PREDICTION OF HEATING LOAD FLUCTUATION BASED ON FUZZY INFORMATION GRANULATION AND SUPPORT VECTOR MACHINE

by

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District heating systems are an important part of the future smart energy system and are seen as a tool to achieve energy efficiency goals in the EU. In order to achieve the real sense of heating on demand, based on historical heating load data, first of all, the heating load time series data was dealing with fuzzy information granulation, and then the cross-validation was used to explore the advantages of the data potential. Then the support vector machine regression prediction model was used for the prediction of the granulation data, finally, the heating load of a district heating system is simulated and verified. The simulation results show that the prediction model can effectively predict the trend of heating load, and provide a theoretical basis for the prediction of district heating load.

Key words: *prediction of heating load fluctuation, fuzzy information granulation, cross validation, support vector machine*

Introduction

With the increase of worldwide demand for energy, improving the efficiency of the energy system is an important problem, in the social goals of the sustainable development of energy efficient system, district heating system has huge potential [1], however, still need more efforts to identify, evaluate and implement these potential, in order to get the global benefits by district heating [2]. With the rapid development of central heating system, the energy consumed by heating takes up a larger and larger proportion in the energy consumption of the whole society, and the energy demand is increasing day by day. Therefore, it is necessary to develop to the 4th-generation district heating. The heating control system should be transformed from simple automatic control to big data and intelligence [3], and heating load prediction will be a prerequisite for the successful completion of this transformation. At present, many scholars have conducted studies on thermal load prediction different degrees. For example, Nielsen and Madsen [4] applied the gray box method to thermal load prediction and obtained the relationship between building heat and outdoor temperature, wind speed, solar radiation and other variables. Popescu *et al.* [5] used multiple regression analysis to build the structure of the heat load prediction

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model. Fu *et al.* [6] used Elman neural network and wavelet neural network to predict the hourly thermal load in the next 24 hours, and verified the importance of solar radiation and weather data. Sajjadi *et al.* [7] used three models of extreme learning machine (ELM), genetic programming (GP) algorithm, and artificial neural networks (ANN) to predict the heat load in the future 1, 2, 3, 4, 5, 8, 12, and 24 hours, respectively. The results showed that ELM method could improve the prediction accuracy and generalization ability compared with GP and ANN. Liu *et al.* [8] proposed a grey neural network model combining grey correlation analysis with back propagation neural network prediction model, and screened out the main factors affecting district heating load. Mehmood *et al.* [9] believed that the combination of artificial intelligence and building design could greatly improve the energy efficiency of buildings, provide a comfortable indoor living environment for occupants, and play a dominant role in future energy buildings. Machine learning algorithm, mainly support vector machine (SVM), has been proved to be suitable for building energy assessment, [10]. By using SVM and firefly algorithm (FFA), Al-Shammari *et al.* [11] established a short-term multi-step advance prediction model of user heat load connected to district heating system, which was compared with GP model and ANN model. The experimental results showed that the established SVMS-FFA model performed better in accuracy. Therefore, SVM algorithm was used for analysis. The SVM algorithm is a new machine learning algorithm, with small sample size and non-linear characteristics, and can effectively inhibit the problems of underfitting and overfitting [12]. In the process of using SVM method, there is no unified theoretical guidance for the selection of performance parameters, which is usually obtained through repeated trial calculation or subjective experience, and it often takes a lot of time and cannot get ideal parameters. Many scholars have carried out researches on SVM parameter optimization methods in their respective fields and achieved good results [13-15]. However, due to the use of fixed training sets and verification sets, the data mining potential has been weakened to a certain extent. At the same time, only the point prediction of heating load can be obtained, and the approximate variation interval cannot be obtained [16]. Therefore, k-fold cross validation and fuzzy information granulation (FIG) were combined in heat load forecasting, which takes advantage of artificial intelligence algorithm, furthermore, the advantages of cross validation in data mining and the ability of simplifying the algorithm are used to overcome the shortcomings of insufficient experience in selecting parameters and the resulting long training time, the simulation results showed that the model had practical significance for the prediction of the variation interval of heating load data.

Method

Fuzzy information granulation

Information granulation was first proposed by professor Zadeh [17], who divided the whole set of complex information data into several small sets according to certain characteristics, and then studied each set, and each divided set was an information particle. When the data is fuzzy granulated, it mainly includes two steps [18]: divide the fuzzy granulation window and fuzzify window information. Fuzzification is the most important part. Dividing the fuzzy granulation window is to divide the historical time series into several sub-sequences and then use them as an information granulation window. The fuzzification of window information is to build a fuzzy set on the divided window, and replace the original window information with fuzzy information particles, and how to establish a reasonable fuzzy set is the key. Window information fuzzification is the establishment of a fuzzy particle, h, on the partitioned data sequence, X, that is, a fuzzy concept, G, that can reasonably describe, X (fuzzy set with X as the theoretical domain). When G is determined, the corresponding fuzzy particle h can be obtained.

The relationship is:

$$h \triangleq x \text{ is } G \tag{1}$$

where x is the variable of the value in G, and the fuzzy concept G is a the convex fuzzy subset of X in the domain. The essence of the fuzzification process is to determine the function, A, which is the membership function of the fuzzy concept G. In the process of fuzzy granulation, the form of fuzzy particles should be determined first and then the specific membership function A should be determined.

In this paper, the granulation model of *W*. Pedrycz [19, 20] is applied. The general method is:

– fuzzy particles must effectively represent the original data and
– the fuzzy particles should have the corresponding particularity.

In this paper, triangular fuzzy particle is selected, and its membership function is:

$$A(x,a,m,b)=\begin{cases} 0,\ x<a \\ \dfrac{x-a}{m-a},\ a\le x\le m \\ \dfrac{b-x}{b-m},\ m<x\le b \\ 0,\ x>b \end{cases} \tag{2}$$

In the aforementioned formula, a, m, and b are the parameters of the membership function, which correspond to the three parameters after the fuzzy granulation of the original data: *Low*, *R*, and *Up*. For a single fuzzy particle, the *Low* parameter describes the minimum value of the corresponding original data of the particle, the *R* parameter describes the average value of the corresponding original data of the particle, and the *Up* parameter describes the maximum value of the corresponding original data of the particle.

Support vector regression model

The SVM was first proposed by Chapelle *et al*. [21], whose basic idea of regression is to find an optimal classification surface and minimize the sum of errors of all training samples from the optimal classification surface. The SVM uses a non-linear mapping to map low dimensional input data to a high dimensional feature space where linear regression can be performed [22]. In general, if the training set sample is $\{(x_i, y_i),\ i = 1, 2, ..., l\}$, the training sample $x_i \in R^d$, $x_i = [x_i^1, x_i^2, ... x_i^d]^T$ and the output of the corresponding $y_i \in R$. If the linear regression function constructed in the new space is: $f(x) = w\varphi(x) + b$. In the previous formula, $\varphi(x)$ is the non-linear mapping kernel function of the selected SVM. Loss function is usually introduced into SVM to solve the regression problem. The process of regression fitting is to solve the unknown parameters w and b:

$$\begin{cases} \min \dfrac{1}{2}w^2 + C\sum_{i=1}^{l}\varepsilon_i + \varepsilon_i^* \\ s.t.\begin{cases} y_i - w\Phi(x_i) - b \le \varepsilon_i + \varepsilon_i^*,\ i = 1,2,\cdots,l \\ -y_i + w\Phi(x_i) - b \le \varepsilon_i + \varepsilon_i^* \\ \varepsilon_i \ge 0,\ \varepsilon_i^* \ge 0 \end{cases} \end{cases} \tag{3}$$

where ε_i, ε_i^* are the relaxation variables, y_i is the true value of the training sample, x_i – the input data of the training sample, and C – the penalty factor. The larger C is, the greater the penalty is for the sample whose training error is greater than ε, ε – the error requirement of the regression function.

This model is a quadratic convex optimization model. By introducing Lagrange multiplier, the regression function of SVM can be further obtained:

$$f(x) = w^*\Phi(x_i) + b = \sum_{i=1}^{l}\left(a_i - a_i^*\right)\Phi(x_i)\Phi(x) + b^* = \sum_{i=1}^{l}\left(a_i - a_i^*\right)K(x_i, x) + b^* \tag{4}$$

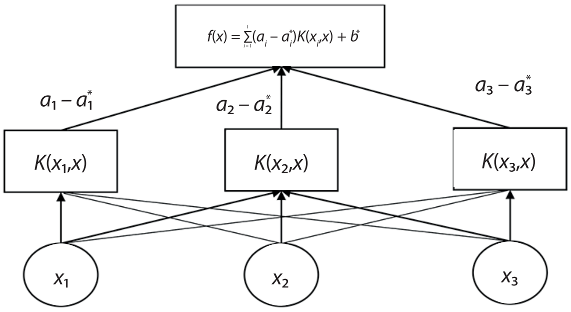


Figure 1. The SVR structural diagram

where only when parameter $(a_i - a_i^*)$ is not 0, the corresponding sample data is the support vector, as shown in fig. 1. Each intermediate node corresponds to a support vector, and its output is the relevant linear combination of intermediate nodes to obtain the regression predicted value.

The SVM model based on fuzzy information granulation

The traditional SVM classifier uses a continuous classification hyperplane to divide the whole feature space, but the SVM model based on FIG, the whole feature space is divided into a series of subspaces, and the objective function is turned to construct the SVM classifier in the subspace. This reduces the size of the original feature space, simplifies the computation complexity, and more importantly, makes the SVM classifier simple, also guarantees the error accuracy, does not occur over-learning phenomenon, at the same improves the generalization ability of the classifier, and this kind of learning algorithm can be implemented in parallel in essence, and can obtain higher learning efficiency [23, 24]. The prediction process of SVM heating load time series based on FIG is:
– the heating load time series that needs to be studied is obtained,
– the FIG processing to the time series data is carried on,
– the k-step cross validation method to the fuzzy information granulated data is applied, and then the corresponding training to SVM is carried on, and the optimal penalty parameter, c, and kernel parameter, g, is solved, and
– using the optimal c and g to establish the FIG SVM model, and then the time series of heating load is analyzed by regression and prediction.

According to the regression function, the heating load variation range of the next window (that is, the next day) is obtained, and its variation trend is judged.

The model flow chart is shown in fig. 2.

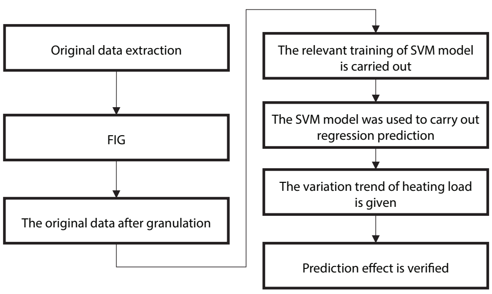


Figure 2. The flow chart of SVM model based on FIG

Evaluation index

In order to evaluate the effectiveness of statistical analysis of a particular data set, it is necessary to determine the degree to which the statistical prediction matches the actual data set, that is, the range of the actual values of the quantitative prediction corresponding to the observed situation. The most common method used to determine the effectiveness of the analysis is the mean square error (MSE) of the training data:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left[y_i - \hat{f}\left(x_i\right)\right]^2 \tag{5}$$

The MSE can evaluate the degree of data change, and the smaller the value of MSE is, the better accuracy the model has in describing experimental data. Since the MSE is calculated on the training data set, and the accuracy of the prediction in the future should be on the new data set, the root MSE was used to analyze the result. In this way, the result of the target variable is got, rather than the square of the result, which is easier to interpret.

Results

According to the method mentioned previously, the heating load data (96 heating load data per day) of a district heating system in a heating station were selected, which were sampled every 15 minutes from December 1, 2008 to February 28, 2009, a total of 11520 heating load data were used as training sets for model training to predict the heating load range on March 1, and the actual heat load data were used to test the model, assuming that the heat load data are related to the daily average water supply temperature, the daily average instantaneous flow, the daily minimum temperature, the daily maximum temperature and the heat load data of the previous moment, therefore, the heat load data from the 2nd to the 11520th were used as dependent variables, data of daily average water supply temperature, daily average instantaneous flow, daily minimum temperature, daily maximum temperature and heat load from day 1 to day 120 were taken as independent variables, the variation trend and variation space of heating load data of the next day are predicted. The time series diagram of heating load data is shown in fig. 3.

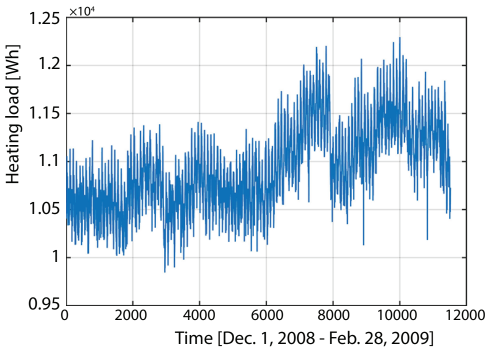


Figure 3. Time series diagram of heating load

Fuzzy information granulation of heat load data

Fuzzy granulation method was adopted; triangular fuzzy particle was selected for FIG. 96 load data (1 day) were used as fuzzy granulation windows, and the number of windows is 11520/96 = 120. After the triangular fuzzy particles blur the load data, three parameters, *Up*, *Low*, and *R*, will be generated, corresponding

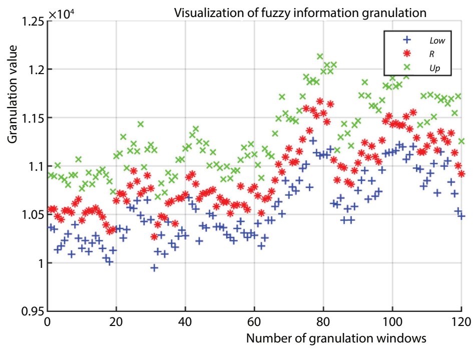


Figure 4. Visualization of FIG

to the three parameters of the subordinate function a, m, and b. The *Up* corresponds to the maximum value of the original data change, the *Low* corresponds to the minimum value of the original data change, and the *R* corresponds to the average value of the original data change. The visualization of FIG is shown in the fig. 4.

Selection of the SVM kernel function parameter and penalty factor

Before modelling with SVM, two problems need to be solved. First, many factors will directly or indirectly affect the heating load. Their respective units have different ranges. The final prediction results will be greatly affected if directly involved in the calculation without processing. Here, the common normalization method was used to process all fuzzy granulation data, and the conversion is in the probability distribution of [–1, 1], so that different dimensional expressions become for a unified dimensionless expression, simplify the calculation. Second, which SVM kernel function choose and how to find the kernel parameter, g, and error penalty factor, C, corresponding to the selected kernel function. In most cases, the Gaussian radial basis kernel function can obtain better prediction results [25], then the Gauss radial basis kernel function was selected here, and its expression is:

$$Kx_i, x = \exp\left(-\frac{|x - x_i|^2}{g^2}\right) \tag{6}$$

where g is the broadband coefficient of the radial basis kernel function.

A large number of research results show that when cross validation is used to find the kernel function parameter error penalty factor, good prediction results can be obtained [26]. The basic idea of the cross validation method is: in each calculation of MSE, the first data is extracted from the existing data set as the validation data set of the model, and the remaining data is used as the training set of the model [27]. Therefore, the cross validation method is selected to solve the related parameters. The specific operation steps are:

- normalize the fuzzy granular data to the interval of [–1, 1],
- define the reasonable initial range of penalty parameter, C, and kernel function parameter, g, set step size C and g to 1, and make rough selection through cross validation within the initial range to roughly determine the occurrence interval of the optimal parameter, and
- after observing the rough structure drawing, redefine the parameter range and set the step length of C and g to 0.5 for fine selection.

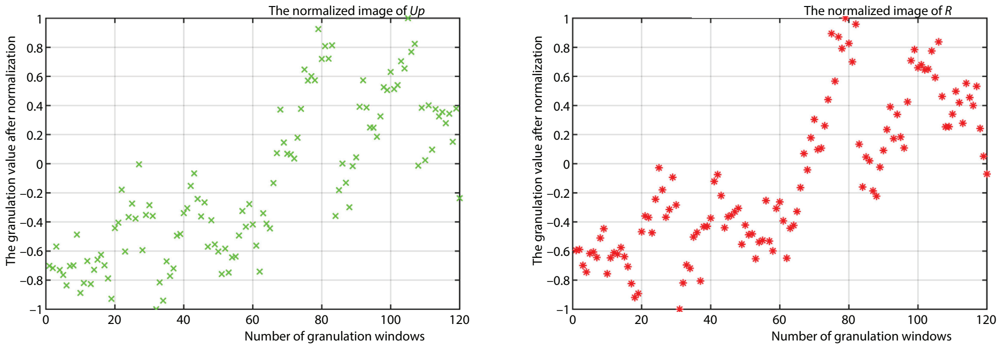
The normalized images of *Up*, *R*, and *Low* are shown in fig. 5.

The parameter optimization of the k-step cross validation method is performed on the normalized *Up*, *R*, and *Low* data. Here, only the parameter selection diagram of the fuzzy particle *Up* is shown. The diagram is indicated as figs. 6 and 7.

The results of the optimal parameters C, g are shown in tab. 1.

Table 1. The best parameters for *Up*, *R*, and *Low*

	C	g
Up	256	0.044
R	128	0.085
Low	208	0.032



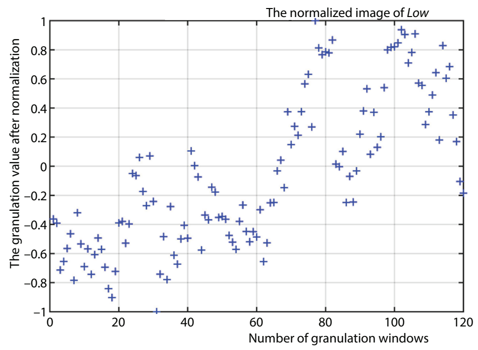


Figure 5. Normalized images of *Up*, *R*, *Low*

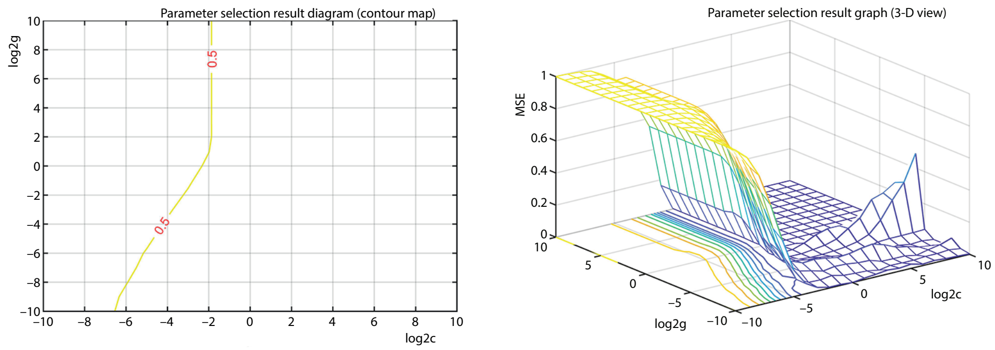


Figure 6. Parameter rough optimization diagram

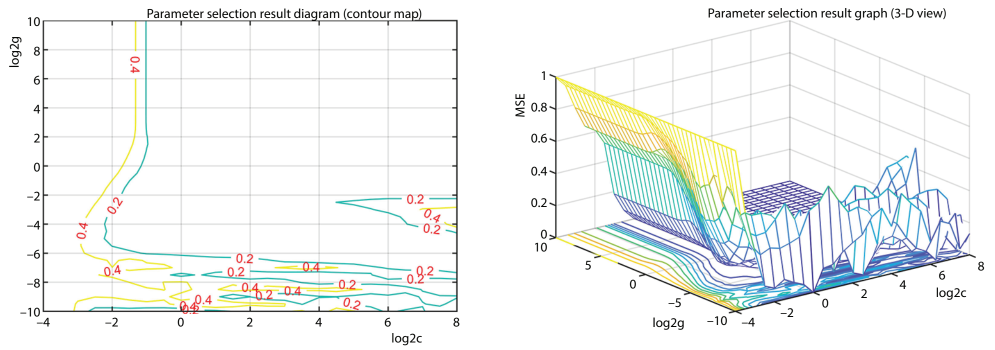


Figure 7. Parameter fine optimization diagram

Regression analysis using SVM model

Using these optimized parameters for training and regression analysis of the SVM model, a regression fitting diagram of the heating load sample data is shown in fig. 8.

As can be seen from the aforementioned fitting diagram, the SVM model can achieve better results when fitting the heat load data.

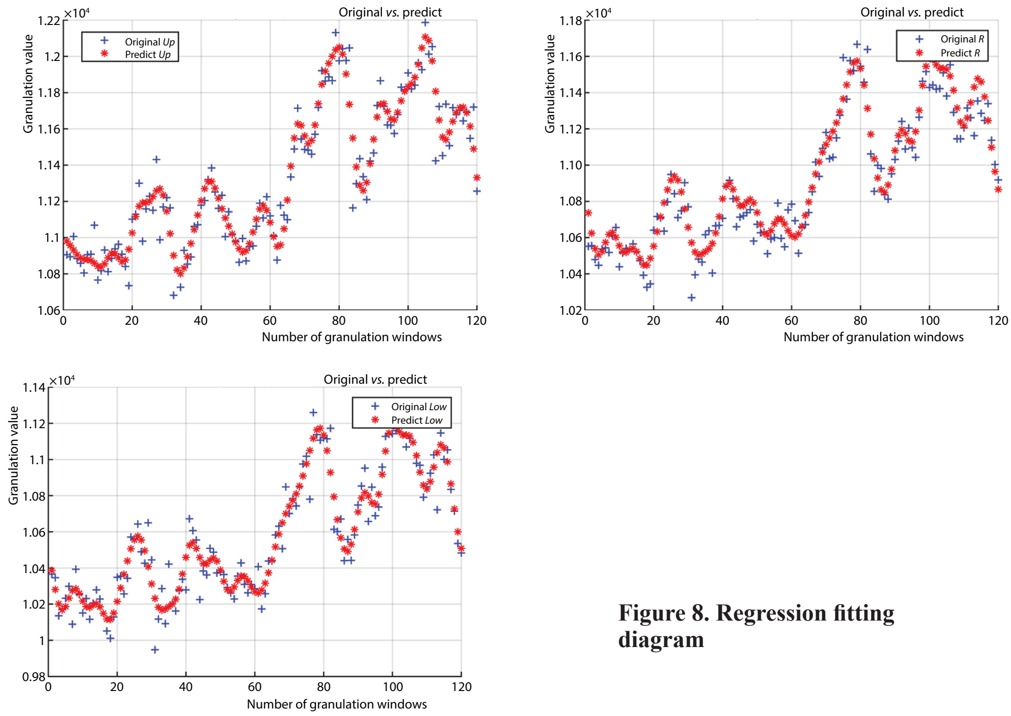


Figure 8. Regression fitting diagram

Define L as the actual value, L' as the regression prediction value, the regression prediction error value is $E_{\text{error}} = L' - L$, the upper bound is taken as an example to explain the situation, the error diagram is shown in fig. 9.

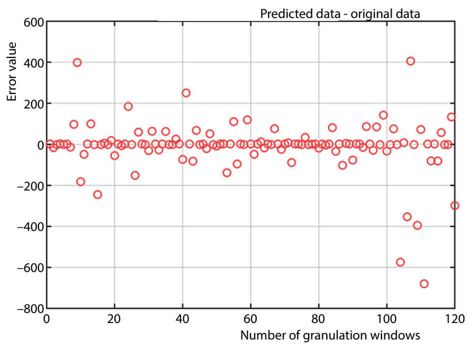


Figure 9. Error diagram

It can be clearly seen from fig. 9 that the fit of the algorithm to the *Up* data is ideal, and the image matching degree of the granulation data *Up* and the prediction data *Up* is also very high.

Comparison of actual and predicted values

The root MSE of the parameter *Up* is 0.0629, the predicted value of the heat load in the future under the parameter *Up* is 11501.89, the root MSE of the parameter *Low* is 0.0924, the predicted value of the heat load in the future under the parameter *Low* is 10613.21, and the root MSE of the parameter R is 0.0567, and the predicted value of the heat load in the future under parameter R is 10986.36. The actual heat load data for the next time window ($t_1 \sim t_{96}$) is shown in tab. 2.

Table 2. Actual heating load

Time window	Actual load data									
$t_1 \sim t_{60}$	10775.87	10794.71	10881.64	10950.07	11018.86	11010.85	11053.33	11028.64	11040.35	11035.59
$t_{11} \sim t_{20}$	11137.44	11170.27	11136.24	11147.78	10831.32	10697.1	10727.97	10793.44	10799.29	10898.04
$t_{21} \sim t_{30}$	10715.44	10730.02	10689.47	10664.83	10663.53	10706.54	10675.62	10714.87	10613.8	10626.17
$t_{31} \sim t_{40}$	10620.66	10839.23	10855.96	10886.2	10843.63	10881.37	10871.99	10835.4	10735.81	10788.71
$t_{41} \sim t_{50}$	10820.98	10903.01	10924.85	11005.65	11072.85	11131.14	11052.37	11115.94	11261.66	11360.12
$t_{51} \sim t_{60}$	11362.01	11410.28	11350.19	11405.77	11501.61	11345.85	11197.45	11180.35	11115.04	11190.15
$t_{61} \sim t_{70}$	11154.27	11120.92	11126.63	11196.2	11338.57	11368.67	11405.93	11285.41	11254.31	11177.08
$t_{71} \sim t_{80}$	11253.02	11094.44	11102.84	11319.8	11243.05	11191.15	11167.46	11128.8	10994.1	10842.2
$t_{81} \sim t_{90}$	10842.2	10845.83	10838.17	10877.35	10805.9	10883.9	10802.29	10847.48	10840.19	10837.33
$t_{91} \sim t_{96}$	10799.12	10769.87	10881.99	10871.75	10890.56	10757.42				

The predicted change range obtained by this method:

$$[Low, R, Up] = [10613.21, 10986.36, 11501.89]$$

From the predicted load change range and tab. 2, it can be seen that the actual load change range is consistent with the predicted load change range and the prediction is more accurate.

Conclusion

Accurate heating load forecast is the premise of the 4th generation heating system. Because the time series of heating load is relatively volatile and has the characteristics of non-linearity, time-varying, and easy to interfere, it is often difficult to accurately predict it. Traditional SVM can only make point predictions on heating load, and the accuracy is not high, the actual application effect is poor, and its change trend and change space cannot be predicted. In recent years, FIG has played an important role in many methods and technologies. The algorithm can divide the sample space into multiple subspaces, which reduces the sample size and simplifies the calculation complexity. The idea was introduced into the SVM. First, the Witold Pedrycz fuzzy granulation method was used to perform fuzzy granulation preprocessing on the heat load time series, and a SVM regression prediction model based on FIG was established. The simulation calculations show that the model can better realize the short-term heating load forecast and meet the actual application needs.

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