COST PREDICTION ON FABRICATED SUBSTATION CONSIDERING SUPPORT VECTOR MACHINE VIA OPTIMIZED QUANTUM PARTICLE SWARM OPTIMIZATION

by

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At present, the prediction of the life cycle cost of fabricated substation is of great significance for the construction of fabricated substation. An enhanced prediction model based on quantum particle swarm optimization (QPSO) via least squares support vector machine is established. The relevant characteristic index of the life cycle of the fabricated substation is used as the input of the model, and the output is the life cycle cost. The simulation results are compared with the prediction results of QPSO optimized least squares support vector machine (LS-SVM), PSO optimized LS-SVM, traditional LS-SVM, and backpropagation neural network, which shows that the QPSO optimized LS-SVM model has better prediction accuracy, can predict and evaluate the life cycle cost more quickly, and can improve the benefits of fabricated substation construction.

Keywords: *life cycle cost, quantum PSO, LS-SVM, characteristic parameters, fitness function*

Introduction

Fabricated substation is the direction of developing on the construction of substations. At present, the fabricated substation construction has the major problem, which is the high cost of operation and maintenance. While the attention is only paid to the construction cost in the early stage but little to the management in the long-term stage, which leads to the low benefit of fabricated substation construction. Therefore, taking the whole life cycle cost of fabricated substation as the target is needed to guide the cost of construction of fabricated substation [1-3].

As the classification of life-cycle cost (LCC) cost in fabricated substation is more and more detailed, the complexity and calculation amount of the mathematical model are gradually increased [4, 5]. The error of calculating LCC cost by using the mathematical model increases, and the objectivity decreases [6]. A prediction model is needed that can objectively estimate LCC. Using intelligent algorithm to predict LCC in fabricated substation has become a hot research topic at present [7].

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In this paper, the LS-SVM algorithm with good regression and fitting ability is selected to predict LCC cost [8, 9]. The QPSO is used to optimize the parameters of LS-SVM. QPSO algorithm solves the premature convergence problem of PSO algorithm, and improves the convergence speed compared with PSO algorithm [10, 11]. The global optimal solution of LS-SVM model parameters is found by QPSO algorithm, and the LCC prediction model of LS-SVM fabricated substation based on QPSO optimization is established. Selecting some representative characteristic vectors in the whole life cycle of fabricated substation as input vectors of the prediction model, the paper compares the LS-SVM model optimized by QPSO, LS-SVM model optimized by PSO, traditional LS-SVM model, the prediction results of BP neural network model and related prediction performance indicators through example analysis, and proves that the prediction model of QPSO-LS-SVM has better prediction performance and accuracy in LCC cost prediction of fabricated substation.

Least squares support vector machine

The SVM 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 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.

According to the optimization conditions of Karush-Kuhn-Tucker (KKT) the partial derivatives of eq. (1) for ω, b, e_i, and α_i are obtained, respectively, and they are all 0. The optimum conditions are obtained:

$$\begin{cases} \dfrac{\partial L}{\partial w} = 0 \rightarrow w = \sum\limits_{i=1}^{N} \alpha_i \varphi(x_i) \\ \dfrac{\partial L}{\partial b} = 0 \rightarrow \sum\limits_{i=1}^{N} \alpha_i = 0 \\ \dfrac{\partial L}{\partial e_i} = 0 \rightarrow \alpha_i = \lambda e_i \\ \dfrac{\partial L}{\partial \alpha_i} = 0 \rightarrow \omega^T \varphi(x_i) + b + e_i - y_i = 0 \end{cases} \tag{1}$$

Eliminate ω and e_i to get LS-SVM regression model:

$$y(x) = \sum_{i=1}^{N} \alpha_i K(x, x_i) + b \tag{2}$$

where $K(x, xi)$ is the kernel, x represents the input vectors of training samples, and x_i is the centre of kernels, and α and b are solutions of eq. (2). Because of the non-linear relationship between fabricated substation LCC and the selected vectors, the radial basis function (RBF), which is suitable for solving non-linear problems and has fewer kernel parameters, is selected as the kernel function used in the study:

$$K(x, x_i) = \exp\left(-\frac{\|x - x_i\|^2}{2\sigma^2} \right) \tag{3}$$

where σ^2 is the nuclear parameter. Penalty parameter, γ, and kernel parameter, σ^2, have great influence on the accuracy of LS-SVM prediction model. The generalization ability of the model increases with the decrease of γ, but the training error of the sample increases. The smaller σ^2 is, the higher the complexity of the model, and the larger σ^2 is, the easier it will lead to under-learning. Reasonable values of γ and σ^2 are the key to the success of the prediction model.

The LCC prediction model of fabricated substation based on QPSO optimized LS-SVM algorithms

The LS-SVM model of fabricated substation LCC

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 tab. 1.

Table 1. Input and output of the LS-SVM model

Input 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}	fabricated 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
Output vector	y	Total cost of LCC

From the research of LS-SVM model in the last section, the prediction model of LCC total cost of fabricated substation based on LS-SVM can be gotten:

$$LCC(x) = \sum_{i=1}^{N} \alpha_i K(x, x_i) + b \tag{4}$$

where x_i is the input variable and the total cost of LCC is the output of the prediction model.

The LS-SVM model based on QPSO optimization

The QPSO is an improvement and optimization of PSO. The convergence speed is significantly faster than PSO, and the optimal solution can be obtained in the whole space. The purpose of QPSO is to solve the premature convergence problem of PSO algorithm [12]. The position and velocity of particles cannot be determined simultaneously in quantum space. How to describe the state of particles is the core of QPSO algorithm. Wave function is used to solve the problem of describing the state of particles. The probability density function of particles at a certain position in space can be obtained by Schrodinger equation, and then the specific position of particles can be obtained by Monte-Carlo stochastic simulation. In QPSO, the updating of particle position is determined by the following formula:

$$\begin{cases} x_{ib}\left(t+1\right)=p_b \pm \beta\left|m_{\mathrm{best}b}-x_{ib}\left(t\right)\right|\ln\dfrac{1}{u} \\ m_{\mathrm{best}b}=\dfrac{1}{M}\sum\limits_{i=1}^{M}p_{ib} \\ p_b=\varphi p_{ib}+\left(1-\varphi\right)p_{gb} \\ \beta=0.5+0.5\dfrac{T_{\max}-t}{T_{\max}} \end{cases} \tag{5}$$

where $x_{ib}(t)$ and $x_{ib}(t+1)$ represent the position of particles in t dimension after t times and $t+1$ times iteration, β – the contraction expansion coefficient affecting the convergence rate, $T_{\max}$ – the maximum number of iterations, $m_{\mathrm{best},b}$ – the optimal position of the mean value of particle swarm in t dimension, M – the number of particles in particle swarm, p_b – the random point of particle convergence in b dimension, p_{ib} – the suboptimal position of i particle in b dimension historically, p_{gb} – particle swarm is the global optimal position, and u and φ are the random number between (0,1).

In order to verify the predictive effect of the proposed model, the mean square error (MSE) and the average relative error (e_{MAPE}) are selected as the evaluation indexes:

$$MSE=\frac{1}{N}\sum_{i=1}^{N}\left(y_i^{'}-y_i\right)^2 \tag{6}$$

$$e_{\mathrm{MAPE}}=\frac{1}{N}\sum_{i=1}^{N}\left|\frac{y_i^{'}-y_i}{y_i}\right| \tag{7}$$

where $y_i^{'}$ is the output value of the prediction model and y_i is the true value.

Using QPSO to optimize LS-SVM parameters (γ, σ^2) and the algorithm steps of LCC cost prediction for fabricated substation are as:

– Because of the different dimension of sample data and the large difference of data magnitude, data normalization is carried out first.
– Determine the particle swarm parameters, such as the number of particles M, the range of contraction expansion coefficient β, $T_{\max}$, *etc.*, and initialize all particle position vectors (γ, σ^2).
– Selecting MSE as fitness function, LS-SVM is trained through the current particle position vector, and fitness value is calculated to update the optimum p_{ib} and global optimum p_{gb} of each particle.
– Calculate the optimal position of the particle swarm $m_{\mathrm{best},b}$, and update the new position of each particle.
– Check the particle position to determine whether it satisfies the end-of-iteration condition.

If the fitness value satisfies the accuracy requirement or reaches the maximum number of iterations, the optimization process ends, and the current particle optimal position is the final optimization result. Otherwise, returned to step 3 and continue the iteration.

Example analysis

Sources of simulation data

The simulation data in this paper are derived from the fabricated 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. Some training samples are shown in tab. 2.

Table 2. Partial training sample

Group number	1	2	3	4	5	6	7	8
x_1	0.02399	0.02695	0.02601	0.02817	0.02252	0.02765	0.02243	0.02789
x_2	0.0793	0.0746	0.07333	0.07958	0.07847	0.0769	0.0746	0.0683
x_3	0.02430	0.0302	0.02896	0.02828	0.02656	0.0289	0.0259	0.0283
x_4	0.02327	0.0247	0.02835	0.02171	0.02474	0.0256	0.0236	0.0236
x_5	3.39	3.63	3.49	3.7774	3.2118	3.68	3.16	3.79
x_6	33789.7	29888.9	32710.6	29327.7	34514.5	30340.9	35247.5	27871.9
x_7	48.0495	45.42	49.9902	46.8842	49.1567	45.5234	48.98	46.35
x_8	31	28	28	25	26	23	29	30
x_9	0.00253	0.002795	0.002536	0.002595	0.002354	0.002532	0.002455	0.002469
x_{10}	0.047	0.039	0.038	0.048	0.058	0.053	0.037	0.035
x_{11}	39	38	39	37	42	38	41	35
x_{12}	150000	170000	110000	250000	260000	250000	230000	180000
x_{13}	0.00004	0.00004	0.00005	0.00005	0.00004	0.00004	0.00005	0.00005
x_{14}	10	7	7	9	8	10	6	9
x_{15}	16000	18000	15000	26000	29290	16000	15000	23000
y	53004.5	51837.3	55073.2	54301.8	60514.6	53834.2	59602.6	51888.4

Data preprocessing

As the training sample data have different dimensions and large differences, in order to avoid its impact on the prediction performance of the model, the training sample data are normalized:

$$x_i' = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{8}$$

where x_i' is the normalized value of the sample data x_i, and $x_{\min}$ and $x_{\max}$ are the minimum and maximum values of each sample data.

The LS-SVM parameter optimization results

In this paper, QPSO and PSO are used to optimize LS-SVM model, and training samples are forecasted. Value of γ, σ^2 is obtained when it meets the accuracy requirement of fitness function, and parameter optimization of γ, σ^2 is completed [13]. When using QPSO optimization algorithm, the particle dimension is 2, the population number M = 30, the maximum number of iterations $T_{\max}$ = 300, the range of γ, σ^2 is [0,100], [0,500] [14], and the termination accuracy is 10^{-6}. When using PSO algorithm, particle dimension, population number, maximum number of iterations, range of γ, σ^2 is as same as QPSO, acceleration coefficient C_1, C_2 are 1, adaptive threshold k = 0.5. When optimization genetic algorithm is adopted, the mutation probability is set to 0.01 and the crossover probability is set to 0.9.

The fitness curve of LS-SVM optimized by QPSO is shown in fig. 1, when the evolution algebra is about 50 generations, and the corresponding parameter combination is LS-SVM optimal parameter combination.

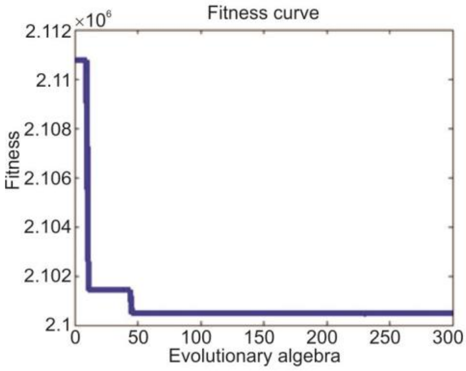

Figure 1. The QPSO-LS-SVM fitness curve

The results of LS-SVM parameters optimization by the two optimization algorithms are shown in tab. 3.

Table 3. The LS-SVM parameter optimization results

Optimization algorithm	Parameter	Parameter
PSO	245	14.152
QPSO	266	11.213

Analysis of prediction results

In this paper, LS-SVM model optimize by QPSO, LS-SVM model optimize by PSO, traditional LS-SVM model and BP neural network model are tested by the data in tab. 2.

Because the value of γ, σ^2 in traditional LS-SVM model is mostly based on experience, in [7], the value of γ, σ^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 fig. 2 and tab. 4.

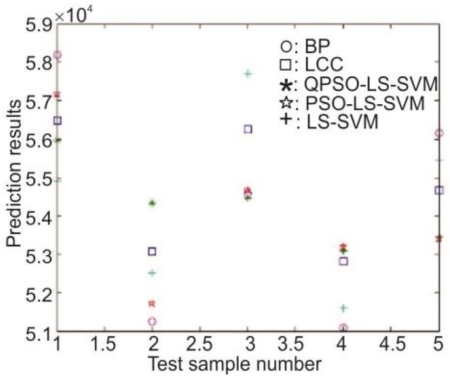

Figure 2. Comparison of prediction results of four prediction models

Table 4. Comparison of predicted and actual values of different models

Test sample number	1	2	3	4	5
LCC actual value	59315.69	54131.67	56822.76	56508.18	59029.58
QPSO-LS-SVM	58771.00	55418.96	55015.80	56817.91	57708.37
PSO-LS-SVM	60033.40	52756.73	55203.32	56915.03	57666.01
Traditional LS-SVM	57631.12	53563.28	58288.79	55202.84	59896.74
BP	61112.95	52280.28	55129.45	54660.36	60642.10

According to fig. 2 and tab. 4, the prediction results of the QPSO-LS-SVM model are closer to the actual values than other prediction models, so the prediction accuracy is higher.

The relative error curves between the simulated predicted values and the actual values obtained by the four prediction models are shown in fig. 3.

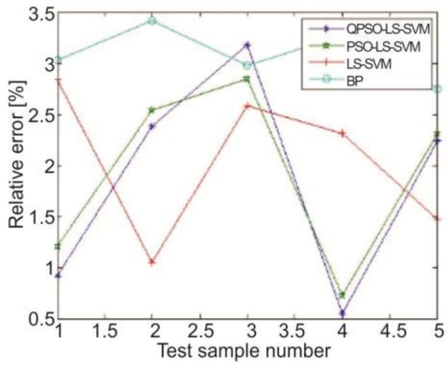

Figure 3. Relative error of four prediction models

From fig. 3, the analysis shows that LS-SVM model has higher prediction accuracy in dealing with LCC prediction of fabricated substation than BP neural network model, which is easy to be over-saturated and trapped in local optimum in solving small sample problems. The prediction accuracy of LS-SVM model optimized by QPSO is better than that of LS-SVM optimized by PSO, which proves that the optimization and selection of LS-SVM parameters adopted by QPSO algorithm can improve the prediction performance of the prediction model.

The prediction performance of the four prediction models is compared and shown in tab. 5. The e_{MAPE} is used as an evaluation index to evaluate the prediction performance of the model.

Table 5. Comparison of prediction performance of different models

Prediction model	e_{MAPE}
QPSO-LS-SVM	1.59%
PSO-LS-SVM	1.85%
Traditional LS-SVM	2.79%
BP	3.13%

Table 5 shows that the average relative error of QPSO-LS-SVM prediction model is 1.59%, 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. QPSO-LS-SVM model solves the problem of poor generalization ability of BP neural network model 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.

Conclusions

In this paper, QPSO 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 LCC cost prediction model of fabricated substation based on QPSO optimization LS-SVM is established. The forecasting results and performance indexes of four models, QPSO-LS-SVM, PSO-LS-SVM, traditional LS-SVM and BP neural network, are analysed and compared by examples. The simulation results show that the QPSO-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 fabricated substation can be predicted quickly and accurately, which has a certain reference to the planning and construction of fabricated substation.

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Nomenclature

ω, b, e_i, α_i	– partial derivatives of KKT	y_i	– true value
$K(x,x_i)$	– kernel	y_i'	– output value of the prediction model
σ^2	– nuclear parameter	p_b	– random point of particle
γ	– penalty parameter	p_{ib}	– suboptimal position
$x_{ib}(t)$	– position of particles	p_{gb}	– global optimal position
β	– contraction expansion coefficient	u	– random number between (0,1)

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