A spatial load forecasting method based on load regularity analysis

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Abstract: A new method, based on regularity analysis of cellular load, is presented to determine the reasonable maximum of the load density index method of spatial load forecasting (SLF). Through analysis of cellular historical load data, each cellular load is decomposed into regular and random components. The regular part is used to reveal the regularity of the cellular load in different cycles, using random components to describe and characterize the intrinsic error of the cellular load. Adverse effects that occur by eliminating random components to suppress the intrinsic error allow extraction of the maximum of the regular part as the Class I cellular reasonable load maximum. Using the reasonable maximum and the land use information of Class I cells, load density of I is obtained. The load density is used to determine the coordination coefficient of the classification load density. According to the constraint relationship of the historical load, we established the power supply area, land information, classification load density, relationship equation between Class I cellular load, and classification load density. Classification load density index is obtained by using the least square method and is used to predict its value in the target year. Then the load of Class II cell can be obtained, so that the spatial load forecasting of the urban power system is realized. The analysis of an example indicates that the method is effective in improving the prediction accuracy of spatial load forecasting.

Key words: Urban power system, spatial load forecasting, intrinsic error, load density index method, geographic information system

1. Introduction
Spatial load forecasting (SLF) is used to forecast spatial and temporal load characteristics. It is the basis for urban power system planning design and a complex problem involving a wide range of uncertain factors [1–6]. The accuracy of SLF affects urban power system layouts and determines whether the selection of a power supply path operating equipment is technically feasible and economically reasonable [7,8].

In short-term urban power system planning, SLF generally uses the largest value of cellular load per year from historical load data. If the cellular load data are selected without considering the overall trend in load development to establish a load forecasting model, it becomes difficult to simulate a development rule for the load variation and the accuracy of the model prediction cannot be guaranteed. Therefore, it is necessary to research load regularity and the method of data preprocessing to ensure that the cellular historical load data, used in modeling and forecasting, can reflect trends and rules of cellular development and improve SLF quality [9,10].

A short-term load forecasting method, based on intrinsic error evaluation, is proposed in [11]. This
method can effectively diagnose the main factors leading to errors, and can estimate the upper and lower bounds of the forecast errors to improve the accuracy of load forecasting. A method is proposed in [12] that uses learning vector quantization to eliminate bad data. A novel hybrid model, which combines denoising methods and optimization algorithms with forecasting techniques, is developed to solve the above problems and forecast the key indicators in the electrical power system [13]. However, the preprocessing methods of the historical load data above do not take into account the regularity of the load and its influence on the prediction error. Data preprocessing affects the accuracy of the results, as does the selection of SLF method.

At present, the SLF method is mainly divided into the distinct methods of simulation, direct vision, trend, multivariate variable, and load density index. An autonomous agent-based system, tightly coupled with geographic information systems (GIS), is presented in [14]. The objective is to model a city’s dynamic in order to foresee both its urban evolution and the influence that the appearance of new settlements has on the overall electricity demand. A grid-based simulation method to forecast the spatial growth of load density in a distribution utility service zone is presented in [15]. A power law distribution with fractal exponent is used to determine the load density, depending on different factors. A spatial analysis of points is proposed in [16], especially suited to estimating a preference map for new consumers, which is then used as an analytical tool in spatial electric load forecasting. However, the methods of the above references have neglected mining and have not utilized historical data. Use of the known conditions can improve the accuracy of prediction.

In order to comprehensively consider the effect of load regularity on prediction error, and fully excavate and utilize the intrinsic information of historical data to further improve prediction accuracy, a load density index method, based on load regularity analysis, is employed in this work. We use intrinsic error analysis [11] to obtain reasonable maximum value (IE-MV) in a cellular load for SLF. Then we use the load density index method, based on historical data of cell load for SLF.

2. Fundamental principle

The method is based on the analysis of the historical load data while taking the regularity of load as a supplementary tool. It can be broadly divided into the following steps:

**Step 1:** Generate cell

A 10-kV feeder scope of the urban power system is used to generate a “Class I cell”. The area of each cell is the corresponding 10-kV feeder power supply range. Cell load is the load history data measured by the 10-kV feeder line.

A grid to partition the spatial area is used to generate a “Class II cell”. Each “Class II cell” is a small square. If each Class II cell load can be determined, the spatial load forecasting is achieved. Due to the variability of Class II cells, the SLF of urban power grid and the prediction results are not accurate enough for the urban power system SLF. In contrast, Class II cell is relatively fixed and shows more flexibility.

**Step 2:** Analysis of load regularity

Through an analysis of Class I cellular historical load data, each cellular load is divided into regular and random components. Through analyzing and inducing the fluctuation curves of the two components, the error of the cellular load is regular and intrinsic.

**Step 3:** Determine the reasonable maximum of the cellular load

Restrain the adverse effects caused by intrinsic error by eliminating random components, which can affect the general trend of the load development. The maximum amplitude of the component is extracted as the reasonable maximum of Class I cellular load, which is a token of the load features.
Step 4: Spatial load forecasting

The reasonable maximum obtained from the third step can be used as historical load data of Class I cell. By introducing load density coordination coefficient of different cells, the problem of uneven distribution of the same kind of load in different cells is overcome.

3. Determining reasonable maximum in a cellular load

3.1. Fundamental idea for determining reasonable maximum in a cellular load

Changes to the power load depend mainly on human requirements and daily routines, but are also affected by incidental factors. Therefore, there is regularity and randomness in the load variation.

The maximum cellular load is determined based on the characteristics of the load changes. Each day, load cellular value changes over a certain period with disturbances resulting from accidental factors. The cellular load is divided into a simple harmonic vibration, whose frequency is an integer multiple of the fundamental, representative regular, and random components [17,18]. Moreover, the maximum is extracted from the sum of the decomposition of the corresponding regular component moment as a reasonable maximum of the cellular load for one year.

3.2. Method of determination of reasonable maximum in a cellular load

Cellular load data measurement, acquisition, and transmission will be affected by uncertainty factors. The direct application of historical cellular load data in SLF most likely results in an error that is influenced by uncertainty factors in the prediction of results; therefore, prediction accuracy is poor.

To suppress the adverse effects that arise from the uncertainties, Eq. (1) is used to decompose the cellular load, compute the characterization of cellular load regularity and randomness of the component, and remove the random component to avoid the intrinsic error that affects trends in the cellular load development [19].

\[
X_t = a_0 + \sum_{i=1}^{N/2-1} \left[ a_i \cos(2\pi it/N) + b_i \sin(2\pi it/N) \right] + a_{N/2} \cos(\pi t) = a_0 + \sum_{i=1}^{N/2} R_i \cos(w_i t + \phi_i),
\]

where \(a_0\) is a constant component, and \(R_i, \omega_i,\) and \(\phi_i\) are the cellular load amplitude, angular frequency, and initial phase angle of \(X_t\), respectively.

A decomposition of the respective frequency components in Eq. (1), according to the rules of electricity consumption from human requirements and daily routines, and a rearrangement yield:

\[
P(t) = a_0 + D(t) + W(t) + L(t) + H(t),
\]

where \(P(t)\) is the cellular data and \(D(t), W(t), L(t),\) and \(H(t)\) are the sum of several harmonic components.

These loads are decomposed and reconstructed according to the inherent law of load variation of power system, which represents the daily period, the weekly period, the slowly varying part, and the random part of the load variation.

Although SLF uses an annual maximum cellular load, we use a cellular load of only 14 days of historical data in the scenario analysis to visualize the waveform characteristics of the cellular load and components more clearly, and to illustrate a regular and random problem easily. We show the sequential waveform for the cellular load in Figure 1 and the decomposition of power load in Figure 2.

\(a_0 + D(t)\) is the component’s waveform, shown in Figure 2a. The period of \(D(t)\) is 288 time intervals (1 time interval is 5 min). It is the component of the load changing in 24 h; \(a_0 + D(t)\) is the daily period component.
of the load. It reflects daily periodic changes for part of a cellular load and has obvious characteristics of daily double peaks with large amplitude that are close to the cellular peak load.

$W(t)$, the component waveform, is shown in Figure 2b. The period of $W(t)$ is a $7 \times 96$ time interval, and is the weekly period component of the load. It reflects weekly periodic changes for part of the cellular load, but with a smaller amplitude.

$L(t)$, the component waveform, is shown in Figure 2c. $L(t)$ is the sum of the low-frequency components of the residual component, which reflects the influence of slow-changing factors such as meteorological factors on the load.
The three components show the trend in development of cellular load or regularity with a variation in cellular load for a longer duration of a certain stability and periodicity.

\( H(t) \) is the component waveform, as shown in Figure 2d. It is the sum of the high-frequency components of the remaining components, mainly reflecting the randomness of the load changes, namely the intrinsic random component.

The total load of an area is the sum of quantities of individual loads; hence, there must be random variation of the load. If the annual maximum value of the measured data is directly used to predict the spatial load of the urban power network, it is very likely that errors, such as measurement and communication, will be brought into the prediction result, leading to a decrease in prediction accuracy.

Therefore, to overcome the influence of intrinsic error by removing the random component, IE-MV is extracted from the regular component that is the main component for the cellular load, as computed using Eq. (3):

\[
M(t) = a_0 + D(t) + W(t) + L(t) \tag{3}
\]

For the existence of load transfer, the method of correcting for load transfer is used before the IE-MV method.

### 3.3. Load density index method based on IE-MV

Power geographic information system is established in the case of a known 10-kV feeder load and its power supply range. With the perspective of GIS, combined with the current land information, the position and area of the classified load in each feeder can be obtained. Then the relationship equation between the feeder load and the classified load density can be established. Past classified load density index can be obtained with the least square method. According to the classified load density index obtained above, the classified load density index in the target year can be predicted. At the specified space resolution, the load value of each Class II cell is calculated, thus implementing the spatial load forecasting [20,21].

Taking into account that the formation time and development of each cell are different, there must be a great error if we use a uniform classified load density to predict. Therefore, we introduce the load density coordination coefficient \( \beta \).

The load density of a Class I cell is calculated with Eq. (4):

\[
d_{ik} = P_{ik}/S_i, \tag{4}
\]

where \( d_{ik} \) is the load density of Class I cell \( k \) in the year \( i \), \( P_{ik} \) is the cellular load, and \( S_i \) is the area.

The maximum load density of the cells in each year is the reference, which is to normalize the load density of all cells in the year and determine the coefficient \( \beta \) as follows:

\[
\beta_{ik} = d_{ik}/d_{\text{max}_k} \tag{5}
\]

\( \beta_{ik} \) is the coordination coefficient of the classified load density of cell \( k \) in the year \( i \), \( d_{ik} \) is the load density, and \( d_{\text{max}_k} \) is the maximum load density of all cells in the year.

The maximum value of the historical load, combined with the land information of the Class I cell in the past years, is used to calculate the classified load density index. Eq. (6) was established during the time section
of each year.

\[
\begin{align*}
    P_1 &= \beta_{11}s_{11}d_1 + \cdots + \beta_{1j}s_{1j}d_j + \cdots + \beta_{1m}s_{1m}d_m \\
    \vdots \quad &
    \vdots \\
    P_i &= \beta_{i1}s_{i1}d_1 + \cdots + \beta_{ij}s_{ij}d_j + \cdots + \beta_{im}s_{im}d_m \\
    \vdots \quad &
    \vdots \\
    P_n &= \beta_{n1}s_{n1}d_1 + \cdots + \beta_{nj}s_{nj}d_j + \cdots + \beta_{nm}s_{nm}d_m
\end{align*}
\]

where \( P_i \) is the load value of cell \( i \) (\( i = 1, 2, \ldots, n \), \( n \) is the cell number), \( \beta_{ij} \) is the load density coordination coefficient of the \( j \) class land used in this cell (\( j = 1, 2, \ldots, m \), \( m \) is the number of land use types), \( s_{ij} \) is the land area, and \( d_j \) is the load density index.

Now that the classified load density index in the past years has been obtained, trend method can be used to predict the values in the target year. The various types of land contained within each Class II cellular are multiplied by their own classified load density index and the load density coordination coefficient. The load values for each Class II cellular have been obtained; thus the SLF is completed.

4. Case study

A power supply branch in a city in Northeast China is taken as an example. According to the branch in the jurisdiction, the respective supply range of 10-kV feeders generates a Class I cellular. On the basis of load characteristics and various types of land, the land is divided into 8 types: residential land, commercial land, industrial land, administrative land, culture and entertainment land, municipal public land, green land, and special land, namely a total of eight classified loads.

The establishment of GIS contains area and land information layers of Class I cellular in the planning area [17], shown in Figure 3.

![Land information and power supply area of 10kV feeders](image)

**Figure 3.** Land information of Chuanying and power supply area of 10-kV feeders.

Use the established GIS to obtain the area of various types of land in the branch, as shown in Table 1.
Table 1. Various types of land area in Class I cellular.

<table>
<thead>
<tr>
<th>Cell name</th>
<th>Various types of land area/km²</th>
<th>Residential land</th>
<th>Commercial land</th>
<th>Industrial land</th>
<th>Administrative land</th>
<th>Culture land</th>
<th>Municipal land</th>
<th>Green land</th>
<th>Special land</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beida</td>
<td></td>
<td>0.363</td>
<td>0.014</td>
<td>0.000</td>
<td>0.034</td>
<td>0.000</td>
<td>0.002</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Beiji</td>
<td></td>
<td>0.321</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.008</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Beijing</td>
<td></td>
<td>0.187</td>
<td>0.008</td>
<td>0.000</td>
<td>0.049</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Changchun</td>
<td></td>
<td>0.851</td>
<td>0.156</td>
<td>0.000</td>
<td>0.130</td>
<td>0.000</td>
<td>0.000</td>
<td>0.013</td>
<td>0.000</td>
</tr>
<tr>
<td>Changxing</td>
<td></td>
<td>0.404</td>
<td>0.072</td>
<td>0.000</td>
<td>0.028</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Zhihe</td>
<td></td>
<td>0.886</td>
<td>0.133</td>
<td>0.000</td>
<td>0.104</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
</tbody>
</table>

4.1. Calculate the reasonable maximum of a cellular load
Knowing the load history data from 2004 to 2008, obtain the maximum value of cell load in a year as a point. The reasonable maximum values of all the cells corresponding to Table 1 are shown in Table 2.

Table 2. Reasonable maximum loads of Class I cellular.

<table>
<thead>
<tr>
<th>Cell name</th>
<th>Annual load/MW</th>
<th>2004</th>
<th>2005</th>
<th>2006</th>
<th>2007</th>
<th>2008</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beida</td>
<td>4.925</td>
<td>4.268</td>
<td>2.357</td>
<td>2.989</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Beiji</td>
<td>1.934</td>
<td>1.669</td>
<td>2.509</td>
<td>2.23</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Beijing</td>
<td>4.225</td>
<td>5.623</td>
<td>3.658</td>
<td>4.941</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Changchun</td>
<td>2.257</td>
<td>3.807</td>
<td>1.549</td>
<td>2.286</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Changxing</td>
<td>3.156</td>
<td>3.596</td>
<td>2.969</td>
<td>3.143</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Zhihe</td>
<td>3.591</td>
<td>3.593</td>
<td>4.094</td>
<td>4.567</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

4.2. Obtain classified load density coordination coefficient
By using the data of the various land area of all Class I cells in Table 1 and the reasonable maximum values of each calendar year in Table 2, as well as Eqs. (4) and (5), the coordination coefficient of classified load density for each year is calculated as shown in Table 3.

Table 3. Coordination coefficient of classified load density in previous years.

<table>
<thead>
<tr>
<th>Cell name</th>
<th>Coordination coefficient of classified load density in each Class I cells β</th>
<th>2004</th>
<th>2005</th>
<th>2006</th>
<th>2007</th>
<th>2008</th>
<th>Target year</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beida</td>
<td>0.464 0.438 0.354 0.227 0.281 0.353</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Beiji</td>
<td>0.229 0.378 0.174 0.304 0.264 0.270</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Beijing</td>
<td>0.675 0.606 0.790 0.597 0.788 0.691</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Changchun</td>
<td>0.076 0.085 0.113 0.053 0.077 0.081</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Changxing</td>
<td>0.243 0.233 0.244 0.234 0.242 0.239</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Zhihe</td>
<td>0.125 0.116 0.109 0.145 0.158 0.131</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

4.3. Calculate the classified load density index
The results of the classified load density index of the planning area, obtained by Eq. (6), are shown in Table 4.
Table 4. Classified density index load in previous years.

<table>
<thead>
<tr>
<th>Land use types</th>
<th>Classified load density index in previous years (MW/km^2)</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2004</td>
<td>2005</td>
<td>2006</td>
<td>2007</td>
<td>2008</td>
</tr>
<tr>
<td>Municipal land</td>
<td>21.658</td>
<td>22.430</td>
<td>29.349</td>
<td>22.570</td>
<td>23.612</td>
</tr>
<tr>
<td>Green land</td>
<td>21.485</td>
<td>22.655</td>
<td>29.048</td>
<td>22.236</td>
<td>22.905</td>
</tr>
<tr>
<td>Special land</td>
<td>24.469</td>
<td>25.879</td>
<td>29.048</td>
<td>24.607</td>
<td>25.123</td>
</tr>
</tbody>
</table>

Using the classified load density index of the past years, the classification load density index in the target year, predicted with the trend extrapolation method, is shown in Table 5.

Table 5. Classified load density index in objective year.

<table>
<thead>
<tr>
<th>Land use types</th>
<th>Classified load density index (MW/km^2)</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Residential land</td>
<td>26.90</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Commercial land</td>
<td>26.04</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Industrial land</td>
<td>21.26</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Administrative land</td>
<td>26.33</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cultural land</td>
<td>26.16</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Municipal land</td>
<td>24.15</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Green land</td>
<td>24.12</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Special land</td>
<td>25.82</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

In order to reduce the adverse effects of the load transfer and jump growth, the average value of the load density coordination coefficient in this paper is used as the target year load density coordination coefficient. The values are given in Table 3. The generation of Class II cellular, based on established GIS, uses a grid to partition the spatial area, so that the length of each small square is 200 m (or 300 m, 400 m, or more), as shown in Figure 4.

![Figure 4. Cellular generation.](image-url)
According to data and information from Figures 3a and 4 and Tables 3 and 4, Class II cellular load values in 2009 (the target year) can be predicted by applying the aforementioned theory. Due to numerous Class II cells and limited space, Table 6 shows the detailed information of only a few Class II cells that are labeled in Figure 4, where the numbers indicate cell numbers and $C(x, y)$ indicates the position of cells.

Table 6 shows a portion of the results, which is not obvious, and so all the results are displayed in the GIS, as shown in Figure 5. It is easy to see that predictions based on Class II cellular are very close to the actual load density of Class I cellular in the region.

### Table 6. Forecasting results and errors of Class II cells.

<table>
<thead>
<tr>
<th>Number</th>
<th>Cell</th>
<th>Predicted value/MW</th>
<th>Actual value/MW</th>
<th>Absolute error/MW</th>
<th>Relative error/%</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$C(38,21)$</td>
<td>0.125</td>
<td>0.179</td>
<td>0.054</td>
<td>30.17%</td>
</tr>
<tr>
<td>2</td>
<td>$C(38,22)$</td>
<td>0.144</td>
<td>0.202</td>
<td>0.058</td>
<td>28.71%</td>
</tr>
<tr>
<td>3</td>
<td>$C(38,23)$</td>
<td>0.139</td>
<td>0.267</td>
<td>0.128</td>
<td>47.94%</td>
</tr>
<tr>
<td>4</td>
<td>$C(38,24)$</td>
<td>0.353</td>
<td>0.423</td>
<td>0.070</td>
<td>16.55%</td>
</tr>
<tr>
<td>5</td>
<td>$C(37,21)$</td>
<td>0.104</td>
<td>0.119</td>
<td>0.015</td>
<td>12.61%</td>
</tr>
<tr>
<td>6</td>
<td>$C(37,21)$</td>
<td>0.265</td>
<td>0.357</td>
<td>0.092</td>
<td>25.77%</td>
</tr>
<tr>
<td>7</td>
<td>$C(37,21)$</td>
<td>0.349</td>
<td>0.394</td>
<td>0.045</td>
<td>11.42%</td>
</tr>
<tr>
<td>8</td>
<td>$C(37,21)$</td>
<td>0.291</td>
<td>0.337</td>
<td>0.046</td>
<td>13.65%</td>
</tr>
</tbody>
</table>

(a) Load density distribution of class I cells  
(b) SLF results of class II cells

**Figure 5.** Spatial load forecasting results and load density distribution of Class I cells.

The generation of Class II cellular is subjective and arbitrary, and generally there are no actual historical load data. This article gives the values of the Class I cellular load, which are translated back by the Class II cellular prediction results shown in Table 6. This result can be directly compared with the measured historical load data. Under the same condition, the trend forecasting method of linear regression is used to predict as a comparison. The method has been compared with the traditional forecasting methods (such as gray prediction, exponential smoothing, and linear regression) and verifies its superiority in the prediction accuracy. Prediction results and their comparative analysis are shown in Figure 6. Obviously, the prediction results of this method are the closest to the actual values, which shows that the method is advantageous overall.

In order to investigate the specific error distribution, Figure 7 gives the prediction error distribution of the four methods. Apparently, the prediction results of using this method in our paper show that the 16 cellular relative errors are less than 20%, accounting for 61.54% of all cells. The maximum prediction error is
significantly lower than the maximum error of the other three kinds of methods. Consequently, the load density index method, based on analyzing the regularity of cellular load, shows superior accuracy.
5. Conclusion

This paper presents the load density index method, based on analyzing the regularity of cellular load. SLF can be realized more accurately by analyzing the regularity of load history data to eliminate the intrinsic error in load data and by combining with the load density method. The method has the following two characteristics:

1. Through research into wave propagation in cellular load data, the cellular load maximum is determined without intrinsic error. This approach is used in the SLF of an urban power system to avoid adverse effects from the direct application of cellular data, which reduces the forecasting accuracy.

2. The load density coordination coefficient is introduced to solve the nonuniform distribution of the classified load. The relationship between the classified load density and the cellular load is established. A more accurate spatial load forecasting can be achieved by obtaining the classified load density index in the past years and the usage of trend method predicting that in the target year.

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References


