



Research Paper

Temperature prediction of power cable joint based on LS-SVM optimized by PSO

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ABSTRACT

The temperature of high-voltage cable has a great significance in reflecting the operation status, and the accurate prediction of the joint temperature can improve the safe operating level of the wire. This paper points out a temperature prediction model based on Least Squares Support Vector Machine (LS-SVM) to forecast short-term cable joint temperature. This paper also conducts a test on a Shanghai 110 kV cable line with its joint's history temperature, environmental temperature and humidity, the wire core/sheath current ratio data and the Particle Swarm Optimization algorithm (PSO) can be adapted to optimize model parameter standardization and regularization parameter dynamically. The results prove that this method can predict the temperature of cable joint with high prediction accuracy and also provide a reliable basis for cable temperature detection and early warning system.

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INTRODUCTION

The power cable transmission system can beautify city's appearance and largely save urban land resources, completely meet the needs of resources saving and is environment-friendly (Zhou et al., 2014). Power cables are widely used in the urban grid and its demand is fast growing. According to the field operation experience, the weakness of the cable system is the cable joint and there are over 90% of the cable failure that occurs in the position of the cable joints (Gao et al., 2016). The internal defects of cable joint will cause electric field concentration, local temperature increase (Peng et al., 2014) and electric-thermal breakdown on power cable insulation (Gao et al., 1997), if its temperature is more than 137°C and finally hardly damage the safe operation of power grid. Although joint temperature can properly reflect the operation situation of cable joint, existing cable monitoring system for cable joint temperature can only achieve real-time data acquisition without forecast. Therefore, it is necessary to forecast the temperature of the joint, prognosis the insulation level of the cable joint and detect fault in time for the temperature monitoring system's warning foundation.

There is non-linear and random relationship between cable joint temperature and environmental temperature, humidity and wire core current. Tian (2015) in a study used the coefficient of the first-order and second-order adaptive optimization predict group legal while Xiao et al. (2013) used the method of generalized regression neural network to forecast, but there is weakness on high requirement to the sample data and convergence insufficiency. SVM (Support Vector Machines) regression model which follows the principle of risk minimization can effectively solve the practical problems such as small sample, non-linearity and high latitudes (Vapnik, 2000).

SVM has been successfully applied to short-term load forecasting, wind power prediction and wind velocity prediction (Xiao et al., 2015; Huang et al., 2014; Mao et al., 2013; Tian et al., 2018). SVM is long and computationally intensive (Zhu and Han, 2016). LS-SVM (Least Squares Support Vector machines) is the improved algorithm of SVM (Gu et al., 2010; Mellit et al., 2013); it can convert quadratic programming problem into solving linear equations, reduce the computational complexity, and

reduce convergence time when forecasting. Like SVM, LS-SVM takes the kernel parameters and penalty parameters by experience, and there are too many human factors (Wu et al., 2015; Yang et al., 2018). Hence, this approach requires intelligent optimization of parameters.

In this article, LS-SVM is firstly adapted to establish joint temperature prediction model with environment temperature, environment humidity, sheath/wire core current ratio and the duration cable joint temperature as the training sample. In order to improve the prediction precision, Particle Swarm Optimization (PSO) for dynamic optimization of regularization parameters C and standardization parameters σ of LS-SVM and building the PSO-LSSVM forecasting method was used. A 110 Kv cable line's termination joints in Shanghai was tested and the prediction results showed that this method can properly forecast the cable joint temperature with high accuracy and also provide reliable judgment for cable temperature detection and pre-warning system.

A PREDICTION METHOD OF LS-SVM

The basic idea of SVM's data regression is that influencing factor x which is closely related to the number of influencing factors is defined as input, while forecast expectations y is defined as output and the non-linear mapping $\phi(x)$ from the input space is mapped to high-dimensional feature space (Vapnik, 2000) and its non-linear relationship defined as:

$$y(x) = (\omega, \phi(x)) + b \tag{1}$$

Where $\phi(x)$ is defined as the non-linear mapping. $\omega \in R^d$ is defined as the weight vector and $b \in R$ is defined as the deviation value. There are l d dimensional data point (x_i, y_i) , $i = 1, \dots, l$ and $x_i \in R^d$, $y_i \in R$ and quadratic norm of error is chosen as the loss function according to the risk minimization principle. LS-SVM optimization model can be expressed as:

$$\begin{cases} \min \frac{1}{2} \|\omega\|^2 + \frac{1}{2} C \sum_{i=1}^l e_i^2 \\ \text{s.t. } \omega^T \phi(x_i) + b + e_i = y_i, i = 1, 2, \dots, l \end{cases} \tag{2}$$

In Equation (2), e_i is defined as error, and is regularization parameter which controls the degree of punishment of error. Equation 3 is given as:

$$\min L = \frac{1}{2} \|\omega\|^2 + \frac{1}{2} C \sum_{i=1}^l e_i^2 - \sum_{i=1}^l \lambda_i (\omega^T \phi(x_i) + b + e_i - y_i) \tag{3}$$

By the KKT condition:

$$\frac{\partial L}{\partial \omega} = 0, \frac{\partial L}{\partial b} = 0, \frac{\partial L}{\partial e_i} = 0, \frac{\partial L}{\partial \lambda_i} = 0 \text{ and}$$

$$\begin{cases} \frac{\partial L}{\partial \omega} = 0 \rightarrow \omega = \sum_{i=1}^l \lambda_i \phi(x_i) \\ \frac{\partial L}{\partial b} = 0 \rightarrow \sum_{i=1}^l \lambda_i = 0 \\ \frac{\partial L}{\partial e_i} = 0 \rightarrow \lambda_i = C e_i, i = 1, 2, \dots, l \\ \frac{\partial L}{\partial \lambda_i} = 0 \rightarrow \omega^T \phi(x_i) + b + e_i - y_i = 0 \end{cases} \tag{4}$$

Delete ω and e , there is a system of linear equation given as:

$$\begin{bmatrix} 0 & U^T \\ U & \Omega + C^{-1} \end{bmatrix} \begin{bmatrix} b \\ \lambda \end{bmatrix} = \begin{bmatrix} 0 \\ Y \end{bmatrix} \tag{5}$$

In Equation 5, $\lambda = [\lambda_1, \lambda_2, \dots, \lambda_l]^T$, $U = [1, 1, \dots, 1]^T$, $Y = [y_1, y_2, \dots, y_l]^T$ is 1 \times 1 dimensional column vector; $\Omega \in R^{l \times l}$ and $\Omega_{ij} = \phi(x_i)^T \phi(x_j)$ is kernel function.

A radial basis kernel function (Keerhi and Lin, 2003) with good performance is chosen as LS-SVM kernel function and the form is given as:

$$K(x, x_i) = \exp(-\|x - x_i\|^2 / \sigma^2) \tag{6}$$

Where x_i is the i th center of radial basis function, σ is standard function, which determines the width of the center of the function.

$$y = \sum_{i=1}^l \lambda_i K(x_i, x) + b \tag{7}$$

USING PSO TO OPTIMIZE THE PARAMETERS OF LS-SVM

During the prediction by LS-SVM, regularization parameter,

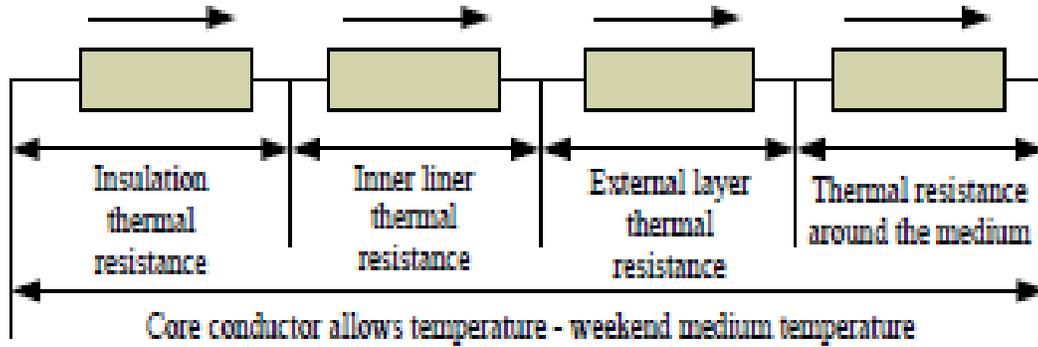


Figure 1: Single core cable heat road diagram.

which is to control the degree of punishment and kernel function's normalizing parameter σ should be given. Low c will cause big error while too much will cause poor promotion ability. Below the expected value will cause excessive localized training while excess of it will cause less training. Artificial selected parameters cannot guarantee the accuracy of the forecasting model. To raise the forecasting precision of LS-SVM, this paper uses particle swarm optimizing algorithm for dynamic optimization.

Particle swarm algorithm was widely applied in the field of optimization (Li et al., 2018). Parameter selection problem of Support Vector Machines (SVM) can be regarded as global search problem of a given space by particle swarm optimization algorithm; specific steps are as follows:

Step 1: The sample data are processed by normalization, initialization parameter c_1, c_2, w, m and N_{max} of PSO, C and σ as a group of initialized particles. Among them, c_1 and c_2 are defined as acceleration constant, w is defined as the inertia weight, m is defined as the population size, N_{max} is defined as the biggest evolution algebra, while the C (regularization parameter) and σ (kernel parameter) are mapped to a group of particles.

Step 2: $f(x_i)$ (the adaptive value of each particle) is calculated to compare the value of particle position and will be the i^{th} particle's current point is set to p_{ibest} (optimal location) and the optimal particle is defined as best g_{ibest} (population optimal position).

Step 3: Updating each particle's speed and position by Equations 8 and 9 and generate $X(n)$ (new population). Equations 8 and 9 is given as:

$$v_{i\delta} = \omega v_{i\delta} + \chi_1 P_1 (\pi_{i\delta} - \xi_{i\delta}) + \chi_2 P_2 (\pi_{j\delta} - \xi_{i\delta}) \tag{8}$$

$$x_{id} = x_{id} + v_{id} \tag{9}$$

Step 4: The adaptive value of $X(n)$, new p_{ibest} and g_{ibest} is calculated making a comparison with historical p_{ibest} and g_{ibest} and making a replacement if new parameters are better, otherwise making no change.

Step 5: Determining whether the evolution algebra has reached N_{max} or precision is less than ϵ , if it has reached, then output optimal C and σ , otherwise, let $n = n+1$ and turn to step 2.

CABLE JOINT TEMPERATURE PREDICTION

Data vector

To predict the temperature of the cable joint using the PSO-LSSVM algorithm, it is necessary to determine sample data such as temperature-dependent variables and historical temperature as input quantities to form training samples and test samples. The high-voltage power cable joints of 110 Kv and above are restored according to the cable structure and materials when the insulation is restored. The equivalent heat map of the joint can be equivalently represented by the equivalent heat path diagram of the cable body, as shown in Figure 1.

The thermal resistance of the insulation layer is related to the core current, while the thermal resistance of the inner liner and the thermal resistance of the outer layer are equivalent to the thermal resistance of the metal sheath and the circulation of the sheath. The thermal resistance of the surrounding medium is related to the ambient temperature and the ambient humidity. Results operating experience and cable joint temperature is related to ambient temperature, humidity, core current and sheath current. The sheath current is generated by the sheath induced voltage in the sheath loop, and there is a certain proportional relationship with the core current. Therefore, the ambient temperature, ambient humidity, sheath/core current ratio, and historical temperature of the cable joint are used as input samples.

All data can be obtained from the high-voltage cable

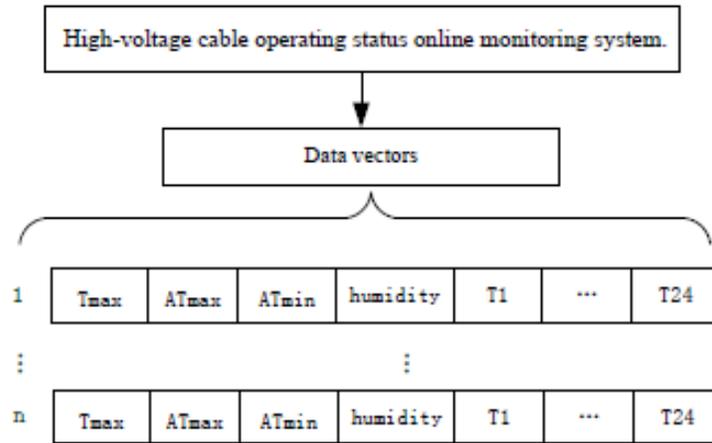


Figure 2: On-line monitoring system interface of high voltage cable.

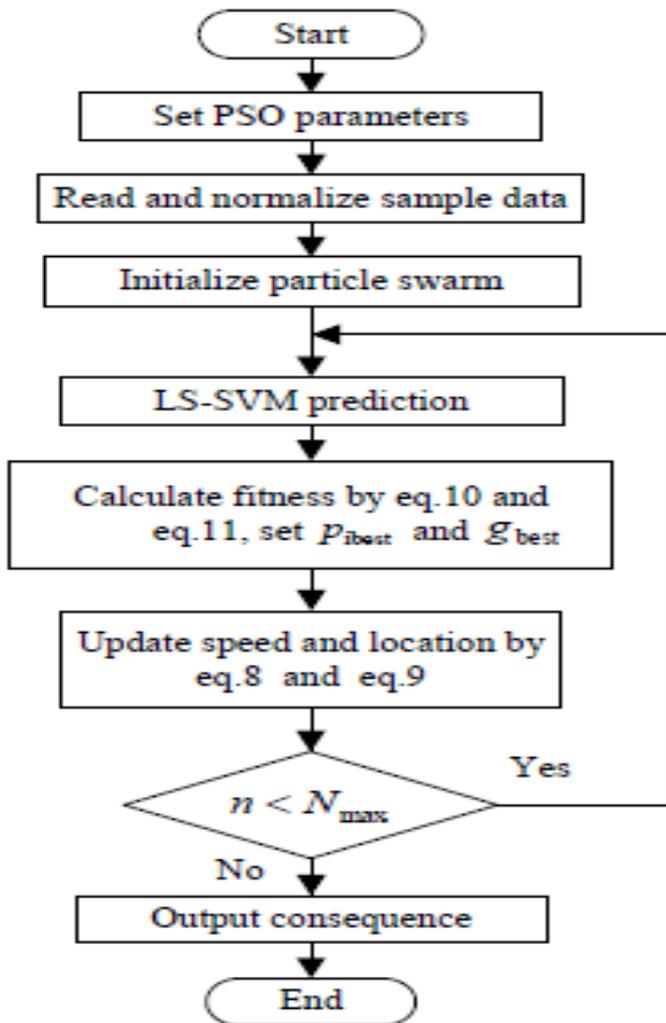


Figure 3: Flow chart of PSO-LSSVM forecast.

collated to form a data vector. Each data vector consists of 29 data of the average ambient temperature, the highest ambient temperature, the lowest ambient temperature, the ambient humidity, the sheath/core current ratio, and the measured temperature of the joint at the hour of the day, as shown in Figure 2. T1, ..., T24 are the measured temperatures of the power connectors at the hour.

Prediction steps and parameters selection

This paper chooses Mean Absolute Percentage Error (MAPE) and Mean Square Error (MSE) which is commonly used in temperature prediction as evaluation standard.

RE-Relative error is given as:

$$E_{RE} = \frac{|L - \hat{L}|}{L} \times 100\% \tag{10}$$

MAPE-Mean absolute percentage error is given as:

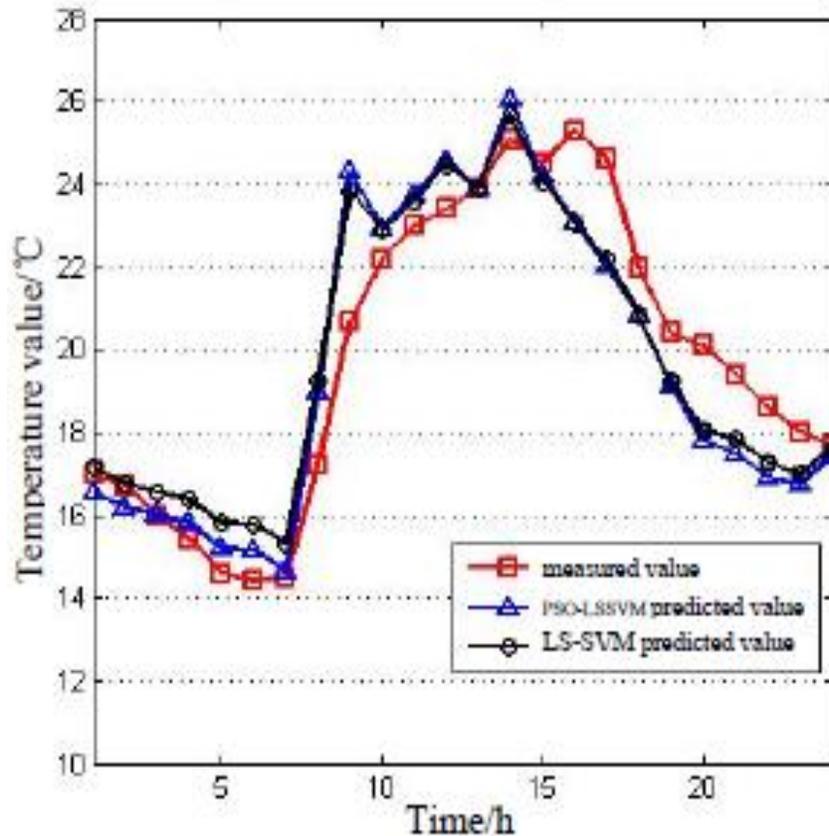
$$E_{MAPE} = \frac{1}{n} \sum_{i=1}^n \left| \frac{L_i - \hat{L}_i}{L_i} \right| \times 100\% \tag{11}$$

In Equations 10 and 11, L and \hat{L} is respectively actual and predicted temperature, while n is the number of temperature data. At this point, the steps to forecast cable joint temperature by PSO-LSSVM have been set up. Figure 3 shows the procedure used in forecasting the cable joint temperature by PSO-LSSVM. Writing programs by Matlab tool, m (the parameter of PSO algorithm) is set as 20, Nmax is set as 10 and w is chosen in [0.4, 0.9]. To balance the effect

operating status online monitoring system. The data is

Table 1: Comparison of model parameter optimization and average relative error.

Experiment	Method	C	σ	MAPE (%)
1	LS-SVM	30	2	0.0572
	PSO-LSSVM	143.52	7.18	0.0553
2	LS-SVM	30	2	0.0271
	PSO-LSSVM	7.0857	10	0.0210

**Figure 4:** Temperature curve of experiment 1.

of random factors, c_1 and c_2 are both 2 in this paper.

RESULTS AND DISCUSSION

To experiment the forecast precision of PSO-LSSVM, test 1 (choosing the data from 2016.10.3 to 10.9 to predict the temperature of 10th day) and test 2 (choosing the data from 10-3-016 to 10-17-2016 to predict the temperature of 16th day), a comparison with prediction data by LS-SVM was simultaneously made. The test subject is the phase A of outdoor terminal connector of 110 kV cable line in Shanghai.

Table 1 shows both tests' optimization results and comparison value of average relative error; the LS-SVM

parameters c and σ in both tests are respectively 30 and 2, while the PSO-LSSVM parameters c and σ in the first experiment is respectively the optimization of 143.52 and 7.18, the PSO-LSSVM parameters c and σ in second experiment is respectively the optimization of 7.0857 and 10. Figure 4 shows the temperature curve of test 1, while the relative error is shown in Figure 5. Figure 6 is the predictive results of experiment 2, while Figure 7 is its relative error. Table 2 shows the prediction results of experiment 2 data.

According to the aforementioned data, the prediction of PSO-LSSVM is closer to the measured data and its relative error and average relative error is better than the prediction of LS-SVM. Thus, parameter optimization is effective. The average relative error of experiment 1 is

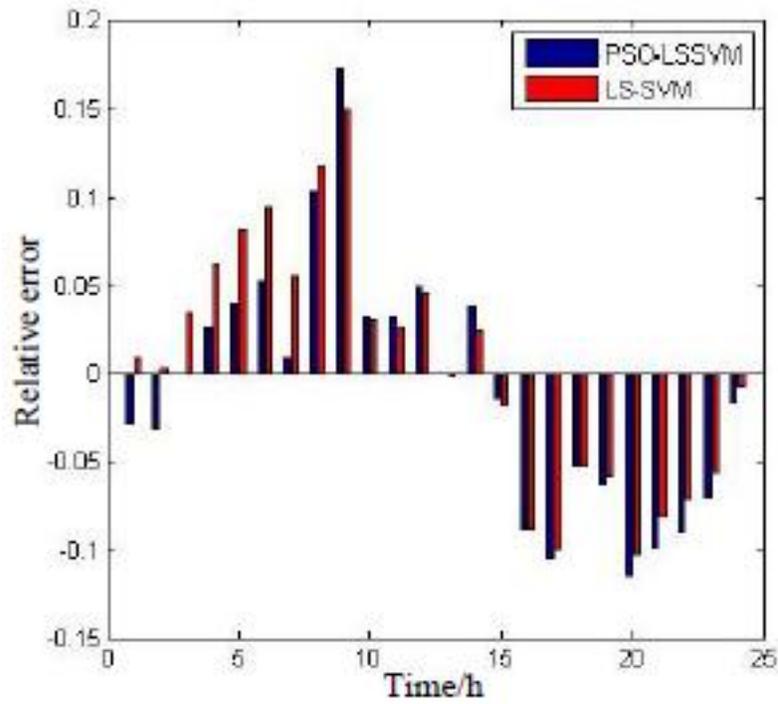


Figure 5: Relative error of experiment 1.

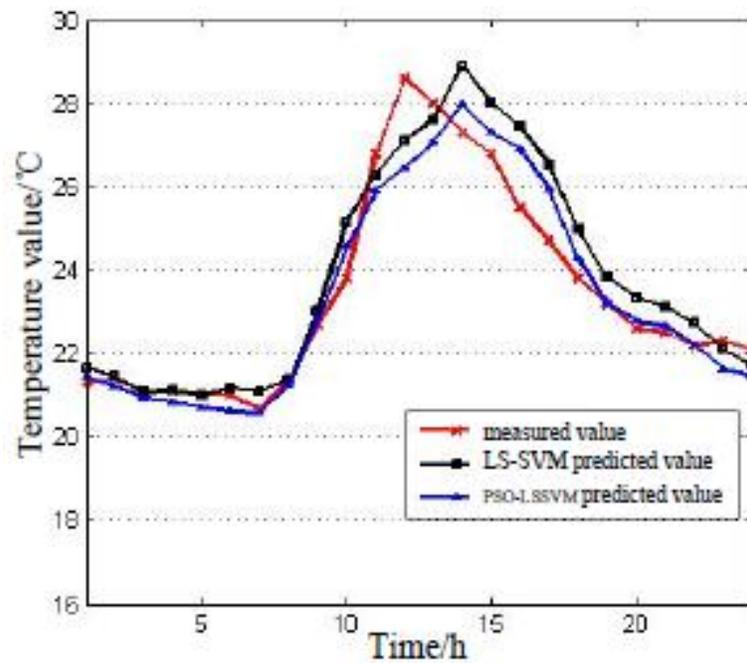


Figure 6: Temperature curve of experiment 2.

0.0553%, more than 0.021% of experiment 2, indicating that the size of the data samples will affect the forecasting result and reasonable selection of data sample is helpful in improving the prediction accuracy. The maximum

temperature error of the experiment is 2.143°C, which occurred at 12, at the same time, its absolute value of the relative error is 0.0748%, which satisfies the requirement of forecast.

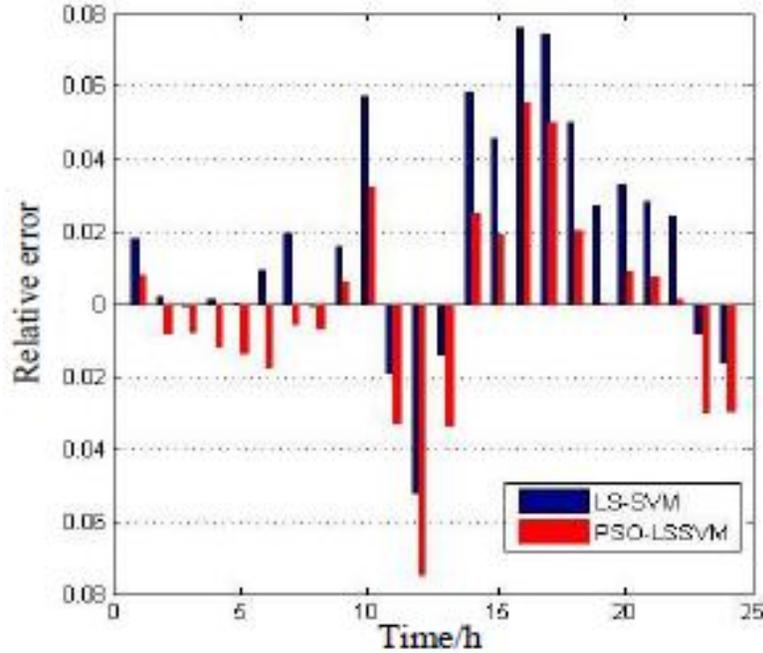


Figure 7: Relative error of experiment 2.

Table 2: Results of experiment 2.

Time	Measured value (°C)	LS-SVM		PSO-LSSVM	
		Predicted value (°C)	Relative error (%)	Predicted value (°C)	Relative error (%)
01:00	21.3	21.688	0.0182	21.460	0.0076
02:00	21.4	21.444	0.0020	21.221	-0.0083
03:00	21.1	21.084	-0.0008	20.931	-0.0079
04:00	21.1	21.122	0.0010	20.852	-0.0117
05:00	21	21.001	0.0000	20.715	-0.0135
06:00	21	21.191	0.0091	20.626	-0.0177
07:00	20.7	21.097	0.0192	20.586	-0.0054
08:00	21.4	21.383	-0.0008	21.247	-0.0071
09:00	22.7	23.055	0.0157	22.831	0.0058
10:00	23.8	25.155	0.0569	24.563	0.0322
11:00	26.8	26.280	-0.0194	25.912	-0.0330
12:00	28.6	27.110	-0.0521	26.457	-0.0748
13:00	28	27.606	-0.0141	27.059	-0.0335
14:00	27.3	28.890	0.0582	27.966	0.0245
15:00	26.8	28.015	0.0453	27.305	0.0190
16:00	25.5	27.445	0.0763	26.903	0.0551
17:00	24.7	26.536	0.0744	25.929	0.0499
18:00	23.8	24.988	0.0499	24.276	0.0201
19:00	23.2	23.828	0.0271	23.203	0.0002
20:00	22.6	23.342	0.0328	22.791	0.0085
21:00	22.5	23.131	0.0280	22.660	0.0072
22:00	22.2	22.735	0.0241	22.221	0.0010
23:00	22.3	22.114	-0.0084	21.630	-0.0300
24:00	22.1	21.745	-0.0161	21.450	-0.0293

CONCLUSION

In this paper, PSO is adapted to dynamically optimize LS-

SVM parameters. Joint history temperature, environment temperature, humidity, wire core/sheath current ratio is selected as the training sample to establish the cable joint

temperature prediction model of PSO-LSSVM, which can improve the prediction performance and effectively predict the cable joint temperature. The size of data samples will affect the forecasting result and reasonable selection of data sample is helpful in improving the prediction accuracy. Experimental results indicate that this method has good convergence, higher precision and faster training speed and it can also provide reliable judgment to cable temperature detection and warning system. Thus, this method is of great value in engineering application.

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