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Research article

# Research on complex network modeling of building materials supply and demand and characteristics of communities

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ABSTRACT

Currently, China's building materials market is large and the supply and demand transactions are very frequent, which requires us to have a comprehensive understanding of the supply and demand transactions of building materials. Based on complex network theory, this paper constructs a complex network model of supply and demand of building materials. And the Louvain algorithm is also improved to identify and characterize the network community relations based on the characteristics of this network. This paper also applies prefabricated components as an example for empirical research and obtains the following findings: (1) From 2017 to 2022, large- and medium-sized communities in the network gradually increase while small communities gradually decrease; the internal connectivity of large communities is higher than that of small communities; and the regional network also has the structural characteristics of the network. (2) The characteristics of geographic agglomeration gradually emerge in the individual communities in the supply–demand network of prefabricated components with the passage of time. Most of these communities are bounded by provinces, and large-scale communities are distributed in the eastern and southern coastal areas. Thus, this paper visualizes the supply and demand of construction materials to provide a theoretical basis and methodological support for the supply and demand of construction materials and the development of the construction industry.

## 1. Introduction

The China Building Materials Federation announced on August 1, 2023, that the building materials market in the first half of 2023 was generally stable with structural improvements in supply and demand. The building materials industry and enterprises have promoted the continuous optimization of industrial structures, and the momentum of development has continued to increase. This phenomenon indicates that the supply and demand situation for current building materials has a superior outlook. However, cases of cross-regional long-distance transport often occur due to the current uneven geographical distribution of construction materials, easily resulting in the wastage of resources and increasing transport costs. Simultaneously, the long-distance transport of building materials generates a large amount of carbon emissions. The data released by the China Community of Building Energy Efficiency show that the carbon emissions of the entire process of national construction in 2020 is 5.08 billion tons of $CO_2$, accounting for 50.9% of the national carbon emissions. The above discussion reveals several existing problems in the current supply and demand situation of building materials. One of the major reasons for these problems is the lack of a comprehensive understanding of the supply and demand of building materials. A reasonable relationship existing between supply and demand is of considerable importance to the development of

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the entire construction industry and the sustainable development of the environment. Therefore, establishing an effective method to understand the supply and demand of construction materials is an urgent problem.

Currently scholars have explored more about building materials, but most of them stay in the quantity and other application questions of building materials [1,2], and less research on the problem of supply and demand transactions of building materials. At the same time, the existing methods are game theory [3], mathematical modeling [4] and other traditional methods. This makes the current stage of research on the supply and demand of building materials mostly stay in the local, lack of macro-structural analysis and spatial correlation analysis. In view of the above problem research deficiencies, this paper considers the use of data to assist decision-making and the establishment of visualization models, which is expected to improve the shortcomings of the above problem research.

In recent years, scholars have gradually introduced the concept of supply chain into the building materials trading relationship [5]. Supply chain refers to the entire chain of upstream and downstream enterprises involved in the production and distribution process of providing products or services to end users. Due to the large scale of China's building materials market and the gradual increase in the number of members, the real building materials supply chain is not a simple chain, but a mesh structure. As mentioned by Li, "with the increase of supply chain members and the complexity of the supply chain "flow", the supply chain from the chain structure gradually evolved into a complex supply and demand network with adaptive capacity" [6]. In this paper, we will apply the theory of complex network to study the supply and demand network of building materials. Complex network is a kind of abstract model to understand the complex system in the real world, which abstracts the entities in the complex system into nodes and the relationship between entities into connections, and it has been applied to many practical fields such as computer networks [7], technological [8] and climate networks [9]. Complex network analysis has been applied to supply and demand in various fields[10,11] due to its ability to identify supply and demand from a global perspective.

The use of complex networks to construct the supply and demand network of building materials plays an important role in the study of the trading relationship of building materials. The supply and demand network of building materials has the special characteristics of more data volume, larger scale and wider distribution range, which can not be well analyzed its structure. At the same time, the distribution of supply and demand enterprises of building materials has a strong correlation with geographical location. In order to analyze the internal structure of the network so as to be able to better study the transaction relationship between the supply and demand sides of building materials, we introduce the concept of community into the study of building materials supply and demand network. Newman and Girvan [12] first introduced the concept of communities. The community structure is a grouping of nodes in a network, with relatively tight connections within groups and relatively sparse connections between groups [13]. Community discovery aims to identify the community structure based on the interactions between the nodes in the network, achieving the purpose of mining the closely connected set of nodes in the network with the same properties [14]. Numerous methods for delineating the community structure of complex networks are currently available[15–17]. Modularity can also be used to measure the goodness of a community's delineation result. A relatively good result will lead to nodes inside the community with a high degree of similarity, while those outside the community have a low degree of similarity. Scholars have used communities to analyze problems in real-life scenarios[.18] [19]. By identifying and categorizing communities in the complex network of building materials, we can better understand the relationship between the supply and demand of building materials, and reveal the potential laws hidden in the network structure. This provides decision support for urban planning and resource optimization.

The above literature reveals that in previous studies, scholars have focused on the application and analysis of complex networks on the topology of networks. In the research of network communities, scholars focus on the research of community identification methods, but the application of community structure analysis in network research is relatively rare. Studies related to geographic features are also few. Therefore, this paper focuses on the communities of the network and analyzes them in terms of structural and geographical characteristics. The topological features of communities and the divided communities are analyzed together with the geographic location of each node to examine their correlation.

This paper aims to utilize the method of big data to assist decision making and provide a clear understanding of the supply and demand situation of China's building materials market. Thus, this paper intends to use complex network theory to construct a complex network model of supply and demand for building materials, adopt the Louvain algorithm to divide the network into communities, and then conduct structural analysis and characterization of the communities. Prefabricated components are taken as an example for empirical analysis, which can visualize the relationship between supply and demand of prefabricated components and geographical distribution in the country. The current research is assumed to present new insights and methods for the visualization and analysis of the complex network of supply and demand for building materials. This research can also provide powerful support and guidance to decision makers in the fields of urban planning and resource optimization. The key issues to be solved in this paper are as follows: 1) The current supply and demand situation of building materials in China is quantified through the construction of the building materials supply and demand network model. 2)Improving louvain algorithm based on the properties of the complex network of supply and demand of building materials, identifying and dividing the communities of the network, and discovering the dynamic evolution of the supply and demand network and its laws. 3) A research methodology for visualizing big data to assist decision-making has been established, providing a new perspective for a global understanding of the supply and demand situation of building materials.

## 2. Methods

The research methodology of this paper will be based on four aspects: data source and processing, supply and demand network construction, community identification, and classification and analysis of communities. The research route of this paper is shown in Fig. 1.

### 2.1. Data sources and processing

This paper uses prefabricated components as the study object. Prefabricated components are building components that are prefabricated in factories or production bases. The traditional method of building construction generally requires numerous manual operations and cumbersome construction procedures on site. Thus, this method is not only time consuming and laborious but is also prone to quality problems. The emergence of prefabricated components ( PC ) has changed this situation. Through standardized

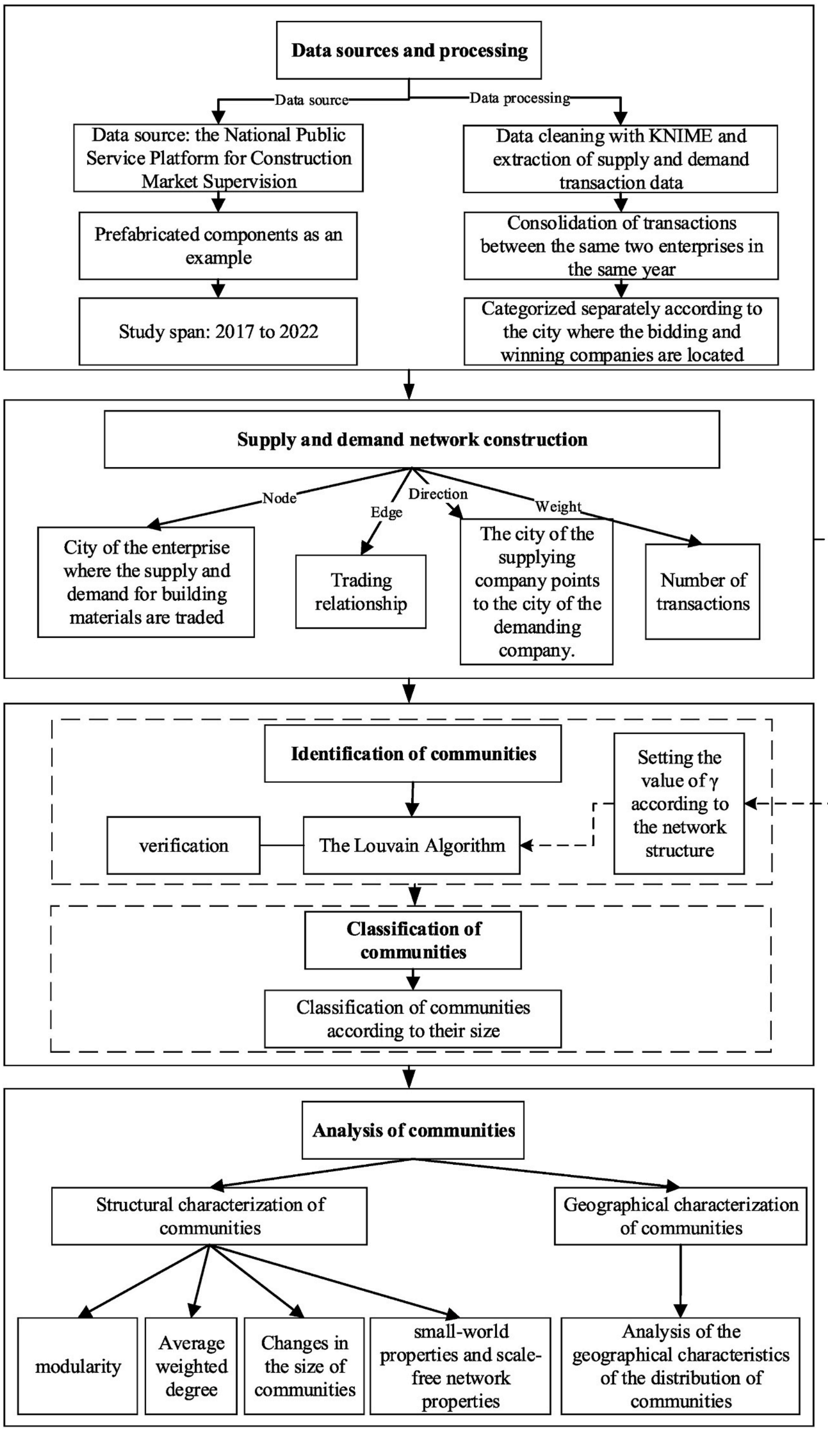


**Fig. 1.** Research methods and processes.

production in factories, prefabricated components can achieve precise control of processes and quality assurance. The application of these components is an important measure to promote the new construction industrialization. Prefabricated components are currently regarded as modern building construction materials and have been widely used in the construction industry. Therefore, using prefabricated components as the research object of this paper is typical and universal.

Based on the timeliness and accessibility of data, this paper chooses 2017 to 2022 as the research span, which is in the transition period of China's "13th Five-Year Plan" and "14th Five-Year Plan." This research span can objectively reflect the supply and demand situation of construction materials and resource allocation in response to the call of the state. The research uses the National Public Service Platform for Construction Market Supervision as the data source to obtain the bidding information of prefabricated components, and a total of 28,654 pieces of data information are obtained.

KNIME is used in this article to filter the data. For the processing of missing values, the Missing Value Column Filter is applied to filter the columns containing missing values, and the rows where they are located are then deleted or filled with Lagrange interpolation. For the processing of duplicate values, the "Duplicate Row Filter" function is used to identify duplicate rows, and the duplicate records will be deleted. For outliers, the "statistics" function is used to explore the data, and the data are visualized to identify possible outliers and delete or reasonably replace the rows where they are located. The final result is 26,321 valid pieces of data.

Attribute information, such as bidding companies, winning companies, and bidding amount, is extracted from each data message. These information details are transformed into supply and demand data between suppliers and demanders. Multiple transactions are merged between the same two enterprises in the same year. The bidding and winning enterprises are then summarized by year according to the cities where they are located. This study also uses the National Geographic Information Public Service Platform as the geographic information data source. The geographic coordinates of each city mentioned above will be imported into the geographic analysis stage.

### *2.2. Network model building*

This paper proposes to construct a weighted, directed, complex network model of supply and demand transactions of building materials. The cities of participating enterprises in the supply and demand transactions of building materials are nodes. The transaction relationships between the cities are edges. If a building materials trading relationship is observed between two cities, then a connected edge exists. The supply–demand relationship of building materials includes two levels: intra-city and city-to-city transactions. The network structure considers the direction of the trading relationship, which is a directed network with the arrow pointing from the supply side to the demand side. This paper also sets the number of transactions as the weight of the edge. Gephi is used to draw the network diagram.

As shown in Fig. 2, some cities are selected to construct a schematic of the complex network model of supply and demand for building materials. The figure reveals that the direction of transactions between cities and the thickness of the connecting line indicate the number of transactions. Some cities not only realize building materials supply and demand transactions with other cities but also conduct supply and demand transactions within the cities.

Then the network and geographic information are combined and imported into a map of China. A complex network map of supply and demand for prefabricated components is formed on the map of China. It can be seen in Fig. 3.

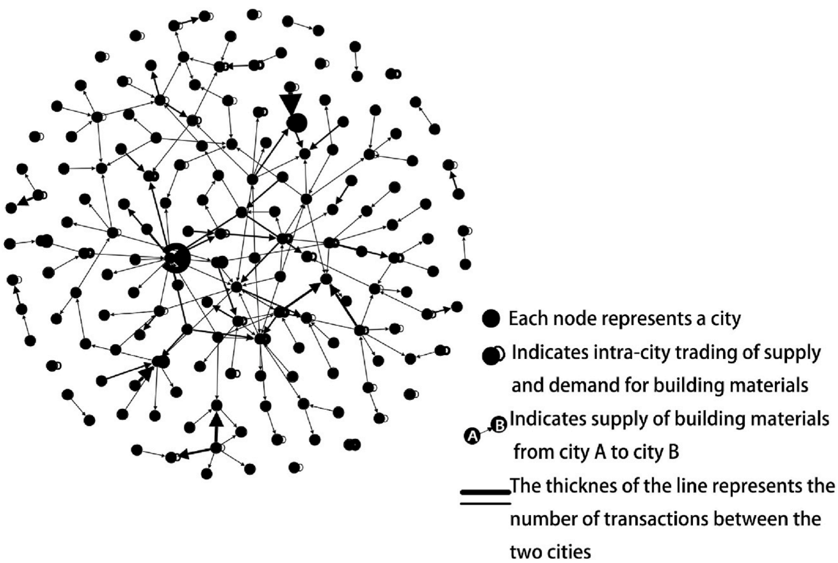


**Fig. 2.** Schematic diagram of the complex network model of supply and demand for building materials in 2017.

### 2.3. Community identification

In 2.2 we constructed a complex network model describing the supply and demand relationships of building materials, which reveals the basic dynamics of transactions in the construction market. However, since this network follows a power rate distribution, contains a large number of nodes and is large in size, it is challenging to analyze it systematically. In addition, considering the constraints of geographic location, we find that building materials not only suffer from long-distance transportation phenomena in supply-demand transactions, but also show certain geographic correlation characteristics. Based on this, this section introduces the concept of community to divide the network, in order to further explore the intrinsic structure of building materials supply and demand networks.

The current method used for community division is the Louvain algorithm [20], which is suitable for the large-scale networks. Louvain algorithm for the division of communities is based on the modularity. Modularity is a commonly used measure of the structural strength of an online community, as shown in Equation (1).

$$Q = \sum_{C} \left( \frac{E_c}{m} - \left( \frac{\sum tot}{2m} \right)^2 \right) \tag{1}$$

*where m denotes the number of edges in the network, c denotes the community, Ec denotes the number of edges within community c, and* $\sum tot$ *denotes the sum of degrees of nodes in this community.*

GVF (Goodness of Variance Fit) is a statistical metric used to assess how well a model fits the data. In community detection, GVF can be used to measure how well the modularity fits as the value of γ changes. The optimal GVF indicates the discovery of a value of γ that allows the modularity curve to best fit the community structure of the actual data. In this paper, based on the structural features of Fig. 2, we traverse the community modularity under all possible values of γ and calculate the GVF values under different γ values, as shown in Fig. 4.

As shown in the figure, we achieve the best GVF fit when the value of γ is 0.88, indicating that the modularity reaches a high level at this point and the community segmentation excels in terms of rationality. This parameter value is highly compatible with the actual structural characteristics of the building material supply and demand network. Based on this, in this study, $\gamma = 0.88$ is selected as a tuning parameter to optimize the application of Louvain algorithm in community division of building materials supply and demand networks.

The Louvain community detection algorithm is used in this paper for the division of communities. This algorithm is divided into three stages and repeated.

1) The first step is to build a weighted network containing N nodes. First, the nodes in the network are randomly assigned to different communities. In the initial communities, the network contains the same number of nodes. Neighbor j is considered for node i. Then, i is removed from its original community and placed in j's community. If a modular gain occurs in this community, then node i is placed in the community with the largest gain. If no positive gain can be achieved, then this node remains in its original community. The above process is repeated and sequentially applied to all the nodes until no further changes are observed, and then the first phase is completed.

The gain of modularity $\Delta Q_{PC}$ obtained by moving a separate node i to a new community can be computed by:

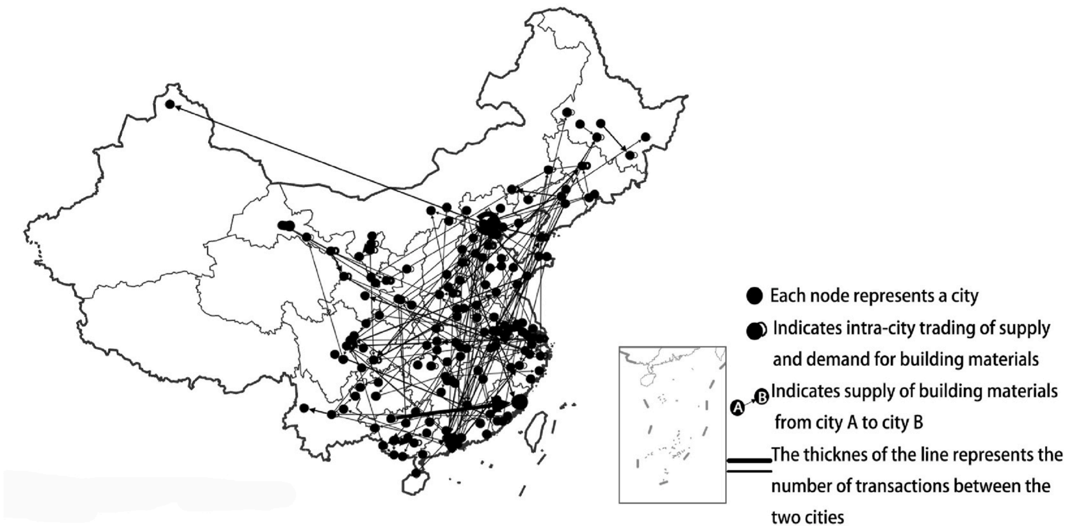


**Fig. 3.** Complex network diagram of supply and demand of building materials in 2017 based on China map.

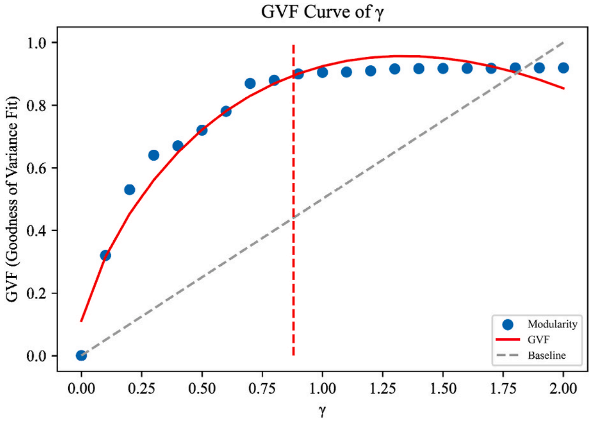


**Fig. 4.** Plot of γ fitting curve.

$$\Delta QPC = \frac{k_{i,in}}{2m} - \gamma_{PC}\frac{\sum_{tot} \bullet k_i}{2m^2} \tag{2}$$

*where $\sum_{in}$ is the sum of the weights of the connections within C. $k_i$ is the sum of the weights of the connections associated with node i. $k_i$ is the sum of the weights of the connections to node i, $k_{i,in}$ is the sum of the weights of the links from i to other nodes in the community, and m is the sum of the weights of all the links in the network.*

2) The second step of the algorithm is to build a new network. The nodes of this network are the communities discovered in the previous step. The weights of the new node connections are associated with the sum of the weights of the node connections in the corresponding two communities. Nodes of the same community connected to each other causes the community to form a self-loop in the new network. The first stage can be applied again to the resulting weighted network and iterated when the second stage is completed.
3) Processes (1) and (2) are iterated until the modularity no longer increases. The modularity finally reaches its maximum value.

The results of community detection have been validated. This paper adopts the method of modularity detection for already-divided communities. If the value of modularity is higher than 0.5, then the division result is superior.

### 2.4. Classification and analysis of communities

This section will examine the structural and geographical characteristics of communities.

#### 2.4.1. Structural characteristics

(1) The number of nodes is counted for each community, and the cities covered by the network can be divided into different communities due to the significant heterogeneity in community size. According to the number of cities included in each community, these cities are divided into large communities (the number of cities ≥30), medium-sized communities (the number of cities is 30~15), and small communities (the number of cities ≤15).
(2) Different colors are used to distinguish each community. In this paper, large-, medium-, and small-sized communities are represented by different colors to intuitively identify various types of communities in each year.
(3) This paper will use the following indicators to analyze the structure of communities:

The average degree is a reasonable metric used to describe the denseness or sparseness of the network. The degree of node i is the number of edges directly connected to the node. The average degree is the mean of the average of the degrees of all nodes in this network. This paper uses a weighted network; thus, the average weighted degree is used in this study.

The average path length is defined as the average of the distances between any two nodes. This metric reflects the accessibility of the network, with small values indicating superior network accessibility.

$$LPC = \frac{1}{n(n-1)/2}\sum_{i>j} d_{ij}PC \tag{3}$$

where $d_{ijPC}$ is the geodesic path length from node i to j.

The clustering coefficient reflects the degree of interconnection between neighboring nodes at a point and can be used to describe the clustering degree of nodes in a network. The number of neighboring nodes of node *i* is $m_{PC}$, and the number of existing edges among these $m_{iPC}$ nodes is $M_{iPC}$. The ratio of $E$ to the maximum possible number of edges is defined as the clustering coefficient of this node. The average of the clustering coefficients of all nodes is the average clustering coefficient. That is,

$$C_iPC = \frac{2M_iPC}{m_iPC(m_iPC - 1)} \tag{4}$$

$$CPC = \frac{1}{n}\sum_{i=1}^{n} C_iPC \tag{5}$$

Small-world property is an important attribute of complex networks, indicating the average clustering coefficient of this network is relatively high and the average shortest distance is relatively low. In networks with small-world properties, the vast majority of nodes are not neighbors of each other, and nodes are closely connected to the surrounding nodes. Simultaneously, reaching any other node generally requires passing through only a few nodes. This property can be reflected by the small-world index C, which is calculated as follows:

$$C = \left[\frac{C_{actual}}{L_{actual}} \times \frac{L_{random}}{C_{random}}\right] \tag{6}$$

where $L_{random}$ and $C_{random}$ are the average shortest path and the average clustering coefficient of a random network of the same size, obtained by w/t and lnt/lnw calculations, respectively. t is the number of nodes, and w is the average degree of all the nodes. $C_{actual}$ and $L_{actual}$ are the average clustering coefficients and the average shortest paths of the actual network, respectively.

A scale-free network is also an important characteristic of complex networks. Scale-free networks have a high degree of heterogeneity. A few nodes in the network have numerous connections, while most nodes have only a few connections. The scale-free nature of a network can generally be scaled by the degree distribution pattern.

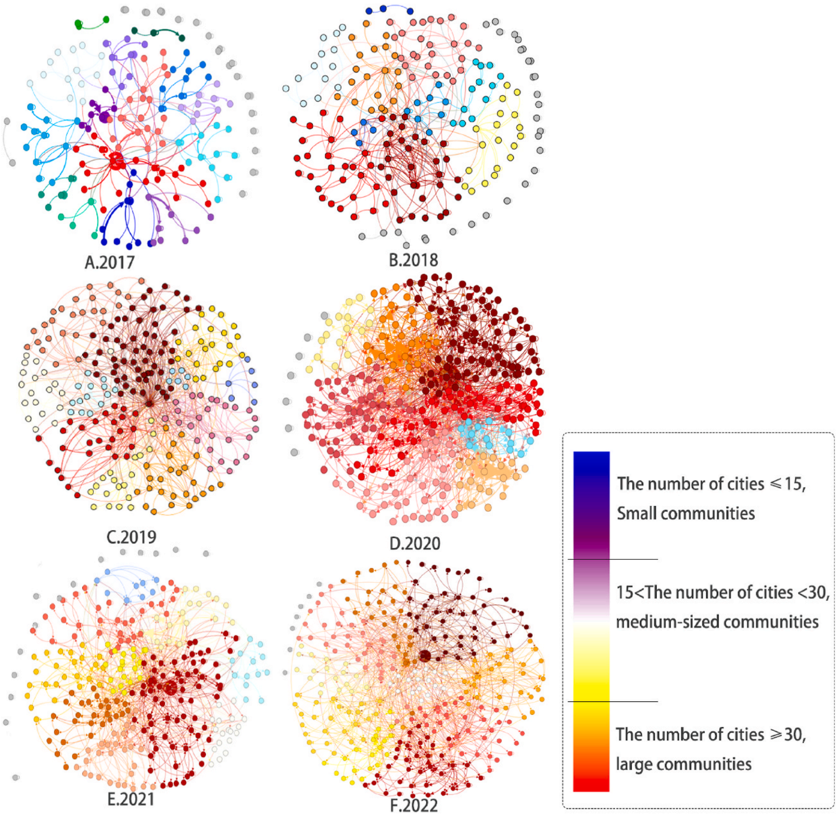


**Fig. 5.** Supply-demand networks of prefabricated components in China. *Note. Where A-F are the supply and demand network diagrams of prefabricated components from 2017 to 2022, respectively. Each collection of nodes of the same same color represents an community. According to the legend, the color of the size of the community transitions from blue to red, representing the transition from small to large communities. The gray nodes are nodes that are not associated with other nodes (the city does not have prefabricated component transactions with other cities) and do not form community with other nodes.* (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

### 2.4.2. Geographical characteristics

(1) The geographic coordinates of the cities involved in the supply and demand transactions are imported by Gephi into the network diagram drawn in Section 1.2. The communities are similarly divided, and the colors of the communities are differentiated. The geographically relevant network map is imported into the map of China, forming a network of supply and demand for building materials that can be presented on the map.
(2) In this part, the geographical characteristics will be analyzed in terms of the distribution characteristics of communities, the size of communities, and other perspectives.

## 3. Results

In this section, the structural and geographic characterization of communities will be conducted using the analytical approach of Section 2.4.

### 3.1. Analysis of the structural characteristics of communities

Fig. 5 ( A-F ) shows the constructed national supply and demand network map of prefabricated components from 2017 to 2022. First, the accuracy of the division of communities is determined. Table 1 shows that the value of modularity in each year is greater than 0.5, which indicates that the results of the community division of the network during the six years have a high degree of accuracy, and the community division is evident. According to the definition of modularity, the results of community division are superior when the modularity is high. From the modularity data from 2017 to 2022, the network with the highest modularity was the supply and demand network of prefabricated components in 2017. Moreover, the gap between the values of modularity in 2018 and 2017 is large and continues to increase from 2018, and the result of community division is becoming increasingly better until it reaches 0.612 in 2022.

Fig. 5 ( A-F ) shows that different communities can be distinguished by their colors. Different colors will be used in this paper to indicate various types of communities, in which the blue and red color systems are for small and large communities, respectively. We can see that the network graph for 2017 represented in Fig. 5(A) has a preponderance of blue colored nodes. A-F of this graph indicates the transition of nodes from blue to red from 2017 to 2022. Until there are no blue nodes left in the network graph of 2022 represented by Fig. 5(F). This finding indicates that from 2017 to 2022, small communities are gradually decreasing and being slowly replaced by large- and medium-sized communities. The results on the graph can also be confirmed from the actual community size data in Table 1. From 2017 to 2022, the number of communities in the national supply and demand network of prefabricated components gradually decreased from 21 to 10, the largest community contained 68 cities from 20, and the smallest community contained 16 cities from 2. The number of cities contained in each community will be divided into large, medium, and small communities, as shown in Table 1. With the change in time, the number of small communities in the network gradually decreased from 19 to 0 in 2017 and 2022, respectively. Meanwhile, the number of medium- and large-sized communities gradually increases, and the number of medium- and large-sized communities is only 2 and 0 in 2017; both numbers grow to 6 and 4 in 2022. The main reason is that with the change of time, the supply and demand enterprises have increased, so that the nodes of the cities that were once not connected to the edge have become connected to each other, which makes the structure of the network more and more complex, and the size of the communities has changed accordingly. And transportation is gradually developed, prefabricated components supply and demand network nodes are increasingly globalized, no longer a small area for supply and demand transactions.

The average weighted degree of communities in the six network models are calculated separately, and the results are shown in Fig. 6. The weighted average degree value of large communities is high, and the weighted average degree value of large communities in the four networks from 2019 to 2022 ranges from 38.82 to 58.65, with an excellent level of internal connectivity. This finding indicates that large communities contain numerous supplier firms with high supply and demander firms with high demand. These dominant suppliers and demanders are connected to other cities and form a large group of communities centered on them. The weighted average degree values of the six medium-sized communities range from 6.18 to 48.80, which is a large difference, but the level of internal connectivity is relatively good. The weighted average degree values of the small communities range from 1.5 to 3.0, and the level of internal connectivity is poor.

Communities have small-world properties. Calculation results reveal that the average path length of each community is 2.5–4, more than 1/2 of the communities have average paths less than 3.3, and the clustering coefficient is large. These results demonstrate typical small-world properties. The existence of small-world properties of regional networks facilitates active and anti-destructive

**Table 1**
Indicators of the structure of communities.

| | Modularity | Number of communities | Large community | Medium community | Small community |
|---|---|---|---|---|---|
| 2017 | 0.565 | 21 | 0 | 2 | 19 |
| 2018 | 0.585 | 18 | 0 | 5 | 13 |
| 2019 | 0.594 | 15 | 1 | 7 | 7 |
| 2020 | 0.593 | 10 | 3 | 4 | 3 |
| 2021 | 0.612 | 10 | 2 | 6 | 2 |
| 2022 | 0.616 | 10 | 4 | 6 | 0 |

**Table 2**
Top five provinces in terms of clustering coefficient per year.

| Year | Top ten provinces in terms of clustering coefficient per year |
|---|---|
| 2017 | 1Guangdong 2Hebei 3Gansu 4Guangxi 5Hubei |
| 2018 | 1Shandong 2Sichuan 3Fujian 4Guangxi 5Zhejiang |
| 2019 | 1Sichuan 2Fujian 3Guangdong 4Guangxi 5Hubei |
| 2020 | 1Sichuan 2Guangxi 3Henan 4Guangdong 5Jiangsu |
| 2021 | 1Sichuan 2Guangxi 3Henan 4Zhejiang 5Liaoning |
| 2022 | 1Sichuan 2Guangdong 3Guangxi 4Henan 5Hunan |

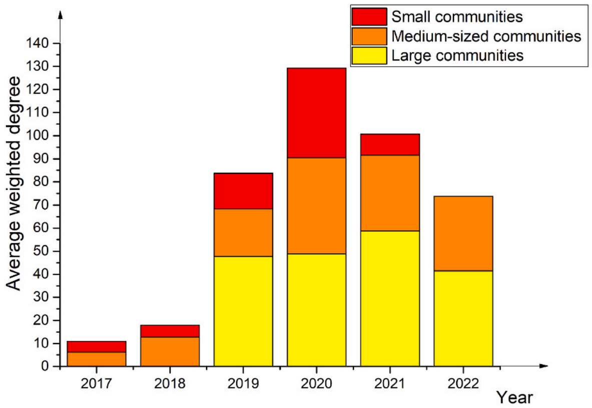


**Fig. 6.** Chart of year-to-year changes in weighted average degree.

communication and interaction within the regional network. These properties also promote the transaction transport efficiency of regional networks.

Communities have scale-free network properties. Through further exploration, the distribution degree of large- and medium-sized communities is still consistent with the power law distribution; the $r^2$ of large communities is greater than 0.8, and that of medium- and small-sized communities is greater than 0.5. These findings indicate a scale-free network property. The distribution degree of prefabricated components supply and demand networking is unaffected by the size of the network, and the regional network is also applicable to the scale-free network model.

For scale-free and small-world network research, conditions are required to meet the high quality requirements of the network card data. The research data in this paper are obtained from the national construction market supervision public service platform, and the data are authoritative and recognized by the state. These data cover all the bidding information during the research period, which ensures their integrity. This paper also applies KNIME to organize the data, remove duplicate information, and ensure no missing data. The traditional research on the characteristics of scale-free and small-world networks only focuses on a single static network and ignores the changes introduced by the increase of network nodes in the network. By contrast, this paper calculates the characteristic indexes of each year. The results show that the communities of the supply and demand networks of each year are consistent with those of the small-world and scale-free networks.

### *3.2. Analysis of the geographic characteristics of communities*

This section analyzes the geographic characteristics of prefabricated component supply and demand network communities.

(1) From the nature of the community structure of the network, the formation of the community structure indicates that the nodes within the community interact efficiently and the prefabricated component transactions are centralized. By contrast, the prefabricated component transaction links between different communities are sparse. Fig. 7(a) shows that the supply and demand network of prefabricated components in 2017 has not yet been characterized by a clear distribution of communities, and the distribution of communities is highly scattered. At that time, the demand for precast components across the country could not be regionally matched, and precast component demand traders in several places should make precast component purchases over long distances. From Fig. 7(b–f), it can be seen that from 2018 to 2022, boundaries that gradually appear in the communities of the network become increasingly clear. The distribution of communities in the supply and demand network is characterized by geographic clusters. As of 2022 represented in Fig. 7(f), most of the communities in the country have clear boundaries, and the types of communities in the same region are distinct, indicating that the market structure of the prefabricated components is stable in most regions of the country. By contrast, the blurred boundaries and regional overlap of communities in the Northwest and Northeast regions indicate that the two regions have not yet formed a complete trading

market of prefabricated components. The structural stability of this part of the supply and demand network of prefabricated components must be further strengthened.

The colors of the communities in the graph indicate a strong correlation between the size of the community and the geographical location of the community. From Fig. 7(a–f), it can be seen that from 2017 to 2022, large communities are consistently concentrated in the eastern coastal region, while small communities are consistently concentrated in the central and western regions. These findings can be attributed to the following reasons: The eastern coastal regions are economically developed and densely populated. Thus, these regions tend to have large-scale construction projects and high building standards, which result in a high demand for prefabricated components and may require multiple suppliers to supply prefabricated components. The eastern region has a well-developed infrastructure and logistics network that can support the development of large-scale precast component communities, enabling precast component supplier companies to have a large transportation radius. Therefore, this region can form a large range of supply-and-demand trading market. The central and western regions are economically underdeveloped, with relatively low population density and complicated terrain. Thus, the demand for prefabricated components is minimal, while the transportation conditions are relatively inconvenient. Therefore, these regions are mostly concentrated in a small range of supply and demand transactions for prefabricated components.

Compared to previous years, the supply and demand network in 2022 has a distribution of communities without cross-geographic communities and is mostly concentrated in one region, bounded by provinces, or a few neighboring provinces. As time advances, the precast development of each geographic region is becoming increasingly superior and can be self-sufficient within the region, with a close distance between suppliers and demanders without the need for long-distance transportation. This phenomenon markedly reduces transportation costs and carbon emissions during transportation, thereby saving costs and protecting the environment.

(2) The calculation of the average clustering coefficient is conducted by provinces. Table 2 shows the changes in the ranking of the clustering coefficient over the past six years, and the top five provinces in the yearly ranking of the clustering coefficient are obtained. The clustering coefficient reflects the degree of interconnection between neighboring nodes of a point, which can be used to describe the degree of aggregation between nodes in the network graph. Sichuan is at the top of the rankings each year; it ranks first in 2019, 2020, 2021, and 2022. Guangdong and Guangxi are also highly ranked provinces, appearing in the top five in multiple years. Henan Province is ranked third in 2019, 2020, and 2021, displaying some stability. Meanwhile, Zhejiang, Hubei, and Jiangsu appear in the top five in various years. The high clustering coefficients of these provinces indicate that when cities in these provinces trade supply and demand, they also trade supply and demand with each other among several other cities with which they trade. The supply and demand transactions of prefabricated components in the province are closely linked and, to some extent, self-sufficient within the province.

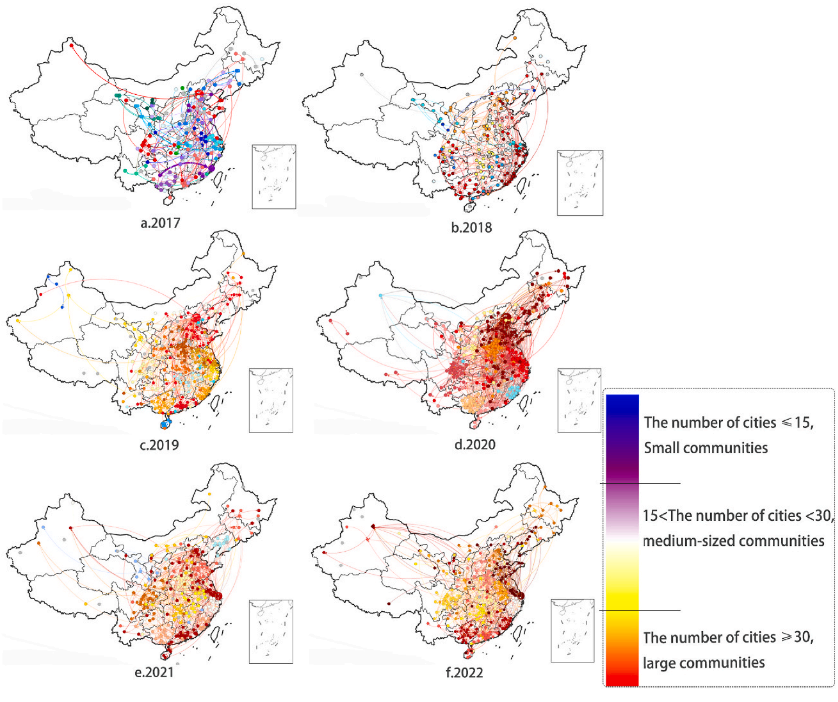


**Fig. 7.** Supply-demand networks of prefabricated components based on Chinese map. Note. Where a-f are the supply and demand network diagrams of prefabricated components from 2017 to 2022, respectively. The color rules are the same as Fig. 5. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

At the national and regional levels, the average clustering coefficient in 2022 is higher in southern China than in the north. This finding will be analyzed in conjunction with the image. The image reveals that the size of communities in the south is relatively small, and the boundaries of the communities mostly overlap with the province boundaries. This phenomenon indicates that most of the southern provinces have close links between suppliers and demanders within the province, and prefabricated components are self-sufficient within the province. The communities in the North are large in size and wide in scope, and the communities are mostly cross-provincial. This finding indicates that a large amount of inter-provincial trading of precast components exists in the North. Some provinces have a high demand for prefabricated components, but the production capacity does not match the demand. Therefore, these components must be purchased from neighboring provinces.

Overall, with the passage of time, the national prefabricated component networks are increasingly becoming regional communities. An analysis of the reasons can be attributed to the active guidance by the government of prefabricated component enterprises in the process of promoting regional economic integration and synergistic development of industries to form communities in the region. Cooperation and exchanges between enterprises have also been strengthened, thereby improving the competitiveness and influence of the prefabricated component industry in the entire region.

## 4. Conclusion

According to the actual situation of building materials, this paper utilizes the method of complex network to construct the supply and demand network of building materials. Combined with the structural characteristics of the complex network of supply and demand of building materials, it improves the traditional Louvain algorithm and scientifically divides the communities in the network of supply and demand of building materials. Then, we analyze the structural characteristics and geographical distribution of the communities. Taking the national prefabricated components transaction data as an example for empirical analysis, the conclusions obtained are:

(1) This paper used big data, digital-assisted decision making and constructed a visualization model. The complex network theory of supply and demand problems is applied, and resource allocation is optimized. Thus, this paper constructs a complex network model of supply and demand for building materials and applies 2017–2022 bidding data of prefabricated components for research. The method of community division is also applied to analyze the network and community. The paper also discusses the community structure evolution of China's prefabricated component supply and demand network according to time and explores the supply and demand situation of China's prefabricated components. The limitations of the current research on the supply and demand situation of building materials are then solved. And this paper provides a new perspective to understand the supply and demand situation of building materials globally.

(2) This paper measures and analyzes the community structure index of the complex network of prefabricated components supply and demand. From 2017 to 2022, the size of communities in the network changes year by year, from small communities to large and medium communities, and the internal connectivity of large communities is higher than that of small communities. And the divided communities have small-world and scale-free characteristics. Overall, the main reason is that with the change of time, the supply and demand enterprises have increased, so that the nodes of the cities that were once not connected to the edge have become connected to each other, which makes the structure of the network more and more complex, and the size of the communities has changed accordingly. And transportation is gradually developed, prefabricated components supply and demand network nodes are increasingly globalized, no longer a small area for supply and demand transactions. There are far more supply and demand transactions within large communities than small ones, so internal connectivity is high.

(3) This paper analyzes the geographic characteristics of the communities in the complex network of prefabricated components supply and demand, and obtains the conclusion that they are geographically relevant. The communities in the prefabricated components supply and demand network are gradually characterized by geographic clustering over time, and most of them are bounded by provinces. Large communities are distributed in the eastern and southern coastal regions, while small and medium-sized communities are concentrated in the central and western regions. The clustering feature is more obvious in the south than in the north. Analyzing the phenomenon, we attribute the reasons to the following:1) It shows that the planning and policies of a province make the whole range of building materials market develop together. 2) The eastern coastal areas are economically developed and densely populated, so there is a large demand for prefabricated components and other building materials. At the same time, these areas have developed transportation network, precast components supplier enterprises can have a large transportation radius, so it can form a large range of supply and demand market. While the central and western regions are economically underdeveloped, the population density is relatively low and the terrain is more complex. The demand for prefabricated components is less while the transportation conditions are relatively inconvenient, it is mostly concentrated in a small range of prefabricated components supply and demand transactions. 3) This indicates that the southern region itself is rich in prefabricated components, and it can be self-sustained within the provincial area, while in the northern region, the resources of prefabricated components are relatively few, and the transaction of prefabricated components needs to be carried out across the provincial area. trading of prefabricated components.

This study also presents the following intellectual contributions: First, this paper constructs a complex network of supply and demand of building materials in China, and improves the Louvain algorithm according to the properties of the network, and divides the communities more scientifically. The results of this paper show that the communities in the supply and demand network of building materials in China are characterized by the change of scale over time and geographic relevance. This provides a theoretical basis for future cross-city collaboration of building materials. Second, the study of the evolution mechanism of suppliers–demanders in the industry-level network of building materials from a dynamic network perspective expands the study of organizational networks in the construction field and fills the gap in the study of supplier–demander transaction networks. Third, the results of the current study provide valuable insights for a comprehensive understanding of the supply–demand relationship in China's building materials market as well as the evolution of the supply–demand relationship of building materials at the city level. These results also provide a basis for future policy formulation on the optimization of resources for regulating the supply–demand market of building materials on regional and national scales. The methods and ideas of this study can also be used to explore the supply and demand relationships of other building materials and the supply and demand transactions in other industries.

However, this paper has the following shortcomings. (1) Due to the limitation of data acquisition, the weights of the edges of the network defined in this paper are the number of transactions between cities instead of the amount of transactions between cities. It may affect the accuracy of the results. (2) Only one network graph is made each year, which may not reflect its dynamic changes well. In the subsequent research, the time slice will be made smaller so that it can better reflect the dynamic changes. Optimization and improvement will be made from these two aspects in the future.

## CRediT authorship contribution statement

**Likun Zhao:** Writing – review & editing, Funding acquisition, Conceptualization. **Mengqian An:** Writing – original draft, Visualization, Software, Resources, Methodology, Investigation, Conceptualization. **Hui Yuan:** Validation, Data curation. **Xiaoqing Bao:** Supervision, Formal analysis.

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## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## References

[1] H. Lu, H. Wang, Y. Xie, H. Li, Construction material safety-stock determination under nonstationary stochastic demand and random supply yield, IEEE Trans. Eng. Manag. 63 (2) (May 2016) 201–212, https://doi.org/10.1109/TEM.2016.2536146.
[2] D. Yang, J. Guo, L. Sun, F. Shi, J. Liu, H. Tanikawa, Urban buildings material intensity in China from 1949 to 2015, Resour. Conserv. Recycl. 159 (Aug. 2020) 104824, https://doi.org/10.1016/j.resconrec.2020.104824.
[3] Huihong Feng, Yi Xue, Shengjie Hu, Research on evolution path and incentive mechanism of green building materials from the perspective of supply and demand, Sci. Technol. Dev. 16 (5) (2020) 576–584.
[4] G. Schiller, T. Bimesmeier, A.T.V. Pham, Method for quantifying supply and demand of construction minerals in urban regions—a case study of hanoi and its hinterland, Sustainability 12 (11) (May 2020) 4358, https://doi.org/10.3390/su12114358.
[5] J. Zhu, J. Xu, Driving factors of green supply chain management in building materials enterprises, IOP Conf. Ser. Earth Environ. Sci. 295 (2) (Jul. 2019) 012063, https://doi.org/10.1088/1755-1315/295/2/012063.
[6] C. Li, E. Qi, J. Li, Dynamic Equilibrium of Supply Chain Network, vol. 39, Journal of Tianjin University, 2006, pp. 274–278.
[7] L.-X. Yang, X. Yang, J. Liu, Q. Zhu, C. Gan, Epidemics of computer viruses: a complex-network approach, Appl. Math. Comput. 219 (16) (Apr. 2013) 8705–8717, https://doi.org/10.1016/j.amc.2013.02.031.
[8] D.S. Bassett, O. Sporns, Network neuroscience, Nat. Neurosci. 20 (3) (Mar. 2017) 353–364, https://doi.org/10.1038/nn.4502.
[9] J.F. Donges, Y. Zou, N. Marwan, J. Kurths, The backbone of the climate network, Europhys. Lett. 87 (4) (Aug. 2009) 48007, https://doi.org/10.1209/0295-5075/87/48007.
[10] S.-J. Zhang, X.-D. Lu, S.-P. Wang, W. Guo, Supply-demand matching in non-cooperative social networks, IEEE Access 8 (2020) 162458–162466, https://doi.org/10.1109/ACCESS.2020.3021286.
[11] Z. Li, J. Chang, Z. Wang, Y. Chen, C. Li, Stability of regional ecological supply–demand is enhanced by complex network modeling: evidence from the xuzhou metropolitan area, China, IEEE J. Sel. Top. Appl. Earth Obs. Rem. Sens. 17 (2024) 1857–1873, https://doi.org/10.1109/JSTARS.2023.3342985.
[12] M.E.J. Newman, M. Girvan, Finding and evaluating community structure in networks, Phys. Rev. E 69 (2) (Feb. 2004) 026113, https://doi.org/10.1103/PhysRevE.69.026113.
[13] M.E.J. Newman, Detecting community structure in networks, Eur. Phys. J. B Condens. Matter 38 (2) (Mar. 2004) 321–330, https://doi.org/10.1140/epjb/e2004-00124-y.
[14] S. Kelley, M. Goldberg, M. Magdon-Ismail, K. Mertsalov, A. Wallace, Defining and discovering communities in social networks, in: M.T. Thai, P.M. Pardalos (Eds.), Handbook of Optimization in Complex Networks: Theory and Applications, Springer US, Boston, MA, 2012, pp. 139–168, https://doi.org/10.1007/978-1-4614-0754-6_6.
[15] J. Zhu, B. Chen, Y. Zeng, Community Detection Based on Modularity and K-Plexes, vol. 513, Information Sciences, Mar. 2020, pp. 127–142, https://doi.org/10.1016/j.ins.2019.10.076.
[16] C. Zhe, A. Sun, X. Xiao, Community detection on large complex attribute network, in: Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, ACM, Anchorage AK USA, Jul. 2019, pp. 2041–2049, https://doi.org/10.1145/3292500.3330721.
[17] S. Peng, W. Ser, B. Chen, Z. Lin, Robust semi-supervised nonnegative matrix factorization for image clustering, Pattern Recogn. 111 (Mar. 2021) 107683, https://doi.org/10.1016/j.patcog.2020.107683.
[18] X.L. Huang, S.Y. Hu, J.X. Chen, W.Q. Feng, Air quality analysis of Sichuan province based on complex network and CSP algorithm, Int. J. Mod. Phys. C 33 (1) (Jan. 2022) 2250007, https://doi.org/10.1142/S0129183122500073.
[19] T. Chen, Y. Li, X. Jiang, L. Shao, Spatiotemporal patterns of risk propagation in complex financial networks, Appl. Sci. 13 (2) (Jan. 2023) 1129, https://doi.org/10.3390/app13021129.
[20] V.D. Blondel, J.-L. Guillaume, R. Lambiotte, E. Lefebvre, Fast unfolding of communities in large networks, J. Stat. Mech. 2008 (10) (Oct. 2008) P10008, https://doi.org/10.1088/1742-5468/2008/10/P10008.