

Application of Fuzzy Support Vector Machine in Short-Term Power Load Forecasting

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ABSTRACT

The realization of short-term load forecasting is the basis of system planning and decision-making, and it is an important index to evaluate the safety and economy of power grid. In order to accurately predict the power load under the influence of many factors, a new short-term power load prediction method based on fuzzy support vector machine and similar daily linear extrapolation is proposed, which combines the method of fuzzy support vector machine and linear extrapolation of similar days. The method first selects similar days according to the effect of integrated weather and time on load. Then the fuzzy membership of the training sample is obtained by the normalization processing, and the daily maximum and minimum load is predicted by the fuzzy support vector machine. Finally, the load prediction value is obtained by combining the load trend curve obtained by the similar daily linear extrapolation method, and this method is feasible and effective for short-term forecasting of power load.

KEYWORDS

Fuzzy Support Vector Machine, Linear Extrapolatio, Load Forecasting, Power System, Short-Term Forecast of Power

1. INTRODUCTION

In recent years, the electric power industry has become one of the core industries in China, and its position is increasingly stable. The most basic requirement of qualified power system is to provide users with more safe, reliable, high-quality and economical power service. With the increasing scale and complexity of the power system, the accuracy of short-term load prediction of the power system directly affects the normal operation of the power system, which plays a key role in effectively reducing generation costs and implementing optimal control of the power system in various regions.

Realizing short-term forecasting of power system workload is the basis for system planning and decision-making, and it is also the key work for grid to achieve safety and economic indicators. Z Lan (2013) proposed that a complex nonlinear relationship between load demand and various influencing load factors. Select and process the factors affecting the load, and fit the intrinsic relationship between the load and various selected factors. Bisoi R, Dash P K and Das P P (2018) proposed that load forecasting work is not only the nature of work, but its implementation is very difficult. For better accuracy of short-term load forecasting, a GRU-CNN hybrid neural network model which combines the gated recurrent unit (GRU) and convolutional neural networks (CNN) was proposed by Wu L

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(2020). The proposed model was tested in a real-world experiment, and it can make more fully use data and achieve more accurate short-term load forecasting.

Selecting similar days plays an important role in improving the accuracy of load forecasting. The biggest feature of short-term load forecasting is that it has periodicity. When the external factors of the two different days have similar effects on the short-term load, the changes of the load curve for the two days are similar. Dash S K and Patel D (2016) analyzed the effect of objective factors such as time, temperature and daily type on load size reasonably based on the principle of “near large and far small” and “periodicity” of load. The prediction model of the load correction algorithm based on the similar day theory is constructed and improved. Smolen J, Landewé R B, and Mease P (2013) proposed the linear extrapolation method can obtain the trend of future load changes based on the characteristics of the load cycle change. The similar day method is combined with the linear extrapolation method to form a short-term load forecasting algorithm based on the similar linear extrapolation theory. This algorithm can estimate the future load change trend, but the accuracy of load forecast is easily affected by the drastic changes of external factors.

Selakov A, Cvijetinović D, and Milović L (2014) a hybrid model of short-term power load forecasting based on particle swarm optimization (PSO) and support vector machine (SVM). The effect of predicting the load over a significant period of temperature change is better. Tharwat A, Hassanien A E, Elnaghi B E (2017) and Liu Y, Wen K, Gao Q, et al (2018) proposed that Support vector machine is a machine learning algorithm based on structural risk, which has better generalization performance and prediction accuracy. Compared with support vector machines, fuzzy support vector machines is proposed by Zarbakhsh P, Demirel H (2017) and Lakshmi G, Panicker J R, Meera M (2017) that can use different learning intensities for different training samples. Therefore, the fuzzy support vector machine is used for load forecasting, which is more in line with the reality.

A hybrid short-term power load forecasting method based on fuzzy support vector machine and curve extrapolation is presented in this paper. The method firstly selects similar days for weather, day type and time to load impact. By normalizing the similarity corresponding to the similar day, it is taken as the fuzzy membership degree of the corresponding training samples, and the maximum daily minimum load is estimated according to the fuzzy support vector machine method. Then, combined with the forecast daily load trend curve based on the similar daily linear extrapolation, the complete future load forecast is obtained. Finally, using a historical data of a power company to carry out simulation research, the results prove the effectiveness of the method.

2. CORRELATION ANALYSIS OF LINEAR EXTRAPOLATION AND FUZZY SVM

2.1. Linear Extrapolation

The linear extrapolation of the phenomenon of constant growth rate over time is the simplest extrapolation. It is one of the common methods for short-term power load forecasting. The main principle is to obtain the curve of load growth by fitting the variation curve of working load in the past time. M Fan, Q Hong, and H Meng proposed that the value corresponding to the desired time is found on the curve to realize the load prediction, according to the variation characteristics of the curve.

The general model can be expressed as $y = a + bt + \varepsilon$. Where y is the load value at time t , and a and b are the undetermined coefficients of the model. ε is random interference, and the total interference is zero for the whole process. The general model of linear extrapolation principle is linear curve, which can predict the general change. The disadvantage is that the prediction error for large changes in weather is large. Then, the linear extrapolation method of similar days is used to predict, and better prediction results can be obtained.

2.2. Fuzzy Support Vector Machine

A set of sample training sets $\{(x_i, y_i, s_i) \mid i = 1, 2, \dots, l\}$ with fuzzy membership S class labels is given, where each input point $x_i \in R^N$, $y_i \in [0, 1]$. The fuzzy membership degree $s_i \in [\sigma, 1]$, $i = 1, 2, \dots, l$, where $\sigma > 0$, and σ is sufficiently small. Since the fuzzy support vector machine is based on the nonlinear mapping $\varphi(x)$, the data x to be sought is mapped into the high-dimensional feature space F , and linear regression processing is implemented in it. Therefore, the regression function is set as $f(x) = \omega\varphi(x) + b$, where $\varphi(x)$ is a mapping of the projection of data $x_i \in R^N$ into the high-dimensional feature space F .

Since the fuzzy membership degree s_i represents a reliable measure that the sample points belong to a certain type of sample and the parameter ξ_i represents the error term of the support vector machine prediction, $s_i\xi_i$ represents the error term with weights. The obtained optimal linear regression function is the optimal solution of the following objective function.

$$\begin{cases} \min J(w, e) = \frac{1}{2} w^T \cdot w + C \cdot \sum_{i=1}^l s_i \xi_i \\ s.t. y_i [w^T \cdot \varphi(x) + b] - 1 + \xi_i \geq 0, \xi_i \geq 0 \quad i = 1, 2, \dots, l \end{cases} \quad (1)$$

Where C is the penalty factor. For the above formula, the Lagrange multiplier α_i ($i = 1, 2, \dots, l$) is introduced to obtain its dual form as follows

$$\begin{cases} \min \frac{1}{2} \sum_{i=1}^l \sum_{j=1}^l \alpha_i \alpha_j y_i y_j K(x_i, x_j) - \sum_{i=1}^l \alpha_i \\ s.t. 0 \leq \alpha_i \leq s_i C, \sum_{i=1}^l \alpha_i y_i = 0 (i = 1, 2, \dots, l) \end{cases} \quad (2)$$

where $K(x_i, x_j)$ is the kernel function and satisfies $K(x_i, x_j) = \varphi(x_i) \cdot \varphi(x_j)$. By optimizing the above formula, the optimal solution $\hat{\alpha}_i = (\hat{\alpha}_1, \dots, \hat{\alpha}_l)^T$ is obtained, and the optimal linear regression function thus obtained is as follows

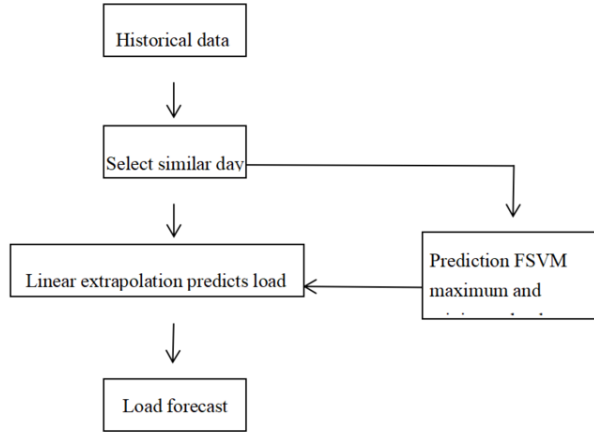
$$f(x) = \text{sgn} \left[\sum_{i=1}^l \hat{\alpha}_i y_i K(x_i, x) + \hat{b} \right] \quad (3)$$

In FSVM, $s_i C$ is the importance of using SVM to train sample point x_i . The larger $s_i C$ is, the larger the training effect of sample point x_i affecting support vector machine. When x_i is noise data or isolated point, let s_i be small, then $s_i C$ is small, which greatly reduces the effect of the sample point on the training of SVM.

3. COMBINED SHORT-TERM LOAD FORECASTING BASED ON SIMILAR DAILY EXTRAPOLATION AND FSVM

In this paper, the maximum and minimum load is predicted by fuzzy support vector machines firstly. Then, the forecast daily load trend curve is obtained based on the similar daily linear extrapolation

Figure 1. Process of load forecasting



method. Finally, the minimum and maximum load value is extrapolated according to the load change trend curve to obtain the future time load value. Figure 1 shows the process of load forecasting.

3.1. Similar Day Selection

The main factors influencing the load change contain daily maximum temperature, minimum temperature, average temperature, humidity, daily type and time interval. Those main factors can be classified as three different classes of load change, daily structure and meteorology. The differences in load days are described as follows

$$K = K_1\delta_1 + K_2\delta_2 + K_3\delta_3 \quad (4)$$

where K_1 and K_2 , and K_3 are weighting coefficients. The selection is based on experience and does not vary slightly in different seasons. δ_1 , δ_2 , and δ_3 represent the differences in load structure, daily structure, and meteorology between historical and predicted days, respectively.

The load structure will change slowly over time, then $\delta_1 = \begin{cases} \sqrt{\Delta D}/N \diamond & \Delta D \leq D_L \\ 1 \diamond & \Delta D > D_L \end{cases}$, and

different day structures correspond to different δ_2 . The specific data are shown in Table 1.

δ_3 indicates the meteorological difference. Meteorological conditions have a greater impact on the load, especially in summer and winter, and more abnormal weather, the meteorological difference can be expressed as $\delta_3 = c_1\gamma_1 + c_2\gamma_2 + c_3\gamma_3$. Where γ_1 , γ_2 and γ_3 represent precipitation, temperature and illumination, respectively. c_1 , c_2 , and c_3 represent the weighting coefficients of the items.

The K values of each candidate day are calculated by the above formula, and the size comparison is performed. When the value is the smallest, the day is selected as the similar day. The traditional similar day method has certain defects in effect and stability. Combining the current extrapolation method with similar days can complement each other and improve the effectiveness and stability.

Table 1. Values of different daily structure differences

Week	1	2	3	4	5	6	7
1	0						
2	0.1	0					
3	0.1	0.1	0				
4	0.1	0.1	0.1	0			
5	0.1	0.1	0.1	0.1	0		
6	0.4	0.4	0.4	0.4	0.4	0	
7	0.4	0.4	0.4	0.4	0.4	0.2	0

3.2. FSVM Load Forecasting

The fuzzy support vector machine was proposed by Lin Qunfu et al. in 2002. Based on the support vector machine (SVM), the fuzzy membership degree is introduced, then the influence of noise data and isolated point data on SVM are achieved. At the same time, the aim of using sample data rationally is improved.

Currently, fuzzy support vector machines are applied to load forecasting. The deficiency is that the membership function established in this method only considers the law of “near large and far small” of load, and fails to comprehensively measure the correlation between sample data and forecast date. Z Hai, W Song, and Z Zheng proposed that Similarity is the degree of similarity of load change rule under the influence of comprehensive external factors such as history day and prediction day. The greater the similarity, the more similar the load change law is, and vice versa. In order to make rational use of historical data, the purpose of accurately predicting future loads is achieved. In this paper, the similarity θ is used as the fuzzy membership of the training sample points. Since the fuzzy membership degree $s = [0, 1]$, it is necessary to normalize the similarity degree θ before constructing the load prediction model. The specific normalization method is as follows

$$s_i = \frac{\theta_i - \theta_{\min}}{1.2\theta_{\max} - \theta_{\min}} \quad (5)$$

where θ is the similarity correlation degree of the selected similar day. $\theta_{\min}$ and $\theta_{\max}$ are the minimum and maximum values of similarity correlation degree in selected similarity days.

In this paper, the fuzzy support vector load forecasting model is constructed by selecting similar day data. The input and output variables of the fuzzy support vector machine are shown in Table 2.

where, $T_{\max}$, $T_{\min}$ and T_{avg} are the maximum, minimum and average temperatures of similar days, respectively. $T_{o\max}$, $T_{o\min}$, and T_{oavg} are the highest, lowest, and average temperatures for the forecast day, respectively. H , H_0 are the average humidity of the similar day and the forecast day respectively, and $L_{\max}$, $L_{\min}$ are the maximum load and the minimum load of the similar day, respectively. S is the corresponding membership degree.

3.3. Linear Extrapolation Prediction Based on FSVM and Similar Days

According to the advantages and disadvantages of similar days and current extrapolation methods, multiple similar days can be obtained by strict difference measurement function. According to the method of similar day in Section 3.1, the difference value $\|\eta - \nu\| = K_1\delta_1 + K_2\delta_2 + K_3\delta_3$ between the

Table 2. Input and output variables of fuzzy support vector machine

Maximum load forecasting model		Minimum load forecasting model	
Input variable	Output variable	Input variable	Output variable
Tmax,Tomax	$\hat{L}_{\max}$	Tmin,Tomin	$\hat{L}_{\min}$
Tmax,Tomax		Tavg,Toavg	
H,Ho		H,Ho	
Lmax		Lmin	
s		s	

candidate date and the prediction date is obtained, and the similarity between the candidate date and the predicted date is $s_i = 1/\|\eta - \nu\|$. The similarities of the different candidate days obtained are compared, and the M days with the highest similarity are taken.

It is assumed that the M day's similar daily load has been selected and normalized. The normalization method is as follows

$$L'(k, i) = \frac{L(k, i) - L(k, \min)}{1.5L(k, \max) - L(k, \min)} \quad (6)$$

where $L'(k, i)$ is the normalized value of the i-hour load data on the k-th day, and $L(k, i)$ is the i-hour load data on the k-th day. $L(k, \min)$ is the k-day minimum load data, and $L(k, \max)$ is the k-th day maximum load data.

The similarity degree obtained by the normalization of the above M days, according to the weight, the load normalization coefficient of 24 points on the forecast day is obtained.

$$\bar{L}(i) = \sum_{k=1}^M \frac{s_k}{s_1 + \dots + s_M} L'(k, i) \quad (7)$$

where $\bar{L}(i)$ is the load normalization coefficient at the i-th time of the forecast day, and s_k is the load similarity.

The maximum load and minimum load obtained by FSVM, the load at any time on the forecast day is as follows

$$\hat{L}(i) = \bar{L}(i)(\hat{L}_{\max} - \hat{L}_{\min}) + \hat{L}_{\min} \quad (8)$$

where $\hat{L}(i)$ is the load at the i-th time of the forecast day.

4. SIMULATION ANALYSIS

Due to the existence of fuzzy information, the predictive analysis of complex systems under multi-constrained conditions. After the experimental test, the parameter selection setting of FSVM is as that the kernel function in this paper selects the radial basis function, $c=40$, and σ takes the value 0.01. Using this method, a simulation experiment is performed based on historical data provided by

a city. According to the actual data of the grid load for the 40 days from August 1st to September 9th, 2017, the training samples will be used to predict the load value from September 10 to 16, 2017. Figure 2 is a comparison of the load change trend for the week from September 10 to September 16, 2017, and the load change trend predicted by the method. Figure 3 is a comparison of the actual load for the week from September 10 to September 16, 2017, and the predicted load predicted by the method.

Figure 2. Actual load change trend and predicted load change trend from September 10 to September 16, 2017

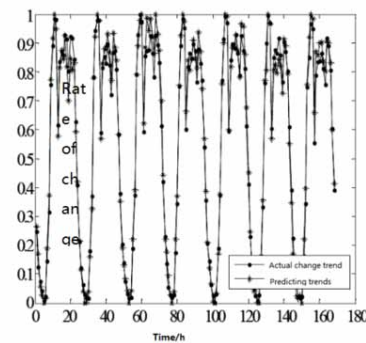


Figure 3. Actual load and predicted load curve from September 10 to September 16, 2017

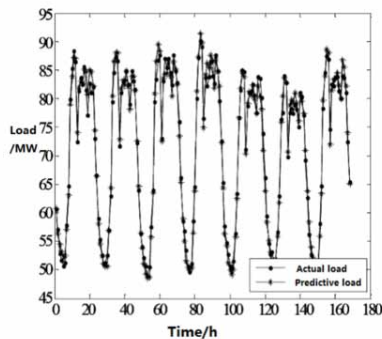


Table 3 gives the average relative error and maximum error of the method (new method) and the literature [5] method. It can be seen from Table 2 that the daily average maximum error for the continuous week obtained by the method is 4.07%. Despite the daily maximum error for a week, the results of this paper are not significantly better than those of the old methods. However, from the daily average error, the daily average error of this method is 1.55%, which is significantly better than the 2.09% of the old method. Therefore, it is effective to use the method of this paper for load forecasting.

Table 3. Maximum error and average error of each day from September 10 to September 16, 2017

Old method			New method	
Date	Maximum error	Average error	Maximum error	Average error
9-10	4.56%	2.58%	3.85%	1.73%
9-11	4.22%	2.48%	3.76%	1.43%
9-12	3.66%	0.98%	3.94%	1.51%
9-13	4.48%	1.80%	4.70%	1.65%
9-14	4.29%	2.40%	3.76%	1.57%
9-15	4.93%	2.21%	3.82%	1.11%
9-16	3.87%	2.13%	4.64%	1.87%

5. CONCLUSION

In this paper, a hybrid short-term load forecasting method based on fuzzy support vector machine and linear extrapolation of similar days is proposed. The method firstly selects similar days for weather, day type and time to load impact. Then, the normalized similarity data is taken as the fuzzy membership degree of the corresponding training samples, and the maximum daily minimum load is estimated by the fuzzy support vector machine algorithm. Finally, the forecast value of future time is obtained by combining the forecast trend curve of daily load based on the similar daily linear extrapolation method. Simulation experiments show that the proposed method is feasible and has high prediction accuracy.

DATA AVAILABILITY STATEMENT

The labeled dataset used to support the findings of this study are available from the corresponding author upon request.

CONFLICT OF INTEREST

The author declare no competing interests.

REFERENCES

- Bisoi, R., Dash, P. K., & Das, P. P. (2018). Short-term electricity price forecasting and classification in smart grids using optimized multikernel extreme learning machine. *Neural Computing & Applications*, 1–24.
- Dash, S. K., & Patel, D. (2016). Short-term electric load forecasting using Extreme Learning Machine - a case study of Indian power market. In *IEEE Power, Communication and Information Technology Conference*. IEEE.
- Fan, M., Hong, Q., & Meng, H. (2014). Method of Short-term Load Forecasting Based on GA and SVM. *Computer Science*, 41(6), 91–95.
- Hai, Z., Song, W., & Zheng, Z. (2017). Power Load Forecasting Based on Periodic Truncated Grey System. *Jisuanji Celiang Yu Kongzhi*, 25(12), 271–274.
- Lakshmi, G., Panicker, J. R., & Meera, M. (2017). Named entity recognition in Malayalam using fuzzy support vector machine. In *International Conference on Information Science*. IEEE.
- Lan, Z. (2017). On Application of Improved PSO-WNN to Model Load Forecasting. *Journal of Southwest China Normal University*, 42(6), 100–104.
- Liu, Y., Wen, K., Gao, Q., Gao, X., & Nie, F. (2018). SVM based multi-label learning with missing labels for image annotation. *Pattern Recognition*, 78, 307–317. doi:10.1016/j.patcog.2018.01.022
- Selakov, A., Cvijetinović, D., Milović, L., Mellon, S., & Bekut, D. (2014). Hybrid PSO–SVM method for short-term load forecasting during periods with significant temperature variations in city of Burbank. *Applied Soft Computing*, 16, 80–88. doi:10.1016/j.asoc.2013.12.001
- Smolen, J., Landewé, R. B., Mease, P., Brzezicki, J., Mason, D., Luijstens, K., van Vollenhoven, R. F., Kavanaugh, A., Schiff, M., Burmester, G. R., Strand, V., Vencovsky, J., & van der Heijde, D. (2013). Efficacy and safety of certolizumab pegol plus methotrexate in active rheumatoid arthritis. *Annals of the Rheumatic Diseases*, 68(6), 797–804. doi:10.1136/ard.2008.101659 PMID:19015207
- Tharwat, A., Hassanien, A. E., & Elnaghi, B. E. (2017). A BA-based algorithm for parameter optimization of support vector machine. *Pattern Recognition Letters*, 93, 93. doi:10.1016/j.patrec.2016.10.007
- Wu, L., Kong, C., & Hao, X. (2020). A Short-Term Load Forecasting Method Based on GRU-CNN Hybrid Neural Network Model. *Mathematical Problems in Engineering*.
- Zarbaksh, P., & Demirel, H. (2017). Fuzzy SVM for 3D facial expression classification using sequential forward feature selection. In *Computational Intelligence and Communication Networks (CICN), 2017 9th International Conference on*. IEEE. doi:10.1109/CICN.2017.8319371
- Zhou, M., Li, X., Wang, Y., Li, S., Ding, Y., & Nie, W. (2021). 6G multi-source information fusion based indoor positioning via Gaussian kernel density estimation. *IEEE Internet of Things Journal*, 8(20), 15117–15125. Advance online publication. doi:10.1109/JIOT.2020.3031639
- Zhou, M., Li, Y., Tahir, M. J., Geng, X., Wang, Y., & He, W. (2021). Integrated statistical test of signal distributions and access point contributions for Wi-Fi indoor localization. *IEEE Transactions on Vehicular Technology*, 70(5), 5057–5070. doi:10.1109/TVT.2021.3076269
- Zhou, M., Long, Y., Zhang, W., Pu, Q., Wang, Y., Nie, W., & He, W. (2021). Adaptive genetic algorithm-aided neural network with channel state information tensor decomposition for indoor localization. *IEEE Transactions on Evolutionary Computation*, 25(5), 913–927. Advance online publication. doi:10.1109/TEVC.2021.3085906
- Zhou, M., Wang, Y., Liu, Y., & Tian, Z. (2019). An information-theoretic view of WLAN localization error bound in GPS-denied environment. *IEEE Transactions on Vehicular Technology*, 68(4), 4089–4093. doi:10.1109/TVT.2019.2896482

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