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# A Regional Power Loads Coordinated-forecasting Method Based on Real Time Lightning Detection

Jianqiang Miao, Chong Tong, Yunfeng Cai, Ning Wang, Yang Xu, Jinwen Mai
JiangSu Electric Power Co., Ltd Suzhou Branch
SGCC (State Grid Corporation of China)
Suzhou, China
chong.tong@smartpdg.com

Haiyan Jiang
City & Energy Research Institute Co., Ltd (Suzhou)
SGCC (State Grid Corporation of China)
Suzhou, China
jianghy3@js.sgcc.com.cn

Jianyong Zheng
School of Electrical Engineering
Southeast University
Nanjing, China
jy_zheng@seu.edu.cn

Jian Xu
School of Electrical Engineering
Wuhan University
Wuhan, China
xujian@whu.edu.cn

***Abstract*—In order to improve system reliability and lightning performance of the smart grid, the dynamic lightning protection was introducedin recent years. One of the solutions of dynamic mode is to transfer and control power loads in those areas which are threatened by lightning. Thus, an accurate regional load prediction method becomes necessary to guide the proper fast loads transfer. This paper proposes a coordinated-forecasting method of regional power loads which is based on real time lightning detection. It is expected to improve the precision of short-term load forecasting under lightning climate so as to improve the efficiency of generation planning, and to promote the safety, stability & economical operation for the smart grids.**

***Keywords—Dynamic Lightning Protection; Load prediction; Smart grid; Regional coordinated prediction***

## I. INTRODUCTION

With the continuous development of smart grids and the transformation of social energy consumption, electricity has become one of the indispensable energy sources. Due to the non-mass storage characteristics of electric energy, real-time load forecasting technologies are significant for generation outputs in power production and are beneficial to achieve the dynamic balance between power supply and demand [1].

As a common natural phenomenon, lightning continually affects the operation of power systems since the utility were established and developed. The equipment faults caused by lightning strikes would lead to power load losses [2]. On the other hand, the difference between meteorological factors (such as temperature and rainfall) in the lightning climate and normal days has a greater impact on power production and power user behavior [3]. The renewable energy generation will also be influenced.

Traditional load forecasting methods mostly rely on large historical data [4]. Due to the increasing randomness of load changes, insufficiency of historical data as well as the data of increasing renewable energy generation, load forecasting in lightning weather and their analysis results are not satisfactory at this stage [5].

Therefore, establishing an accurate load forecasting method associate with lightning detection and improving the load forecasting accuracy under lightning weather are of great significance for the safety, stability and economical operation of the smart grids [6 - 8].

This paper proposes a power system load forecasting method suitable for lightning climate, which can improve the short-term load forecasting accuracy under lightning weather, thereby improving the efficiency of power generation planning and promoting the safety, stability and economical operation of the power system. Meanwhile, such a method would be beneficial to improve the rational utilization of data and guide the proper fast loads transfer of dynamic lightning protection [9, 10].

## II. METHOD OF COORDINATED-FORECASTING FOR REGIONAL POWER LOADS

As far as the present concerned researches on load forecasting, the achievements focus on the different characteristics of loads, the factors affecting load changes, the forecasting model establishment, and their systematic analysis as well as correlative research. These achievements are effective and meaningful for the stability and economical operation of conventional power systems.

The coordinated-forecasting method is to utilize the connection between real-time load changes within different zones in a lightning storm-affected region, and combines with real time lightning detection. It would effectively improve the prediction accuracy with limited historical data in lightning climate.

To realize the initial goals of accurate load forecasting, the regional coordinated load forecasting method under lightning climates is characterized by three steps, which is illustrated in Fig .1:

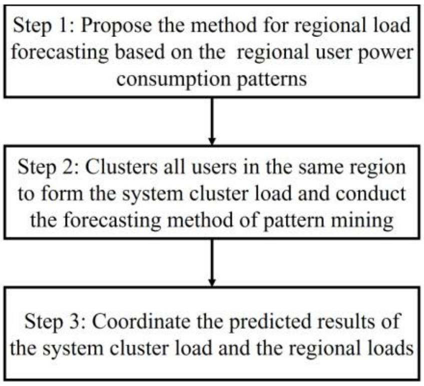


Fig. 1. The flow chart of the coordinated load prediction method under lightning climates

### *A. Step 1*

For the power loads in different areas, the user mode is determined based on their electricity consumption behaviors. The method of big data mining provides an effective way for regional load forecasting. It is able to extract the regional user power consumption patterns through data mining, and establish the forecasting method based on the power consumption patterns to achieve the target of accurate load forecasting.

In this link, different specific load forecasting schemes are designed. Firstly, according to the various regional user load characteristics, a personalized regional user load forecasting method based on decision tree is proposed. The core idea is to use decision tree method to establish the specific load forecasting models and strategies for regional users with different load characteristics. Therefore, high-precision short-term load forecasting for large regional users can be achieved. Specifically, for regional users with stable power consumption patterns, the typical power consumption patterns can be extracted by data mining method. Then the prediction method can be selected according to the number of patterns. For the regional user loads whose power consumption patterns have great changes, their load presents the characteristics of jagged fluctuation. First, the fluctuation components need to be eliminated by frequency domain processing method so as to improve its stability and regularity. Then the load forecasting can be carried out based on the remaining stable components.

### *B. Step 2*

Due to the large fluctuation of user load in a single region, this step clusters all users in the same region to form the system cluster load based on Step 1, and then the system cluster load can be predicted. Firstly, the clustering load of the system is formed by summing all the regional users with the same power consumption mode quantity. Secondly, based on the clustering load of the system, the load forecasting method of pattern mining is adopted.

### *C. Step 3*

This step combines the prediction results of Step 1 and Step 2. The matching factors of users in every region for the clustering load of the whole system are obtained based on the historical data. The prediction results of system clustering load are combined, and the prediction results of the system clustering load and the user load of a single region are coordinated. The randomness of the clustering load is small so its predictability is strong. According to the matching model of the system cluster load and the regional loads, the predicted results are coordinated, so the revised forecast results of each regional user load and system cluster load are obtained.

## III. PROCEDURES OF COORDINATED-FORECASTING FOR REGIONAL POWER LOADS

For the meteorological and load data, the implementation procedure is divided into three steps: regional user load forecasting, system load forecasting, and coordination between regional user and system load forecasting.

### *A. Procedures of Step 1*

Big data mining offers an effective method for regional user load forecasting in the first step. It can help extract the power usage patterns of regional users by mining their historical load data in the thunderstorm climate. Then, a power usage pattern-based prediction method is established to achieve accurate forecasting of regional user loads. In this session, a variety of specific schemes for load forecasting are designed.

Initially, a decision tree-based personalized forecasting approach of regional user loads is put forward based on different regional user load characteristics. Its core idea is to develop targeted load forecasting models and strategies for regional users with different load characteristics using the decision tree method, thereby achieving high-accuracy short-term load forecasting of large regional users. To be specific, for regional users with relatively stable power usage patterns, their typical power usage patterns can be extracted directly through data mining, and then prediction method is selected depending on the number of patterns.

As for the regional users with largely changing power usage patterns, removal of serration components by frequency domain processing is needed firstly given the serration characteristics of their loads, in order to enhance the load stability and regularity.

Afterwards, forecasting is made based on the remaining stable components. In Fig. 2, the decision tree-based personalized forecasting process of regional user loads is displayed.

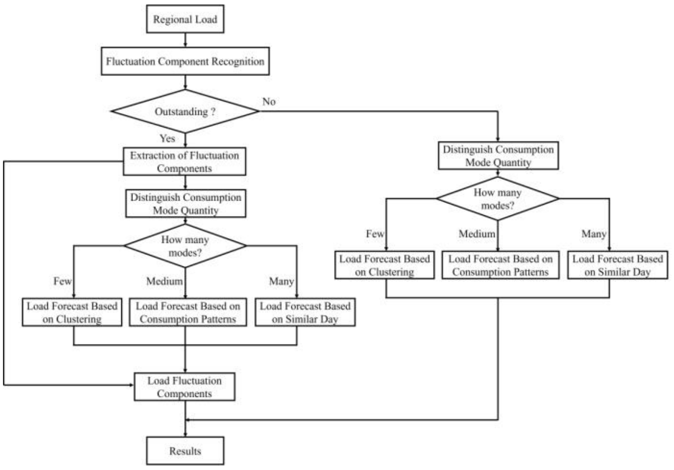


Fig. 2. The block diagram of the personalized user load prediction principle based on decision tree

*1) Forecasting scheme two: Pattern mining forecasting*

This scheme is applicable to the loads of regional users with moderate number of patterns. Through the order statistics of occurrence of their historical power usage patterns, the state transition matrix of the patterns can be derived by statistical decision making. According to this matrix, the power usage patterns of regional users on the forecasting day are decided. Then, the load curves for the same patterns on the historical day are smoothed exponentially to predict the load on the forecasting day.

Algorithmic steps:

*a)* Historical loads are clustered by hierarchical clustering (unsupervised clustering) to generate a set of typical power usage patterns $A=\{1,2,\cdots,i,\cdots,N\}$ and obtain the production pattern for each historical day.

*b)* A state transition matrix $\mathbf{M}$ is generated based on the identification results of historical day production patterns of regional users. It records the probability $M_{ij}$ that the power usage pattern on the forecasting day obeys various typical production patterns $j\,(j=1\sim N)$ on condition of a fixed power usage pattern $i$ on the reference day. The production pattern $M_{ik}$ ($M_{ik}=\max(M_{i1},M_{i2},\cdots,M_{iN})$) with the maximum transfer probability is decided based on the production pattern $i$ on the reference day $u_0$ combined with the above matrix, which is the most likely production pattern on the forecasting day $r_0$.

*c)* All the historical days $\{r_1,r_2,\cdots,r_n\}$ with a power usage pattern $k$ are screened out from the historical days. The smaller their subscript is, the closer they are to the forecasting day. So $r_1$ is the nearest, and $r_n$ the farthest.

*d)* Exponential smoothing weight is taken according to the closeness of historical day loads from the forecasting day $r_0$. The closer to the forecasting day, the greater the weight is. The weight $w_l$ is expressed as follows:

$$w_l=\alpha(1-\alpha)^{l-1},\quad l=1,2,\cdots n \tag{1}$$

*e)* Load curves on the historical day $r_l$ are summed by weight $w_l$ to yield the load curve $\mathbf{P}_{r_0}$ on the forecasting day as

$$\mathbf{P}_{r_0}=\sum w_l\mathbf{P}_{r_l}\ , \tag{2}$$

where $\mathbf{P}_{r_l}$ denotes the load curve on the historical day $r_l$.

*2) Forecasting scheme three: SVM prediction*

While conventional statistics studies the asymptotic theory when the number of samples approaches infinity, in actual practices, the sample number is often limited. The statistical learning theory offers a unified framework for resolving the finite sample problem. The support vector machine (SVM) theory by V. Vapnik has gained widespread attention in recent years owing to its solid theoretical foundation and multiple good features [8]. Currently, many facts have proven that the principle of structural risk minimization, one most basic idea of SVM, is superior to the conventional principle of empirical risk minimization, which has exhibited many unique advantages in solving nonlinear, small-sample and high-dimensional pattern recognition problems. Essentially as a feedforward neural network, SVM originates from the classification problems, which improves the classifier generalization ability as much as possible according to the structural risk minimization criterion on the premise of minimizing the training sample classification error. Kernel function is critical to SVM. Low-dimensional space vector sets are mapped into a high-dimensional space since they are generally difficult to partition, and kernel function just addresses this problem subtly. In other words, the classification function of high-dimensional space can be obtained as long as the appropriate kernel function is selected.

Maximization of classification interval is the core idea of SVM, which is actually the control of generalization ability. In other words, it can not only separate two classes, but also maximize the classification interval. Two linearly separable SVM problems are a quadratic programming problem, which can be transformed into an optimization problem. Meanwhile, nonlinearity is the foremost feature of economic system. One most critical point that SVM can be applied into the economic field is its ability to handle nonlinear problems. Through nonlinear transformation, it can transform the nonlinear problems into linear in a high-dimensional space, and seek the optimal classification plane in the transformed space. In the high-dimensional space, SVM uses a kernel function instead of inner product operation, so as to avoid complex computation. A kernel function corresponds to the inner product in a certain transformed space when it satisfies the Mercer condition, so that it can be transformed into an approximately linear solution, thereby preferably solving the nonlinear classification problem. Existing applications of SVM algorithm for classification are found mainly in the areas of pattern recognition, regression estimation, probability density function estimation, etc.

## *B. Procedures of Step 2*

Algorithmic steps:

*1)* All the regional users with the same numbers of power usage patterns are summed to form system cluster loads.

*2)* Forecasting is performed based on the system cluster loads by adopting the control scheme two.

*C. Procedures of Step 3*

In the third step, the ratio factor of user loads in each region over the total system cluster loads is derived based on the historical load data by combining the forecast results from the prior two steps. Accordingly, the prediction results of system cluster loads and the user loads in individual regions are corrected. Higher level of system cluster loads indicates lower load randomness and stronger predictability. The system cluster load forecasts are coordinated with the user load forecasts for various regions according to the "system cluster load–regional user load" ratio matching model, thereby obtaining the corrected user loads for various regions and the corrected forecasts of system cluster loads. The ratio factors therein can be obtained by smoothing the recent day ratio factors.

Assuming the overall system cluster load forecast is $z_0$, and the regional user load forecast is $z_i(i=1,2,\cdots,n)$. Then, for the physical quantity with "direct additivity", there should ideally be

$$z_0=\sum_{i=1}^{n} z_i \tag{3}$$

That is, the sums of system cluster and regional user load forecasts can be fully matched. In reality, however, the above formula generally does not hold due to the presence of prediction error. In other words, there is an unbalance:

$$\Delta_z=\sum_{i=1}^{n} z_i - z_0 \tag{4}$$

The purpose of load forecast coordination is to calculate the optimal estimate of actual user load $x_i(i=0,1,2,\cdots,n)$ for various regions. In view of the difference in user load prediction accuracy among various regions, the estimated value which minimizes the weighted sum of squares of relative adjustment $\Delta z_i^r=(z_i-x_i)/z_i(i=0,1,2,\cdots,n)$ is precisely the optimal coordination value for the regional user load forecasts. Its mathematical model is:

$$\begin{aligned} &\min\ f=\sum_{i=0}^{n} w_i\left(\frac{z_i-x_i}{z_i}\right)^2 \\ &s.t.\quad x_0=\sum_{i=1}^{n} x_i \end{aligned} \tag{5}$$

Weight $w_i(i=0,1,\cdots,n)$ in the mathematical model represents the reliability of user load forecasts for various regions. Apparently, the reliability should be high if the accuracy of the *i*-th demand forecast is high.

As a typical equality-constrained quadratic programming problem, the above model can be solved by the Lagrangian multiplier method. A Lagrangian function is created by letting the optimal solution be $\hat{x}_i(i=0,1,\cdots,n)$ as:

$$L=\sum_{i=0}^{n}\frac{w_i}{z_i^2}(z_i-\hat{x}_i)^2-\hat{\lambda}(\hat{x}_0-\sum_{i=1}^{n}\hat{x}_i) \tag{6}$$

Finding partial derivatives for each variable in the above formula yields:

$$\frac{\partial L}{\partial x_0}=2\frac{w_0}{z_0^2}(z_0-\hat{x}_0)(-1)-\hat{\lambda}=0 \tag{7}$$

$$\frac{\partial L}{\partial x_i}=2\frac{w_i}{z_i^2}(z_i-\hat{x}_i)(-1)+\hat{\lambda}=0,\quad i=1,2,\cdots,n \tag{8}$$

$$\frac{\partial L}{\partial \hat{\lambda}}=-(\hat{x}_0-\sum_{i=1}^{n}\hat{x}_i)=0 \tag{9}$$

From Eq. (7), we can get:

$$\frac{\hat{\lambda}}{\frac{w_0}{z_0^2}}=-2(z_0-\hat{x}_0) \tag{10}$$

From Eq. (8), we can get:

$$\frac{\hat{\lambda}}{\frac{w_i}{z_i^2}}=2(z_i-\hat{x}_i),\quad i=1,2,\cdots,n \tag{11}$$

Hence

$$\sum_{i=1}^{n}\frac{\hat{\lambda}}{\frac{w_i}{z_i^2}}=2\sum_{i=1}^{n}(z_i-\hat{x}_i)=2(\sum_{i=1}^{n}z_i-\sum_{i=1}^{n}\hat{x}_i)=2(\sum_{i=1}^{n}z_i-\hat{x}_0) \tag{12}$$

From Eqs. (11) and (12), we can get:

$$\sum_{i=0}^{n}\frac{\hat{\lambda}}{\frac{w_i}{z_i^2}}=2(\sum_{i=1}^{n}z_i-z_0) \tag{13}$$

Solving yields:

$$\hat{\lambda}=\frac{2}{\sum_{i=0}^{n}\frac{z_i^2}{w_i}}(\sum_{i=1}^{n}z_i-z_0) \tag{14}$$

By substituting (14) into (11), the coordination values of user load forecasts for various regions are obtained as:

$$\hat{x}_i = z_i - \frac{\frac{z_i^2}{w_i}}{\sum_{i=0}^{n} \frac{z_i^2}{w_i}} (\sum_{i=1}^{n} z_i - z_0), \quad i = 1, 2, \mathrm{L}\ , n \tag{15}$$

By substituting (14) into (10), the coordination value of system load forecasts is obtained as:

$$\hat{x}_0 = z_0 + \frac{\frac{z_0^2}{w_0}}{\sum_{i=0}^{n} \frac{z_i^2}{w_i}} (\sum_{i=1}^{n} z_i - z_0) \tag{16}$$

After analyzing and solving the above model, the coordinated forecasts of regional user and system loads in the thunderstorm climate are obtained ultimately.

## IV. Application Data

A simulation and verification sample of the above regional power loads coordinated-forecasting method was associated and integrated in a Dynamic Lightning Protection System of Smart Grid, which operates in the Power Grid Dispatch & Control Center of Suzhou in China.

Table I shows the comparison data of actual acquired and three loads-forecasting methods which are conventional method A (mainly depending on historical data), conventional method B (independent zone forecasting) and regional coordinated method based on real time lightning detection. The data collected from 12 nodes in the power grid of Suzhou on August 10th, 2018.

Table II shows acquire data comparison between normal & lightning weathers which indicates the advantage of regional coordinated method when was applied in the forecasting of lightning weathers. The data collected from the same power grid of Suzhou from October, 2017 to September, 2018.

TABLE I. Loads-forecasting Methods Comparison

| **NODE** | **Data Comparison (Date: 2018.8.10)** | | | |
|---|---|---|---|---|
| | ***Actual Acquired Data*** | ***Conventional Method A*** | ***Conventional Method B*** | ***Regional Coordinated Method*** |
| Node1 | 574.17 | 652.25 | 595.14 | 551.23 |
| Node2 | 641.32 | 365.26 | 596.11 | 526.67 |
| Node3 | 699.13 | 268.45 | 545.83 | 735.74 |
| Node4 | 372.79 | 520.25 | 453.52 | 286.96 |
| Node5 | 468.29 | 658.33 | 378.43 | 462.75 |
| Node6 | 531.38 | 562.52 | 517.24 | 526.24 |
| Node7 | 160.43 | 196.31 | 253.75 | 186.59 |
| Node8 | 741.12 | 966.24 | 654.59 | 532.25 |
| Node9 | 635.67 | 563.72 | 414.57 | 621.87 |
| Node10 | 197.76 | 365.27 | 195.26 | 226.21 |
| Node11 | 120.94 | 140.65 | 124.25 | 98.16 |
| Node12 | 116.71 | 98.24 | 128.75 | 136.95 |

TABLE II. Acquire Data Comparison between Normal & Lightning Weathers

| **Weather** | **Accuracy Statistics Evaluation (2017.10 – 2018.09)** | | | |
|---|---|---|---|---|
| | ***Actual Acquire d Data*** | ***Conventional Method A*** | ***Conventional Method B*** | ***Regional Coordinated Method*** |
| Regular | 1 | 0.73 | 0.86 | 0.81 |
| Lightning | 1 | 0.78 | 0.65 | 0.84 |

## V. Conclusion

An accurate regional power load prediction method becomes necessary to guide the dynamic lightning protection and its fast loads transfer in those areas which were threatened by lightning.

The coordinated-forecasting method of regional power loads, which is based on real time lightning detection, would improve the precision of short-term load forecasting under lightning weather. Coordinating with dynamic lightning protection actions, the method would also improve the efficiency of generation planning, and promote the safe and economical operation for the smart grids.

The regional power loads coordinated-forecasting method, which was proposed and described in the paper, could enrich the applicability of novel dynamic lightning protection for smart grids.

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