A New Method for Mechanical Fault Recognition of Extra-high Voltage Circuit Breaker

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Abstract

It is of important to recognize the mechanical fault for extra-high voltage Circuit Breakers (CBs) in GIS, when the condition monitoring of CBs is realized. In this paper, a new efficiency fault recognition method is provided, by using improved Support Vector Machines (LibSVMs). The recognition methods, ANN and LibSVM are compared on their recognition accuracy, and the results show that the LibSVM is more efficient than ANN. The algorithm of LibSVM is improved by using Genetic Algorithm (GA), and the GA-LibSVM can obtain higher recognition accuracy than usual LibSVM for mechanical fault recognition of CB.

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Keywords: Circuit Breakers; GIS, fault recognition; LibSVM; mechanical fault

1. Introduction

It is known that for the routine time-based maintenance of circuit breakers (CBs) in GIS, in-between maintenance outages it is never clear if the CBs in GIS operate exactly as desired, so this kind of maintenance is expensive, inefficient, and ineffective [1][2]. However, with increasing awareness of the benefits of condition-based maintenance, it can be expected that there will be advantages to be obtained from monitoring the condition of the CBs in order to ensure that maintenance is carried out only when it is really needed [3][4]. Reference [5] provided a method to obtain the mechanism dynamic features for the CB, and proposed an ANN algorithm for condition recognition of CB. However, with the increasing of fault types, the performance of ANN will decrease due to the dimension of neural increasing.

In recent years, support vector machines (SV machines, SVMs) have been intensively studied and applied into large variety of applications in many fields of science and engineering [6][7]. SVMs are natural outgrowth of neural networks and are classifier based on the optimal hyperplane generation method.
SVMs can overcome the shortcoming of dimension disaster in ANN. LibSVM is a library for support vector machines, which is provided by Chih-Chung Chang and Chih-Jen Lin\cite{8}.

The genetic algorithm (GA) is widely used in industry application, such as improvement of fault diagnosis algorithm\cite{9}\cite{10}.

In this paper, the LibSVM is applied to on-line condition recognition of CB. Firstly, the recognition accuracy of LibSVM is compared with that of ANN by using universal data set (http://archive.ics.uci.edu/ml/); Secondly, the genetic algorithm (GA) is combined with the LibSVM to obtain the optimal value of related parameters; finally, the GA-LibSVM recognition algorithm is applied to the mechanical condition recognition of CB, and the results show that LibSVM can recognize the different fault types with high accuracy.

2. SVM Classifier and Its Testing

2.1 SVM Classifier\cite{6}\cite{11}

The SVM is a powerful solution to the classification problems. In this paper, it is used for recognition and classification of mechanism features. The main advantage of the SVM net work used as a classifier is its good generalization ability and extremely powerful learning procedure and ability, leading to the global minimum of the defined error function.

From the principle of operation, the SVM is a linear machine working in the high-dimensional feature space formed by the nonlinear mapping of \( N \)-dimensional input vector \( x \) into a \( K \)-dimensional feature space (\( K > N \)) through the use of function \( \phi(x) \). The separation of two classes is performed by the hyperplane defined in the form \( g(x) = w^T \phi(x) + b = 0 \), with \( \phi(x) = [\phi_1(x), \phi_2(x), \ldots, \phi_k(x)]^T \), \( w \) as the weight vector of network \( w = [w_1, w_2, \ldots, w_k]^T \), and \( b \) as the bias.

The learning of the SVM network working in the classification mode is aimed at the maximization of the separation margin between two classes, which are denoted here as \( d_1 = 1 \) and \( d_2 = -1 \). Mathematically, it corresponds to the minimization of cost function \( \phi(w, \xi) \) defined as

\[
\min \phi(w, \xi) = \frac{1}{2} w^T w + C \sum_{i=1}^{p} \xi_i
\]

with constraints

\[
d_i (w^T \phi(x) + b) \geq 1 - \xi_i \quad (2a)
\]

\[
\xi_i \geq 0 \quad (2b)
\]

for \( i = 1, 2, \ldots, p \), where \( C > 0 \) is the user-specified constant representing the regularization coefficient, \( \xi \geq 0 \) is the nonnegative slack variable, and \( p \) is the number of given learning data pairs \((x_i, d_i)\).

The solution of the optimization problem is established by defining the Lagrangian function, finally leading to the quadratic programming with respect to the Lagrange multipliers \( \alpha_i \). All operations in the learning and testing modes use the so-called kernel function, satisfying the Mercer conditions\cite{12}. The kernel is a scalar function defined as the inner product of vector functions \( \phi(x_i) \) and \( \phi(x) \) defined as \( K(x_i, x) = \phi^T(x_i) \phi(x) \). The final learning problem of the SVM is transformed to the solution of the so-called dual problem defined with respect to the Lagrange multipliers, i.e.

\[
\max Q(\alpha) = \sum_{i=1}^{p} \alpha_i - \frac{1}{2} \sum_{i=1}^{p} \sum_{j=1}^{p} \alpha_i \alpha_j d_i d_j K(x_i, x_j)
\]

Subject to
\begin{equation}
\sum_{i=1}^{p} \alpha_i d_i = 0 \quad (i=1,2,\ldots,p) \tag{4a}
\end{equation}
\begin{equation}
0 \leq \alpha_i \leq C \tag{4b}
\end{equation}

where \( \alpha_1, \alpha_2, \ldots, \alpha_p \) are the nonnegative Lagrangian multipliers. The data points \((x_1, x_2, \ldots, x_p)\) corresponding to \( \alpha_i > 0 \) lie along the margins of decision boundary and are the support vectors.

The solution of the dual problem results in an optimal weight vector \( w \), where \( w = \sum_{i=1}^{p} \alpha_i d_i \phi(x_i) \). For any test vector \( x \), the output is then given by
\begin{equation}
\hat{y}(x) = \text{sign}(w \cdot \phi(x) + b) = \text{sgn}\left(\sum_{i=1}^{p} \alpha_i d_i K(x_i, x) + b\right) \tag{5}
\end{equation}

Vector \( x \) represents the class when \( \hat{y}(x) \) is positive and the alternative class when \( \hat{y}(x) \) is negative.

To build an SVM classifier, the user needs to tune \( C \) and choose a kernel function and its parameters. So far, no analytical or empirical study has conclusively established the superiority of one kernel over another; thus the performance of SVMs in a particular task may vary with the choice.

2.2 LibSVM

LibSVM is a library for support vector machines. Its goal is to promote SVM as a convenient tool. It integrates C-SVM classification, nu-SVM classification, one-class- SVM, epsilon-SVM regression, and nu-SVM regression. It also provides an automatic model selection tool for C-SVM classification. The latest version 3.0 is released on September 13, 2010.

In LibSVM, four basic kernels are used:
- linear: \( K(x_i, x_j) = x_i^T x_j \);
- polynomial: \( K(x_i, x_j) = (\gamma x_i^T x_j + r)^d, \gamma > 0; \)
- radial basis function: \( K(x_i, x_j) = \exp(-\gamma ||x_i - x_j||^2), \gamma > 0; \)
- sigmoid: \( K(x_i, x_j) = \tanh(\gamma x_i^T x_j + r) \).

Here, \( \gamma, r, \) and \( d \) are kernel parameters.

2.3 The Improvement of LibSVM and Its Testing

The LibSVM has good performance in fault type recognition or data type classification, and the RBF kernel is the best one. But, it’s hard to select the best parameters\((C: \text{cost}, \gamma: \text{gamma})\) of RBF kernel function when using LibSVM\([13]\).

In this paper, the LibSVM is improved to optimize the \( C \) and \( \gamma \) parameters, and the steps are as follows:
step1: preparation of data set and related types for training;
step2: choose the RBF kernel, and set the maximum, minimum and interval of \( C \) and \( \gamma \) by experience.
step3: The genetic algorithm is used to obtain the optimal value of \( C \) and \( \gamma \). The detailed genetic algorithm is described later;
step4: use LibSVM with optimal value of parameters \( C \) and \( \gamma \) to recognition the testing data set.

\begin{equation}
K(x_i, x_j) = e^{-\gamma ||x_i - x_j||^2}, \gamma > 0 \tag{6}
\end{equation}
In order to obtain the optimal values of parameters $C$ and $g$, the GA is improved too, by auto-adjusting of mutation probability $p_m$ during evolution process. The main implement procedures of GA are as follows:

1) Initialize the variables of $C$ and $g$ by experience, and define the objective function $f(x)$ and fitness value. The objective function is the calculation function of recognition precision, and the fitness value here is the value of precision;

2) Set the genetic strategy, such as generation number $N$, selection, cross, mutation method, and related probability, cross $p_c$, mutation $p_m$, respectively. The detailed strategies are as follows: (1) generation number $N=10$; (2) choose roulette method for selection; (3) choose multi-point cross method, $p_c=60\%$; (4) choose binary mutation method, initial $p_m=10\%$. If the difference of $f(x)$ is smaller than 1% for three times, then $p_m$ will be increased to 30%, by 1% interval, else if the difference of $f(x)$ is larger than 10% for three times, the $p_m$ will be decreased to 1%, by 1% interval;

3) Compute the objective function $f(x)$ and fitness value;

4) According to the genetic strategy, choose the value of $p_c$, $p_m$, put the father generation into the offspring generation population;

5) Judge the stop criteria. If the stop criteria is fitted, then stop, else return to step 4).

The training and testing data are downloaded from above mention website, and total 214 data for 6 types of glasses are included, which can be seen in Table I. These data are very difficult to distinguish, so it can check the recognition performance of ANN, LibSVM and GA-LibSVM.

Table I. Data set for glass classification

| Glass type | 1  | 2  | 3  | 4  | 5  | 6  |
|------------|----|----|----|----|----|----|
| data       | 70 | 76 | 17 | 13 | 9  | 29 |

The recognition performance of ANN, LibSVM and GA-LibSVM is compared, and the results are in Table II.

It can be seen from Table II that the GA-LibSVM can recognition the types of glass with higher accuracy.

Table II. Comparison of recognition accuracy

| Methods     | Recognition data | Accuracy |
|-------------|------------------|----------|
| ANN         | 47/117           | 40.2%    |
| LibSVM      | 83/117           | 70.9%    |
| GA-LibSVM   | 89/117           | 76.1%    |

3. Results and Discussions

Fig.1 shows the simulation model for CB in 550kV GIS, by using multi-body dynamic simulation software, ADAMS. Also, the sensor setting place (ABB displacement sensor) is shown in Fig.1. The experiments are conducted with normal and abnormal condition of operation mechanism.
During opening operation of CB studied, there are three operation stages can be defined as follows:

First stage: From movement of pole (also does the moving contact) to separation of contacts. During this stage, the effect forces are oil pressure force (driving force), contact friction resistance and mechanical friction resistance (resistance).

Second stage: From separation of contacts to the contributing moment of buffering ring. During this stage, the effect forces are oil pressure force (driving force), and mechanical friction resistance (resistance).

Third stage: From the role of buffering ring to the maximum displacement of moving contact.

Fig.2 shows the parameterization of the mechanical condition of CB, with parameters $k_1$, $k_2$, $k_3$, represent average speed of each operation stage, respectively.

| Fault types | Mechanical condition | $k_1$ (m/s) | $k_2$ (m/s) | $k_3$ (m/s) |
|-------------|----------------------|-------------|-------------|-------------|
| 1           | Healthy              | 3.78        | 8.63        | 3.52        |
| 2           | Oil leakage          | 3.27        | 7.3         | 2.5         |

The mechanism dynamic features and its parameters of CB are shown in Table III, which are calculated from different mechanical condition of CB during opening process.
Contact friction becomes more 3.31 7.51 3.26
Oil pressure increased \* 3.92 8.66 3.64

* Due to the alternant of summer and winter, if the CB starts serve in winter, the oil pressure will increase in summer.

In this paper, in order to improve the recognition accuracy, the parameters in Table III should be dealt by adding random noise before recognition, whose maximum value is 10% amplitude of parameters. The reasons are as follows:

1) When the CBs are in service, they are under severe electromagnetic condition, so the interference will influence the sampling data of condition monitoring setup.

2) There is dispersion of main axle’s angle displacement under different operations even with the same CB.

The GA-LibSVM algorithm is used to recognize the dealt data, and the recognition results are shown in Table IV, which show that the GA-LibSVM obtains the highest recognition accuracy.

Table IV. Recognition results

| Method     | Recognition data | Total  |
|------------|------------------|--------|
| ANN        | 23/40            | 57.5%  |
| LibSVM     | 34/40            | 85.0%  |
| GA-LibSVM  | 37/40            | 92.5%  |

4. Conclusions

In this paper, LibSVM and GA-LibSVM algorithm are introduced. Compared with ANN, the LibSVM can deal with high dimension problem, so it’s more efficient for condition recognition of CBs.

For universal glass data set, the GA-LibSVM, LibSVM can obtain 76.1% and 70.9% accuracy, respectively, which is much higher than that of ANN, with 40.2%. And for mechanical condition of CB, the GA-LibSVM can obtain 92.5% accuracy, which is also higher than that of LibSVM and ANN, with 85.0% and 57.5% accuracy, respectively.

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