J. COMBIN. MATH. COMBIN. COMPUT. 127a (2025) 4649--4665

Journal of Combinatorial Mathematics and Combinatorial Computing
www.combinatorialpress.com/jcmcc

Combinatorial Press

Research on hierarchical recursive power supply meshing algorithm considering the dynamic change of grid loads

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ABSTRACT

The reasonable division of power supply grid plays an important role in the feasibility and stability of power grid operation. This paper mainly explores the feasible methods of power supply grid division under the dynamic change of grid load. The grid load prediction model is constructed by the improved long and short-term memory network algorithm (ILSTM) based on expert rules to visualize the dynamic changes of the grid load. Based on the study of hierarchical architecture of power supply grid, the objective function is constructed using hierarchical recursive method, and the power supply grid division model is constructed with adjacent connection as the basic constraint. The power consumption information of JH urban area is selected as the data source of this paper, and the method of this paper is used to forecast the grid load of JH urban area and perform the power supply grid division. The power supply network in JH city can effectively meet the objective function and constraints set in the model, and the average number of faults in the power supply network decreases by 94.8% compared with that before the grid demarcation, which fully ensures the safety and reliability of the power supply network operation.

Keywords: ILSTM, hierarchical recursion, grid load, power supply meshing

1. Introduction

In today's society, electricity has become an indispensable energy source in our life and production. With the rapid development of the economy and the continuous progress of science and technology, the demand for electricity is increasing, and the complexity of the power system is also increasing [1-4]. In such a background, dynamic load management and optimization strategies in power systems are particularly important. Dynamic load management refers to the real-time monitoring, analysis and control of the load in the power system in order to realize the safe, stable and economic operation of

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Received 15 January 2024; Revised 25 March 2024; Accepted 30 November 2024; Published Online 15 April 2025.
DOI: 10.61091/jcmcc127a-263

the power system [5-8]. Optimization strategy is to make load management more efficient and reasonable through a series of methods and means. The hierarchical recursive power supply grid division algorithm can play an important role in load management [9-12].

Hierarchical recursive power supply grid division algorithm is based on recursive algorithm developed for electric power algorithm. Recursive algorithms are a common problem solving method that decomposes a problem into subproblems of the same type and solves the original problem by solving these subproblems. Recursive algorithms are usually implemented using recursive calls to functions. The implementation of recursive algorithms can be divided into two steps: the base case and the recursive case. The base case is when the problem returns the result directly when a simple condition is met. The recursive case refers to solving smaller subproblems by calling itself and combining the results of the subproblems into the solution of the original problem [13-16].

In this paper, we study the power supply grid division under the consideration of the dynamic change of grid load. In order to fully show the dynamic trend of grid load, this paper adopts the improved long-short time memory network based on expert rules to predict the grid load with nonlinear and time-varying characteristics. The kernel function is introduced to improve the prediction accuracy of the long and short-term memory network, and the expert rules are introduced to improve the prediction performance of the grid prediction model in practical applications. Aiming at the problem that the traditional power supply grid division method ignores the dynamic change characteristics of the power grid, this paper adopts a hierarchical recursive method to construct a mathematical model containing the objective function and constraints of power supply grid division through an in-depth analysis of the structure of the power grid and the load characteristics. Taking JH urban area as the object of this paper, we collect the power consumption information of each functional area in JH urban area through field investigation, and construct the grid load data set for subsequent research. The method of this paper is used to forecast the grid load of JH urban area, and the dynamic change characteristics of the grid load are analyzed by selecting the forecast results of some lines. The hierarchical recursive method is utilized to divide the power supply network in the JH urban area, and the objective function and constraints set by the division model are used as evaluation indicators to measure the effectiveness of the power supply grid division method in this paper.

2. Study of the dynamics of grid loads

2.1. Characterization of the dynamics of the grid load

1) The time change law of load. Grid load shows obvious cyclical changes on different time scales such as one day, one week and one year. For example, in a day, there are usually morning peak, midday trough, evening peak and other load change stages. In a year, the load tends to be higher in summer in preference to the heavy use of air conditioning and other refrigeration equipment, while the motivating heating load is more prominent in some areas.

2) Spatial distribution characteristics of load. There are differences in load density and growth trends in different regions. The urban center area is concentrated and grows faster, while the load in the suburbs or rural areas is relatively low and grows more slowly. In addition, with the development of the economy and the adjustment of industrial structure, the spatial distribution of load will also change.

3) Uncertainty factors of load. In addition to the predictable cyclical changes mentioned above, the grid load is also affected by many uncertain factors, such as weather changes (temperature, humidity, wind speed, etc.), emergencies (natural disasters, major events, etc.), the randomness of the user's behavior, etc., which make the dynamic changes of the load more complex.

2.2. Grid Load Forecasting Model

In order to fully and intuitively illustrate the dynamic changes of grid load, this section utilizes the expert rule-based Improved Long Short-Term Memory Network (ILSTM) to construct a grid load forecasting model, and elaborates the specific dynamic trends of grid load based on the experimental results.

The long-short time memory network (LSTM) is able to capture the long-term dependencies in the time series by adaptively learning the characteristics of the historical sequence data, and has a better performance for the grid load forecasting problem with nonlinear and time-varying characteristics [17]. The architecture of the LSTM is shown in Fig. 1.

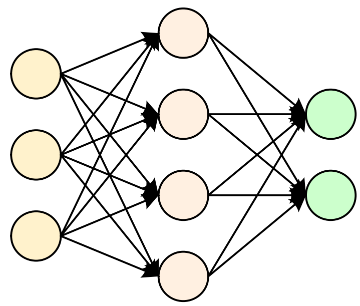


Fig. 1. The architecture of LSTM

As can be seen from Fig. 1, LSTM includes an input layer, an implicit layer and an output layer. The implicit layer includes an affiliation function generation layer, an inference layer and a normalization layer. The mathematical model for designing the affiliation function is:

$$A_i^j = e^{-\frac{\left(x_i - c_{ij}\right)^2}{\sigma_{ij}^2}} \tag{1}$$

Where: A_i^j is the affiliation function. x_i is the i rd each input of the network. c_j is the premise parameter of the j th affiliation function for each of the i th inputs. σ_{ij} is the convergence parameter of the j th affiliation function for the i th input.

In the inference layer, the fitness of the affiliation rule is computed by using the affiliation values generated in layer 2 as:

$$w_k = A_i^{j_1} A_i^{j_2} \tag{2}$$

Where: w_k is the fitness of the affiliation rule.

In the last layer of the implicit layer, the fitness of each rule computed in the inference layer is normalized to obtain:

$$\overline{w}_k = \frac{w_k}{\sum_{k=1}^{49} w_k} \tag{3}$$

Where: $\overline{w}_k$ is the degree of adaptation after performing the normalization process.

From the above design, the fuzzy output of each rule is obtained as:

$$B_k = q_{1\Lambda} x_1 + q_{2\lambda} x_2 \tag{4}$$

Where: q_{1k}, q_{2k} are the conclusion parameters of the rule output. B_k is the fuzzy output of each rule.

The output of the computational system is:

$$y = \sum_{k=1}^{49} \overline{w}_k B_k \tag{5}$$

Where: y is the output of the network.

The indicator function of the LSTM after introducing the kernel function is:

$$E(k) = \frac{1}{2}\left[x(k) - x_d(k)\right]^2 = \frac{1}{2}e(k)^2 \tag{6}$$

Where: $E(k)$ is the performance index function after introducing the kernel function. $x(k)$ is the input of the k rd iteration. $x_d(k)$ is the desired input for the k th iteration. $e(k)$ is the error function of the k th iteration.

The LSTM optimization iteration process adopts the negative gradient descent method, and the mathematical model is:

$$\Delta\Omega = -\frac{\partial E}{\partial \Omega} = -\frac{\partial E}{\partial e}\cdot\frac{\partial e}{\partial x}\cdot\frac{\partial x}{\partial y}\cdot\frac{\partial y}{\partial \Omega} \tag{7}$$

Where: $\Delta\Omega$ is the negative gradient of the performance index function over the error function.

For the regression function in LSTM, the approximate sign function is chosen.

$$\beta(x) \approx sign\left[\frac{\partial x(k)}{\partial y}\right] \tag{8}$$

Where: $\beta(x)$ is the regression function of LSTM.

Thus the generalized form of the weight parameter can be obtained as:

$$\Delta\Omega = -\frac{\partial E}{\partial \Omega} = -e\cdot\beta\cdot\frac{\partial y}{\partial \Omega} \tag{9}$$

To compare the change in error of LSTM and BP neural network, the change in error with the increase in the number of iterations is shown in Fig. 2. From the figure, it can be seen that as the number of iterations increases, the prediction error of both BP neural network and LSTM decreases, but the prediction error of BP neural network is always greater than that of LSTM, and both of them reach the lowest when the number of iterations is 200, which is 3.31% for LSTM and 36.11% for BP neural network, so that LSTM reduces the error in load prediction and improves the prediction accuracy.

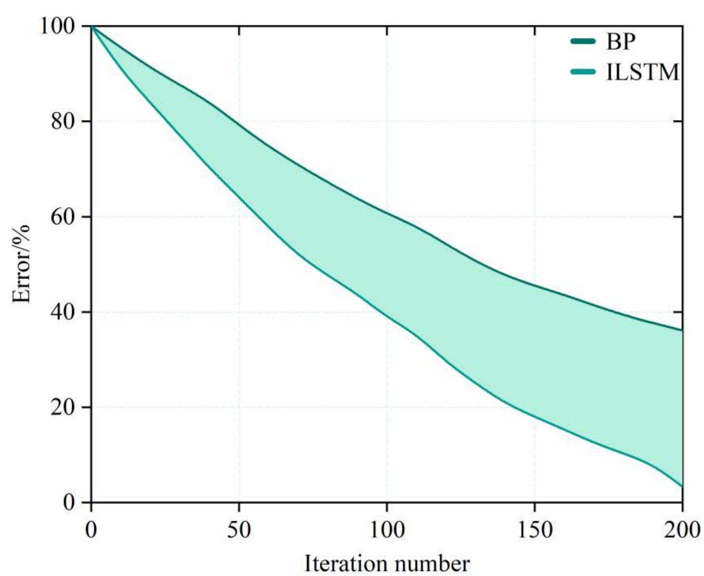


Fig. 2. The error changes with the number of iterations

The expert rule includes three cases such as large absolute error, small absolute error and error located between the maximum and minimum values [18], and let the error between the two types of parameters and the optimal value as the absolute error, i.e:

$$\begin{cases} e_1 = \sigma_{ref} - \sigma \\ e_2 = c_{ref} - c \end{cases} \tag{10}$$

Where: e_1 is the error between the expected and actual values of the premise parameters. e_2 is the error between the expected value and the actual value of the convergence parameter. σ_{ref} is the expected value of the premise parameters; c_{ref} is the expected value of the convergence parameters.
1) When the absolute error is large:

$$\begin{cases} \|e_1\| \geq E_{\max} \\ \|e_2\| \geq E_{\max} \end{cases} \tag{11}$$

Where: $E_{\max}$ is the maximum value of the error.

From equation (11), the regression function is updated when the absolute error is large, i.e., when both types of errors exceed the maximum value of the absolute error, and the new regression function is:

$$\beta(x) = \frac{2\left(x_i - c_{ij}\right)}{\sigma_{ij}^2} \tag{12}$$

2) Absolute error is small:

$$\begin{cases} \|e_1\| \leq E_{\min} \\ \|e_2\| \leq E_{\min} \end{cases} \tag{13}$$

Where: $E_{\min}$ is the minimum value of the absolute error.

From equation (13), the regression function can be updated when the absolute error is small, i.e., when the absolute error is less than the minimum value of the error:

$$\beta(x) = \frac{3\left(x_i - c_{ij}\right)}{\sigma_{ij}^3} \tag{14}$$

3) When the absolute error lies between the maximum and minimum values:

$$\begin{cases} E_{\min} \leq \|e_1\| \leq E_{\max} \\ E_{\min} \leq \|e_2\| \leq E_{\max} \end{cases} \tag{15}$$

When the absolute error lies between the minimum and maximum values, the regression function can be updated as:

$$\beta(x) = \frac{x_i - c_{ij}}{\sigma_{ij}} \tag{16}$$

3. Hierarchical recursive power supply network segmentation algorithm

As an important infrastructure of modern society, the safe and stable operation of power system is intuitively important. Power supply grid delineation is a key link in power system planning and operation, and reasonable power supply grid delineation can improve power supply reliability, reduce network loss, and optimize resource allocation. However, the traditional power supply grid division method often ignores the dynamic change characteristics of the grid load, and it is difficult to adapt to the complex and changing operating conditions of modern power systems. Therefore, based on the research and prediction of the dynamic change characteristics of grid load, this section will study the power supply grid division algorithm considering the dynamic change of grid load.

3.1. Layered architecture of the power supply grid

The power supply network is divided into tiers of supply networks and their subordinate supply units. The power supply network and power supply unit are described below.
1) Power supply grid. The division of power supply grid mainly takes into account the difficulty of construction, operation and maintenance and scheduling of distribution network, and needs to be combined with the actual spatial distribution of loads and geographic factors. The power supply grid should be relatively independent, the type of power supply area should be unified, and should contain two to four substations. The division of the power supply grid mainly focuses on the substation level, by subdividing the large-scale planning area to achieve the purpose of decoupling, thereby reducing the difficulty of distribution network planning and improving the efficiency of planning.
2) Power supply unit: power supply unit is further subdivided on the basis of power supply grid, usually 1-4 groups of 10kV feeder interconnections, which is the basic unit for the determination of MV line contact structure and grid analysis, and it is an important link in the grid-based planning of distribution grid to undertake the division of power supply grid and automatic wiring. The division of the power supply unit mainly focuses on the specific direction of the MV trunk line and the determination of the feeder contact structure, etc. The automatic wiring is carried out by the power supply unit as a unit, which helps to build a clear structure and a strong MV distribution network.

Figure 3 shows the schematic diagram of the hierarchical structure of the power supply grid division, in which the feeder block is the basic element for the formation of the power supply unit, and the feeder block corresponds to the power supply range of a medium-voltage feeder. The schematic diagram of power supply unit and feeder block is shown in Figure 4.

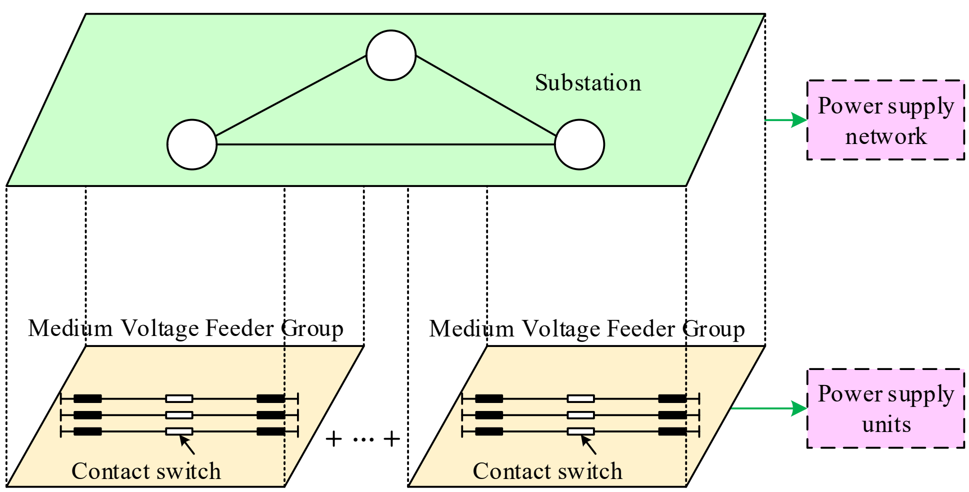


Fig. 3. Grid hierarchy

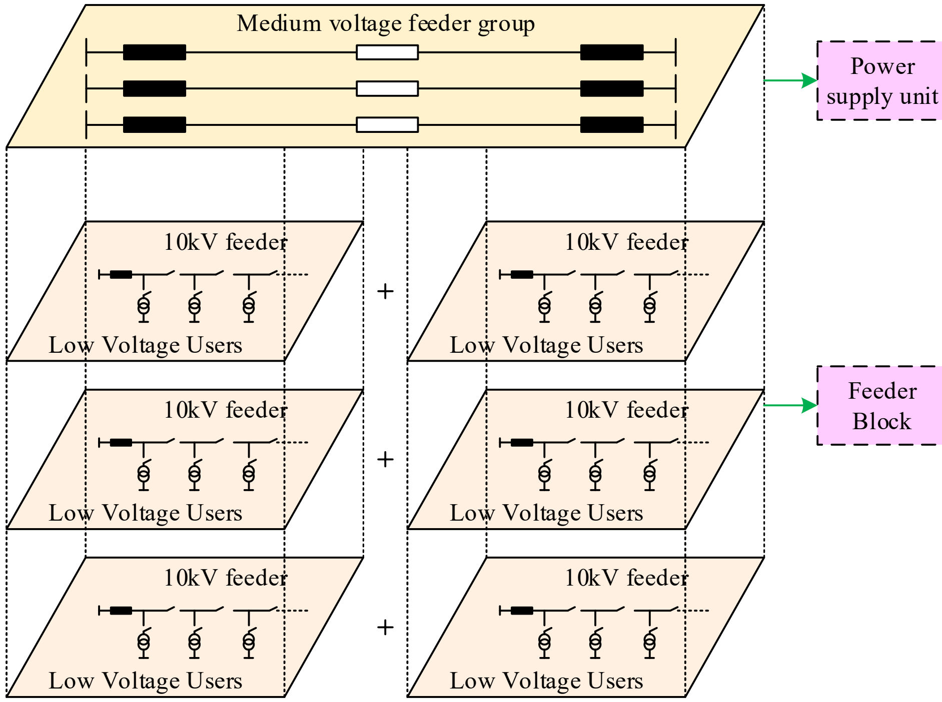


Fig. 4. The relationship between power supply unit and feeder block

3.2. *Hierarchical recursion based power supply meshing algorithm*

By studying the hierarchical architecture of the power supply grid, this paper decides to adopt a hierarchical recursive method for grid division of the power supply grid [19]. The grid is stratified according to factors such as voltage level or regional function, and different segmentation strategies and optimization objectives are adopted at different levels by considering the characteristics of loads and power supply requirements respectively. The specific recursive process can be described as follows: starting from the top level, the entire grid is first preliminarily divided, and then the division results are evaluated and adjusted according to the load conditions and power supply performance indexes of each subregion. If the predetermined optimization conditions are not satisfied, the subregion is further recursively divided into smaller regions, and the above process is repeated until a satisfactory division effect is achieved.

3.2.1. Delineation modeling:

1) Objective function. The objectives of hierarchical recursive based power supply meshing include: The number of cross-grid lines is as small as possible. The current contact lines are in the same grid as far as possible. Line substation in the same grid as far as possible. Due to the different attributes of each optimization objective, the value of the size of the different, so the optimization objective will be normalized into the interval [0, 1]. The objective function of the meshing scheme is obtained by linearly weighted summation of the three optimization objectives as follows:

(1) Optimization objective 1 is the number of cross-grid lines is as small as possible, and its affiliation formula is expressed as:

$$f_1 = \left(\sum_{i=1}^{m} 1/l_i \right) \Big/ m \tag{17}$$

Where: f_1 is the affiliation value of optimization objective 1. i is the feeder number. l_i is the number of grids spanned by feeder i. m is the number of feeder lines.

(2) Optimization objective 2 is for the contact lines to be in the same grid as far as possible, and its

affiliation formula is expressed as:

$$f_2 = \left(\sum_{j=1}^{k} 1/b_j \right) \Bigg/ k \tag{18}$$

Where: f_2 is the affiliation value of optimization objective 2. j is the connection line number. b_j is the number of grids spanned by the connection line j. k is the number of contact lines.

(3) To measure the degree of distribution of the feeder's allotment in different grids, the maximum number of allotments of this feeder in the grid it passes through is taken as a representative value, denoted as:

$$h_i = \max\left(g_{i,u}\right) \Bigg/ \sum_{u=1}^{r} g_{i,u} \tag{19}$$

Where: h_i is the degree of distribution of the distribution of feeder i. u is the grid through which feeder i passes. r is the total number of grids it passes through. $g_{i,u}$ is the number of feeder i distribution in the grid u it passes through.

The optimization objective 3 is that the line distribution variables are in the same grid as far as possible, and its degree of affiliation formula is expressed as:

$$f_3 = \left(\sum_{i=1}^{m} 1/h_i \right) \Bigg/ m \tag{20}$$

Where: f_3 is the affiliation value of the optimization objective 3. h_i is the degree of distribution of allotropy of feeder i.

A linear weighted summation method is adopted to obtain the final objective function value for each meshing scheme:

$$F = s_1 f_1 + s_2 f_2 + s_2 f_3 \tag{21}$$

Where: F is the final objective function value of the meshing scheme; s_1, s_2 and s_3 are the weight factors of the three optimization objectives, respectively. In order to simplify the processing, these 3 weight factors are taken as 1.

2) Constraints. Any region contained in the grid should be at least adjacent to one of the other regions in the grid, i.e., there is no region in the grid that exists separately from the other regions in the grid, forming a region connection constraint, which is a necessary constraint for grid division. Other optional constraints are: (a) The sum of the total capacity of the distribution transformers in each grid is limited. (b) Limit on the total number of feeders contained in each grid. (c) Limit on the area of each grid.

One of the basic constraints, i.e., to determine whether the area contained in the grid in the gridding scheme satisfies the adjacent connection constraints, can be obtained by combining the analysis of the adjacency matrix and the accessibility matrix of the graph. The specific process is as follows:

(1) Based on the topological connectivity links of the plots, establish the adjacency matrix of all plots within the grid $A = a_{pq}$:

$$a_{pq} = \begin{cases} 1 & \textit{Parcel p is adjacent to parcel q} \\ 0 & \textit{Parcel p does not adjoin parcel q} \end{cases} \tag{22}$$

where: p, q are the parcel numbers.

(2) Define the adjacency matrix A to the u th power: $A^u = A \times A^{u-1}$, $A^2 = a_{pq}^2$, where:

$$a_{pq}^2 = \sum_{w=1}^{1} a_{pM} a_{Mq} \tag{23}$$

Where: w is the parcel number; t is the total number of parcels included in the grid. If $a_{pM} a_{Mq} = 1$, it means that parcel p can be connected to parcel q through parcel w; if $a_{pq}^2 = 1$, it means that it is always possible to connect from parcel p and parcel q.

(3) Obtaining the grid reachability matrix $Y = B + B^2 + B^3 + \cdots + B^t$, where the matrix summation is still a logical sum.

(4) Based on the reachability analysis as well as determining whether the regions within each grid satisfy the adjacent connectivity constraints. If the region within that grid satisfies the adjacent connection constraint, the reachability matrix is an all-1 matrix. By obtaining the reachability matrix for each grid, we can determine whether the current meshing scheme satisfies the adjacent connection constraints.

3.2.2. Model solving:

1) Initialization. Obtain the topology of the grid, load data of two points in each sector, line parameters and other information, determine the layered structure and initial division scheme, and set the optimization parameters (e.g., weight coefficients, number of iterations, etc.).

2) Top layer division. According to the overall load distribution of the grid and the approximate scope of the power supply area, the clustering algorithm is used to carry out the initial division of the top layer grid, and the grid is divided into a number of larger sub-areas.

3) Evaluation and Adjustment. For each subregion, calculate its division scheme and whether it satisfies the objective function and constraints of the model. If it does not satisfy them, the grid division scheme is updated by selecting an appropriate division method (e.g., based on electrical distance, load center of gravity, etc.) to further subdivide it into smaller subregions based on the load changes and the take-you-or-leave-you structure in the region.

4) Recursive division. Repeat step (3) for the newly sub-divided subregions, and keep dividing and optimizing recursively until all subregions satisfy the objective function and constraints or reach the maximum recursion depth.

5) Output. Output the final power supply grid delineation scheme, including the boundaries of each power supply region, the nodes and lines contained in the information and so on.

4. Analysis of examples

4.1. Overview of the study area

JH urban area is located in the Yangtze River coastal zone, an area of 39.41 square kilometers, urban private economy features distinctive, is one of the national leather, warp knitting, home textile, solar energy, integrated stove industry base. According to the urban planning plan in the JH urban area to build a modern service industry development platform, fashion textile industry development platform, warp knitting new material innovation platform and Sino-foreign cooperation “garden in the garden” development platform. There are 58 feeder lines, 33 contact lines, 467 distribution transformers, and the total power is up to 239.87 MW. According to the local municipal planning, it is planned to build four development platforms, namely, modern service industry, fashion textile industry, innovation of new warp knitting materials, and Chinese-foreign cooperation “garden in a garden” in JH urban area.

According to the field investigation and analysis, JH urban area contains 15 functional areas, such as industrial design, industrial production, etc., and the information of electricity consumption in each area is shown in Figure 5. Based on the functional areas of JH urban area and the information of power consumption in the area, this paper will predict the grid load and divide the power supply grid.

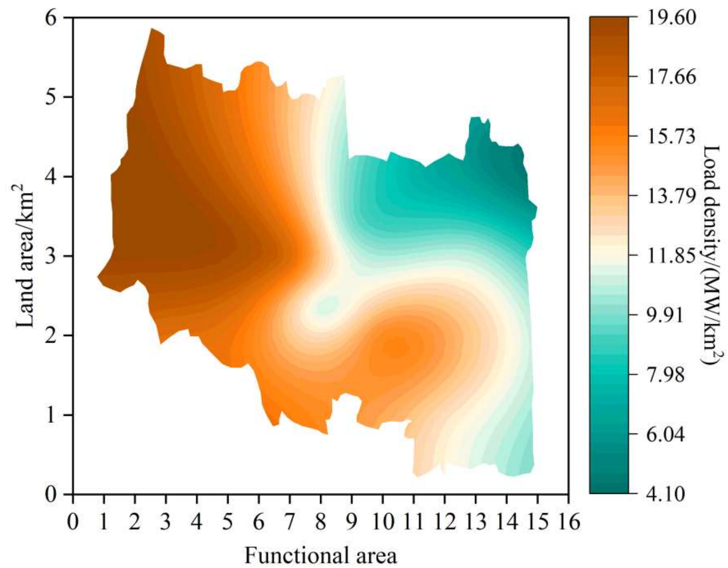


Fig. 5. Power information of the functional area domain

4.2. Analysis of Grid Load Forecasting

4.2.1. Data description and parameterization. The proposed prediction algorithm is tested using the historical load data of users in 15 functional areas of JH urban area, and 2 sets of load data are extracted for simulation and verification, the length of time of the 1st set of data is from November 2018 to January 2019, and the 2nd set of data is from June 2019 to August 2019, and the data sampling is performed in every 20 min interval.

The computer configuration used for the experimental simulation and analysis is i5-8265U processor with 8GB of RAM and the simulation platform is Matlab version 2019a. The parameters of Adam algorithm in the experimental simulation of Improved Long Short-Term Memory Network (ILSTM) model based on expert rules are set to $t_{max} = 200$ and $\alpha = 0.001$, and after 200 rounds of training the learning rate is reduced by multiplying the influence factor. The gradient threshold is set to 1 to prevent gradient inflation.

4.2.2. Input data preprocessing. In addition, the presence of more abnormal load data during training will directly affect the accuracy as well as the reliability of the results of the load prediction analysis in the short term, so the abnormal data are preprocessed to ensure the quality of all its input information before starting the network training. The processing of abnormal data includes the direct elimination of outliers and other methods such as means, plurals, and medians to fill the sample data. Then, the preprocessed data is infused into the model to train the actual application model. Finally, after training the optimal model parameters, the trained model is used for load forecasting of the grid.

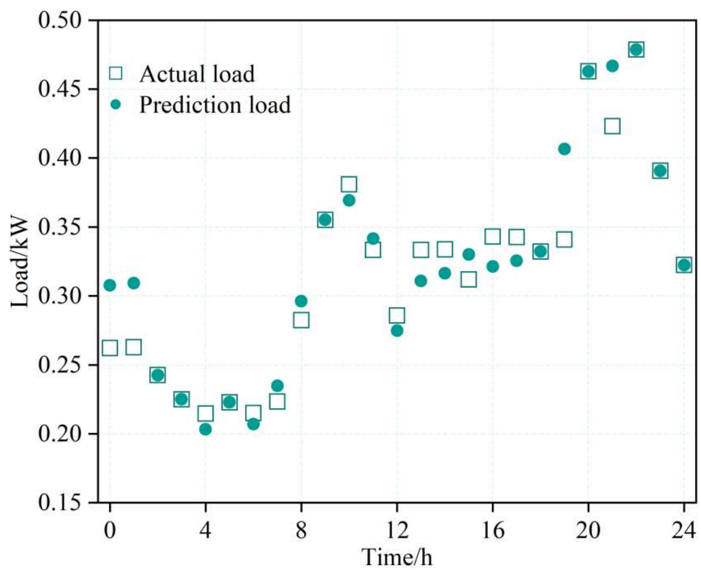
In order to avoid the problems of slow convergence of the model and poor prediction results due to the large difference in the range of values of the input data and the inconsistent distribution of the data, the variables such as the load amount are uniformly normalized. In particular, the day type is treated as follows: Monday through Friday is represented by 1, and Saturday and Sunday are represented by 0. The formula for the regular normalization treatment is:

$$X_g = \frac{X_i - \bar{X}}{\sigma} \tag{24}$$

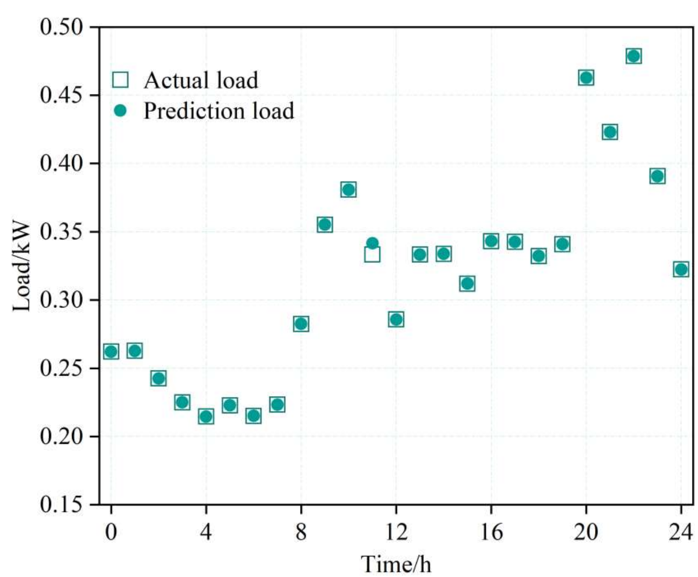
where X_g is the normalized data, $\bar{X}$ is the mean, and σ is the standard deviation.

4.2.3. Analysis of results:

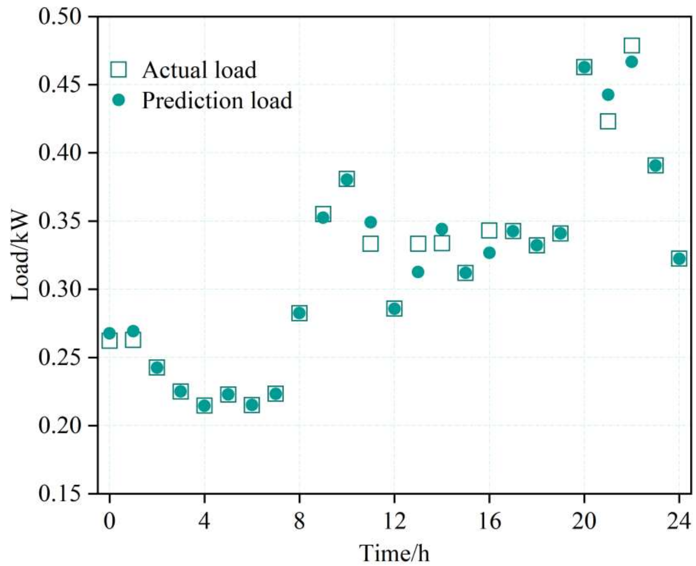
1) Grid load forecasting. In this section, based on the introduction of the previous method, an ILSTM-based grid load prediction model is constructed to predict the grid load in the selected area. The number of hidden layers of the neural network is set to 6, the maximum number of training times is 200, and the mean square error is set to 0.005.Taking line 1 in the grid as an example, the load data of the line for 15 days is taken, and the load data of the first 3 days, the first 8 days, and the first 12 days are used to predict the load on the 15th day, respectively, and the results are shown in Fig. 6, and (a)-(c) denote that the test set of the 3rd day, the 8th day, and the 12th day, respectively, is used as a test set of the prediction results. As can be seen from the figure, there are some accuracy differences in the load prediction results on day 15 obtained by using different load data training, but the three cases can better respond to the load change trend. Especially in the 2nd case, the prediction results are almost the same as the actual load. This also indicates that the ILSTM-based load forecasting technique can predict the load better, but it needs to choose the appropriate training set. Therefore, this paper suggests that in order to perform load forecasting, it is necessary to be able to comprehensively consider the future changes in weather and temperature of the regional load and select a suitable training set.



(a) The prediction results of test set based on the previous 3 day's data



(b) The prediction results of test set based on the previous 8 day's data

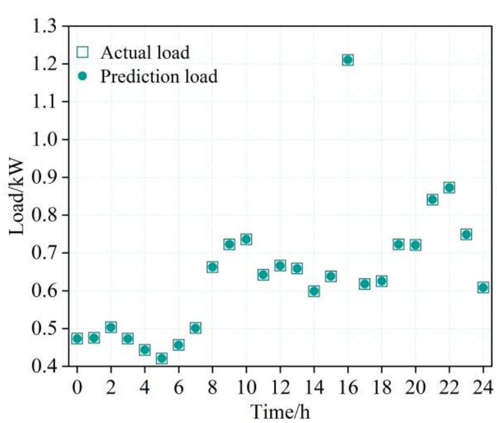


(c) The prediction results of test set based on the previous 12 day's data

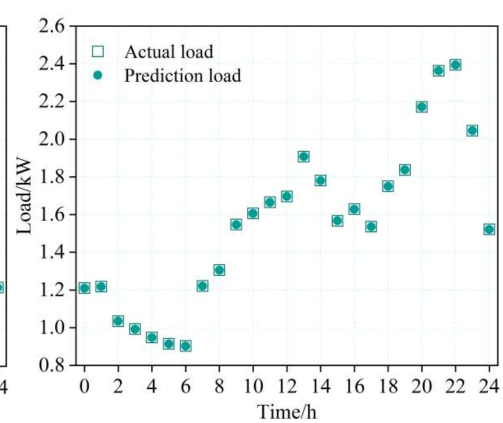
Fig. 6. 15th day load prediction results under different prediction sets

It should be noted that according to the prediction results, the highest prediction accuracy was achieved when the input data was extracted for 8 days. This is because there is underfitting when the input data is 3 days. When the input data is 12 days, there is overfitting. That is, more input data is not better, but there is a reasonable range.

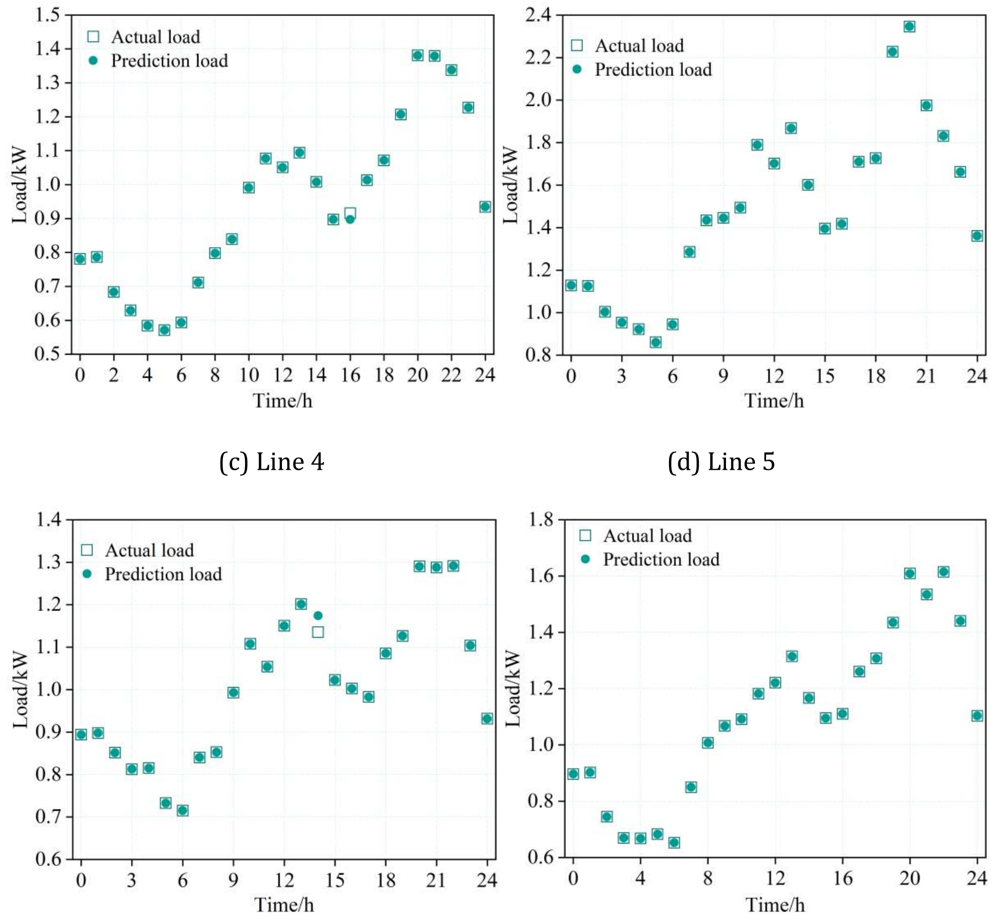
Based on the analysis of the above study, the loads of multiple lines are predicted, the loads of multiple lines are selected, and the same ILSTM technique is applied as in the previous line prediction, and the loads of the first 8 days are applied as the training set for prediction, and the results are shown in Fig. 7, and (a)-(f) represent the prediction results of the 15th day of lines 2-7, respectively. From the figure, it can be seen that when applying the load data of the first 8 days to predict the load on the 15th day, the actual loads of the 6 lines almost coincide with the predicted load changes. Therefore, the model can realize accurate prediction of the load data on the 15th day.



(a) Line 2



(b) Line 3



(c) Line 4

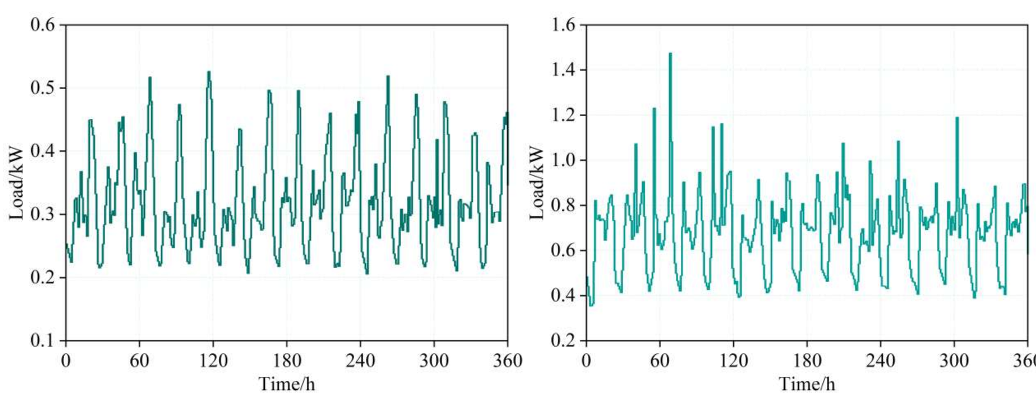
(d) Line 5

(e) Line 6

(f) Line 7

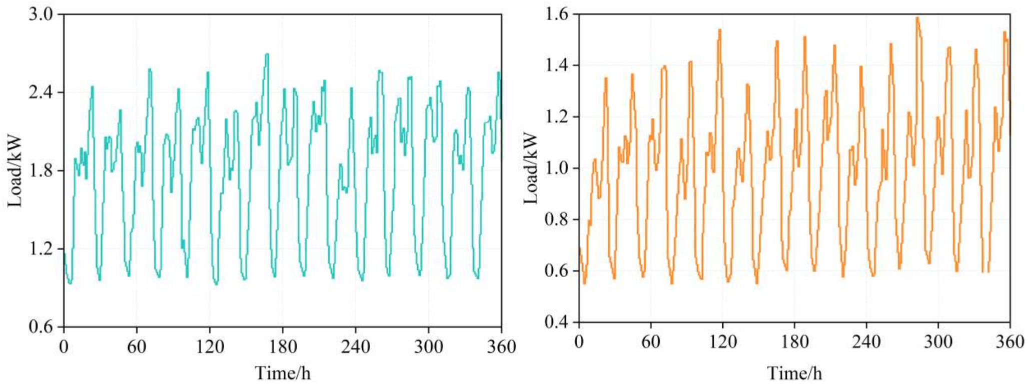
Fig. 7. Different line load prediction results

2) Load change characterization. In order to react to the changing characteristics of the grid load, the load data of any four lines for 15 days are selected from the seven lines selected in the previous section, and the load changes of the four lines are counted as shown in Fig. 8, with (a)-(d) indicating the load changes of the four lines. From the figure, it can be seen that the load data changes of the grid lines have the following characteristics: the load values of the 4 lines differ greatly, in which the active load of line 1 is the smallest and the active load of line 3 is the largest. There are differences in the daily load values, but the range of variation is small. The active load of each line shows a strong periodicity.



(a) Line 1

(b) Line 2



(c) Line 3 (d) Line 4

Fig. 8. Grid load change

4.3. Analysis of Grid Segmentation Results

The results of power supply network division in JH urban area are shown in Fig. 9. Utilizing the hierarchical recursive grid division method proposed in this paper, combined with the distribution of functional areas in JH urban area and electricity consumption information, the power supply grid of JH urban area is divided into five regions. Among them, Region Ⅰ and Region Ⅱ have a higher electricity load density, while Region V has a lower electricity load density.

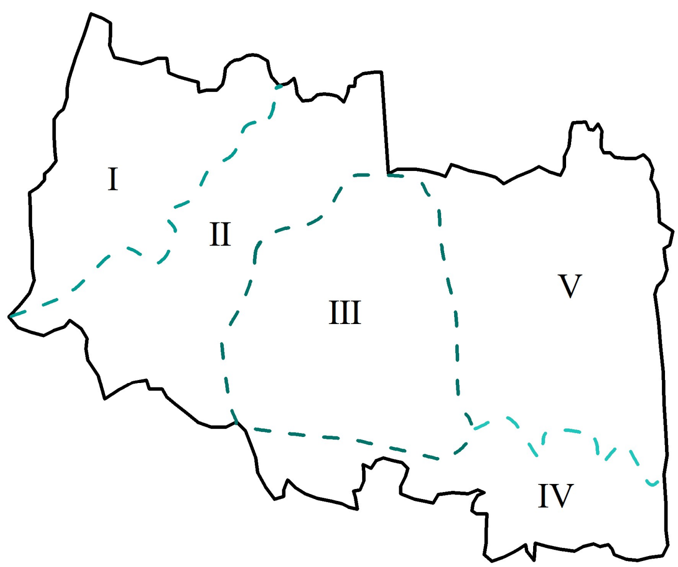


Fig. 9. Dividing result of the grid

In order to further analyze the effectiveness of this paper's hierarchical recursive method for power supply grid delineation, the objectives of power supply grid delineation: the number of lines across the grid is as small as possible, the contact lines are in the same grid as much as possible, the line substations are in the same grid as much as possible, and the basic constraints of adjacent connections are taken as the evaluation indexes (respectively, index 1, index 2, index 3, and index 4), and the evaluation indexes and comprehensive evaluation indexes of each indicator before and after the use of this paper's method for power supply grid delineation are calculated. Calculate the evaluation index of each index before and after using this paper's method for power supply grid division, as well as the comprehensive evaluation index, and the results are shown in Table 1. The results are shown in Table 1. It can be seen from the table that before using the method of this paper to divide the power supply grid of JH urban area, the evaluation indexes of the four indicators and the comprehensive evaluation indexes are 0.432, 0.367, 0.419, 0.498, 0.423, respectively, and after the division of the power supply grid, the evaluation indexes of the indicators and the comprehensive evaluation indexes rise by 102.31%, 144.69%, 105.97%, 105.97%, and 110.64%, respectively, 110.64%. It shows that the power supply grid division method based on hierarchical recursive design in this paper can effectively realize the goals and constraints set by the model and enhance the reliability of power supply in JH urban area.

Table 1. Comparison of partition effect

Index	Pre-partition	After partition
Index 1	0.432	0.874
Index 2	0.367	0.898
Index 3	0.419	0.863
Index 4	0.498	0.904
Composite index	0.423	0.891

Figure 10 shows the comparison of the number of power supply network faults in each month of the year before meshing and the year after meshing of the power supply in the urban area of JH. From the figure, it can be seen that the average number of failures in the 12 months of the year before meshing of the power supply network can be up to 15, while the average number of failures in the year after meshing of the power supply network is only 0.75. This result intuitively shows that the hierarchical recursive power supply grid division method can significantly enhance the stability and safety of power supply network operation, and effectively promote the development of electric power in JH city.

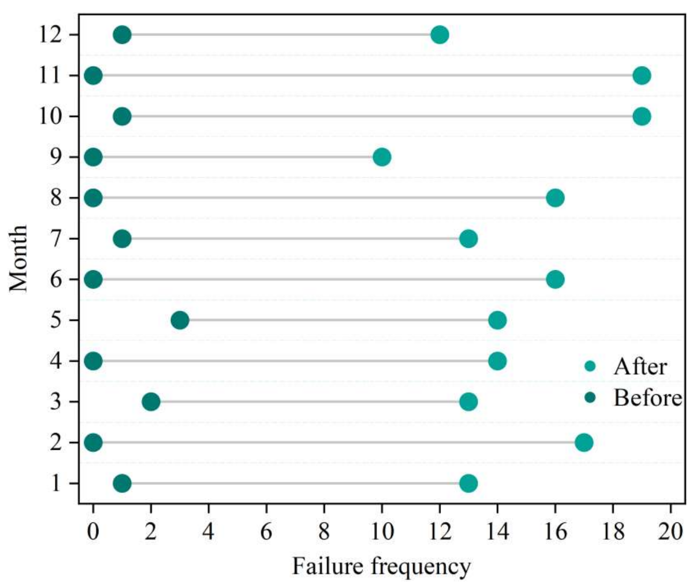


Fig. 10. Failure frequency contrast

5. Conclusion

In this paper, the improved long and short-term memory network based on expert rules is used to forecast the grid load and realize the description of the dynamic change characteristics of the grid load. At the same time, the hierarchical recursive method is utilized to divide the power supply network. The results of case analysis show that the method proposed in this paper can effectively realize the accurate prediction of grid load and the reasonable division of power supply grid, which provides technical support to ensure the safe and reliable operation of power supply network. However, the computational efficiency of the algorithm is still to be further improved when dealing with large-scale complex power grids, and future research can consider combining more efficient optimization algorithms and parallel technology to further improve and expand the application scope of this paper's algorithm.

Funding

This work was supported by Science and Technology Project of State Grid Corporation of China (5400-202318203A-1-1-ZN).

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