Load forecasting method based on SVR under electricity market reform

Weiyuan Wang 1, Fei Dou 1, Xuan Yu 2, Gaowei Liu 3, Luqing Zhang 3, Qian Zhang 4 and Da Xie 5,5

1 State Grid Jiangsu Electric Power Co., Ltd, Nanjing, Jiangsu Province, 210000, China;
2 East China Electric Power of Design Institute Co., LTD. of China Power Engineering Consulting Group, Huangpu District Shanghai, 200001, China;
3 School of Electronic Information and Electrical Engineering, Shanghai Jiao Tong University, Minhang District Shanghai, 200240, China;
4 School of Electrical Engineering, Shanghai Dianji University, Minhang District Shanghai, 200240, China
5 Email: xieda@sjtu.edu.cn

Abstract. Many factors affect the predicted value of power load to varying degrees. The introduction of market mechanisms in power market reform has brought more uncertainty to power load forecasting. The load forecast under the new situation of electricity market reform needs to consider the impact of the market on power load forecasting. The paper improves the SVR algorithm and proposes a mid-long-term load forecasting method under electricity market reform. The simulation shows that the power load will develop rapidly under the new situation of electricity market reform.

1. Introduction
Under the background of electricity market reform, power load forecasting needs to consider the interaction between energy price and market behavior, which is the result of the intertwined willingness of countless individuals behind power supply and consumption [1]. Load Aggregator (LA), as the intermediary between power grid dispatching center and large-scale users, can realize micro-decentralized autonomy and the macro-overall response of its load group[2-3]. The electricity market reform will also deal with the demand fluctuation of scattered users, the transformation of power market trading mode, the new green energy trading policy[4-5], etc. Load forecasting algorithm will be greatly influenced. Therefore, considering the interaction between load, electricity price and renewable energy in the new situation, it is necessary to study the new-type load forecasting algorithm.

Load forecasting methods include parametric methods, non-parametric methods and artificial intelligence methods. Parametric methods include trend extrapolation, gray prediction and regression analysis.[6] The application of parameterization method needs strong pertinence, otherwise the effect will not be acceptable. Artificial intelligence methods consist of machine learning and neural networks [7-8],[9] develops a method for building non-parametric stochastic models of multivariate distributions considering forecasting of the loads in the electrical power grid. Machine learning is widely used in short-term load forecasting. Classical algorithms include KNN, DT, SVM and ensemble learning algorithm, such as random forest [10-13]. In [14], an application of parallel support
vector regression (SVR) algorithm in Hadoop is proposed. However, further improvements are needed before such methods can be applied to power system long-term load forecasting.

This paper analyses the factors that affect power load forecasting in power market environment, improves the SVR algorithm, and proposes a mid-long-term load forecasting algorithm under the new circumstance. The effectiveness of the algorithm is verified by simulation.

The structure of this paper is shown as follows. The second part of the paper introduces the situation of electricity market reform and its influencing factors to load forecasting. Then, this paper theoretically analyzes the load forecasting which takes into account the reform factors of electricity market. The fourth part gives the improved SVR algorithm considering market reform factors. Next, the effectiveness of the improved SVR algorithm is verified by an example in east China. Finally, the conclusion is given.

2. Electricity market reform and its impact on load forecasting
After electricity market reform, load forecasting will be significantly changed. The influence factors can be divided into three parts: competitive price, reform of trading and renewable energy trading.

2.1. Competitive electricity prices
In the electricity market environment, the purchasing and selling of electricity is competitive. The main competitors will be electricity companies, energy service providers and load aggregators (LA). Electricity sales companies participate in the wholesale market to purchase electricity, and then sell electricity to provide basic electricity sales and additional value-added services. Energy service providers participate in day-ahead and intraday electricity market transactions, purchasing a large number of distributed energies to meet users' energy demand. LA aggregates a large number of active load distribution, and uses the power demand as the main indicator to bid and purchase energy from the power market. Competitiveness will bring about the reduction of electricity price and increase of load.

2.2. Reform of trading
After the opening of the power selling side, the structure and operation mode of the power market become more complex. Real-time transaction between buyers and sellers enhances the interaction among the power supply enterprises, the main sellers and the customers. It refers to the pricing mode of real-time electricity price, in which users or their agents trade directly with the seller. In the new-type load forecast, it is necessary to determine the final equilibrium point of the user's response to electricity price and the electricity trading quotation by simulating the real-time transaction.

2.3. Green certificate trading
Green certificate is also known as Tradable Green Certificates (TGC), which represents the amount of renewable energy generated by the manufacturer. It can promote the development and utilization of renewable energy. In turn, power producers are encouraged to adopt more renewable energy generation.

3. Load forecasting considering market reform factors
The modeling of LA, Real-time price response and the change of green certificate trading are realized in this section. They represent the impact of market reform on load forecasting.

3.1. LA load electricity function
By controlling interruptible load, LA can directly control and reduce peak load. A weighted moving average model with limited peak and valley constraints is used to simulate the integration effect of LA.
\[
L_{R,t} = \sum_{i=1}^{n} \sum_{k=1}^{R_t} a_{i,k} L_{R,t-i} \\
\min \{ L_{R,t} + \Delta L_{R,t}, L_{R,\min} \} \leq L_{R,t} \leq \max \{ L_{R,t} - \Delta L_{R,t}, L_{R,\max} \} \\
\sum_{i=1}^{n} \sum_{k=1}^{R_t} a_{i,k} = 1
\]  

(1)

Where \( L_{R,t} \) is the total load at time \( t \) in LA supply area \( R \); \( a_{i,k} \) is weight coefficient; \( L_{R,t-i} \) is the load at time \( t-i \) of node \( k \); \( L_{R,\max} \), \( L_{R,\min} \), \( \Delta L_{R,u} \) and \( \Delta L_{R,l} \) are the upper limit of peak load, lower limit of valley load and corresponding control limit respectively; \( n \) is the average number of load values taken by this model at each time. The effect of LA load function on load integration is shown in Figure 1.

3.2. Forecast on the reform of transaction model

3.2.1. Quoted price forecast. Electric power users will inevitably seek and formulate cheaper power consumption schemes. Users will be affected by the prices and change their consumption behavior, resulting in changes in load and market transaction prices. Therefore, mid-long-term load forecast will also be affected by the quoted price.

![Figure 1. peak-valley effect of LA load in east area of China.](image)

A mid-long-term pricing model is constructed by predicting the marginal price of nodal power.

\[
\begin{align*}
LMP'_{i} &= \frac{\partial TU (PD'_i)}{\partial PD'_i} \\
LMP'_{j} &= \frac{\partial C'_j (PG'_j)}{\partial PD'_j} + \lambda_{r}^{+} + \lambda_{l}^{-}
\end{align*}
\]  

(2)

In formula (2), \( PD'_i \) is the demand of the \( i^{th} \) node in the \( t^{th} \) period; \( PG'_j \) is the generation of the \( j^{th} \) node in the \( t^{th} \) period; \( TU \) and \( C \) are the consumption function and the generation cost function respectively; \( \lambda_{r}^{+} \) and \( \lambda_{l}^{-} \) are the Lagrange multiplier of the maximum and minimum capacity constraints of the generator in the \( t^{th} \) period.

3.2.2. Real-time price response. The response of load facing the change of price can be obtained by elasticity coefficient. The electricity price response model used is as follows.

\[
\begin{align*}
\epsilon_{Q,\Lambda} &= \frac{\partial Q_i}{\partial P_i} / P_i \\
\epsilon_{L,\Lambda} &= \frac{\partial L_i}{\partial P_i} / P_i
\end{align*}
\]  

(3)
In formula (3), $Q_k$, $L_k$ and $P_k$ are the power supply, load and price of node $k$ respectively. Elasticity coefficient $\varepsilon_{Q,k}$ represents the power response of node $k$ to price variation, elasticity coefficient $\varepsilon_{L,k}$ represents the load response of node $k$ to price variation. The annual variation of electricity and load is shown in equation (4).

\[
L_y = \sum_{t=0}^{T} \sum_{k=1}^{K} L_{t,k}
\]

Where $L_y$ expresses the total load in a certain period $T$ and $t_0$ is the beginning time of the period.

3.3. The change of green certificate trading

The amount of green certificate trading directly reflects the development trend of renewable energy. Through the curve prediction method with additional constraints, the proportion of renewable energy in total load can be predicted. The forecast model of the change of renewable energy is established.

\[
\lambda_i = \frac{c}{1 + b e^{-at}}, a > 0, b > 0
\]

In formula (5), $\lambda_i$ is the proportion of renewable energy in the $i^{th}$ period; $a$, $b$, $c$ are the control parameters; $\varepsilon_j$ and $\Delta\lambda_m$ are the minimum and maximum change of renewable energy proportion respectively. Through historical data fitting, the function of predicting future changes is completed.

4. Improved SVR algorithm considering market reform factors

4.1. Principle of SVR algorithm

SVR (Support Vector Regression) is improved from MLR (Multiple Linear Regression) and SVM (Support Vector Machine). The assumption of SVR allows deviations $\varepsilon$ between predictive value $y'_i$ and real value $y_i$. If the absolute difference between $y'_i$ and $y_i$ is greater than $\varepsilon$, the loss will be calculated.

The function of the support vector is $y = \mathbf{w}^T \mathbf{x} + b$. The objective function of the SVR is:

\[
\arg \min \| \mathbf{w} \|^2 + R \sum_{i=1}^{n} \varepsilon_i
\]

In formula (6), $\mathbf{w}$ is the eigenvector, $R$ is the allowable error coefficient and $\varepsilon_i$ is the relaxation coefficient. Constraints can be written as:

\[
y'_i \left( \mathbf{w}^T \mathbf{x} + b \right) \leq 1 - \varepsilon_i
\]

Where $y'_i$ is the load value of the $i^{th}$ sample. The algorithm becomes an optimization problem for solving Lagrange multiplier method. Lagrange function can be written in (8) by introducing constraint coefficient vector $\mathbf{\alpha}$.

\[
L = \frac{1}{2} \| \mathbf{w} \|^2 - \sum_{i=1}^{n} \mathbf{\alpha}_i \left( y'_i \left( \mathbf{w}^T \mathbf{x} + b \right) - 1 \right)
\]

Among them, $i$ and $j$ represent different samples, it can be solved by SMO (Sequential minimal optimization). SVR will change $x^{(i)}$, $x^{(j)}$ into $K(x^{(i)}, x^{(j)})$ (called a kernel function). Basically, there are three main kernel functions: linear function, polynomial function and Gauss function (RBF). In this paper, RBF function as given in (9) is used:
\[ K(x^{(i)}, x^{(j)}) = \exp\left(\frac{-\|x^{(i)} - x^{(j)}\|^2}{2\sigma^2}\right) \]  

Where \( \sigma \) stands for the parameter that can be adjusted.

4.2. Improved SVR algorithm

By combining Bagging algorithm and designing input parameters, the application of SVR is realized.

**Table 1.** Parameter table for improved SVR algorithm.

| Type               | Data name          | Explanation                                         |
|--------------------|--------------------|-----------------------------------------------------|
| Common input       | Year, Month       | Year of load data, Month of load data               |
|                    | Renewable energy  | Proportion of Renewable Energy to Total Load       |
|                    | Previous load     | Last month’s load                                   |
| Processed input    | Season            | Season of load data                                 |
|                    | Policy dynamics   | -1,0,1 for the encouragement for renewable energy  |
|                    | Economic activity | -1,0,1 for Regional economic activities             |
| Output             | Load              | Load predicted                                      |

Bagging is a method of random sampling and synthesis of output results. The specific algorithm flow after combining SVR with bagging is as follows: (1) Random extraction of \( m \) training samples from the original data set; (2) \( n \) rounds were extracted and \( n \) sets of training were obtained; (3) Get \( n \) SVR models by training \( n \) sets; (4) The average value of the prediction results of each model is taken as the final prediction result.

The parameter selection of the sample is shown in Table 1. The integrated forecast model after sample training can realize preliminary load forecasting.

4.3. Process of improved SVR algorithm

![Flow chart of power load forecasting.](image_url)

The flow chart of mid-long-term load forecasting is shown in Figure 2. The model consists of three parts: the first part is LA load forecasting, the second part is transactions simulation of the power market, and the third part is Renewable energy prediction. Considering the impact of green certificate trading, and the change of renewable energy proportion is included in the model to continue iterative forecasting.
5. Simulation

In this section, the validity of the forecast model is verified by simulation according to different influencing factors. This paper chooses the power load in east area of China from January 2014 to December 2017 as the input data. The ordinary SVR load forecast is taken as the control group, and considers the influence of different power reform factors on the load forecasting respectively. The results are shown in Figures 3 and 4.

![Load forecast result diagram](image)

From Figure 3 (a), it can be seen that the ordinary SVR forecast part realizes the forecasting function of power load without considering the power market, and can reflect the seasonal characteristics of load distribution, but the reflection of load growth trend is not obvious. The forecasted power load in 2018 is 1611.302 billion kWh, which is basically the same as the actual load of 1612.56 billion kWh in 2018.

In Figure 3 (b), the increase of load forecasting at this time is only 40.288 billion kWh compared with ordinary load forecasting in 2018, which indicates that LA only suppresses load when it acts alone, but has little effect on load forecasting.

In Figure 3 (c), the load increases by 96.77 billion kWh compared with the original load in 2018, sufficiently reflecting that real-time trading can effectively stimulate the increase of electricity demand.

In Figure 3 (d), the total load increased by 102.004 billion kWh in 2018. The steady development of renewable energy promotes the increase of electricity demand. However, the role of renewable energy in the trading market cannot be reflected only by the change of its proportion.

To prove the method proposed is doing well in prediction, we compared the SVR method with the random forest prediction (RF) method from January 2018 to December 2018, and the result is shown in Figure 4 and Table 2. In the Table 2, we calculate the root mean square error and mean absolute percentage error of SVR and RF. From the result, we can find that the improved SVR model is doing better in prediction than RF in the paper.
Figure 4. Comparison of improved SVR, RF and real value in 2018.

Table 2. Comparison of improved SVR and RF.

| Method | Root Mean Square Error | Mean Absolute Percentage Error |
|--------|------------------------|--------------------------------|
| SVR    | 94.50                  | 0.058                          |
| RF     | 152.99                 | 0.089                          |

Then, three power market factors are incorporated into the SVR model. As shown in Figure 5, the load increased significantly, with an increment of 99.616 billion kWh in 2019 and 173.471 kWh in 2020. Meanwhile it promotes the development of renewable energy, accounting for 8.9% in 2019 and 11.9% in 2020. With the promotion of electricity reform, green certificate, real-time transaction and other power market means, the power load and national economy will grow rapidly.

Figure 5. Improved SVR load forecasting result considering power market.

6. Conclusions

This paper mainly analyses the influence of LA, real-time electricity price, and green certificate on load forecasting under the environment of power market. This paper achieves the following results:

1) The influence of the above factors on load prediction is verified by an example. According to the load prediction results, green certificate transaction and real-time transaction have roughly the same impact on power load prediction, but both have greater impact than LA on power load prediction.

2) The SVR algorithm, LA load function, real-time transaction and green certificate transaction are incorporated into the load forecasting algorithm, and a new load forecasting algorithm is proposed. It can be seen that the proposed algorithm has detailed growth in the load forecast of 2019 and 2020.

3) The validity of the proposed load forecasting algorithm is verified by simulation, which proves that the new power reform in China can promote the power load and economic development.
References

[1] Mohan V, Singh J, Ongsakul W 2016 Sortino ratio based portfolio optimization considering evs and renewable energy in microgrid power market IEEE Transactions on Sustainable Energy 8(1) 219-229

[2] Hu J, Cao J, Guerrero JM, et al. 2017 Improving frequency stability based on distributed control of multiple load aggregators IEEE Transactions on Smart Grid 8(4) 1553-1567

[3] Chunyan L, Wang D, Zhang P, Xie K 2017 Double layer real-time scheduling model of independent microgrid considering scheduling priority of load aggregators Automation of Electric Power Systems 41(6) 37-43 and 167

[4] Ghaffari M, Hafezalkotob Ashkan, Makui Ahmad 2016 Analysis of implementation of tradable green certificates system in a competitive electricity market: a game theory approach Journal of Industrial Engineering International 12(2) 185-197

[5] Zhang G, Wang B 2008 Study of power market operation with demand response and consideration of china’s power market reform Electric Power Automation Equipment 28(10) 28-33

[6] Wang Yaohua, Jiao Bingqi, Zhang Fuqiang, Feng Junshu, Wu Shengyu 2017 Medium and long term power development analysis taking into account the operation characteristics of high proportion renewable energy [J] Automation of Electrical Power system 41(21) 9-16

[7] Voyant C, Notton Gilles, et al. 2017 Machine learning methods for solar radiation forecasting: a review Renewable Energy 105 569-582

[8] Li C, Li Shuke, Liu Yunqi 2016 A least squares support vector machine model optimized by moth-flame optimization algorithm for annual power load forecasting Applied Intelligence 45(4) 1-13

[9] S Shenoy, D Gorinevsky and S Boyd 2015 Non-parametric regression modeling for stochastic optimization of power grid load forecast 2015 American Control Conference (ACC), Chicago, IL, 2015, pp. 1010-1015

[10] Zhiqiong Wang, Junchang Hongxu, et al. 2017 Distributed and weighted extreme learning machine for imbalanced big data learning Tsinghua Science and Technology 22(2) 160-173

[11] Qinghua Chen 2017 Research on intelligent power load forecasting algorithm based on empirical mode decomposition Chemical Engineering Transactions 59 841-846

[12] Chunming Yuan, Yuanying Chi and Xiaojing Li 2019 A combined forecasting method for short term load forecasting based on random forest and artificial neural network IOP Conference Series: Earth and Environmental Science

[13] Liu Wenxia, Xu Xiaoobo, Zhou Fang 2014 Daily load forecasting of electric bus charging/switching station based on support vector machine [J] Electric Power Automation Equipment 34 (11) 41-47

[14] Z Zhang, X Wang and Y Ji 2018 The Power Load Forecasting of SVR Based on Hadoop 2018 37th Chinese Control Conference (CCC), Wuhan, 2018, pp. 4484-4488