Fatigue Life Prediction of Ductile Iron Based on DE-SVM Algorithm

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Abstract

the model, predicting fatigue life of ductile iron, based on SVM (Support Vector Machine, SVM) has been established. For it is easy to fall into local optimum during parameter optimization of SVM, DE (Differential Evolution algorithm, DE) algorithm was adopted to optimize to improve prediction precision. Fatigue life of ductile iron is predicted combining with concrete examples, and simulation experiment to optimize SVM is conducted adopting GA (Genetic Algorithm), ACO (Ant Colony Optimization) and POS (Partial Swarm Optimization). Results reveal that DE-SVM algorithm is of a better prediction performance.

Keywords-SVM; DE; Fatigue life of ductile iron; Prediction

1. Introduction

The failure of ductile iron components during use is mostly related to fatigue damage. To predict the fatigue damage degree can prevent. To predict the fatigue damage degree, can prevent institutions sudden accidents. In the process of ductile iron fatigue, obvious changes will occur to internal dislocation density, stress value, number of crack and size. The magnetic properties are more sensitive to these changes, and magnetic permeability along with the increase of fatigue, presents certain variation. Electromagnetic method, based on this principle, can determine the change value of ductile iron magnetic permeability, and estimate its fatigue damage degree and predict service life. Due to the influence of various factors, however, theoretical model of complete and accurate, between ductile iron fatigue damage degree and

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magnetic permeability, can not be established. Reference [1] adopts BP neural network to predict fatigue damage degree of ductile iron, achieving better effects.

SVM theory is one of the newly arising algorithms, and exhibits many distinctive advantages to solve problems, such as small sample, non-linear and distinguishing high-dimension pattern. Thus, it obtains extensive attention and applies to many fields [2, 3]. The character of the SVM attaches much to the type and parameters of the Kernel function, as well as penalty factor. Traditional method optimized parameters is easy to fall into partial and optimal solution, and slow rate of convergence. DE, standing out in optimized functions, is one of the relatively new evolution algorithms, outstanding in function optimization field. DE-SVM neural network prediction model is constructed in this paper, expecting a new approach provided for fatigue life prediction of ductile iron.

2. Support Vector Regression machine

The basic idea is to map the dates \( x \) to high-dimensional feature space \( F \), and then applied the linear regression method in the space. So for observing the specified dataset \( T = \{ (x_1, y_1), \ldots, (x_i, y_i) \} \in (X, Y)^l \), the equation (1) as follows can be used for regression estimation, here \( \omega, b \) is the regression factor.

\[
f(x) = (\omega \cdot \Phi(x)) + b
\]

(1)

Generally, take loss function as the time-insensitive loss function \( c(x, y, f(x)) \), which is defined as the equation (2). By solving

\[
c(x, y, f(x)) = \begin{cases} y - f(x) - \varepsilon, & y - f(x) > \varepsilon; \\ 0, & y - f(x) = \varepsilon; \\ |y - f(x)| - \varepsilon, & y - f(x) < \varepsilon; \end{cases}
\]

(2)

Solve optimal problem (3), obtaining regression factor \( \omega, b \).

\[
\min_{\omega \in \mathbb{R}^n, \zeta^{(*)}, \xi \in \mathbb{R}^l, b \in \mathbb{R}} \tau(\omega, \zeta^{(*)}) = \frac{1}{2} \|\omega\|^2 + C \cdot \frac{1}{l} \sum_{i=1}^{l} (\zeta_i + \zeta_i^*) \]

s.t. \( (\omega \cdot \Phi(x_i)) + b - y_i \leq \varepsilon + \zeta_i, \quad i = 1, 2, \ldots, l; \)

\( y_i - ((\omega \cdot \Phi(x_i)) + b) \leq \varepsilon + \zeta_i^*, \quad i = 1, 2, \ldots, l; \)

\( \zeta_i^* \geq 0, \quad i = 1, 2, \ldots, l; \)

(3)

Where \( C \) is penalty parameter, \( \zeta^{(*)} \) is the vector \( (\zeta_1, \zeta_1^*, \ldots, \zeta_l, \zeta_l^*)^T \). The dual problem (4) can be solved by equation (3), adopting \( \varepsilon \)-SVRM method to get the regression factor.
\[
\begin{align*}
\min_{\alpha^0, \alpha^*} & \quad \frac{1}{2} \sum_{i=1}^{l} (\alpha_i^* - \alpha_i^*)(\alpha_i^* - \alpha_i) K(x_i, x_i) + C \sum_{i=1}^{l} (\alpha_i^* + \alpha_i) - \sum_{i=1}^{l} y_i (\alpha_i^* - \alpha_i) \\
\text{s.t.} & \quad \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) = 0; \\
& \quad 0 \leq \alpha_i, \alpha_i^* \leq \frac{C}{l}, \quad i = 1, 2, \ldots, l;
\end{align*}
\]

(4)

Where \( K(x_i, x_j) = (\Phi(x_i), \Phi(x_j)) \) = Kernel function, is a Symmetric positive real function, at same time satisfy the conditions of Mercer. The usual Kernel function is RBF kernel function \( K(x_i, x_j) = \exp\left[\frac{-|x_i - x_j|^2}{(2\sigma^2)}\right] \).

According to the optimal solution \( \tilde{\alpha} = (\tilde{\alpha}_1, \tilde{\alpha}_1^*, \ldots, \tilde{\alpha}_i, \tilde{\alpha}_i^*) \) by solving (4), the regression factor \( \omega \) can be obtained:

\[
\omega = \sum_{i=1}^{l} (\tilde{\alpha}_i^* - \tilde{\alpha}_i) \Phi(x_i)
\]

(5)

Choose \( \tilde{\alpha}_j \) or \( \tilde{\alpha}_k \) between open interval \( (0, \frac{C}{l}) \). If \( \tilde{\alpha}_j \) is chosen, that:

\[
b = y_j - \sum_{i=1}^{l} (\tilde{\alpha}_i^* - \tilde{\alpha}_i) (x_i, x_j) + \varepsilon
\]

(6)

Or, if \( \tilde{\alpha}_k \) is chosen, that:

\[
b = y_k - \sum_{i=1}^{l} (\tilde{\alpha}_i^* - \tilde{\alpha}_i) (x_i, x_k) - \varepsilon
\]

(7)

3. DE-SVM algorithms

DE realizes the population optimization by the mechanism of cross and variation. In the calculating process, many starting points occurs randomly in the solution space, meanwhile searching, and are guided the searching direction by the fitness function. The main procedure of DE-SVM:

* **Determine the range of variables:** based on references [2] to fix \( \sigma, C \), and \( \varepsilon \);

* **Population initialization**

The \( \sigma, C \), and \( \varepsilon \) need to be mapped to chromosome string of DE in order to make use of DE to
optimize. The relation of mapping code is shown as follows:

\[ \{ \sigma, C, e \} \]  

(8)

For describing conveniently, let \( X_i(t) \) is the \( i \) chromosome of the \( t \) generation, and

\[ X_i(t) = (x_{i1}(t), x_{i2}(t), x_{i3}(t)) \quad i = 1, 2, \ldots, M; t = 1, 2, \ldots, t_{\text{max}} \]  

(9)

Where \( M \) = the population size of \( M \), 
\( t_{\text{max}} \) = the maximum evolution of algebra.

The population initialization of DE is the same as other evolutionary algorithm and the design variable take the floating number randomly and uniform at the upper and lower boundary:

\[ u_{ij} = \begin{array}{ll}
L_{ij} & \text{if } \text{rand}_{ij} \leq 0.5 \\
U_{ij} & \text{if } \text{rand}_{ij} > 0.5
\end{array} \]  

(10)

Where \( u_{ij} \), \( L_{ij} \), \( U_{ij} \) = the \( i \) variable at the upper bound and lower bound separately. \( \text{rand}(1, 0) \) = the random number of the interval \([0, 1]\)

**Variation Operation**

The variation operation of DE is based on the conduction of individual vector difference. Supposing the present evolution individual is \( X_i(t) \), choose three chromosomes randomly from the population generation: \( X_{p_1}(t), X_{p_2}(t), X_{p_3}(t) \), take the difference between the last two individual vectors, then add to the first individual vector after zooming, at the last get the individual after the variation \( U_i(t+1) \):

\[ u_{ij}(t+1) = x_{p_1j}(t) + \eta(x_{p_2j}(t) - x_{p_3j}(t)) \]  

(11)

Where \( \eta \) = the scaling factor.

**Cross Operation**

Individual after variation and evolution present \( X_i(t) \) execute overlapping operation by the method of the Separated overlapping, producing overlapped individuals to increase the diversity of populations. The \( j \) individual can be described as follows.

\[ c_{ij}(t+1) = \begin{cases} 
 u_{ij}(t+1), & \text{rand}_{ij}(0,1) \leq CR \text{ or } j = \text{rand}(i) \\
 x_{ij}(t), & \text{rand}_{ij}(0,1) > CR \text{ or } j \neq \text{rand}(i)
\end{cases} \]  

(12)

Where
Rand (1, 0) = the random number of the interval [0, 1];
Rand (i) = the stochastic integer,
CR = the crossover probability and \( CR \in [0,1] \)

The strategy of cross ensure that there is at least one component contributed to \( X_i(t+1) \) by \( X_i(t) \).

The Fitness function

Define the fitness function \( fit(C, \sigma, \varepsilon) \): the fitness function can be calculated by the following for the given chromosome \( X_i(t) \):

\[
fit\left(X_i(t)\right) = Y_{\text{max}} - Y_i
\]  

(13)

Where

\[
Y_i = (y_i - \hat{y}_i)^2
\]  

(14)

\( y_i \) = the real value of observation set data;
\( y_{\text{max}} \) = the maximum value of \( Y_i \) in the \( t \) generation;

The Select Options

Comparing the fitness function between the cross individual \( C_i(t+1) \) and the present individual \( X_i(t) \), the optimized result is selected according to the greedy approach:

\[
X_i(t+1) = \begin{cases} 
X_i(t) & \text{if } f(X_i(t)) > f(C_i(t+1)) \\
C_{i(t+1)} & \text{if } f(X_i(t)) \leq f(C_i(t+1))
\end{cases}
\]  

(15)

Repeated implementation of the steps C-F, until achieve the maximum of evolution generation \( t_{\text{max}} \).

4. Fatigue Life Prediction of Ductile Iron

Fatigue damage of ductile iron component has the vital significance for safe operation of the equipment. To predict the fatigue damage degree, can prevent institutions sudden accidents. Analyzing the damage mechanism, obvious changes will occur to internal dislocation density, stress value, number of crack and size. The magnetic properties are more sensitive to these changes, and magnetic permeability along with the increase of fatigue, presents certain variation. Take stress amplitude \( \sigma \) and change value of permeability \( \Delta B \) as the input layer of neural network, and fatigue damage degree \( N / N_f \) as output layer.

Sample data uses references. Fatigue experiment is conduct on MTS, and use symmetry cycle load form, Hz 5.0, and sample material is pearlite ductile cast iron after normalizing process. Permeability uses data of reference [3]. When test, in certain stress loads, stop loading after certain fatigue cycle times
and measure the change value of permeability $\Delta B$, and take $N / N_f$ to express fatigue degree, where $N_f$ is the fatigue life corresponding to the stress loads. The test measured 60 groups of data, including 45 data for training of network and the other for network verification. Limited space, the result is given only when the stress amplitude $\sigma$ is 280MPa. The comparison and the relative error comparison, among prediction results of different algorithms and test results is shown in Fig.1, Fig.2.

Figure 1. Comparison of relative errors of different methods
In Fig.1, Fig.2 can be seen that it is acceptable for DE-BP neural network used in fatigue life prediction of ductile Iron. Among various kinds of algorithms, this network adopted DE algorithm is of better prediction results with the maximal relative error of 5.6%.

5. Conclusions

There has important significance to predict fatigue life of ductile iron for ductile iron components security. SVM prediction can overcome shortage completely, which traditional prediction method requires solving lots of nonlinear equations. DE algorithm can optimize SVM parameters effectively. Optimization results of DE algorithm are more obvious than GA, ACO, POS algorithms, which can be seen from the comparison of prediction results, and prediction precision is improved to a certain extent. This paper provides a new approach for fatigue life prediction of ductile iron.

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