Spatial Correlation of Electricity Consumption in China Based on Social Network Approach

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ABSTRACT Regional electricity consumption presents important network structure features. This article applies the social network approach to construct the regional electricity consumption network in China during the period from 2000 to 2018. It analyses global features, local features and the block division of the networks. Then, the dynamic effect of the global and local features on regional electricity intensity is empirically verified through a quantile regression model. The results first show that the spatial correlation of regional electricity consumption has formed a network structure, exhibiting the characteristics of increasing network density, from 0.2 to 0.24, and decreasing network hierarchy and network efficiency, with network hierarchy decreasing from 0.73 to 0.24 and network efficiency decreasing from 0.64 to 0.56; second, the regional electricity consumption network can be divided into four blocks that play different roles and interact to maintain the sustainable evolution of the network; and third, changes in network structure can have a significant effect on regional electricity intensity, and overall, the effect of density is approximately -0.96, and the effects of hierarchy and efficiency are 0.15 and 0.46, respectively. Finally, some policy suggestions beneficial for reducing regional electricity intensity are provided.

INDEX TERMS Spatial correlation, social network analysis, electricity consumption, centrality, electricity intensity.

I. INTRODUCTION

Electricity plays an extremely significant role in contemporary regional development in China. Growing electricity demand has become an urgent problem to solve during the regional sustainable development process. In recent decades, China has achieved substantial breakthroughs in regional energy savings and carbon emission reduction, but regional imbalance is also a growing threat to sustainable urban development. The question of how to coordinate the regional imbalance of electricity resources and the relationships between electricity consumption among regions have attracted many scholars to research in this field.

Studies of regional electricity or energy consumption were an early focus in the area of regional economics. These studies are mainly divided into two groups focusing on different topics: (1) prediction of electricity consumption. Mahia et al. [1] and Angelaccio [2] propose autoregressive integrated moving average (ARIMA) models for forecasting electricity consumption and use electricity consumption data to compare and predict. Wang et al. [3] focus on seasonal fluctuations in electricity consumption and propose a seasonal grey model (SGM(1,1) model) to accurately identify and predict seasonal fluctuations. Neural networks are also an important method for predicting electricity consumption. He et al. [4] propose a method based on the least absolute shrinkage and selection operator-quantile regression neural network (Lasso-QRNN), which can yield a probability distribution instead of a single-valued prediction and provides better performance in forecasting electricity consumption. Jasiński [5] provides a new approach to measuring electricity consumption via artificial neural networks (ANN) based on night-time light images from visible infrared imaging radiometer suite day/night band (VIIRS DNB) and reports
that electricity consumption can be determined with greater precision by the ANN method. In addition, Song et al. [6] construct a comprehensive prediction model based on the grey model, multiple linear regression and error back propagation neural networks to analyse electricity consumption, and they report that the comprehensive model exhibits greater predictive accuracy. (2) The second topic is the convergence of electricity consumption. Mohammadi and Ram [7] use unconditional $\beta$-convergence, a $\sigma$-convergence criterion and a simple model of conditional $\beta$-convergence to study patterns of convergence in electricity consumption. Kim [8] investigates the dynamic behaviour of electricity consumption and finds that the electricity intensity of countries tends to converge towards a common trend. Solarin [9] applies the beta, sigma and gamma convergence methods to examine the patterns of convergence in electricity intensity in a sample of 79 countries, and the results show that convergence exists in most countries. These studies concluded that decision-making on energy consumption, including electricity consumption, in groups of regions will be affected by competition on energy-savings targets. The energy savings is smaller in regions with a higher initial level of energy consumption [10]–[13]. Spatial econometrics models have been developed and introduced into research on regional energy issues; these models allow empirical analyses of regional issues to consider spatial effects, including those in energy consumption and its drivers [14]–[18]. These studies verified the existence of significant spatial effects in regional electricity consumption in China.

However, most of these works suffer from the limitation that they only study spatial effects from the perspective of geographical distance and ignore the increasingly frequent communications among regions on issues of economic development, which lead to more complex network correlations [19]. The network correlations in electricity consumption among regions mean that the electricity consumption of a given region is affected not only by its own economic development but also by that in neighbouring provinces, which can be viewed as a regional network. There is an increasingly obvious trend towards network correlations in electricity development in China. For example, Herreras and Liu [20] and Herreries et al. [21] investigate the convergence of electricity intensity across Chinese provinces and find that electricity consumption in China reflects the effects of regional concentration, which is associated with the relevance of the level of technology and economic geography. Moreover, there is a substantial disparity in electricity consumption between the eastern and other regions in China and significant divergences among provinces [22].

At present, the development of electricity market in China mainly presents the following characteristics. (1) There is a large spatial imbalance in the allocation of electricity resources between the areas producing and consuming electricity. This is primarily because electricity resources such as coal power, water power, wind power and photovoltaic power are mostly generated in the country’s central and western regions, while the main consumption areas are concentrated in the eastern coastal regions. As a result, there is a large spatial dislocation of electricity resources in China, and cross-regional allocation is necessary to achieve spatial balance in electricity. The specific for doing so are projects such as West-to-East Power Transmission and North-to-South Power Transmission. (2) The pattern of inter-provincial electricity flow in China has shifted over time. In 2006, the electrical source points were mainly concentrated in central regions, such as Inner Mongolia, Shanxi and Hubei, while after 2015, the electrical source points were gradually transferred to the western regions, and Sichuan, Yunnan and Gansu have become important electrical source points. These developments explain the reduction of power transmission capacity in central regions and the improvement of long-distance transmission capacity in western regions. (3) The amount of trans-provincial and trans-regional power transmission is growing rapidly. With the rapid growth of electricity consumption in China, the demand for and dependence on electricity have led to gradual increases in the number of electricity source points. At the same time, the power transmission mode has shifted from the original intra-regional mode to the inter-regional mode, for instance, electricity can be transmitted from Xinjiang, Ningxia, Sichuan, and Shaanxi to provinces in eastern region. By 2019, trans-provincial power transmission had reached 540.5 billion kilowatt-hours and trans-regional power transmission reached 1,444 billion kilowatt-hours with growth rates of 12.2% and 11.4%, respectively [23]. (4) A trans-provincial and trans-regional power trading mechanism has gradually taken shape in China. In 2018, the National Energy Administration of China began to allow temporary inter-provincial annual and monthly transactions among five provinces, Guangdong, Guangxi, Yunnan, Guizhou, and Hainan, and inter-regional annual and monthly transactions between the provinces above and other regions. The trading approaches include agreement plans, direct trading, incremental delivery, contract trading and so forth. (5) As trans-provincial and trans-regional power trading mechanism in China improve, the proportion of clean electricity in total electricity consumption is also increasing, with rapid growth in nuclear power, wind power and solar power. As of 2019, the amount of electricity generated from non-fossil energy was 239 million kilowatt-hours, a 10.4% increase from the previous year, and accounting for 32.6% of total electricity generation. Nuclear power, wind power and solar power grew by 18.2%, 10.9% and 26.5%, respectively, between 2018 and 2019 [23].

Based on electricity development in China, the main mechanisms involved in the formation of the network can be summarized by the following aspects:

A. THE CROSS-REGIONAL FLOW OF ELECTRICITY

There are cross-regional flows of electricity [24], and they are promoted by large-scale projects such as the West-to-East Power Transmission Project and the advancing marketization of electricity, which permits regional communications
on electricity that were formerly limited by geographical constraints, exhibiting a multi-threaded structure akin to a network.

B. IMBALANCES IN REGIONAL ELECTRICITY PRICES

Variations in the price of electricity result from the heterogeneity of electricity endowment and production capacity [25]. At present, as production and transport costs decline, price imbalances will lead to more inter-regional electricity transactions and the formation of an electricity transaction network, thus strengthening the network correlation of electricity consumption.

C. THE SPILLOVER EFFECT OF TECHNOLOGY

With interaction among regions becoming frequent, spillovers of technical progress can also affect regional electricity consumption [26], and the existence of the energy rebound effect indicates that the effect of technical progress on electricity is nonlinear [27], [28]. Thus, the spatial effect caused by technology spillovers become more complex.

D. INTER-GOVERNMENTAL COMPETITION

In the process of implementing energy-savings targets, local governments often examine other provinces and adjust their targets [29], irrespective of the geographical distance between them. Therefore, competition among local governments is also a driver of the formation of network correlations in electricity consumption across regions. Therefore, to effectively improve the performance of governance on regional energy issues, it is of importance to explore the network correlations of electricity consumption among regions. The Social Network Approach is an appropriate method to make research on it because it can describe complex network-shaped relationships [30]. Some scholars have introduced it in the social science [31], economic development [32], environment [33], and other regional issues [34], [35], however, researchers have seldom applied it in the study on regional electricity consumption. Therefore, this article will apply the Social Network Approach to analyze the spatial correlations of regional electricity consumption and how to utilize the spatial correlations to promote the governance in electricity intensity issues.

The main contributions and novelty of this article can be summarized as follows. First, different from the traditional studies on the spatial effects of regional electricity consumption, this article applies the social network approach to analyze and describe the complex spatial correlation structure. Second, the CONCOR method is used to explore the spatial correlation of regional electricity consumption; it can clearly depict the dynamic transmission mechanism of the networks. Third, quantile regression is applied to analyze the electricity intensity effect of the spatial correlation of electricity consumption and explore how to realize energy conservation and emission reduction through the optimization of spatial correlation.

The schematic for the framework of this article is shown in Fig.1 and the remainder of the paper is structured as follows. The social network approach and data used in this article are briefly introduced in Section 2. The structural analysis of the regional electricity consumption network and its evolution during the period from 2000 to 2018 are explored in Section 3. An extended discussion on the electricity intensity effect of the network is presented in Section 4. The final section presents the conclusions and some policy implications.
GDP of region \( i \). Gravity is negatively related to geographic distance and positively related to economic distance. Then, we can construct a comprehensive distance by combining the geographic distance with the economic distance. This comprehensive distance indicates that the spatial correlation is affected not only by long-distance transmission but also by economic attraction.

Using the gravity formula (1), a gravity matrix can be constructed as follows:

\[
Gravity\; Matrix = \begin{bmatrix}
gravity_{11} & \ldots & gravity_{1N} \\
gravity_{21} & \ldots & gravity_{2N} \\
\vdots & \ddots & \vdots \\
gravity_{N1} & \ldots & gravity_{NN}
\end{bmatrix}
\] (3)

For the \( i \)th row, the average value should be calculated as the critical value, and the \( j \)th element of that row is then compared with the critical value. By using the following criterion, the adjacent matrix of the electricity network can be constructed as \( A = (a_{ij})_{N \times N} \).

\[
a_{ij} = \begin{cases}
1 & \text{if gravity}_{ij} \text{ is greater than critical value} \\
0 & \text{otherwise}
\end{cases}
\]

In this adjacency matrix representing the electricity consumption network, if \( a_{ij} \) equals 1, this denotes a spillover from region \( i \) to region \( j \); if \( a_{ij} \) equals 0, this indicates the absence of a relationship between the two regions. The construction of the network also elucidates that the adjacent matrix is not a symmetric matrix, and the regional electricity consumption network is a directed network.

2) THE GLOBAL FEATURES OF THE NETWORK
To characterize the global features of the regional electricity consumption network, this analysis applies a series of indicators, such as network density, network connectedness, network hierarchy and network efficiency [30].

a: NETWORK DENSITY
In a regional electricity consumption network, network density is an indicator that reflects the density of the network. If there are more relationships in the network, the value of network density is higher. In a network containing \( N \) nodes (namely \( N \) regions), the network density can be defined as follows:

\[
Density = \frac{L}{N \times (N - 1)}
\] (4)

where the value of network density ranges from 0 to 1.

b: NETWORK CONNECTEDNESS AND NETWORK HIERARCHY
The network connectedness of a regional electricity consumption network is an important indicator to portray its robustness or vulnerability. If some nodes in a regional electricity consumption network have more connections, this means the network’s dependence on these nodes is higher, and the network has a higher connectedness and greater vulnerability. The connectedness of the network can be measured by the reachability of the nodes, and the detailed indicator is as follows:

\[
Connectedness = 1 - \frac{V_c}{\max V_c}
\] (5)

where \( V_c \) is the number of the unreachable nodes and \( \max V_c \) is the most probable number of node pairs.

Closely related to network connectedness, network hierarchy is also an indicator to describe reachability, especially for directed network. It focuses on the asymmetric reachability of the nodes in a regional electricity consumption network; it can reveal the asymmetric dependence of every node in the network and falls in the range [0,1]. The indicator derived as follows:

\[
Hierarchy = 1 - \frac{V_h}{\max V_h}
\] (6)

where \( V_h \) is the number of symmetric reachable nodes and \( \max V_h \) is the most probable number of symmetric reachable nodes in the network.

c: NETWORK EFFICIENCY
Network efficiency measures the multiple stacking degree of the connections in the network. We obtain network efficiency by exploring the different components in the network and analyse the extent of redundant connections in all the components; this measure takes values in the range [0,1]. The indicator is derived as follows:

\[
Efficiency = 1 - \frac{V_e}{\max V_e}
\] (7)

where \( V_e \) is the number of redundant connections in all the components of a regional electricity consumption network and \( \max V_e \) is the most probable number of redundant connections in all the components.

3) THE LOCAL FEATURES OF NETWORK
In addition to the global indicators, local indicators are also used to characterize the features of a regional electricity consumption network, such as degree and centrality. In a directed network, the degree features of a node mainly contain three centrality features, including node centrality, closeness centrality and betweenness centrality [30].

a: NODE CENTRALITY
Node centrality indicates the extent to which a node is in the central position of the regional electricity consumption network. If a node has more connections, its node centrality will be higher. The node centrality indicator is constructed as follows:

\[
Node\; Centrality = \frac{Degree}{2(N - 1)}
\] (8)
TABLE 1. The variables and economic indicators.

| Variables | Economic Indicators                                                                 | Data Sources                      |
|-----------|-------------------------------------------------------------------------------------|-----------------------------------|
| \( y_i \) | The economic growth level of region \( i \)                                         | CEInet Statistics Database        |
| \( E_i \) | The electricity consumption of region \( i \)                                       | CEInet Statistics Database, the Statistical Yearbook of the provinces |
| \( y_i / P_i \) | The per capita GDP of region \( i \), economic growth level/ gross population        | CEInet Statistics Database, the China Statistical Yearbook |
| \( EI_i \) | The electricity intensity of region \( i \), electricity consumption / economic growth level | CEInet Statistics Database, the Statistical Yearbook of the provinces |

b: CLOSENESS CENTRALITY

Closeness centrality is an indicator measuring the summation of the shortest distance between a given node and others, reflecting the uncontrollability of the given node. For node \( i \), the closeness centrality is obtained by the following formula:

\[
\text{ClosenessCentrality} = \frac{1}{N} \sum_{j=1}^{N} d_{ij} \quad (9)
\]

where \( d_{ij} \) is the shortest distance between \( i \) and \( j \).

c: BETWEENNESS CENTRALITY

Betweenness centrality measures the controllability of a node regarding the interactions among other nodes. If the betweenness centrality of a given node is higher, it is more likely to be an intermediary node in the network. For region \( k \) in a regional electricity consumption network, if the summation of the shortest distance between region \( i \) and region \( j \) is \( G_{ij} \), and the summation of the distances from them through region \( k \) is \( g_{ij} \), then the betweenness centrality is derived as follows:

\[
\text{BetweennessCentrality} = \frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{N} \frac{g_{ij}}{G_{ij}} \quad (10)
\]

4) THE CONCOR METHOD

Blockmodel analysis is also an important method of social network analysis, and it is essential to derive the spatial clustering of the nodes in the network and form multiple blocks with similar features and then analyse the role of every block in the network. The convergent correlations method (in the following, the abbreviation CONCOR method is used for brevity) is a widely used approach for dividing into blocks [36]. The CONCOR method’s division into blocks allows for the exploration of the spatial connections among intra-block nodes and inter-block nodes and a more detailed analysis of the network structure. In an economic network, the features of a block can be generally summarized in terms of three categories: (1) net spillover, with obviously more overflowing connections than receiving connections; (2) net-benefited, with obviously more receiving connections than overflowing connections; and (3) intermediary, with a relatively balanced relationship between receiving connections and overflowing connections.

B. DATA

With the aim of studying the spatial correlation of regional electricity consumption in China, 30 provinces in Mainland China (excluding Tibet) are selected as the research subject, and the time window for this study is from 2000 to 2018.

The data used in this article come from the CEInet Statistics Database (China Economic Information Net Statistics Database), the China Statistical Yearbook (2001 to 2019) and the Statistical Yearbook of the Provinces (2001 to 2019). The detailed variables and corresponding economic indicators used in this article are listed in Tab.1.

III. STRUCTURAL ANALYSIS OF THE REGIONAL ELECTRICITY CONSUMPTION NETWORK

A. THE NETWORK STRUCTURE

After determining the connection relationships among all of the subjects (all provinces) in regional electricity consumption and constructing the adjacency matrix among them, the adjacency matrix can be used to portray the connection network connecting all of the subjects and form a regional electricity consumption network. The structural features of the network can be analysed based on this approach. This article uses the Igraph Toolbox of the R software package to realize the visualization of network structure in 2000, and it is shown in Fig.2(A).

According to the electricity consumption network shown in Fig.2(A), the spatial correlation of regional electricity consumption in China formed a network structure with complex features at the beginning of the sample period, and there are no isolated nodes in the network, which indicates that the inter-provincial electricity consumption in China has a relatively high level of the network connection during this period. To make an intuitive comparison over the sample period, we also visualize the network structure in other years, but only that representing the end of the sample period, namely 2018, is shown in Fig.2(B).

By observing the regional electricity consumption network over the sample period, this analysis reveals that regional electricity consumption in China formed a network structure during the sample period, and there are no isolated nodes, which indicates good connection. As expected, the number of edges in the network in 2018 is relatively denser than that in 2000, indicating that the spatial correlation of regional
electricity consumption in 2018 is greater than that in 2000. However, to better analyse the evolution of the network structure, it is necessary to calculate the values of the corresponding statistical indicators and describe the structural features of the regional electricity consumption network.

B. ANALYSIS OF THE GLOBAL FEATURES OF NETWORK

1) THE EVOLUTION OF NETWORK DENSITY

First, the trend of the regional electricity network over time can be analysed through network density. According to the calculation of the number of edges and network density obtained from UciNet software, we can analyse the trend in the density of the regional electricity consumption network's connections, and the results of these two indicators are exhibited in Fig.3.

From the results in Fig.3, we find that the connections in the network increased gradually during this period, the number being 174 in 2000 and 216 in 2018, which indicates that regional electricity is becoming more interlinked and the spatial correlation is strengthened. In terms of the number of edges, the network density also gradually increased from 0.20 in 2000 to 0.24 in 2018, which also means increasingly greater spatial correlation. Over the sample period from 2000 to 2018, the main reason that the spatial correlation of regional electricity strengthened is the financial support for the energy delivery engineering provided by the Chinese government. Especially after 2004, we can see that the spatial correlation of the regional electricity consumption network increases substantially with a large amount of growth. This was facilitated by, on the one hand, the development of the large West-to-East Power Transmission Project, and, on the other hand, the gradual realization of energy marketization in China, which is gradually breaking down the trade barriers among regions, facilitating the flow of electricity resource among regions, and ultimately promoting the spatial correlation of regional electricity.

2) THE EVOLUTION OF NETWORK CONNECTEDNESS AND HIERARCHY

According to the calculation of network connectedness, the values are all equal to 1 within the period from 2000 to 2018, which indicates that the regional electricity consumption network exhibits good reachability. However, as an indicator, network connectedness is limited in its ability to measure the reachability of the network. Therefore, we further study the evolution of the asymmetric reachability of network structures by using the network hierarchy indicator, as shown in Fig.4.

From Fig.4, we can see that network hierarchy has a sharp decrease in 2000, and it shows a stable trend over the years 2001-2009, remaining at approximately 0.45. However, after 2009, another sharp reduction in network hierarchy appears, only slightly fluctuating around a new equilibrium of 0.25. This phenomenon indicates that the hierarchy structure of the regional electricity consumption network exhibits stable periods and that the sharp reduction in 2000 is due to the establishment of electricity marketization. The second decrease is attributable to the infrastructure investment caused by the financial crisis of 2008, which generated a
shock to the hierarchical structure of the network, which then stabilized again at a new level. From 2000 to 2018, the network hierarchy decreased from 0.73 to 0.25. A decreasing of network hierarchy means that the hierarchical structure of the network is weakened, and it is beneficial to promote the spatial spillover effect of electricity consumption among regions and optimize the allocative efficiency of regional energy consumption.

3) THE EVOLUTION OF NETWORK EFFICIENCY

The calculation of network efficiency is shown in Fig.5.

According to the trend, we can see the network efficiency is gradually decreasing, and this phenomenon corresponds to the gradual increase in network density. From 2000 to 2018, network efficiency decreased from 0.64 to 0.56. The decrease in network efficiency indicates that the interaction of regional electricity consumption among provinces and the spillover effect can be influenced through more channels, resulting in multiple super-positions of the connections among provinces in the network and increasing the complexity of the network structure. The result of the decrease in network efficiency is increased network robustness, which is beneficial for the interaction of regional electricity consumption and the allocation of regional energy distribution.

The decreases in network hierarchy and network efficiency both indicate that the allocation roles of electricity resources among regions using market forces are becoming increasingly prominent. The improvements in the energy factor marketization system led to a reduction in the transaction cost of electricity among regions, an enhancement of inter-provincial cooperation in electricity utilization, and an increase in the spatial correlation among regions and is ultimately conducive to the realization of regional energy conservation and emission reduction goals.

C. ANALYSIS OF THE LOCAL FEATURES OF THE ELECTRICITY CONSUMPTION NETWORK

To analyse the network structure, it is also necessary to analyse the network from the perspective of local features, mainly including the node degree and some centrality indicators. The local feature analysis is exhibited as follows.

1) ANALYSIS OF THE IN-DEGREE AND OUT-DEGREE OF THE NETWORK

Based on the network constructed above, the in-degree, the out-degree, and the total number of degrees of every node in the electricity consumption network can be calculated, and the results are reported in Tab.2.

Regarding in-degree and out-degree of the network, no node exists with degree 0, which indicates that an interconnected network has been established in the spatial correlation of regional electricity consumption and there are no isolated provinces. The provinces with a degree higher than average value include Beijing, Tianjin, Shanghai, Jiangsu, Zhejiang, Guangdong and Guizhou. Some of these provinces, such as Beijing and Shanghai, represent economically developed regions with high demand for electricity, which means that they will have a large number of degrees. By contrast, some regions, such as Guizhou, have rich electricity endowments, and their high degree is due to the spillover effect.

2) ANALYSIS OF NODE CENTRALITY

Then, the node centrality of every node in the electricity consumption network can be calculated, and the results on their average values and order are depicted in Fig. 6.

From the Fig.6, the average node centrality in the country is 35.61, and the provinces with node centrality higher than the average value include Beijing, Tianjin, Shanghai, Jiangsu, Zhejiang, Guangdong and Guizhou. Some of these provinces, such as Beijing and Shanghai, represent economically developed regions with high demand for electricity, which means that they will have a large number of degrees. By contrast, some regions, such as Guizhou, have rich electricity endowments, and their high degree is due to the spillover effect.
TABLE 2. The node degree results for the regional electricity consumption network.

| Provinces       | In 2000 | In 2018 |
|-----------------|---------|---------|
|                 | Out-degree | In-degree | Degree | Order | Out-degree | In-degree | Degree | Order |
| Beijing         | 6        | 23       | 29     | 2     | 5          | 23        | 28     | 2     |
| Tianjin         | 8        | 21       | 29     | 2     | 5          | 23        | 28     | 2     |
| Hebei           | 4        | 3        | 7      | 21    | 5          | 5         | 10     | 18    |
| Shanxi          | 6        | 3        | 9      | 15    | 6          | 3         | 9      | 22    |
| Inner Mongolia  | 3        | 2        | 5      | 29    | 8          | 11        | 19     | 7     |
| Liaoning        | 5        | 2        | 7      | 21    | 8          | 2         | 10     | 18    |
| Jilin           | 5        | 2        | 7      | 21    | 6          | 2         | 8      | 25    |
| Heilongjiang    | 5        | 1        | 6      | 27    | 7          | 2         | 9      | 22    |
| Shanghai        | 4        | 28       | 32     | 1     | 9          | 24        | 33     | 1     |
| Jiangsu         | 2        | 16       | 18     | 6     | 4          | 23        | 27     | 4     |
| Zhejiang        | 2        | 17       | 19     | 4     | 5          | 17        | 22     | 5     |
| Anhui           | 3        | 8        | 11     | 10    | 3          | 11        | 14     | 12    |
| Fujian          | 4        | 8        | 12     | 7     | 10         | 7         | 17     | 8     |
| Jiangxi         | 7        | 3        | 10     | 12    | 8          | 6         | 14     | 12    |
| Shandong        | 4        | 8        | 12     | 7     | 7          | 10        | 17     | 8     |
| Hainan          | 6        | 5        | 11     | 10    | 7          | 10        | 17     | 8     |
| Hubei           | 7        | 3        | 10     | 12    | 7          | 2         | 13     | 14    |
| Hunan           | 8        | 2        | 10     | 12    | 7          | 3         | 10     | 18    |
| Guangdong       | 8        | 11       | 19     | 4     | 11         | 9         | 20     | 6     |
| Guangxi         | 7        | 2        | 9      | 15    | 7          | 1         | 8      | 25    |
| Hainan          | 8        | 0        | 8      | 18    | 7          | 1         | 8      | 25    |
| Chongqing       | 8        | 1        | 9      | 15    | 7          | 3         | 10     | 18    |
| Sichuan         | 7        | 1        | 8      | 18    | 9          | 2         | 11     | 17    |
| Guizhou         | 9        | 3        | 12     | 7     | 10         | 2         | 12     | 15    |
| Yunnan          | 7        | 0        | 7      | 21    | 10         | 2         | 12     | 15    |
| Shaanxi         | 7        | 0        | 7      | 21    | 7          | 2         | 9      | 22    |
| Gansu           | 7        | 1        | 8      | 18    | 11         | 4         | 15     | 11    |
| Qinghai         | 7        | 0        | 7      | 21    | 7          | 1         | 8      | 25    |
| Ningxia         | 6        | 0        | 6      | 27    | 6          | 1         | 7      | 29    |
| Xinjiang        | 4        | 0        | 4      | 30    | 7          | 0         | 7      | 29    |
| Average         | 5.8      | 5.8      | 11.6   | --     | 7.2        | 7.2       | 14.4   | --    |

Heilongjiang, and this is because their economic development levels are relatively backward or their geographic locations are relatively remote, which makes it difficult for spatial correlation to form, so they have a smaller number of spatial connections with other regions.

3) ANALYSIS OF CLOSENESS CENTRALITY

The closeness centrality of every node in the electricity consumption network can be calculated, and the results on their average values and order are depicted in Fig.7.

From Fig.7, we can see that the average closeness centrality in the country is 62.09. The provinces with above-average closeness centrality values include Beijing, Tianjin, Shanghai, Jiangsu, Zhejiang, and Guangdong, indicating that these provinces can make spatial connections with other provinces autonomously and that their connections are seldom controlled by others. Therefore, they can be regarded as serving as core actors in the network. The least developed provinces include Jilin, Shanxi and Heilongjiang, with relatively low levels of economic development and unremarkable electricity resources. Therefore, they become marginal actors in the network.

4) ANALYSIS OF BETWEENNESS CENTRALITY

The betweenness centrality of every node in the electricity consumption network can be calculated, and the results on their average values and order are depicted in Fig.8.

From Fig.8, the average betweenness centrality in the country is 2.30. The provinces with above-average betweenness centrality values include Beijing, Tianjin, Shanghai, Jiangsu, Zhejiang, Guangdong, indicating that these regions not only possess the controlling ability to make connections.
D. BLOCKMODEL ANALYSIS OF THE REGIONAL ELECTRICITY CONSUMPTION NETWORK

In this section, we apply the CONCOR method to divide the network into several blocks. The maximum division is set to 3, and the concentrate standard is set to 0.2. The block division results obtained through the CONCOR method are shown in Tab.3.

| Blocks    | The Provinces Included                                                                 |
|-----------|--------------------------------------------------------------------------------------|
| First     | Beijing, Tianjin, Shandong, Inner Mongolia                                          |
| Second    | Jiangsu, Zhejiang, Shanghai, Fujian, Guangdong                                      |
| Third     | Hubei, Henan, Anhui, Jiangxi, Hunan, Guizhou, Yunnan, Guangxi, Hainan, Sichuan, Xinjiang |
| Fourth    | Ningxia, Hebei, Gansu, Shanxi, Qinghai, Shaanxi, Heilongjiang, Liaoning, Jilin, Chongqing |

Using the CONCOR method, the regional electricity consumption network is divided into four blocks. Based on this, we can calculate the mutual connections among the blocks, and the results are shown in Tab.4.

| Block | First | Second | Third | Fourth |
|-------|-------|--------|-------|--------|
| First | 6     | 2      | 7     | 8      |
| Second| 3     | 9      | 29    | 0      |
| Third | 30    | 47     | 3     | 3      |
| Fourth| 29    | 22     | 5     | 13     |

In the network in 2018, there are 209 edges; the number of connections among the nodes of the internal block is small, with a maximum of 13 in the fourth block and a minimum of 3 in the third block. Therefore, the spatial correlations are mainly connections among the inter-block nodes, not intra-block nodes. There were 178 connections among inter-block nodes, with the ratio of 85.2%, indicating that the spatial correlation among blocks is significant and that there exist strong spatial spillover effects among these blocks.

Then based on the results in Tab.4, we can also calculate the number of receiving connections, the number of overflowing connections, the ratio of expected inner connections and the ratio of real inner connections to analyse the block features of every block. The results are shown in Tab.5.

According to the results in Tab.5, the first block and second block mainly contain receiving connections and have a smaller of overflowing connections. In contrast, the third block and fourth block mainly contain overflowing connections, and the share of receiving connections is small. We also see that the number of real inner connections in every block is relatively small, which can be attributed to the strong spillover effect among these four blocks in the Chinese regional electricity consumption network.
Based on the definitions provided above, we can define the first block and second block as the net-benefitted block, indicating that they have considerable demand for electricity for their economic development and are located in regions with substantial electricity supply and needing ample electricity support. Therefore, a majority of receiving connections appear in the first block and second block. The provinces in these two blocks belong to developed regions such as Circum-Bohai-Sea Region, Yangtze River Delta and Pearl River Delta, and they can transform electricity consumption into economic growth. Their electricity source is the third block and fourth block, because the provinces with rich electricity resources in the central and western areas of China mainly belong to these two blocks, and they can provide a constant supply of electricity for the first block and second block, called the net-spillover block. We find no evidence of an intermediary block exists in the network in 2018, and the reason may be that spillover effect among blocks is strengthened. An intermediary block may not have a necessary role to play in the network.

Therefore, if the regional electricity consumption network were regarded as a machine, as shown in Fig.9, it could be described as follows: the third block and fourth block are batteries that send energy to the first block and second block, which can be regarded as the main engines. This is how the networked machine operates and maintains the sustained evolution of the regional electricity consumption network.

### IV. EMPIRICAL ANALYSIS: AN EXTENDED DISCUSSION

As described above, the regional electricity consumption network has been constructed, and its global features and local features are further explored below. We consider whether a change in the network structure can influence regional electricity intensity and whether regional energy problems can be addressed by adjusting the spatial correlation of electricity consumption, with the aim of realizing the a network governance approach to energy problems. Therefore, we proceed with an extended discussion on the effect of the spatial correlation of regional electricity on electricity intensity. The effect of the spatial correlation of electricity consumption on electricity intensity and its provincial variation can be explored from the two perspectives: global features and local features.

#### A. THE EFFECT OF GLOBAL NETWORK FEATURES ON ELECTRICITY INTENSITY

First, from the perspective of the global network, we discuss the effect of global features, including network density, network hierarchy and network efficiency, on global electricity intensity in China and the provincial variation of electricity intensity. Here, we use the ratio of electricity consumption to economic output, $EI_t = E_t/Y_t$, to measure electricity intensity and the variance of provincial electricity intensity, $\text{VAR}(EI_t)$, to measure the provincial variation in electricity intensity. Therefore, based on the three indicators calculated above, data on global electricity intensity and provincial variation in electricity intensity are obtained, and a time series OLS (ordinary least squares) regression model is used for the analysis. The results are shown in Tab.6.

#### TABLE 6. OLS regression results on the effect of global network features on electricity intensity.

| Variables       | Dependent Variable: $EI_t$ |
|-----------------|-----------------------------|
| Intercept       | 0.3217*** (0.0318)          |
| Density         | -0.9673*** (0.1413)         |
| Hierarchy       | 0.1593*** (0.0065)          |
| Efficiency      | 0.4760*** (0.0483)          |
| $R^2$           | 0.7335 0.8495 0.8507        |

Note: *** and ** denote statistical significance at the 1%, 5%, and 10% level, respectively

According to Tab.6, the network density, network hierarchy and network efficiency of the regional electricity consumption network all play a significant role in determining global electricity intensity. Overall, the effect of density is approximately $-0.96$ and the effects of hierarchy and efficiency are

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**TABLE 5. The interaction characteristics among blocks.**

| Block        | First | Second | Third | Fourth |
|--------------|-------|--------|-------|--------|
| The number of nodes | 4     | 5      | 11    | 10     |
| The number of receiving connections | 68    | 80     | 44    | 24     |
| The number of overflowing connections | 23    | 41     | 83    | 69     |
| The ratio of expected inner connections | 0.103 | 0.138  | 0.345 | 0.310 |
| The ratio of real inner connections   | 0.261 | 0.220  | 0.036 | 0.188 |

Note: N-B is Net-benefit, N-S is Net-spillover

**FIGURE 9. The operating mechanism of the network blocks.**
The effect of network density on electricity intensity is negative, indicating that an increase in network density promotes a reduction in global electricity intensity. The reason is that when the network density is higher, the number of channels for electricity to flow among regions is larger, which avoids the overlapping of regional electricity usage and waste, thus improving the allocative efficiency of regional electricity usage and reducing the level of global electricity intensity.

Network hierarchy and network efficiency both have a positive effect on global electricity intensity, indicating that an increase in these two features is not conducive to achieving regional electricity intensity reduction targets. This is the case for network hierarchy because if the hierarchal structure of a network becomes expands, some nodes with high attachment will have difficulty forming two-way connections. They can only increase their attachment to the rest of the nodes. This does not favour the constrained formation of regional electricity consumption and thus has an insignificant effect on decreasing electricity intensity. The explanation for network efficiency is that higher network efficiency means fewer network edges, which means that electricity flow can only occur in local network structures. Fewer network connections will reduce the benefits of energy flowing in the network, leading to the undesirable outcome that it because difficult for many provinces to exploit their energy-saving advantages. Therefore, the improvements in network hierarchy and network efficiency are not conducive to reducing regional electricity intensity.

From the results in Table 7, we can see further that the network density, network hierarchy and network efficiency of the regional electricity consumption network can also have a significant effect on the variation in regional electricity intensity. Increased network density is beneficial because it reduces the variation in regional electricity intensity, and increased network density is also beneficial for the energy flow among regions, thus improving the fairness of provincial electricity consumption and narrowing the spatial differences in regional electricity intensity. Network hierarchy and network efficiency have a negative effect on electricity intensity because increased network hierarchy and network efficiency reduce the number of edges. On the one hand, this reduces the number of two-way edge pairs and leads to inequities in regional energy consumption, which intensifies the difference in regional energy intensity; on the other hand, it reduces overall network robustness, which leads the polarization of electricity intensity among regions.

The evolution of regional electricity intensity is a dynamic process, so when the electricity intensity changes, the effects of network features on electricity intensity do not remain static. To consider the different effect of network features on electricity intensity under different distributions, we apply quantile regression to conduct the empirical analysis and compare the results with the OLS results above [37]. The results obtained by quantile regression are exhibited in Tab.8 and Tab.9.

Tab.8 shows that the results of the quantile regression on the effect of the global features of electricity intensity correspond to those based on OLS regression. Moreover, we find that when we move from a high to a low level of the electricity distribution, the effects of these three variables gradually weaken, and the significant results appear at the 0.5 quantile, which means that there is a marginal reduction in the effect of network features as electricity intensity decreases.

Similarly, the results of the quantile regression on the effect of global features on the variation in electricity intensity in Tab.9 correspond to those obtained by OLS regression, and we also observe a marginal reduction in these effects, which indicates that the effects will also be influenced by the distribution of the variation in electricity intensity.

### B. THE EFFECT OF LOCAL FEATURES OF THE ELECTRICITY CONSUMPTION NETWORK ON ELECTRICITY INTENSITY

Having completed the analysis of the effects of global features on electricity intensity, we proceed to analyse whether...
TABLE 9. Results of the quantile regression of the effect of global network features on the variation in electricity intensity.

| Variables | Quantiles | Dependent Variable: $\text{VAR}(EI)$ |
|-----------|-----------|-------------------------------------|
|           | 0.1       | 0.5                                 |
|           | 0.9       | 0.1                                 |
|           | 0.5       | 0.9                                 |
| Intercept | 0.0208    | 0.0277*** 0.0298 0.0023 0.0002 0.0004 |
|           | 0.0206    | 0.0197** 0.0199** 0.0205** 0.0203** |
| Density,  | -0.0713   | -0.0957*** -0.0995                 |
| Hierarchy | 0.0061    | 0.0168*** 0.0189                    |
| Efficiency | 0.0435    | 0.0448*** 0.0464                    |
| Pseudo $R^2$ | 0.1045   | 0.5434 0.5212 0.2204 0.6057 0.6399 |

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

TABLE 10. Results of the panel OLS regression of the effect of local features on electricity intensity.

| Variables | Dependent Variable: $EI_t$ |
|-----------|-----------------------------|
|           | 0.168*** 0.189             |
|           | 0.0231 (0.0034) (0.0321)   |
| Node,     | 0.1905*** 0.3344*** 0.1384** |
|           | (0.0106) (0.0451) (0.0038) |
| Closeness | -0.0035*** -0.0041***      |
|           | (0.0003) (0.0007)          |
| Betweenness | -0.0001*** -0.0006*** -0.0025*** |
|           | (0.0001) (0.0001) (0.0003) |
| $R^2$     | 0.8012 0.7921 0.544         |
| Hausman Test | 4.62** 8.55*** 1.78        |
| Individual effect | FE, FE, RE |

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Regarding the individual effects to be used in the panel regression model, the Hausman Test indicates that the specifications using node centrality and closeness centrality as the dependent variable and estimate a panel regression. The results are shown in Tab.10.

TABLE 11. Results of the quantile regression of the effect of local features on electricity intensity.

| Variables | Quantile | $EI_t$ |
|-----------|----------|--------|
|           | 0.1      | 0.5    |
|           | 0.9      | 0.1    |
|           | 0.5      | 0.9    |
| Intercept | 0.0738*** | 0.1287*** | 0.3337*** |
|           | 0.1028*** | 0.1852*** | 0.5379*** |
| Node,     | 0.0034    | 0.0048   | 0.0256   |
|           | 0.0097    | 0.0134   | 0.0589   |
| Closeness | -0.0001*** | -0.0006*** | -0.0025*** |
|           | (0.0001)  | (0.0001)  | (0.0003)  |
| Betweenness | -0.0006*** | -0.0012*** | -0.0047*** |
|           | (0.0002)  | (0.0002)  | (0.0006)  |
| Pseudo $R^2$ | 0.0285   | 0.0347 0.1081 0.0303 0.0311 0.0921 |

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

The centrality features of the nodes affect the regional electricity network. Therefore, we use node centrality, closeness centrality and betweenness centrality as the independent variables, which are denoted as $\text{Node}_t$, $\text{Closeness}_t$, and $\text{Betweenness}_t$, and regional electricity intensity ($EI_t$) as the dependent variable and estimate a panel regression. The results are shown in Tab.10.

Regarding the individual effects to be used in the panel regression model, the Hausman Test indicates that the specifications using node centrality and closeness centrality as the dependent variable should employ a fixed effect (FE) model, while the specification using betweenness centrality should employ a random effect (RE) specification. From the regression results, we can see that the three centrality variables have significant effects on electricity intensity and that the effects are all negative, indicating that an increase in the centrality of a node in the regional electricity consumption network can reduce regional electricity intensity. We next consider each of the three centralities individually: increasing node centrality means that the degree of nodes increases, which indicates that the spatial correlations among nodes have been strengthened and the individual electricity intensity can be reduced due to the benefits of spatial spillover effect. Increasing closeness centrality weakens the control of spatial connections between the node itself and another node, effectively promoting the circulation efficiency of regional electricity and reduce regional electricity intensity. Increasing betweenness centrality promotes the intermediate effect of a node in the electricity transmission network and improve its ability to absorb the spatial spillover effect, which ultimately improves the potential to reduce electricity intensity.

Considering the spatio-temporal heterogeneity of electricity intensity, the effects of the centrality variables also vary with the position in the distribution of electricity intensity. Therefore, quantile regression is also applied in the analysis of the effect of the three centralities on electricity intensity. The results are shown in Tab.11.

The quantile regression results generally align with the panel OLS results, and the effects of the three centralities are significant at different quantiles of electricity intensity.
As we move down electricity intensity quantiles, the effects of all three centralities decrease. Based on this observation, we conclude that in some nodes with higher electricity intensity, the effects on electricity intensity caused by increasing centrality are also larger. Thus, regions with higher electricity intensity should attempt to improve their centrality position in the regional electricity consumption network and effectively address energy issues.

V. POLICY SUGGESTIONS AND CONCLUSION

This article applies the social network approach to study a regional electricity consumption network, including its global features, local features, and block division and its effect on the ability to reduce regional electricity intensity. Based on above analysis, if the network’s advantages can be sufficiently exploited and its structure can be optimized, an effective network governance mechanism can be established to realize the energy-savings goals. Therefore, some policy suggestions are provided as follows.

(1) Although the network density is gradually increasing, the connections in the network remain sparse. Therefore, it is necessary to fully exploit government and market action, and more channels for the flow of electricity should be created by supporting large electricity projects connecting regions and strengthening electricity transactions among regions, thus optimizing the network and realizing the goal of reducing electricity consumption.

(2) In the regional electricity consumption network, more opportunities for cooperation between the regions with network advantages and the regions with network disadvantages should be established to allow the gradual formation of two-way spatial connections. Increasing two-way spatial connections can not only promote equity in electricity consumption among regions by weakening the hierarchal structure but also promote allocative efficiency in electricity to reduce electricity consumption.

(3) In terms of regional development, the advantages of logistics, information and energy endowment should be maximally utilized. The opportunity to become an intermediary platform for regional cooperation should be created and seized, which would improve the centrality of the network and absorb the spillover effect among regions, ultimately reducing electricity intensity and realizing the goal of sustainable development.

In summary, the following conclusions can be obtained.

First, the spatial correlations of regional electricity consumption have formed a network structure with some complexity. As shown by the evolutionary process from 2000 to 2018, network density is increasing, indicating that the spatial correlations in electricity have been strengthened. Moreover, the network hierarchy and network efficiency are decreasing because of the allocative effect of energy marketization, which decreased the transaction cost of exchanging electricity among regions. From the perspective of local features, the nodes with higher centrality are mainly located in developed coastal areas, while the nodes with lower centrality are in areas with slow economic growth and remote geographic location.

Second, the regional electricity consumption network can be divided into four blocks. Of these blocks, third block and fourth block act as batteries and send energy to the first block and second block, which act as engines, translating electricity consumption into economic growth and maintaining the sustainable evolution of the network.

Third, changes in the network structure can have a significant effect on electricity intensity. Regarding the global features, network density can reduce electricity intensity, while decreasing network hierarchy and network efficiency

### TABLE 12. Acronyms and their definitions.

| Acronyms | Full names                          |
|----------|-------------------------------------|
| GDP      | Gross Domestic Product              |
| CONCOR   | Convergent Correlations Method      |
| CEinet   | China Economic Information Net Statistics Database |
| OLS      | Ordinary Least Squares              |
| PE       | Fixed Effect                        |
| RE       | Random Effect                       |
| VAR      | Variance                            |
| EI       | Electricity Intensity               |

### TABLE 13. The node centrality results for the nodes in the regional electricity consumption network.

| Provinces | Average | Order |
|-----------|---------|-------|
| Beijing   | 83.85   | 2     |
| Tianjin   | 81.85   | 3     |
| Hebei     | 17.42   | 30    |
| Shanxi    | 20.15   | 28    |
| Inner Mongolia | 32.49 | 9 |
| Liaoning  | 21.96   | 25    |
| Jilin     | 19.06   | 29    |
| Heilongjiang | 20.87 | 27   |
| Shanghai  | 91.11   | 1     |
| Jiangsu   | 69.69   | 4     |

| Provinces | Average | Order |
|-----------|---------|-------|
| Zhejiang  | 63.16   | 5     |
| Anhui     | 30.49   | 11    |
| Fujian    | 32.30   | 10    |
| Jiangxi   | 25.41   | 17    |
| Shandong  | 41.02   | 7     |
| Henan     | 29.04   | 14    |
| Hubei     | 25.41   | 18    |
| Hunan     | 24.32   | 21    |
| Guangdong | 50.27   | 6     |
| Guangxi   | 23.78   | 22    |

Average in Total 35.61
TABLE 14. The closeness centrality results for the nodes in the regional electricity consumption network.

| Provinces  | Average | Order |
|------------|---------|-------|
| Beijing    | 86.14   | 2     |
| Tianjin    | 84.65   | 3     |
| Hebei      | 54.47   | 30    |
| Shanxi     | 55.62   | 28    |
| Inner Mongolia | 60.26 | 8     |
| Liaoning   | 56.20   | 25    |
| Jilin      | 55.27   | 29    |
| Heilongjiang | 55.84 | 27    |
| Shanghai   | 91.90   | 1     |
| Jiangsu    | 77.22   | 4     |

Average in Total 62.09

TABLE 15. The betweenness centrality results for the nodes in the regional electricity network.

| Provinces  | Average | Order |
|------------|---------|-------|
| Beijing    | 13.73   | 2     |
| Tianjin    | 12.69   | 3     |
| Hebei      | 0.10    | 29    |
| Shanxi     | 0.17    | 27    |
| Inner Mongolia | 1.29 | 8     |
| Liaoning   | 0.24    | 19    |
| Jilin      | 0.09    | 30    |
| Heilongjiang | 0.21  | 24    |
| Shanghai   | 16.49   | 1     |
| Jiangsu    | 7.57    | 4     |

Average in Total 2.30

can reduce electricity consumption, and these effects may marginally decrease as electricity intensity declines. Regarding the local features, the three centralities can reduce regional electricity intensity, and there is also a marginal decreasing in this case.

APPENDIX

A. ACRONYMS AND THEIR DEFINITIONS

See Table 12.

B. THE NODE CENTRALITY RESULTS

See Table 13.

C. THE CLOSENESS CENTRALITY RESULTS

See Table 14.

D. THE BETWEENNESS CENTRALITY RESULTS

See Table 15.

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