Study of Short-term Load Forecasting Based on PSO-SVR

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Abstract. Support vector machine (SVM) algorithm was used to predict the energy load of an energy station in Shanghai, including hourly and half-day load two parts. The input parameters were the outdoor temperature, the air relative humidity, the temperature difference between the supply and return water and the flow of the supply water at the moment, adding the load at the last moment. The output parameter was the load at the moment. The results showed that the predicted value was in good agreement with the measured value. The average absolute errors of all results were less than 1.5, and the average relative errors were less than 3.

Key words: Short-term Load Forecasting; SVR; PSO.

1. Introduction
In recent years, gas distributed energy system [1] has been used widely because of its high efficiency, energy saving, security and flexibility. However, most gas distributed energy stations have energy waste problems due to inaccurate estimation of energy supply load, resulting in low efficiency of system operation and poor economic benefits.

Load forecasting [2] is defined as analyzing the regularity of historical load data in order to realize scientific prediction of future load, based on the characteristics of system operation, natural factors, social factors and other important factors, under certain precision conditions. Accurate load forecasting can properly guide the operation of the system and reduce energy waste. As a result, a simple and accurate method of load forecasting is urgently needed, which is suitable for engineering practice.

Support Vector Machine (SVM) algorithm is a general machine learning method first proposed by Cortes and Vapnik [3] in 1995. SVM is suitable for nonlinear and high dimensional pattern recognition with a small number of samples, which can be used for classification, nonlinear regression and prediction. Support Vector Regression (SVR) algorithm is widely used for prediction, as an extended algorithm for SVM.

In this thesis, SVR was used to predict the load of a gas distributed energy station in Shanghai, based on the load data in January, July and August. Particle swarm optimization (PSO) algorithm was used to optimize important parameters in SVR to ensure the accuracy of the calculation results.
2. Algorithm principle

2.1. Support Vector Regression
SVM is originally suitable for pattern recognition, and then develops into the field of regression estimation by introducing insensitive loss function. SVR mapped the input samples of low dimensional space to high dimensional feature space by applying the appropriate kernel function $\phi(x)$, and then search a linear regression function to solve the problem of linear regression in the high dimensional feature space. Instead of directly calculating the value of the complex nonlinear transformation, SVR calculates the inner product of the nonlinear transformation, namely the kernel function $k(x, y)$, so as to solve the problem of high dimensional calculation. The relationship between input and output is as follows:

$$f(x) = w^T \phi(x) + b$$

(1)

Where $\phi(x)$ is the nonlinear mapping from the input space to the high dimensional feature space and $w$ and $b$ are position parameters.

The kernel functions are mainly divided into linear kernel function, polynomial kernel function, radial basis kernel function and two-layer perceptron kernel function, which are introduced to get position parameters. The book [4] concluded that the radial basis kernel function (RBF) had the highest final regression accuracy by comparing the testing and prediction accuracy of different kernel functions.

Therefore, SVR was used to predict the load of the energy station by LIBSVM toolbox in MATLAB software, using the kernel function RBF.

2.2. Particle Swarm Optimization
PSO is a population-based stochastic optimization technique proposed by Eberhart and Kennedy [5] in 1995. PSO refers to that the group search for objects in a cooperative way, and each member of the group constantly changes its search pattern by learning other members’ and its own experience. The algorithm has the advantages of simple rules, fast convergence rate and easy implementation.

The SVR model has two very important parameters $c$ and $\sigma$. $c$ means the tolerance for error. If $c$ is too large or too small, the generalization ability of the model becomes poor. $\sigma$ is a parameter of RBF function. $\sigma$ decides the number of support vectors which affects the speed of training and prediction.

In this thesis, PSO was adopted to select the two optimal parameters so as to reduce the error of the prediction results and improve the prediction accuracy.

3. Calculation and results
The energy station in Shanghai has a $5 \times 4.4$MW CCHP (Combined Cooling, Heating and Power) system. The main engine system is the gas generator set with the lithium bromide unit. The annual capacity of providing load can reach 180,000 GJ. PSO-SVR was used to predict the load of the energy station. The calculation steps are shown in figure 1.

3.1. Screening of Sample Data
There are many factors influencing the load of energy station, including meteorological factors, date factors, economic factors and project characteristics. Economic factors are not taken into account here.

(1) meteorological factors
Meteorological factors are important factors affecting the load. Here, only outdoor temperature and air relative humidity are considered, which have great influence on the load.

(2) date factors
The system load varies at different times of day and on different days. Figure 2 shows the load curve of a typical week. It can be seen that the daily load is similar. Usually, the load level of weekday (Monday to Friday) is slightly higher than that of Saturday and Sunday, which is caused by the large number of school activities.
(3) supply water factors
The heat transfer medium is water, and the flow of the supply water and the temperature difference of the supply and return water have certain influence on the load.

(4) historic load
Because the load has continuity, which means the load change will follow the original characteristics, the load value at the last moment is also an important factor.

To sum up, the SVR input parameters include the outdoor temperature, the air relative humidity, the temperature difference between the supply and return water and the flow of the supply water at the moment, adding the load at the last moment. A prediction model is established by training sample data, using to predict the load in the future.
3.2. Data Normalization Processing
In order to unify the units and orders of magnitude of the influencing factors, the training data were normalized.

3.3. Optimal Parameters Determination
According to section 2.2, PSO was used to optimize c and σ in the SVR model.

3.4. Model Establishing
There are five input parameters and one output in the SVR model. The input parameters include the outdoor temperature $T_t$, the air relative humidity $U_t$, the temperature difference between supply and return water $\Delta T_t$, the flow of supply water $F_t$ and the load value $Q_{t-1}$, expressed as a vector $X$, $X = [T_t, U_t, \Delta T_t, F_t, Q_{t-1}]$. The output parameter is load $Q_t$, expressed as a vector $Y$. The total number of samples is $N$, and the sample set is $\{(X_t, Y_t)\}_{t=1}^N$. The sample set is used to train the prediction model.

3.5. Hourly Load Forecasting
Hourly load data were selected as sample data to train the SVR model. Then, the SVR model was used to predict the load. The representative SVR prediction values are shown in table 1, using absolute error and relative error as quantitative evaluation indexes. The comparison between the predicted values and the measured values is shown in figure 3-4.

| Time (h) | $T_t$ (°C) | $U_t$ (%) | $\Delta T_t$ (°C) | $F_t$ (kg/h) | $Q_{t-1}$ (GJ/h) | Measured value (GJ/h) | Predicted value (GJ/h) |
|---------|------------|----------|-------------------|-------------|-----------------|----------------------|----------------------|
| 1       | 8.4        | 94       | 2.3               | 4165.5      | 40.8            | 40.0                 | 40.2                 |
| 2       | 7.9        | 93       | 2.2               | 4162.9      | 40.0            | 41.2                 | 39.6                 |
| 3       | 7.3        | 92       | 2.2               | 4206.5      | 41.2            | 39.8                 | 39.6                 |
| 4       | 6.8        | 91       | 2.3               | 4170.6      | 39.8            | 41.9                 | 40.4                 |
| 5       | 6.4        | 92       | 2.3               | 4177.5      | 41.9            | 39.5                 | 40.7                 |
| 6       | 5.9        | 94       | 2.2               | 4217.6      | 39.5            | 41.9                 | 40.0                 |
| 7       | 5.5        | 95       | 2.1               | 4203.8      | 41.9            | 38.8                 | 39.1                 |
| 8       | 5.4        | 95       | 2.2               | 4190.5      | 38.8            | 41.2                 | 39.6                 |

Table 1. SVR prediction values.

As can be seen from the figures, the predicted values are in good agreement with the measured values. The range of absolute error in winter and summer is generally between -6 and 6, and the relative errors are generally less than 10%. The average absolute errors in winter and summer are 1.3901 and 1.2531, and the average relative errors are 2.9531 and 2.4989 respectively.

![Figure 3](image_url)  
(a) winter  
(b) summer  

Figure 3. Comparison of predicted values and measured values (a) winter (b) summer.
3.6. Half day load forecasting

Hourly load forecasting is not very suitable for engineering applications, mainly for two reasons: on the one hand, the system itself can store some energy, which can maintain the water temperature for a certain period of time; On the other hand, it is very difficult to make fine adjustments hour by hour. Therefore, the same input and output parameters are used to build a 12 hours load forecasting model in order to guide the operation mode of the energy station. The comparison between the predicted values and measured values is shown in figure 5-6.

As can be seen from the figures, the predicted values are in good agreement with the measured values. The range of absolute error is generally between -2 and 2, and the relative error is basically below 5. The average absolute error is 0.7579 and the average relative error is 1.5700.
4. Conclusion
According to the measured data of the energy station and the meteorological data, the PSO-SVR was used to build a load forecasting model. The results showed that the predicted values were in good agreement with the measured values, which meant the prediction model could accurately and effectively predict the load. For hourly load forecasting, the average absolute error in winter and summer is 1.3901 and 1.2531, and the average relative error is 2.9531 and 2.4989, respectively. For half day load forecasting, the average absolute error is 0.7579 and the average relative error is 1.5700. After the prediction model is completed, the predicted value $Y$ can be obtained by directly inputting the sample $X$ value, which is simple and practical in practical engineering.

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