors, randomly initialize the particle position x_i^* = (c, ε, σ), the particle velocity $v_i^* = (v_{ic}, v_{iε}, v_{iσ})$, i = 1, 2,... , m
- Let the individual best position p_{ibest} of each particle is equal to x_i^*. Calculate the initial fitness values of each particle and select the particle position that has the best fitness value as the initial global optimal position g_{best}
- SVM trains accident samples and gets the prediction model
- Use the prediction model to predict the samples of test set and get the prediction accuracy
- Compare each particle's current fitness value with the fitness value of its historical best position $p_{ibest} = (p_{ic}, p_{iε}, p_{iσ})$, if the current value were more better, then $p_{ibest} = x_i^*$
- Compare each particle's current fitness value with the fitness value of its global best position $g_{best} = (g_c, g_ε, g_σ)$, if the current value were more better, then $g_{best} = x_i^*$
- Update the position and speed of each particle according to Eq. 9-11
- If t_{max} were met, then stop and get the optimal prediction model would, otherwise, return to the step (3)
- Use the optimal model to predict the real-time drilling data, if the prediction result is error, then the misclassification accident would be amended and added to the training set and then return to step (3); otherwise, output the correct category of the accident and stop

EXPERIMENT AND ANALYSIS

To verify the effect of the prediction model, this study takes the common sticking accident for example. Twenty sticking accidents from a block of an oilfield were selected as the sample set, in which 10 samples selected randomly were used to train and the remaining 10 were to optimize SVM parameters (Wang *et al*., 2009). The normal state was represented by 1, -1 meant sticking state (Table 1). Initialized the particle size m is equal to 20 and set $C_{min} = 1$, $C_{max} = 500$, $ε_{min} = 0.0001$, $ε_{max} = 0.1$, $σ_{min} = 0.01$, $σ_{max} = 1$, $V_{min} = -0.01$, $V_{max} = 0.01$; then the model began to train and optimize the sample set and the optimal prediction model was got after 50 iterations, at this time, the prediction accuracy β = 100% and the optimal parameters: $C_{opt} = 292$, $ε_{opt} = 0.008$, $σ_{opt} = 0.01$.

Using the optimal prediction model to predict the test temples (Table 2), in which the five samples 11-15 are from another block in the oilfield in order to increase the diversity of test data. To validate the improvement of

Table 1: Part of sample data

Sample	Drilling pressure (N)	Pump pressure (MPA)	Pump volume (L min^{-1})	Drilling speed (r min^{-1})	Rotation speed (r min^{-1})	Torque (N m)	Accident Type	State value
1	8500	8	130	4.0	300	350	Normal	1
2	7600	8	130	4.0	300	360	Normal	1
3	7500	7	130	3.7	300	320	Normal	1
4	7000	20	80	1.3	100	1750	Sticking	-1
5	9000	21	130	1.8	300	450	Sticking	-1
6	4000	5	110	2.0	150	1400	Sticking	-1

Table 2: Test samples and predictive results

Sample	Drilling pressure (N)	Pump pressure (MPA)	Pump volume (L min^{-1})	Drilling speed (r min^{-1})	Rotation speed (r min^{-1})	Torqe (N m)	State value	Adaptive PSO-SVM prediction	Traditional PSO-SVM prediction
1	7600	7.0	130	3.7	300	420	1	1	1
2	7500	7.0	130	3.8	300	350	1	1	1
3	8500	8.0	130	4.2	300	360	1	1	1
4	8000	7.0	130	4.5	300	320	1	1	1
5	7500	7.0	130	3.6	300	410	1	1	1
6	8600	8.0	130	4.0	300	450	1	1	1
7	7000	7.0	130	4.5	300	320	1	1	1
8	7000	1.0	130	1.8	150	1600	-1	-1	-1
9	8000	23.0	100	3.8	150	1700	-1	-1	-1
10	7600	7.0	130	2.3	150	1500	-1	-1	-1
11	6000	20.0	25	1.7	90	1700	-1	1	1
12	8000	20.0	28	3.2	80	1060	-1	-1	-1
13	4000	19.5	40	1.6	40	1500	-1	-1	1
14	3000	19.0	34	1.5	70	480	-1	-1	1
15	4500	18.0	37	4.2	100	1400	-1	-1	-1

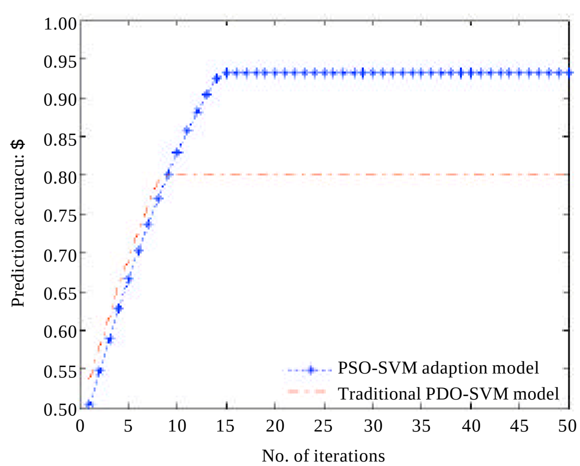

Fig. 4: Curve of prediction accuracy with the iterations

performance of the adaptive prediction model based on PSO-SVM, we used the traditional prediction model based on PSO-SVM to train and predict the same data at the same time. The results are shown in Table 2.

Analyzing the data in Table 2, the samples1-10 are correctly identified by the both models, since they and the data of sample set are from the same block and their data characteristics are similar. Samples 11-15 are quite different from the samples 1-10 due to they are from another block which increases the difficulty of accident prediction. When the adaptive prediction model based on PSO-SVM misclassified the abnormal sample 11, it amended this misclassification sample and added it to the training set, then the model retrained, re-optimized and regenerated the optimal prediction model which could identify the similar samples well; thus the follow-up samples 12-15 can be completely recognized. This model had only one misclassification sample and its prediction accuracy is 93.3%, the optimal parameters had been adjusted to: $C_{opt} = 293$, $\varepsilon_{opt} = 0.0001$, $\sigma_{opt} = 0.01$. However, the traditional prediction model based on PSO-SVM is less able to identify abnormal accident, since it has no the adaptive capacity; it misclassified three samples (11, 13 and 14) and its prediction accuracy is only 80%. The results show that adaptive prediction model based on PSO-SVM has better adaptability and higher prediction accuracy under the complex drilling conditions.

Figure 4 is the curve of the prediction accuracy changing with the number of iterations. We can draw that the adaptive prediction model based on PSO-SVM has faster convergence speed and higher prediction accuracy.

CONCLUSION

This study proposes an adaptive prediction model for drilling accident based on PSO-SVM. The model uses the strong global search ability of PSO algorithm to optimize SVM parameters; it re-trains, re-optimizes and regenerates the new optimal prediction model through adding misclassification accident to the training set in order to adapt different drilling conditions and improve the accuracy of accident prediction. The case study shows that this model has better adaptability and higher prediction accuracy.

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