Quantitative Identification Modeling of Drilling Pipe Damage Levels Based on Metal Magnetic Memory Characteristic Parameters

Si-qi LI1,*, Yang YU1, Si-yu CHEN2 and Qing-hua ZHANG2

1Harbin Institute of Technology, Harbin 150001, China
2Northeast Petroleum University, Daqing 163318, China

*Corresponding author

Keywords: Drilling pipe, Damage levels, FSVM, Metal magnetic memory testing.

Abstract. In order to quantitatively identify drill pipe defect levels by using Metal Magnetic Memory (MMM) technology, an optimized multi-classification FSVM model is first proposed. The material of drill pipes is S355 low carbon alloy steel. The MMM signal characteristics of different damage levels are obtained through a lot of field testing. Considering the dispersion and small samples of MMM data in practical engineering, SVM is introduced to solve the bottleneck of small samples and dispersion. The fuzzy membership degree function and the parameter combinatorial optimization are adopted to improve the robustness of SVM. By extracting four dimension characteristic parameters, the quantitative MMM identification model is proposed based on optimized multi-classification FSVM algorithm. The test results show that the model precision is 90.17%, which provides a new method for the quantitative MMM evaluation on drilling tool damage levels.

Introduction

Drill pipe is an essential tool in the field of petroleum drilling and production. Once drill rods break during drilling operation, it will cause a malignant accident and a huge economic loss. Meanwhile, in order to effectively save resources and promote the development of circular economy, most of the drilling tools will be reused after use [1]. Therefore, damage testing, especially early hidden damage and stress concentration evaluation, is very significant for drill pipes. However, early damage couldn’t be found through traditional Non-Destructive Testing (NDT), such as ultrasonic testing, X-ray inspect and eddy current testing, until the macroscopic defect has been formed [2]. In1997, Doubov A.A. first introduced Metal Magnetic Memory (MMM) technology in the 7th NDT European Conference [3]. As a developing NDT, MMM testing can not only detect macroscopic damage, but also effectively evaluate the stress concentration and micro damage by scanning magnetic induction density distribution. MMM testing has attracted the attention of scholars and a lot of research has been done, but there still exist bottlenecks in the quantitative defect level evaluation for drill pipes [4-5].

In order to solve this problem, an optimized quantitative MMM identification model of drilling pipe damage levels is presented based on Fuzzy Support Vector Machine (FSVM). First, the MMM signal characteristics of different damage levels have been extracted through a lot of field tests for drill rods. Then, the quantitative MMM damage grades are classified by comparing with the eddy current testing standard Q/SHXB0021-2015 of drill pipe grades. Finally, by using multi-dimensional MMM characteristic parameters, a quantitative MMM classification model of drilling pipe defect grades is established based on multi-classification FSVM, which provides a new method for the quantitative evaluation on the defect level of drilling tools.

Experiments and Analysis

Drilling pipes used for drilling site are detected in the field condition in order to get the actual MMM signal characteristics. The drilling rod material is S355 low carbon alloy steel. The MMM testing
Instrument is the TSC-2M-8 metal magnetic memory detector produced by the Russian power diagnosis company. The measurement is carried out along the axial direction of drill pipes.

Figure 1(a) shows MMM curves of a new drilling pipe. The normal component $H_p(y)$ and the tangential component $H_p(x)$ fluctuate slowly in the middle of the drill pipe body. The sharp fluctuation marked out with the rectangular box is near the threaded end of the drill rod, and the maximal peak-peak value is $150 \text{[A/m]}$. Figure 1(b) displays MMM curves of a damaged drill pipe. The violent reciprocating fluctuations locate on the threaded end of the body. The maximal peak-peak value gets to $600 \text{[A/m]}$, which is 4 times the new drill pipe in Figure 1(a). Contrasting Figure 1(a) to (b), the MMM feature of defect drill rods is obvious, which indicates MMM curves can reflect the damage state of drill rods.

![Figure 1. Drilling pipe MMM curves.](image)

However, working load, environmental magnetic field and measurement noises often lead to the dispersion and uncertain of MMM data, which brings difficulty to quantitative evaluation on drill pipe damage levels. To solve the problem, a large number of data samples are usually needed to determine the damage levels quantitatively. But in actual engineering, the number of samples is often limited. As a machine learning algorithm, Support Vector Machine (SVM) has the advantage of solving the nonlinear and complex problems based on small training samples [6]. Therefore, it is necessary to introduce SVM to solve the problem of small samples and dispersion for quantitative MMM evaluation on drill pipe damage levels.

**Optimized Multi Classification FSVM Algorithm**

If there are noises or outliers in training samples, the accuracy of traditional SVM will be greatly reduced. This is due to the fact that the hyper plane is not optimal for the classification of training samples. By using fuzzy membership degree function, FSVM integrates the importance degree of each sample into the SVM algorithm, which improves the classification accuracy and noise-resistibility. Set $\{(x_1, y_1, s_1), (x_2, y_2, s_2), \ldots, (x_l, y_l, s_l)\}$ as a set of training data. Here, $x_i \in \mathbb{R}^n$ denotes sample input value, $y_i \in \{-1, +1\}$ represents sample output value, and $s_i \in [0, 1]$ is the membership degree corresponding to $x_i, i = 1, 2, 3, \ldots, l$. Then, the quadratic programming problem for solving the optimal hyper plane can be defined as:

$$
\begin{aligned}
\min & \quad \frac{1}{2} \|\omega\|^2 + C \sum_{i=1}^{l} s_i \xi_i \\
\text{s.t.} & \quad y_i (\omega \cdot x_i + b) \geq 1 - \xi_i, \quad \xi_i \geq 0, \quad 0 \leq s_i \leq 1, \quad i = 1, 2, \ldots, l
\end{aligned}
$$

(1)
where, $C$ is the penalty factor, which indicates the degree of punishment for the sample of the wrong classification; $\omega$ is the hyper plane normal and $b$ is intercept; $\xi_i$ is relaxation factor which control the sample number of the wrong classification; $s_i\xi_i$ controls the weight of error sample.

By constructing the Lagrange function, the dual problem of the above problem can be obtained:

$$\max \sum_{i=1}^l \alpha_i - \frac{1}{2} \sum_{i=1}^l \sum_{j=1}^l \alpha_i \alpha_j y_i y_j (x_i \cdot x_j)$$

(2)

$$\sum_{i=1}^l \alpha_i y_i = 0, \quad 0 \leq \alpha_i \leq s_i C \quad i = 1, 2, ..., l$$

(3)

where, $\alpha_i$ and $\alpha_j$ are the Lagrange Multipliers corresponding to $i$ and $j$, respectively. The introduction of membership degree $s_i$ makes the Lagrange multiplier change from $0 \leq \alpha_i \leq C$ to $0 \leq \alpha_i \leq s_i C$. By considering the influence of samples on the range of Lagrange multipliers, the noise-resistibility and classification accuracy can be improved. Therefore, correct membership function is the key to guarantee the F SVM classification effect and generalization ability. In view of the fact that the distance from each sample to class center is the basis for measuring the importance degree of samples, the membership degree function based on distance is presented in Eq.(4) and Eq. (5).

$$s_i = 1 - \frac{\|x_i - x\|}{r} + \delta$$

(4)

$$r = \max\|x_i - x\|$$

(5)

where, $x$ is the class center, and $r$ is the class radius. $\delta > 0$ is the presetting parameter in order to avoid the membership degree $s_i = 0$.

In actual calculation, in order to avoid the dimension disaster in high dimension feature space, kernel function $k(x_i, x_j)$ is used instead of inner product $(x_i, x_j)$ shown in Eq.(2). Different kernel functions generate different F SVM, which affects the classification effect. Currently, the common kernel functions include linear kernel function, polynomial kernel function and radial basis kernel function. The radial basis kernel function is not only suitable for small samples and low dimensional conditions, but also suitable for large sample and high dimensional cases. The linear kernel is a special kind of the radial basis function. The polynomial kernel has more parameters, which makes the calculation more difficult. Therefore, the radial basis kernel function shown in Eq.(6) is used to build the F SVM.

$$k(x_i, x_j) = \exp(-g\|x_i - x_j\|^2)$$

(6)

where, $g$ is the undetermined parameter of radial basis kernel function.

The traditional SVM is suitable for binary classification. But drill rod damage evaluation is multilevel classification. The common multi classification algorithms include 1 to N-1 method, 1 to 1 method and DAG method. Compared with the other two multi classification algorithms, 1 to 1 method has higher accuracy. When the samples are classified, each decision judges the sample and votes for its corresponding category. In the end, the category with the most votes is just the category that the sample belongs to. Further, considering that the penalty factor $C$ and kernel function parameter $g$ have important influence on the F SVM accuracy, the combinatorial optimization of the two parameters is carried out in order to avoid blind fixed parameter selection. So far, the optimized Multi Classification F SVM algorithm is established for drill pipe damage level identification.
MMM Characteristic Parameters

Because of the complexity of the actual situation, the single MMM signal can not accurately characterize the damage state. Therefore, four-dimension MMM characteristic parameters are extracted as follows:

1. Peak to Peak Value $\Delta H_p$

$$\Delta H_p = H_p(i)_{\text{max}} - H_p(i)_{\text{min}}$$  \(7\)

where, $H_p(i)_{\text{max}}$ and $H_p(i)_{\text{min}}$ are the maximal magnetic field intensity and the minimal magnetic field intensity on the stress concentration or defect zones, respectively.

2. Gradient $K_m$

$$K_m = \left| H_p(m+1) - H_p(m) \right| / \Delta L$$  \(8\)

where, $H_p(m+1)$ and $H_p(m)$ is magnetic field intensity values of two adjacent sampling points. $\Delta L$ stands for the distance between two adjacent selected points.

3. Intensity Change Rate $\Delta H_p / \Delta x$

$$\Delta H_p / \Delta x = (H_p(i)_{\text{max}} - H_p(i)_{\text{min}}) / (x(i)_{\text{max}} - x(i)_{\text{min}})$$  \(9\)

where, $x(i)_{\text{max}}$ is the $x$ coordinate of $H_p(i)_{\text{max}}$, and $x(i)_{\text{min}}$ is the $x$ coordinate of $H_p(i)_{\text{min}}$.

4. Signal Energy Value $\Delta H_p \cdot \Delta x$

$$\Delta H_p \cdot \Delta x = (H_p(i)_{\text{max}} - H_p(i)_{\text{min}}) \cdot (x(i)_{\text{max}} - x(i)_{\text{min}})$$  \(10\)

Quantitative MMM Identification Modeling and Verification

According to the eddy current testing standard Q/SHXB0021-2015, drilling pipe defect levels are divided into grade I, II and III. By comparing with this standard, the MMM testing standard is originally proposed to be 4 levels. Level 1 is normal state, and Level 2 is early stress concentration state. Level 1 and Level 2 correspond to Level I of the eddy current testing standard, which the residual wall thickness is not less than 80% of the nominal value. Level 3 is hidden damage state corresponding to Level II of the eddy current testing standard, which the remaining wall thickness is not less than 70% of the nominal value. Level 4 is macroscopic damage state corresponding to Level II of the eddy current testing standard, which the residual wall thickness is less than 70% of the nominal value. It can be seen that the MMM standard is more meticulous, which can effectively avoid malignant accidents by taking early measures.

Through a lot of field test and analysis, sixteen groups of MMM data, shown in Table 1, are selected as the training samples of the optimized multi classification FSVM model. $L$ is the level label defined as 1, 2, 3, 4 corresponding to the normal state, early stress concentration, hidden damage and macroscopic damage state, respectively. Other eight groups of MMM data, with the same material and load, are used as the testing samples in order to check the accuracy of the model. Different kernel function parameter $g$ and penalty factor $C$ will produce different classification accuracy. In the optimization process, when $g = 1.1$ and $C = 16$ the highest accuracy rate is 90.17%, the prediction results are shown in Table 2, which shows the accuracy of the multi classification FSVM model with parameter optimization is greatly improved.
Table 1. Training Samples.

<table>
<thead>
<tr>
<th>L</th>
<th>No.</th>
<th>$\Delta H_p$</th>
<th>$K_m$</th>
<th>$\Delta H_p/\Delta \chi$</th>
<th>$\Delta H_p \cdot \Delta \chi$</th>
<th>No.</th>
<th>$\Delta H_p$</th>
<th>$K_m$</th>
<th>$\Delta H_p/\Delta \chi$</th>
<th>$\Delta H_p \cdot \Delta \chi$</th>
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<tr>
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Table 2. Testing Samples.

<table>
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<th>$\Delta H_p/\Delta \chi$</th>
<th>$\Delta H_p \cdot \Delta \chi$</th>
<th>Prediction Level</th>
<th>Actual level</th>
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<td>Level 4</td>
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</tbody>
</table>

Conclusions

(1) The violent reciprocating fluctuations appear on the MMM curves of damaged drill pipe, of which $\Delta H_p$ is often 4 times the new drill pipe. The field MMM testing results show that MMM data can reflect damage degree of drill pipes.

(2) According to Class I, II and III of the eddy current testing standard, the MMM testing standard is originally proposed to be 4 levels. Level 1 is normal state, and Level 2 is early stress concentration state, both corresponding to Class I of the eddy current testing standard. Level 3 is hidden damage state, and Level 4 is macroscopic damage state. It can be seen that the MMM standard is more meticulous, which can effectively avoid malignant accidents by taking early measures.

(3) Due to the dispersion and limitation of MMM data in practical engineering, it is necessary to introduce SVM to solve the problem of small samples and dispersion. By using MMM characteristic parameters, the quantitative identification model is presented based on optimized multi-classification FSVM. The test results show that the model precision is 90.17%, which provides a new method for the quantitative MMM evaluation on drilling tool damage levels.

Acknowledgement

This work was supported by National Nature Science Foundation of China (No. 61571161 and No. 11272084) and China Petroleum and Chemical Industry Federation Guidance Program (No. 2017-01-05).

References


