Life Cycle Cost Prediction of Substation Based on Advanced PSO and Least Squares Support Vector Machine

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Abstract: The rapid prediction of the full life cycle cost of substation has guiding significance for the construction of substation. In this paper, a substation full life cycle cost prediction model based on advanced particle swarm optimization (advanced PSO, APSO) least squares support vector machine is established. The relevant characteristic index of the substation life cycle is used as the input of the model, and the output is the substation full life cycle cost. The simulation results are compared with the prediction results of APSO optimized LS-SVM, traditional LS-SVM, BP neural network four prediction models and related performance indicators. The simulation results show that the APSO optimized LS-SVM model has better prediction accuracy, and can predict and evaluate the life cycle cost quickly and accurately during substation design and construction, and improve the economics of substation construction.

1. Introduction
Substation construction is an important part of power grid construction, and its level of construction is directly related to the economy and security of power grid[1]. At present, the substation construction in our country has problems such as long period of construction, highcost of operation and maintenance. Attention is only paid to the construction cost in the early stage and little to the management in the later stage, which leads to the low benefit of substation construction. In the long term, a solution is needed to take the whole life cycle cost of substation as the target to guide the construction of substation[2-3].

Life cycle is defined as the process from planning, construction, operation to scrapping. Substation Life Cycle Cost (LCC) includes all direct and indirect costs in research stage, design stage, construction stage, operation stage and scrap stage. Literature [4] introduced the composition analysis of substation cost in each stage, and revised the relevant economic parameters of LCC; Literature [5] introduced some estimation methods of LCC; Literature [6] summarized some defects of LCC cost analysis. With the continuous development of LCC theory, more and more research on LCC modeling has been done. Current studies have proposed that the cost of substation LCC includes initial, operation, fault and scrap costs, and established their mathematical models respectively for the above four costs[7].
Due to the incomplete preservation of the relevant historical data of substation LCC, the establishment of LCC prediction model belongs to small sample and non-linear problem. Relevant scholars use neural network algorithms which have strong performance in solving non-linear problems to model prediction, but ignore the problem that neural network is easy to oversaturate on small sample problems and then fall into local optimum\[^8\]. The least squares support vector machine (LS-SVM) algorithm has a good effect in solving small sample problems, but its parameters are selected by experience, leading to a certain chance\[^9\]. Therefore, in order to improve the prediction performance of LS-SVM algorithm, it is necessary to optimize the parameters of LS-SVM algorithm. In reference \[^10\], ant colony optimization (ACO) algorithm is used to optimize LS-SVM to fit measurement data, but it fails to solve the problem of poor generalization ability of ACO algorithm. Document \[^11\] uses particle swarm optimization (PSO) to optimize LS-SVM for data prediction, but slow convergence speed of PSO leads to a certain impact on the prediction accuracy, while the advanced PSO is needed to improve the convergence speed.

2. Least squares support vector machine

Support Vector Machine (SVM) is a kind of machine algorithm. It can get better results in the face of non-linear and small sample problems, and it has significant advantages over other machine algorithms in over-fitting and falling into local optimum. The least squares support vector machine (LS-SVM) algorithm uses the square sum error loss function to replace the insensitive loss function in the SVM algorithm, and uses equality constraints to obtain linear equations, which is an improvement and extension of the SVM algorithm.

Given the following training sample set \(D=\{(x_i, y_i)\mid i=1,2,3...N\}\), where \(x_i\) is the input sample and \(y_i\) is the output sample. For non-linear regression, LS-SVM uses the following model to model sample data

\[
y(x) = \omega^T \phi(x) + b + e_i
\]

In Formula above, \(\omega\) represents the weight vector and \(\phi(x)\) represents a non-linear function. Its function is to map the input space to the high-dimensional feature space. \(b\) is the deviation, and \(e_i\) represents the fitting error. It is the actual training output and estimated output error of data of group \(i\). \(\omega\) and \(b\) can be obtained from the following optimization problems:

\[
\min_{\omega, b, e} J(w, e) = \frac{1}{2} \omega^T \omega + \gamma \frac{1}{2} \sum_{i=1}^{N} e_i^2
\]

Formula above satisfies equality constraints:

\[
y_i = \omega^T \phi(x_i) + b + e_i, i = 1,2,3...N
\]

The first part on the right side of Formula 2 is to adjust the weight and punish the large weight. The second part represents the error of training data.

Formula above defines Lagrange function \(L\):

\[
L(w, b, e, \alpha) = J(w, e) - \sum_{i=1}^{N} \alpha_i \{ \omega^T \phi(x_i) + b + e_i - y_i \}
\]

In formula above, \(\alpha_i\) is a Lagrange multiplier and \(\gamma\) is a penalty parameter, which balances the complexity of LS-SVM model, such as \(y(x)\) and training error. According to the optimization conditions of KKT (Karush-Kuhn-Tucker), the partial derivatives of Formula 4 for \(\omega, b, e\) and \(\alpha_i\) are obtained respectively, and they are all 0. The optimum conditions are obtained.
Eliminate $\omega$ and $e_i$ to get LS-SVM regression model:

$$y(x) = \sum_{i=1}^{N} \alpha_i K(x, x_i) + b$$

Among it, $K(x, x_i)$ is the kernel, $x$ represent the input vectors of training samples, and $x_i$ is the center of kernels. $\alpha$ and $b$ are solutions of formula ahead.

### 3. LCC Prediction Model of Substation Based on APSO Optimized LS-SVM Algorithms

#### 3.1 SVM Model of Substation LCC

In recent years, the research on the life cycle cost of substation has become a hot research topic, because the data related to LCC of substation have the problems of serious data loss and small quantity, and the related parameters have obvious non-linear relationship with LCC cost, so the LCC prediction of substation accords with the characteristics of small sample and non-linear prediction. In this paper, LS-SVM algorithm with good performance for solving small sample and non-linear prediction problem is selected for regression prediction.

Feature parameters have an important impact on LS-SVM. Excessive selection of feature parameters will increase the complexity of the algorithm, and inadequate selection will affect the accuracy of the algorithm prediction. Most of the existing studies on characteristic parameters are based on the comprehensive sensitivity analysis system to study the impact of each parameter on the cost of LCC. In this paper, the following 15 representative variables are selected as input vectors of LS-SVM model and the total cost of LCC as output vectors, as shown in Table 1.

| Input vector | Output vector |
|--------------|---------------|
| $x_1$ | Operation and Maintenance Rate |
| $x_2$ | Social discount rate |
| $x_3$ | Inflation rate |
| $x_4$ | Scrap rate |
| $x_5$ | Average annual failure rate of equipment |
| $x_6$ | Initial investment cost/10,000 yuan |
| $x_7$ | Annual breakdown time |
| $x_8$ | Average annual overhaul cost/10,000 yuan |
| $x_9$ | Unit Outage Compensation Cost |
| $x_{10}$ | Average annual cost of troubleshooting/10,000 yuan |
| $x_{11}$ | Substation life cycle |
| $x_{12}$ | Annual Outage Power/kw*h |
| $x_{13}$ | Electricity price |
| $x_{14}$ | Average Annual Failure Repair Time |
| $x_{15}$ | Annual average unplanned outage |
| $y$ | Total cost of LCC |
From the research of LS-SVM model in the last section, the prediction model of LCC total cost of substation based on LS-SVM can be gotten as:

$$LCC(x) = \sum_{i=1}^{N} \alpha_i K(x, x_i) + b$$

Among it, $x$ is the input variable and the total cost of LCC is the output of the prediction model.

### 3.2 SVM Model Based on advanced PSO Optimization

Advanced particle swarm optimization (APSO) is an improvement and optimization of particle swarm optimization (PSO). The convergence speed is significantly faster than PSO, and the optimal solution can be obtained in the whole space. The purpose of APSO is to solve the premature convergence problem of PSO algorithm[12]. In APSO, the updating of particle position is determined by the following formula:

$$x_{ib}(t+1) = p_b + \beta \frac{1}{M} \sum_{i=1}^{M} p_{ib} - x_{ib}(t)$$

$$m_{bestb} = \frac{1}{M} \sum_{i=1}^{M} p_{ib}$$

$$p_b = \varphi p_{ib} + (1-\varphi)p_{gb}$$

$$\beta = 0.5 + 0.5(T_{max} - t) / T_{max}$$

In formula above, $x_{ib}(t)$ and $x_{ib}(t+1)$ represent the position of particles in $t$ dimension after $t$ times and $t+1$ times iteration; $\beta$ is the contraction expansion coefficient affecting the convergence rate; $T_{max}$ is the maximum number of iterations; $m_{bestb}$ is the optimal position of the mean value of particle swarm in $t$ dimension; $M$ is the number of particles in particle swarm; $p_b$ is the random point of particle convergence in $b$ dimension; $p_{ib}$ is the suboptimal position of $i$ particle in $b$ dimension history; $p_{gb}$ particle swarm is the global optimal position; $u$ and $\varphi$ are the random number between $(0,1)$.

### 4. Example analysis

The simulation data in this paper are derived from the substation parameters provided by a Party A unit of the National Grid. There are 35 sets of data, 30 of which are training samples and 5 are testing samples.

As the value of $\gamma, \sigma^2$ in traditional LS-SVM model is mostly based on experience, in reference [7], the value of $\gamma, \sigma^2$ is 10, 2 respectively. The input and output nodes of the BP neural network model are 15 and 1 respectively. Purelin function is chosen as the output layer function, Tansig function as the hidden layer function, Levenberg-Marquardt algorithm as the training function, the learning rate is 0.01, and the termination accuracy is $10^{-4}$. The comparison between the four predictions and the actual LCC values is shown in Table 2.

| Test sample number | 1     | 2     | 3     | 4     | 5     |
|--------------------|-------|-------|-------|-------|-------|
| LCC actual value   | 61010.42 | 57315.88 | 60760.97 | 57036.29 | 59029.58 |
| APSO-LS-SVM        | 61748.64 | 55860.06 | 59029.29 | 57446.95 | 57666.01 |
| Traditional LS-SVM | 59277.72 | 56714.06 | 62328.60 | 55718.76 | 59896.74 |
| BP                 | 62859.03 | 55355.59 | 58950.30 | 55171.21 | 60642.10 |

From Table 2, it can be seen that the prediction results of APSO-LS-SVM model are closer to the actual values than other prediction models, so the prediction accuracy is higher.

The prediction performance of the four prediction models is compared and shown in Table 3. The $e_{MAPE}$ is used as an evaluation index to evaluate the prediction performance of the model.

| prediction model | $e_{MAPE}$ |
|------------------|------------|
| APSO-LS-SVM      | 2.04%      |
Traditional LS-SVM  2.95%  
BP  3.87%

Table 3 shows that the average relative error of APSO-LS-SVM prediction model is 2.04%, which is less than the other three prediction models. BP neural network model based on empirical risk minimization principle is easy to over-fit when dealing with small sample problems. Compared with PSO optimization LS-SVM model, it also has a certain improvement in prediction accuracy and convergence speed, and has better prediction function and adaptability.

5. Concluding remarks
In this paper, APSO is used to optimize the parameters of LS-SVM model, which avoids the problem that the parameters of traditional LS-SVM model depend on experience and the accuracy of simulation results is low. The forecasting results and performance indexes of four models, APSO-LS-SVM, traditional LS-SVM and BP neural network, are analyzed and compared by examples. The simulation results show that the APSO-LS-SVM prediction model has better prediction accuracy than other models. By investigating the corresponding characteristic parameters and introducing the proposed prediction model, the whole life cycle cost of substation can be predicted quickly and accurately, which has a certain reference to the planning and construction of substation.

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