Application of RS-SVM method in diagnosis of small sample fault of cement rotary kiln

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Abstract. The rough set (Hereinafter referred to as RS) and support vector machine (Hereinafter referred to as SVM) are combined and applied to the diagnosis of small sample fault of cement rotary kiln. In this paper, the basic knowledge of RS and SVM theory is introduced firstly. Then the knowledge of application of RS theory in cement rotary kiln fault is reduced. Lastly, SVM theory is utilized to train and classify the reduced data. This combined diagnosis method not only brings the advantages of two theories into full play, but also overcomes the limitation of SVM in identification of redundant information and useful information, effectively reduces the space dimensionality of input information of SVM and makes up the disadvantages of sensitive to noise of input information and poor interference immunity of RS theory. Therefore, the efficiency and accuracy of diagnosis are improved effectively.

1. Introduction

The most important equipment in new dry process cement production is the rotary kiln system whose faults are generally classified into the production process faults and operating equipment faults. The process faults refer to those caused by the abnormal technological parameters due to the process problems during the production of cement and the equipment faults refer to those caused by the mechanical and electrical problems of equipment [3]. After comparing these two kinds of faults, we find that the process faults are diversified and complicated. It is difficult to analyze all technological parameters, but it is feasible to select some of the main process parameters and secondary process parameters for fault diagnosis.

The rough set theory is a new mathematical tool for processing the knowledge of ambiguity and uncertainty. It does not require any initial or additional information of the original data. The main concept is that the terminal decision or classification rule is derived after the reduction of data attribute under the premise that the classification ability is kept unchanged [5]. The support vector machine is a kind of kernel method essentially. In case of few samples, the classification method of support vector machine possesses high adaptability, better classification ability and higher computational efficiency which can provide a good real-time data processing method for equipment fault diagnosis.

We take the small sample fault data of cement rotary kiln as the research object, utilize the RS-SVM diagnostic model to diagnose the fault of rotary kiln [1], select the same data samples and compare the diagnosis results with those obtained with the SVM diagnostic model to prove the high
real-time performance, effectiveness and reliability of this method.

2. Basic theories of rough set and support vector machine

2.1. Basic theory of rough set

2.1.1. Basic definition. Definition 1: Set the knowledge base (approximation space) as \( K = (U, S) \), where \( U \) is the domain of discourse and \( S \) is the equivalence relation cluster on the domain of discourse \( U \). Then the equivalence relation between \( \forall X \subseteq U \) and \( U \) is \( R \in \text{IND}(K) \). The lower approximation and upper approximation of subset \( X \) about knowledge \( R \) is respectively defined as:

\[
R(X) = \{x \mid \forall x \in U \land (\{x\} \subseteq X)\} = \bigcup \{Y \mid \forall Y \in U / R \land (Y \subseteq X)\}
\]

\[
\overline{R}(X) = \{x \mid \forall x \in U \land (\{x\} \subseteq X)\} = \bigcup \{Y \mid \forall Y \in U / R \land (Y \subseteq X)\}
\]

Figure 1 shows the schematic diagram of lower approximation and upper approximation of set \( X \).

\[\text{Figure 1. Schematic diagram of lower approximation and upper approximation of rough set}\]

Definition 2: Set the domain of discourse as \( U \) and the equivalence relation as \( R \), \( \forall X \subseteq U \). If \( R(X) = \overline{R}(X) \), the set \( X \) is considered as the \( R \)-precise set about \( U \) with respect to \( U \). If \( R(X) \neq \overline{R}(X) \), the set \( X \) is considered as the \( R \)-rough set about \( U \) with respect to \( R \).

2.1.2. Differential matrix method for attribute reduction. Definition 3: Set \( DT = (U, C \cup D, V, f) \) as a decision table, where the domain of discourse is a nonempty finite set of the object, \( U = \{X_1, X_2, \ldots, X_k\} \) and \( |U| = n \). Then

\[
M_{n \times n} = (c_{ij})_{n \times n} = \begin{bmatrix}
c_{11} & c_{12} & \cdots & c_{1n} \\
c_{21} & c_{22} & \cdots & c_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
c_{n1} & c_{n2} & \cdots & c_{nn}
\end{bmatrix} = \begin{bmatrix}
c_{11} & * & \cdots & * \\
* & c_{22} & \cdots & c_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
* & * & \cdots & c_{nn}
\end{bmatrix} = \begin{bmatrix}
c_{11} & c_{21} & \cdots & c_{n1} \\
c_{21} & c_{22} & \cdots & c_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
c_{n1} & c_{n2} & \cdots & c_{nn}
\end{bmatrix}
\]

is the differential matrix of decision table, where \( i, j = 1, 2, \ldots, n \).
The lower or upper triangular matrix is usually used to represent the differential matrix of the decision tables. For this algorithm, the reduction results and knowledge kernel can be obtained through running the program in Microsoft Visual FoxPro 6.0.

2.2. Basic theory of support vector machine

The support vector machine is a new statistical learning method and a useful data mining method, which realizes the structural risk minimization. Its solution is related to the distribution of sample data, and the global optimal solution can be obtained finally.

2.2.1. Basic principle. The basic idea of classification of support vector machine is the optimal separating hyperplane shown in Figure 2. It can be seen that using this classification method can not only get two different classes, but the spacing between the two classes is maximum too. The vector nearest to the optimal separating hyperplane is called support vector (SV).

![Figure 2. Schematic drawing of optimal separating hyperplane](image)

The support vector (SV) can be calculated by solving the optimal problem. Then combining the relevant parameters, the final optimal discriminant function (1) (i.e. SVM) can be obtained:

\[
f(x) = \text{sgn}[(w^*)^T \phi(x) + b^*] = \text{sgn}\left(\sum_{i=1}^{n} a_i^* y_i K(x_i, x) + b^*\right)
\]

(1)

If the above function is regarded as a neural network, the support vector network as shown in Figure 3 can also be obtained:
2.2.2. Design of SVM diagnostic model. To make the SVM diagnostic model more suitable to the data information of small samples and enhance its classification and diagnostic capability, we can take the following four steps to design the diagnostic model:

Firstly, preprocess the data information of small samples; secondly, select the proper kernel function according to Formula (1); thirdly, select the construction and parameters of fault classifier; lastly, apply the preprocessed data information to the model and obtain the diagnosis results [2].

1) Preprocessing the samples
The sample data is normalized by using Formula (2) to find the characteristic information.

\[ \overline{X_i} = \frac{X_i - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}} \]  

(2)

2) Selection of kernel function
There are three frequently-used types of kernel functions: polynomial kernel function, radial basis kernel function and s-shaped kernel function. In this paper, the radial basis kernel function is used with the functional expression as follows:

\[ K(x, x_i) = \exp\left(-\frac{|x - x_i|^2}{\sigma^2}\right) \]  

(3)

3) Selection of construction and parameters of fault classifier
To realize the classification and identification of fault forms, the multi-classification algorithm should be selected to construct the support vector machine multi-classifier [6]. The one-vs-rest (1-a-r) method which possesses better classification effect is adopted.

3. Diagnosis of cement rotary kiln fault based on rough set and support vector machine

3.1. Principle and steps of fault diagnosis
In this paper, the rough set and support vector machine are combined to diagnose the fault data of small samples of cement rotary kiln. The diagnostic flow chart is shown in Figure 4 below:
3.2. Example verification

3.2.1. Sample data of cement rotary kiln faults. The fault information of 36 cement rotary kilns is selected as the samples here. See Table 1 below. For the decision attributes, the common process faults and normal state are selected as the analysis objects, which are respectively the large material clump in the kiln, ring formed behind the kiln, raw materials running out of kiln without being sintered, red kiln, grate cooler “building a snowman” and normal state corresponding to Working condition 1, 2, 3, 4, 5 and 6 in Table 1; for the condition attributes, seven parameters are selected, which are respectively the electric current of major equipment in kiln, temperature and negative pressure at the rotary kiln terminal, temperature and negative pressure at the rotary kiln head, decomposing furnace outlet temperature and kiln cylinder temperature expressed by F1, F2, F3, F4, F5, F6 and F7 as shown in Table 1.

Table 1. List of cement rotary kiln fault information

| Fault samples | Condition attributes | Working conditions |
|---------------|----------------------|-------------------|
|               | F1  | F2  | F3  | F4  | F5  | F6  | F7  | S  |
| 1             | 123 | 781 | -211| 1080| -67 | 826 | 298| 1  |
| 2             | 161 | 843 | -69 | 1097| -81 | 878 | 303| 1  |
| 3             | 117 | 713 | -59 | 1092| -75 | 791 | 292| 1  |
| 4             | 115 | 727 | -199| 1088| -62 | 787 | 283| 1  |
| 5             | 145 | 736 | -59 | 1103| -58 | 707 | 276| 1  |
3.2.2. Preprocessing by RS. When preprocessing the decision tables with rough set, we firstly discretize the list of fault information, and then obtain the optimal reduction as \{F1, F2, F3, F7\} using the attribute reduction method based on attribute difference matrix. The attribute core is F1.

3.2.3. Construction of fault classifier and sample training. Table 2 is the normalized list of fault information. Divide the 36 groups of sample data into two categories and select 24 groups as the training samples and 12 groups as the test samples.

| Fault samples | Condition attributes | Working conditions |
|---------------|----------------------|--------------------|
|               | F1  | F2    | F3    | F7    | S    |
| 1             | 0.5125 | 0.445652 | 0.813084 | 0.194969 | 1    |
| 2             | 0.9875 | 0.782609 | 0.149533 | 0.226415 | 1    |
| 3             | 0.4375 | 0.076087 | 0.102804 | 0.157233 | 1    |
| 4             | 0.4125 | 0.152174 | 0.757009 | 0.100629 | 1    |
| ...           | ...  | ...   | ...   | ...   | ...  |
| 32            | 0.425 | 0.972826 | 0.429907 | 0.333333 | 6    |
| 33            | 0.3875 | 0.902174 | 0.738318 | 0.163522 | 6    |
| 34            | 0.45   | 0.858696 | 1      | 0.138365 | 6    |
| 35            | 0.35   | 0.929348 | 0.771028 | 0.113208 | 6    |
| 36            | 0.475  | 1      | 0.934579 | 0.144654 | 6    |

Take the 24 groups of sample data as the training samples and the radial basis function and 1-a-r SVM multi-classification algorithm are adopted for all classifiers. It should be noted that the LIBSVM software has strict format requirements for input data, so before SVM calculation, the sample data files should be converted to conform to the format requirements for LIBSVM input data [4]. 1-a-r SVM: Take the four samples of normal state and 4×5=20 samples of five other faults as two categories of input to classifier and identify them as +1 and -1 respectively. Build two categories of classifiers totaling six corresponding to six working conditions: SVM0, SVM1, SVM2, SVM3, SVM4 and SVM5 (where SVMn represents the two categories of support vector machines built between n class(es) of samples and the rest classes of samples). Figure 5 shows the flow chart of 1-a-r SVM multi-fault classifier [7], where X is the test sample.

![Figure 5. Flow chart of 1-a-r SVM multi-fault classifier](image-url)
3.2.4. Analysis and comparison of diagnosis results. Twelve groups of sample data for six states are tested and the test samples are input to six 1-a-r SVM classifiers. In the classification test, $C=10$ and $\sigma=0.2$. See Table 3 for the classification results which show that the 1-a-r SVM classification algorithm realizes the correct classification of all test samples and the identification results are completely correct.

Table 3. Classification results of 1-a-r SVM

| Test (Two samples) | Working condition 1 (0 0) | Working condition 2 (1 1) | Working condition 3 (2 2) | Working condition 4 (3 3) | Working condition 5 (4 4) | Working condition 6 (5 5) |
|--------------------|--------------------------|--------------------------|--------------------------|--------------------------|--------------------------|--------------------------|
| SVM0 output        | 1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 |
| SVM1 output        | -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 |
| SVM2 output        | -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 |
| SVM3 output        | -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 |
| SVM4 output        | -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 |
| SVM5 output        | -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 |

In order to verify the validity of the model in the diagnosis of the cement rotary kiln fault, the same five fault test samples are selected and the diagnosis results are shown in Table 4.

Table 4. Comparison of fault diagnosis results

| Fault samples | Diagnosis results | Actual faults |
|---------------|------------------|---------------|
| 1             | 1 (large material clump in the kiln) | 1 (large material clump in the kiln) |
| 2             | 2 (ring formed behind the kiln) | 2 (ring formed behind the kiln) |
| 3             | 3 (raw materials running out of kiln without being sintered) | 3 (raw materials running out of kiln without being sintered) |
| 4             | 4 (red kiln) | 4 (red kiln) |
| 5             | 5 (grate cooler “building a snowman”) | 5 (grate cooler “building a snowman”) |

It can be seen from Table 4 that the diagnosis results are all correct, which shows that this combination method is feasible and effective. In this paper, to demonstrate the effect of this combination method, 36 groups of small sample fault data are respectively tested using only support
vector machine method and the combination of rough set and support vector machine and the test results are compared. See Table 5 for the test results.

| Fault diagnosis model | Number of fault samples | Number of correct diagnosis | Diagnosis time |
|-----------------------|-------------------------|----------------------------|----------------|
| RS-SVM model          | 36                      | 33                         | 0.32s          |
| SVM model             | 36                      | 30                         | 0.67s          |

It can be evidently seen from Table 5 that the RS-SVM model is twice as fast as the SVM model in time, and the number of correct diagnosis is also large. Therefore, the RS-SVM diagnosis model is more efficient and accurate, which is more suitable for the real-time fault diagnosis.

4. Conclusions
The theoretical methods of rough set and support vector machine are introduced in this paper. They are combined and applied to the diagnosis of small sample fault of cement rotary kiln. It has been proved that this RS-SVM diagnostic model is more effective.

The cement rotary kiln fault diagnosis method proposed in this paper provides a platform for the fault diagnosis knowledge sharing between the rotary kiln equipment manufacturers, cement manufacturers and related research institutes, improves the actual diagnostic ability and plays a very good role in production.

References
[1] Wu Lishuai etc. 2014 Transformer fault diagnosis based on rough set and support vector machine Power Technology 4 768–770
[2] Zheng Hanbo etc. 2014 Fault diagnosis method of power transformers using multi-class LS-SVM and improved PSO High Voltage Engineering 11 3424–29
[3] Liu Shihui 2016 Research on fault diagnosis system of cement rotary kiln Jinan: Jinan University 51–56
[4] Lang Xufei 2013 Research on rotor fault diagnosis of asynchronous motor based on rough set and support vector machine Heilongjiang: Northeast Forestry University, Detection Technology and Automatic Equipment 44–57
[5] Li Tianrui 2015 Rough set theory and its application Wuhan: International Academic Development 2 13–15
[6] Huang Jianfeng 2016 Research on diagnosis method for blockage fault of shell-and-tube heat exchanger based on vibration signal SVM Guangdong: South China University of Technology 30–52
[7] Shi Yonghong 2016 Research on reasoning and fuzzy Bayesian network for rotary kiln fault diagnosis method Yanshan University 87–91