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Optimization of Generator Stator End Winding Structure Based on Improved PSO and SVM

Yucai Zhou, Ting Wang, Hua Bai, Shuyuan Wang, Bo Deng

School of Advanced Manufacturing, Chongqing University of Posts and Telecommunications, Chongqing, 400065, China

*Yucai Zhou: zhouyucai183@163.com

Abstract. The selection of parameters in the support vector machine (SVM) approximation model plays an important role in the performance of the model. Therefore, the support vector machine parameters need to be optimized. Because the particle swarm algorithm is easy to be premature and easy to fall into the local optimal solution, the improved particle swarm optimization algorithm is used to optimize the parameters, and the support vector machine approximation model with optimal parameters is established. Finally, the support vector machine approximation model of optimal parameters and particle swarm optimization algorithm are combined and used in the optimization of stator end winding structure of large steam turbine generator. The validity of the method is verified by the analysis of the results, and good optimization results are obtained.

1. Introduction

The optimization of the stator end winding structure of a large steam turbine generator is an important part of the overall structural design of the generator. The vibration of large steam turbine generators during operation may affect the structure of the generator and cause serious impact on its life [1,2]. The stator end winding of the generator vibrates under the action of twice the power frequency electromagnetic force or under the action of the electromagnetic force, which will cause damage to the end winding structure, thereby causing serious consequences.

The relationship between the structural characteristics of the stator end windings of the turbogenerator and the load response is complicated. Finite element is needed to accurately calculate the structural characteristics and structural response of the end winding as the objective function or constraint characteristic value in the optimization process. However, finite element calculations typically take a long time, making the time cost of optimization increase.

Support Vector Machine (SVM) is a new machine learning method [5]. SVM is based on the minimization of structural risk and is suitable for high-dimensional nonlinear problems of small samples. It can avoid the over-fitting of neural networks and reduce the generalization ability. In the case, there is a good generalization ability. SVM usually uses radial basis kernel to solve nonlinear regression problems. The selection of penalty parameters, kernel parameters and insensitive parameters is related to the learning and prediction ability of SVM, which directly affects the accuracy of model prediction.

PSO has the advantages of fewer parameters, good convergence, and achievability. Aimed at the shortcomings of PSO being premature and easy to fall into the local optimal solution, the particle swarm optimization algorithm is improved. An improved particle swarm optimization algorithm (IPSO) is proposed and applied to the SVM approximation model parameters. Finally, the SVM approximation model with optimal parameters and the improved particle swarm optimization algorithm are combined into the structural optimization design of the generator stator end winding.

2. Support vector machine regression

Given training samples $D=\{(\boldsymbol{x}_i, y_i) \mid i=1,2,\cdots,n\}$, $\boldsymbol{x}_i$ represent input samples and y_i represents output samples. Construct a linear regression equation as shown in the following equation (1):

$$f(\boldsymbol{x})=(\boldsymbol{w}\cdot\boldsymbol{x})+b \tag{1}$$

Where, $\boldsymbol{w}$ represents the weight vector of n dimension and b represents the bias vector.
Firstly, considering the linear separability of samples, it is assumed that all samples can be fitted with linear functions within the accuracy ε.

$$\begin{cases} y_i-\boldsymbol{w}\cdot\boldsymbol{x}_i-b\le\varepsilon \\ \boldsymbol{w}\cdot\boldsymbol{x}_i+b-y_i\le\varepsilon \end{cases} \tag{2}$$

The original problem is transformed into the following optimization problems. As follows:

$$\begin{aligned} &\min_{w,b}\ \frac{1}{2}\|\boldsymbol{w}\|^2 \\ &s.t.\begin{cases} y_i-\boldsymbol{w}\cdot\boldsymbol{x}_i-b\le\varepsilon \\ \boldsymbol{w}\cdot\boldsymbol{x}_i+b-y_i\le\varepsilon \end{cases} \end{aligned} \tag{3}$$

If the fitting error is allowed to exceed ε, the relaxation factor is introduced, and then the optimization problem in equation (3) is transformed into:

$$\begin{aligned} &\min_{w,b}\ \frac{1}{2}\|\boldsymbol{w}\|^2+C\sum_{i=1}^{N}(\xi_i+\xi_i^*) \\ &s.t.\begin{cases} y_i-\boldsymbol{w}\cdot\boldsymbol{x}_i-b\le\varepsilon+\xi_i \\ \boldsymbol{w}\cdot\boldsymbol{x}_i+b-y_i\le\varepsilon+\xi_i^* \\ \xi_i,\xi_i^*\ge 0,(i=1,2,\cdots,n) \end{cases} \end{aligned} \tag{4}$$

Using the dual principle of the optimal method, the following form can be obtained:

$$\begin{aligned} &\min\ \frac{1}{2}\sum_{i,j=1}^{n}(\alpha_i-\alpha_i^*)(\alpha_j-\alpha_j^*)(\boldsymbol{x}_i\cdot\boldsymbol{x})-\sum_{i=1}^{n}(\alpha_i-\alpha_i^*)y_i+\sum_{i=1}^{n}(\alpha_i+\alpha_i^*)\varepsilon \\ &s.t.\ \begin{cases} \sum_{i=1}^{n}(\alpha_i-\alpha_i^*)=0 \\ 0\le\alpha_i,\alpha_i^*\le C \end{cases} \end{aligned} \tag{5}$$

The support vector machine fitting function is obtained by equation (5):

$$f(\boldsymbol{x})=\sum_{i=1}^{n}(\alpha_i-\alpha_i^*)(\boldsymbol{x}_i\cdot\boldsymbol{x})+b \tag{6}$$

In the high-dimensional feature space, the kernel function is used to replace the inner product operation in the linear problem, that is:

$$K(\boldsymbol{x}_i,\boldsymbol{x})=\phi(\boldsymbol{x}_i)\phi(\boldsymbol{x}) \tag{7}$$

The final regression function expression is as follows:

$$f(\boldsymbol{x})=\sum_{i=1}^{n}(\alpha_i-\alpha_i^*)K(\boldsymbol{x}_i,\boldsymbol{x})+b \tag{8}$$

The commonly used kernel function is Radial Basis Function (RBF), that is:

$$K(\boldsymbol{x}_i,\boldsymbol{x})=\exp(-\|\boldsymbol{x}_i-\boldsymbol{x}\|^2/2\sigma^2) \tag{9}$$

3. Particle Swarm Optimization

The update equation of position and speed is:

$$v_i^{k+1} = wv_i^k + c_1 r_1 (p_i^k - x_i^k) + c_2 r_2 (p_g^k - x_i^k)$$
$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{10}$$

In order to better balance the global search ability and the local search ability. In literature [8], the author proposed a linear decline strategy based on inertia weight value, which can be expressed as follows:

$$w = w_{\max} - \frac{(w_{\max} - w_{\min}) \times k}{k_{\max}} \tag{11}$$

Where, $w_{\max}$ and $w_{\min}$ are the initial inertia weight and the final inertia weight respectively, $k_{\max}$ is the maximum number of iterations, and k is the current number of iterations.

3.1. Improved Particle Swarm Optimization

3.1.1. Improvement of inertia weight

In order to maintain a high search efficiency for the particle swarm optimization algorithm, it should be ensured that the previous period is kept large for a long period of time and kept small for a long period of time. Therefore, the inertia weight is corrected as shown in Equation 12.

$$w=\begin{cases} w_{\max} - \dfrac{w_{\max} - w_{\min}}{k_{\max}^2} k^2 & ,k \le \dfrac{k_{\max}}{2} \\ w_{\max} + \dfrac{w_{\max} - w_{\min}}{k_{\max}^2} (k_{\max} - k)^2 & ,k > \dfrac{k_{\max}}{2} \end{cases} \tag{12}$$

3.1.2. Discrete Processing

In the optimization process, variables such as the cross-sectional area of the bar, the stiffness of the ring, and the stiffness of the radial bracket are discrete. In the literature [9], the author proposed the binary particle swarm optimization algorithm (BPSO) to solve the discrete problem. The iterative formula for particle position is modified as follows:

$$x_i^k = \begin{cases} 1, & if\ rand() < sig(v_i^k) \\ 0, & else \end{cases} \tag{13}$$

$$sig(v_i^k) = \frac{1}{1 + e^{(-v_i^k)}} \tag{14}$$

$sig(v_i^k)$ represents the sigmoid function, which constrains v_i^k between [0,1] and $rand()$ represents a random number between [0,1].

4. SVR parameter optimization

The improved particle swarm optimization SVR parameters. The sample points are first obtained by finite element calculation. In order to realize the modeling of SVR, the LIBSVM toolbox developed by Professor Chih-Jen Lin of Taiwan University [11] was adopted. In the parameter selection process, the K-fold cross-validation selection method can avoid over-fitting and improve the accuracy of the support vector machine. The effect of the approximate model prediction is evaluated using the mean square error MSE and the square correlation coefficient r^2, where the mean square error is used as the fitness value of the optimization problem.

4.1. Parameter settings

The value range of C is [2^{-10},2^{10}], the value range of σ is [2^{-10},2^{10}], the value range of ε is [0,1], and the cross-validation K has a value of 5, and the population size is 50, the number of iterations is 200, the crossover rate is 0.4, the mutation rate is 0.01, the learning factor $c_1 = c_2$ =2, the initial inertia weight is w_{max} =0.9, the final inertia weight is w_{min} =0.4.

4.2. Optimization results

Figures 1, 2 and 3 show the fitness curves for optimized SVR for PSO and IPSO when K is 5. When using PSO to optimize SVR parameters, the accuracy is not ideal. IPSO has the highest accuracy and short running time. Therefore, the SVR approximation model based on IPSO optimization has achieved good results in predicting the nonlinear structure response of the end windings. It can also be concluded that IPSO has a good ability to select SVR parameters.

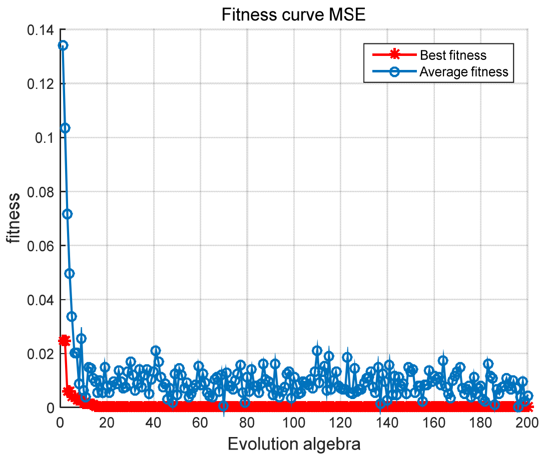

Figure 1. PSO optimized SVR fitness curve

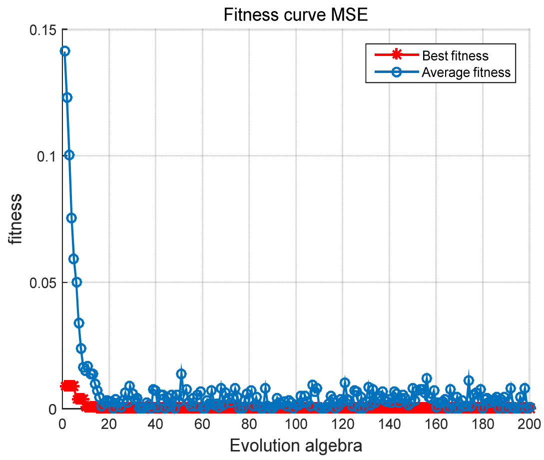

Figure 2. IPSO optimized SVR fitness curve

5. End winding structure optimization

5.1. Optimization problem mathematical model

The stator end winding of 600MW steam turbine generator is taken as the research object. The structure diagram is shown in Figure 3. The structural parameters and material parameters are used as design variables. The meaning of each design variable is shown in Table 1，the optimal objective function is the minimum vibration displacement.

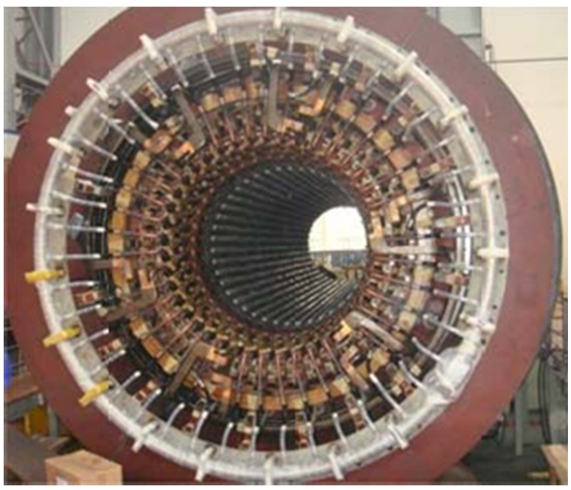

Figure 3. Finite element model of the end winding structure

Table 1. Design Variable Information Table

variable	variable name
x_1	Bar cross-sectional area
x_2	Binding stiffness
x_3	Radial bracket stiffness
x_4	Linking stiffness between sliding pin and copper bracket
x_5	Linking stiffness between L-type bracket and pin bolt
x_6	Linking stiffness between sliding pin and radial bracket
x_7	Number of spacers between upper and lower rods

5.2. Optimization Process

The optimization method combining the support vector machine approximation model and the particle swarm optimization algorithm is carried out in two steps: the first step is to collect samples by finite element analysis, and the MATLAB platform is programmed to establish a support vector machine approximation model with optimal parameters; The step is to support the vector machine approximation model instead of the finite element calculation, and the improved particle swarm optimization algorithm is used to search for the optimal value.

5.3. Optimization results

The end winding structure model of turbogenerator stator is optimized by improved particle swarm optimization (PSO), standard particle swarm optimization (PSO) and genetic algorithm (GA). The population size was set as 100, the learning factor $c_1 = c_2 = 2$, $w_{max} = 0.9$, $w_{min} = 0.4$, the mutation rate was 0.06, and the crossover rate was 0.5. The final optimization results are shown in Figure 7.

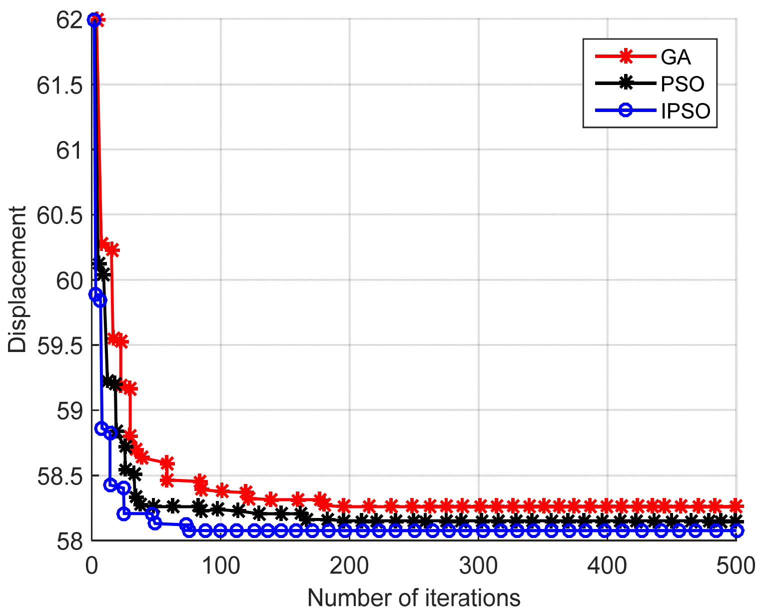

Figure 4. Comparison of convergence of various optimization algorithms

In the three algorithms, the natural frequencies corresponding to the elliptical modes satisfy the constraints, and it can be concluded that the improved particle swarm optimization algorithm can reduce the maximum displacement of the end windings by 1.45 μm. The standard particle swarm optimization (PSO) method can reduce the maximum displacement of the end winding by 1.37 μm, and the genetic algorithm (GA) can reduce the maximum displacement of the end winding by 1.26 μm.

As can be seen from Figure 4, the improved particle swarm optimization algorithm has a faster convergence speed and a better solution.

6. Conclusion

The improved particle swarm optimization algorithm is used to optimize the parameters of the support vector machine approximation model, and the support vector machine approximation model with optimal parameters is established. The support vector machine approximation model and the improved particle swarm optimization algorithm are then used to optimize the stator end winding structure. Through the result analysis, the approximate model is used instead of the finite element calculation to optimize the structure, so as to deal with the long time-consuming problem in the optimization of the end winding structure of the large steam turbine stator generator, improve the optimization efficiency, and obtain the optimized analysis result with good precision, which provides new practical and feasible solutions for the optimization of complex structures.

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