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Electromechanical equipment state forecasting based on genetic algorithm – support vector regression

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ABSTRACT

Prediction of electromechanical equipments state nonlinear and non-stationary condition effectively is significant to forecast the lifetime of electromechanical equipments. In order to forecast electromechanical equipments state exactly, support vector regression optimized by genetic algorithm is proposed to forecast electromechanical equipments state. In the model, genetic algorithm is employed to choose the training parameters of support vector machine, and the SVR forecasting model of electromechanical equipments state with good forecasting ability is obtained. The proposed forecasting model is applied to the state forecasting for industrial smokes and gas turbine. The experimental results demonstrate that the proposed GA-SVR model provides better prediction capability. Therefore, the method is considered as a promising alternative method for forecasting electromechanical equipments state.

1. Introduction

With the rapid development of science and technology, the composition and structure of electromechanical equipment are more and more complicated. Once a certain equipment breaks down, chain reaction will be caused (Acevedo-Rodríguez, Maldonado-Bascón, Lafuente-Arroyo, Siegmann, & López-Ferreras, 2009; Katagiri and Abe, 2006; Zhu, Xu, & Zhang, 2009). The whole production system cannot operate smoothly, then huge economic loss will be caused. Prediction of electromechanical equipments state nonlinear and non-stationary condition effectively is significant to forecast the lifetime of electromechanical equipments (Elish & Elish, 2008; Hämäläinen, Klapuri, Saarinen, Ojala, & Kaski, 1996; Valentini, 2002; Whitley et al., 1990). Running conditions of large-scale electromechanical equipment are complicated. When the equipment is in the fault state, its thermal dynamics characteristic exerts complexity and nonlinear. As artificial neural networks have general nonlinear mapping capabilities, it becomes a popular prediction technique in the prediction of electromechanical equipments (Jain, Rahman, & Kulkarni, 2007; Nandi et al., 2004). But the prediction results of artificial neural networks are affected by their drawbacks, such as lack generalization and local optimization solution.

Support vector regression (SVR) is a novel learning machine based on statistical learning theory, which has been successfully used for nonlinear systems modeling. Compared with artificial neural networks, SVM provides more reliable and better performance under the same training conditions (King, Bennett, & List, 2000; Yuan, Zhang, Hu, & Ruan, 2009). How to choose the best training parameters is an important problem for SVR because this problem will directly affect its regression accuracy. In our work, genetic algorithm (GA) is used to optimize the model parameters, and so the generalization ability and forecasting accuracy are improved. Based on the Darwinian principle of 'survival of the fittest', GA can obtain the optimal solution after a series of iterative computations (Chang, Chen, & Liu, 2007; Hardas, Doolen, & Jensen, 2008; Weile & Michielssen, 2000). Therefore, support vector regression optimized by genetic algorithm (GA-SVR) is proposed to forecast electromechanical equipments state. In the model, GA (Jagielska, Matthews, & Whitfort, 1999; Kwon, Kwon, Jin, & Kim, 2003; Pereira & Lapa, 2003) is employed to determine training parameters of support vector machine, and the SVR forecasting model of electromechanical equipments state with good forecasting ability is obtained. The data of electromechanical equipments state are used to test the accuracy of the proposed model. The experimental results show that the GA-SVR model is considered as a promising alternative method for forecasting electromechanical equipments state.

In this paper, Section 2 introduces the theory of support vector regression. In Section 3, GA-based optimization of SVR model is introduced. The structure of electromechanical equipment state forecasting model is introduced in Section 4. In Section 5, experimental analysis for electromechanical equipment state prediction is gained. Finally, the conclusion is gained in Section 6.

2. The theory of support vector regression

SVR follows the principle of structural risk minimization, which has been successfully used for nonlinear systems modeling.

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Consider a training data $g = \{(x_i, y_i)\}_i^n$, such that x_i is a input vector, y_i is the corresponding output value. To fulfill the stated goal, SVR considers following linear estimation function

$$f(x) = \langle w, x \rangle + b \tag{1}$$

where w denotes the weight vector; b denotes the bias.

The coefficients w and b can be estimated by minimizing the regularized risk function

$$R(f) = C\frac{1}{n}\sum_{i=1}^{n} L_\varepsilon(f(x_i) - y_i) + \frac{1}{2}\|w\|^2 \tag{2}$$

where $L(f(x) - y) = \begin{cases} \|f(x) - y\| - \varepsilon & |f(x) - y| \geqslant \varepsilon \\ 0 & |f(x) - y| < \varepsilon \end{cases}$ is called ε-insensitive loss function, the constant $C > 0$ stands for the penalty degree of the sample with error exceeding ε.

Two positive slack variables ξ and ξ^* represent the distance from actual values to the corresponding boundary values of ε-tube. A dual problem can then be derived by using the optimization method to maximize the function:

Maximize

$$-\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}(\alpha_i - \alpha_i^*)\left(\alpha_j - \alpha_j^*\right)K(x_i, x_j) + \sum_{i=1}^{n} y_i(\alpha_i - \alpha_i^*) - \varepsilon\sum_{i=1}^{n}(\alpha_i + \alpha_i^*) \tag{3}$$

Subject to

$$\sum_{i=1}^{n}(\alpha_i - \alpha_i^*) = 0 \quad \alpha_i, \alpha_i^* \in [0, C], \tag{4}$$

where α_i and α_i^* are Lagrange multipliers. Only some of the coefficients, $(\alpha_i - \alpha_i^*)$ are non-zero and the corresponding input vectors are called support vectors.

The SVM obtained by using the above-mentioned maximization function is given by

$$f(x) = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)\langle x_i, x \rangle + b \tag{5}$$

As for the nonlinear cases, the solution can be found by mapping the original problems to the linear ones in a characteristic space of high dimension by kernel function, which is denoted as $k(x_i, x_j) = \varphi(x_i)\varphi(x_j)$.

In the study, radial basis function (RBF) is used to construct SVR as kernel function, where σ is the width of radial basis function.

Hence, the nonlinear regression function is:

$$f(x) = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)k(x_i, x) + b \tag{6}$$

3. GA-based optimization of SVR model

The use of SVR is affected in academic research and industrial applications, because the parameters must be defined appropriately. To construct the SVR model efficiently, SVR's parameters must be set carefully. Inappropriate parameters in SVR lead to over-fitting. Here, the SVR's parameters include C, σ and ε. So the proposed GA-SVR model dynamically optimizes the values of SVR's parameters C, σ and ε, where GA is used to search for better combinations of the parameters in SVR.

Genetic algorithm consists in maintaining a population of chromosomes, each chromosome in the population is randomly generated, and has an associated fitness, the chromosomes are evaluated according to the fitness. Based on the evaluation of fitness, a new population is formed using selection, crossover and mutation.

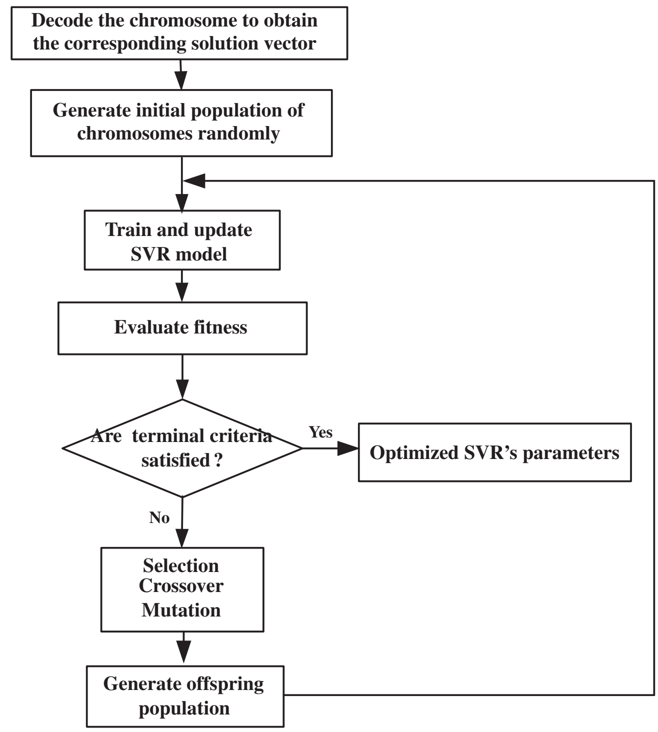

Fig. 1. Schematic for SVR algorithm implementation.

As shown in Fig. 1, the framework of optimizing the SVR's parameters with genetic algorithm is presented, which is described as followings.

(1) **Decode the chromosome:** The SVR's parameters C, σ and ε are directly coded to form a chromosome.
(2) **Generate initial population of chromosomes:** Here, the range of σ is defined as [0 1], the range of C is defined as [1 100], and the range of ε is defined as [0.0001 0.01]. Randomly generate an initial population of chromosomes which represent the values of parameters in SVR. The population size is 20.
(3) **Evaluate fitness:** Leave-one-out cross-validation (LOOCV) of SVR is adopted to seek the optimal values of these SVR's parameters, where LOOCV is used to evaluate fitness. In this study, the fitness function $\frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right|$ is used to evaluate fitness, where y_i represents the actual values in the training data and $\hat{y}_i$ represents validation values in the training data.
(4) **Genetic algorithm operators:** In the operators, standard roulette wheel is performed to select excellent chromosomes to reproduce. Single point crossover is randomly adopted to exchange genes between two chromosomes, the probability of creating new chromosomes in each pair is set to 0.5. The mutation operation follows the crossover operation, and determines whether a chromosome should be mutated in the next generation. Each chromosome in the new population is subject to mutation with a probability of 0.02.
(5) **Judge termination conditions:** If the termination conditions are met, genetic algorithm would be terminated. The best C, σ and ε would be output according to the optimum fitness function value. On the contrary, steps 3–4 are repeatedly executed until C, σ and ε are satisfied with minimum model error.