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Research Article

Research on Deep Integration of the "Belt and Road" Aviation Network Based on Community Structure from the Perspective of China

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Air transport has broad development potential along the " Belt and Road" by owing to its fast, direct, and comfortable advantages, and the community structure is an important factor determining the efficiency and service functions of the aviation network. The community detection and community structure analysis of the "Belt and Road" aviation network would help to understand the internal relationship of the "Belt and Road" aviation network spatial structure and better integrated and optimized the network. Based on the data of international routes between 522 airports along the "Belt and Road" in 2019, this paper establishes an aviation network model and calculates the degree, average path, clustering coefficient, and centrality index of the "Belt and Road" aviation network. Through Louvain community detection method, 522 airports in the aviation network were divided into four communities, and the structural characteristics and geographical distribution characteristics of the community network were analyzed. The key node identification model in the community is constructed, the hierarchy of each community network is analyzed using the k-core decomposition method, the core node set of the community network is found, the core boundary node set of four aviation community networks is identified, the core node set and core boundary nodes are analyzed repeatedly, and the key node set of the whole network is obtained. Finally, from the perspective of China, a deep integration scheme between Chinese airports, their communities, and other key node sets was proposed. The research found that there are four associations in the "Belt and Road" aviation network: West Asia and North Africa, Russia, Central and Eastern Europe, and China and Southeast Asia. Chinese and Southeast Asian societies rank third among the four societies in terms of scale. They not only have the largest number of key nodes but also the lowest repetition rate of the key nodes. The international airline links in the "Belt and Road" aviation network are more complex. A total of 118 key nodes were identified, of which 83.1% were in the top 20% of overall network centrality.

1. Introduction

Air transport exhibits important effects in promoting international trade and enhancing personnel exchanges by right of its superiority in time effectiveness, reachability, and safety. Since the announcement of the Belt and Road Initiative, China has signed air transport agreements with 8 countries and bilateral intergovernmental air transport agreements with 62 countries of the 65 the "Belt and Road" countries and started direct flights to 45 countries. Meanwhile, 403 more international routes have been opened, and nearly 5100 flights fly to the "Belt and Road" countries per week [1]. In addition, airlines in other countries have also operated more than 20 new routes for BRI countries. The concerted efforts have brought new development opportunities for air transport of BRI countries [2]. Taking China as an example, since 2013, in international trade with countries along the "Belt and Road," the trade volume achieved by air transport has always been in second place, second only to maritime transport, with an average annual growth rate of more than 20% [3]. In particular, with the tension between countries caused by the conflict between Russia and Ukraine, air transport will play a greater role in the "Belt and Road" countries in the future.

The "Belt and Road" aviation network is like a network structural entity formed by international airports of the "Belt and Road" countries and international routes connecting these airports. The "Belt and Road" countries are from Asia, Europe, and Africa, so the distribution of the international airports and routes is endowed with distinct regional features. China airport neither has close links with air transport hubs in the "Belt and Road" countries nor leads a prominent position in the "Belt and Road" aviation network [4]. To enhance economic, trade, and personnel exchanges between the "Belt and Road" countries, it is necessary to integrate and optimize the existing aviation network and promote its deep integration [5]. Currently, geographical factors still play a dominant role in determining which airport of the "Belt and Road" countries is the hub airport [6]. As a result, a large number of community structures form in the "Belt and Road" aviation network.

As important latent structures in complex networks, community structures are ubiquitous in real networks. They determine the aviation network efficiency and play a vital part in network optimization. There is no a widely accepted definition of community structure at present. It is generally believed that in a community structure, the nodes can be divided into multiple groups. The nodes in the same group are closely linked by edges, while the nodes between different groups are relatively loosely connected by edges [7]. Community detection refers to the recognition of the community structure by the analysis of the interaction between nodes in a network, with the purpose of mining a set of closely connected nodes with the same properties in the network [8]. Community detection also identifies the node group relationships in a network. The identification results often reveal the deeper features of the network and thus provide a perspective of great significance for studying the internal structure and generation mechanism of networks [9]. The community detection research of the "Belt and Road" aviation network can help us understand the connection mode of communities in the network, clarify the internal relationships of the network spatial structure, find the key nodes that play a core role, and promote route integration and optimization, having great significance in boosting the deep integration of the "Belt and Road" aviation network.

2. Literature Review

Given the close link between nodes in the same community and loose connection between nodes of different communities, community detection analysis should be conducted first to find the key nodes in communities, and then, the links between the key nodes of different communities should be strengthened, in order to achieve deep integration of the BRI aviation network.

2.1. Community Detection. Community detection is to identify modular community structures in a network according to structural information contained in the network topology. It is of great theoretical and application significance in topology analysis, functional analysis, and behavior prediction of complex networks. According to whether the network is static or dynamic, community detection algorithms can be divided into two types, namely, static network-based and dynamic network-based [10]. Community detection of static networks is studied by many scholars, who have proposed community detection algorithms based on different theoretical frameworks, such as modularity and tag propagation. However, a majority of the real networks change dynamically with the time. Compared to static networks, community detection of dynamic networks is a huge challenge. Currently, several community detection algorithms for dynamic networks have been developed, but there is a plenty of burning issues to be solved [11].

Since the edge betweenness-based GN algorithm was designed [12], numerous community detection algorithms have been proposed successively to solve the community detection issues in various sectors. Currently available community detection algorithms are mostly designed for static networks, including 5 types, namely modularity optimization, tag propagation, local expansion, streaming analysis, and deep learning [13]. Each of the 5 types of algorithms has its own features. The modularity optimization algorithm is able to accurately identify the community structures in a network, but its computation is complex, and its search space greatly expands as the network scale enlarges [14]. The tag propagation algorithm requires no input of any parameters, with linear time complexity and fast convergence speed, so it can well adapt to large-scale networks. However, the results are highly random, and different results yield each time the algorithm runs. This indicates the poor stability of the tag propagation algorithm [15]. The local expansion algorithm is applicable to large-scale networks because it only needs local information of nodes, and the expansion processes of multiple seeds take place in a parallel way. Moreover, since each seed expands independently from other seeds, some of the communities obtained are overlapped, which can be detected by the local expansion algorithm [16]. The streaming algorithm does not need to store the entire network in the memory and processes each edge only once, which tremendously reduces the computation time and memory consumption. Hence, it can be used to handle ultralarge-scale networks [17]. However, processing each edge only once leads to a limited amount of useful information and thus unsatisfactory accuracy of the algorithm. The deep learning-based community detection algorithm extracts network features using the neural network, which greatly improves its accuracy, compared to the traditional methods. Nevertheless, due to complex deductions and model pretraining, the deep learning algorithms have high computational complexity, and most of them require computing units of graphics servers such as GPU [18].

A lot of real networks evolve with the passing time, and new nodes and edges are added and deleted all the time. The variations of the relationship among nodes with time contribute to the evolution of communities in the network.

Traditional static network-based approaches are not applicable to dynamic networks [19]. To facilitate the analysis of dynamic networks, evolutionary clustering-based and incremental clustering-based community detection algorithms are developed [20]. In the evolutionary clustering-based algorithm, the community structure does not change abruptly but relatively slowly between two adjacent moments. That is, the community structure at current time t is affected by that at time $t-1$. Therefore, the evolutionary clustering-based algorithm takes into account the community division results of both current and last snapshots. Specifically, the algorithm performs static clustering of snapshots at time t and $t-1$ and requires that the community structure at time $t-1$ remains the same to that at time t as much as possible [21]. The incremental clustering-based community detection algorithm takes the community division results of the last moment as the initial condition of the community division at the current moment and carries out incremental updating based on the community division result of the last moment [22]. This method updates community changes adaptively. It only considers the changed nodes and edges in the network, retains most of the original community structures, and only conducts incremental clustering updating of the changed data [23].

The community detection methods change gradually with the increasing complexity of network data. Scholars always tend to develop community detection methods that can extract more and deeper useful information from the network to guide community division [24]. Currently available community detection algorithms are mainly designed for directed networks, undirected networks, and networks with weighted graphs, and they divide different communities by information provided by the network structure [25]. However, with the continuous development of complex networks, attributed graphs in which nodes have attributes have emerged. For instance, in the "Belt and Road" aviation network, the airport is a node [26], which contains such attribute information as geographical location, operation scale, economic environment, etc. It is often difficult to achieve accurate results if the community detection relies only on the network structure and ignores other information [27]. Hence, how to integrate the network topology information with external information such as node attributes to guide the community division is worthy of research.

2.2. Key Node Identification. Compared with other nodes in a complex network, key nodes have greater influence on the network function and structure. Strengthening the connections between key nodes in the community is vital to improving the connectivity of the entire network and fulfilling deep integration of the network [28]. Key node identification facilitates the analysis of the relationship between the function and structure of the network and the exploration of the special pattern hidden in the network, thereby further shedding light on the network evolution and optimization [29].

Researchers have developed two types of methods to identify key nodes in the aviation network. One type is centrality featured-based to key node identification methods. For different calculation methods, node centrality indexes are constructed to quantify and reorder the nodes and extract the key nodes [30]. Early methods include calculations of traditional indices, such as degree centrality based on local attributes of networks, eigenvector centrality based on global attributes of networks, closeness centrality, betweenness centrality, K-shell centrality based on network location attributes, and PageRank centrality based on random walk [31]. Later, improvements have made, and K-shell-based coreness centrality, neighborhood centrality based on the centrality of nodes and their neighbors, and travel centrality based on Katz centrality have been proposed. Among them, K-core decomposition is regarded as an effective method to determine key nodes [32]. The K-core decomposition method deletes nodes step by step according to the number of their degree, and peels and separates nodes layer by layer. Nodes on different layers are of different importance, and nodes closer to the center are more important. This method divides the nodes by layer, with low computation complexity, and is applicable to the analysis of large-scale networks [33]. In addition, to overcome the shortcomings of a single index, a global structure model (GSM) that combines indices of node attributes and its global centrality in the network is proposed, which, however, involves more complex computation processes.

In the "Belt and Road" aviation network, due to the geographical location, the status and role of Chinese airports are not prominent, which is inconsistent with China's trade status. Chinese airports, especially hub airports, should be deeply integrated into the "Belt and Road" aviation network through route optimization to better promote trade development between countries. Previous research has revealed that communities and key nodes in a network have a significant impact on network efficiency and function. Therefore, analyzing the community structure in the "Belt and Road" aviation network, determining the key nodes in the community, and strengthening the connection with the key nodes, it is a new way to achieve the deep integration of the "Belt and Road" aviation network.

3. Topology Statistical Characteristics of the "Belt and Road"

Based on information of international air routes between airports on the website of Variflight (https://www.variflight.com/), this study selects 522 airports, which have international routes, along the "Belt and Road," and constructs an unweight aviation network model for the "Belt and Road." If a city has two or more airports, it chooses an airport with more international routes. The graph theory representation of the network is $G=(V,E)$, where V is the set of points, E is the set of all edges, and $e_{ij} \in E(i,j) \in V$ represents the edge connecting nodes i and j. The "Belt and Road" aviation network is expressed as $A_{\text{airports}} = \{e_{ij}\}$, i, $j=1, 2, \ldots, n$, n is the number of nodes. When there is a direct international flight between the two nodes i and j, then $e_{ij}=1$, otherwise, $e_{ij}=0$. Figure 1 shows a visualization of the "Belt and Road" aviation network. The larger the node,

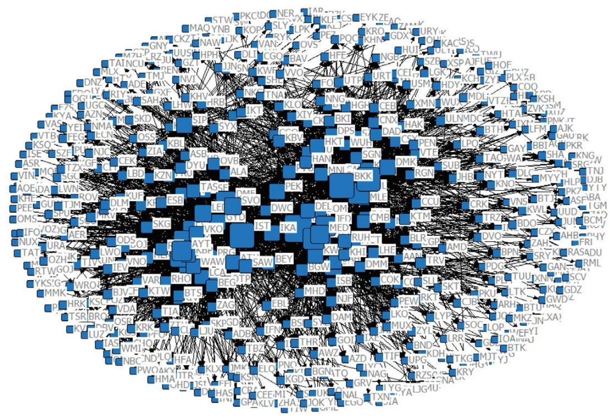

Figure 1: Schematic diagram of the “Belt and Road” aviation network.

the more international routes that the airport has. The “three-letter code” developed by the International Air Transport Association (IATA) is used to represent the airports in the network.

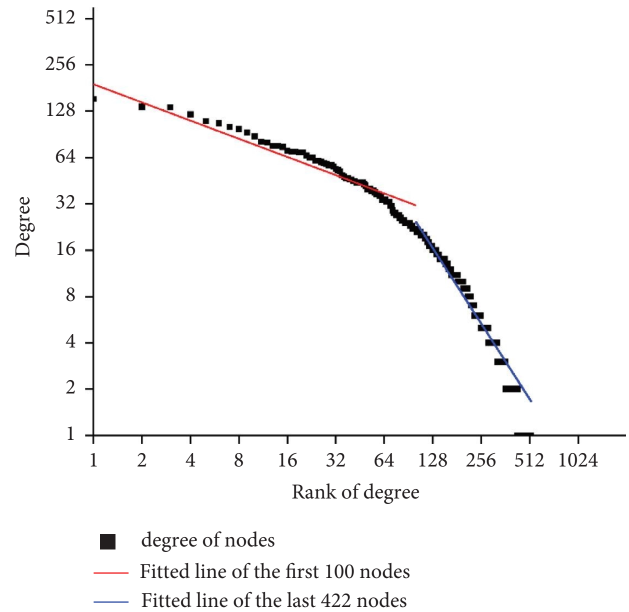

Figure 2: Degree distribution curve.

3.1. Scale-Free Characteristic. The social network analysis software Ucinet was used to measure the degree of the “Belt and Road” aviation network. The results showed that the total number of degrees in the network was 7340. The average degree is 14; that is, each airport has established 14 international routes with other airports on average. Figure 2 shows the distribution of degrees in double logarithmic coordinates. The abscissa represents the sequence of degrees from large to small, and the ordinate represents the degree of airports. The degree distribution of the “Belt and Road” aviation network obeys the “double-truncated power law distribution,” and its node distribution is curve-fitted. The degree distribution function is shown in equation (1). The degree of fit is $R_1^2 = 0.921$, $R_2^2 = 0.977$ at a high fitting level.

$$\mathbf{y} = \begin{cases} 191.77x^{-0.393}, & k \leq 99, \\ 45221.59x^{-1.631}, & k > 99. \end{cases} \tag{1}$$

Inflection point No. 100 had a degree value of 22, and nodes with a degree higher than 22 accounted for 19.2%. In contrast, the proportion of nodes with a degree less than 22 accounted for 80.9%. The nonuniform distribution of degrees shows the scale-free characteristics of the “Belt and Road” aviation network.

3.2. Small World Characteristic. The measured average path distance is 2.796; that is, an average of three edges is required from any airport to other airports in the “Belt and Road” aviation network. The clustering coefficient is 0.417, indicating that airports are more likely to form short distance connections. The “Belt and Road” aviation network is large in scale and complex in connections. Therefore, the “Belt and Road” aviation network exhibits strong “small-world” characteristics.

3.3. Centralities. Centrality is used to measure the importance of nodes in the network. The centrality of a single node is mainly divided into degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality. Degree centrality reflects the importance and centrality of nodes in the network; the maximum degree centrality of the “Belt and Road” aviation network is 0.296 (Dubai), the minimum is 0.002 (Xi’an Xiguan, Sultan Taha, Tarragan Juwata, Shan Dakan, Tawau, Zamboanga), and the difference in degree centrality between the two is 148 times. It can be seen that there is a large gap between the two poles in terms of the nodes’ importance status.

Closeness centrality reflects the organizational efficiency of nodes and the control ability of nodes in the overall network, which is a type of global centrality. The airports with the largest closeness centrality of the “Belt and Road” aviation network are Dubai and Istanbul (0.128), and the smallest is 0.110 (Taizjanad). The overall level of closeness centrality was much higher than that of the other centralities, showing a slow downward trend. The overall accessibility of nodes is good, reflecting the high connectivity efficiency of the “small world” effect of the “Belt and Road” aviation network.

Betweenness centrality reflects the transit and connection capabilities of the nodes. The largest betweenness centrality is Thailand’s Bangkok Suvarnabhumi (0.12), and the smallest value is only 0. There are 40 airports whose betweenness centrality is higher than 0.01, and seven airports whose betweenness centrality is higher than 0.05. The overall transit and connection capacity of the “Belt and Road” aviation network is low.

Eigenvector centrality reflects the centrality of the relationship between a node and other important nodes in the network and is suitable for describing the long-term influence of a node. 24.14% of the nodes had eigenvectors greater than 0.05. The eigenvectors of Dubai, Istanbul, Doha, Bangkok Suvarnabhumi, Singapore Changi, and Kuala Lumpur were higher than 0.2, which has a long-term influence on the network.

Figure 3 shows the statistical results for the centrality indices. The ordinate represents the value of the centrality index, and the abscissa represents the nodes sorted by degree centrality from small to large. For the overall network, the statistical distributions of the other three centralities are positively correlated with degree centrality, among which eigenvector centrality and betweenness centrality have the strongest correlation, with the Pearson correlation coefficient higher than 0.95. However, the correlation between closeness centrality and degree centrality was the weakest, with the Pearson's correlation coefficient of 0.34. It can be seen that long-term influence and transfer capacity of the node are strongly correlated with the scale of the node in the "Belt and Road" aviation network.

4. Community Structure of the "Belt and Road" Aviation Network

4.1. Louvain Algorithm. The Louvain algorithm compensates for the high time complexity of the GN algorithm. Through multilevel optimization of modularity, it finds the optimal subsituation of the network and the optimal number of subnetworks. The Louvain algorithm has several advantages.

(1) The community structure obtained was hierarchical, and the new graph obtained after each calculation round was the test result of subdividing a large community.

(2) The Louvain algorithm is easy to implement and the entire calculation process is unsupervised. The community division results depend entirely on algorithm clustering, and there is no need to artificially set community quantities in advance.

(3) The performance of the algorithm was excellent. The Louvain algorithm has no upper limit on the size of a given graph and can quickly converge after several rounds of iterations, which is suitable for mobile communication networks with more than one million nodes.

The Louvain algorithm measures the quality of community division through modularity Q. The algorithm can be roughly divided into two stages: modularity optimization and network aggregation. The upper limit of Q was 1. The closer it is to this value, the more obvious the community structure, and the better the community division. In actual networks, modularity Q is generally 0.3~0.7, and networks with high modularity are very rare. By comparing the results of modularity after each calculation round to find the maximum modularity and its corresponding community division, the optimal number of subnetworks can be obtained. The physical meaning of modularity is the difference between the number of edges in a community and random cases. The calculation method for modularity Q is shown in the following equation:

$$
\begin{aligned}
Q &= \frac{1}{2m}\sum_{i,j}\left[A_{ij} - \frac{k_i k_j}{2m}\right]\delta\left(C_i, C_j\right),\\
\delta(u,v) &= \begin{cases} 1; \text{if } (u = v) \\ 0; \text{else} \end{cases},
\end{aligned}
\tag{2}
$$

where k_i, k_j are the degrees of nodes i, j. The probability of a connection between j and the other nodes is $k_j/2m$. The number of edges between i and j under random conditions was $k_i k_j/2m$. C_i is community i belonging. The m is the sum of all the edges.

4.2. Community Detection of the "Belt and Road" Aviation Network. Louvain algorithm is used to detect the "Belt and Road" aviation network community. Finally, 522 airports were divided into seven communities, and the corresponding maximum modularity was 0.451. The "Belt and Road" aviation network is divided into 4 large-scale communities and 3 small-scale communities. The three small-scale communities are "Xi'an Xiguan—Sultan Taha," "Tarakan Juwa Tower—Tawau," "Sandakan—Zamboanga," which only have an international route with another node, with a degree value of 1. The size of the community is generally more than three nodes, so four large-scale communities are the main research objects.

The size of the four large-scale communities was 137, 89, 154, and 136. The proportion of the number of community nodes in the entire network was used to represent the community size coefficient. The community size coefficients of the four large-scale community networks were 0.266, 0.172, 0.298, and 0.264. The geographic divisions of airports in the community are shown in Table 1.

According to regional and national characteristics, the four large-scale communities of the "Belt and Road" aviation network are named as West Asia and North Africa Community, Russian Community, Central and Eastern European Community, China, and Southeast Asian Community, respectively. Figure 4 shows a schematic diagram of the four communities of the "Belt and Road" aviation network.

4.3. Geographical Distribution of the "Belt and Road" Aviation Community Networks. The standard deviational ellipse (SDE) is an important method for revealing the spatial distribution and statistical characteristics of geographic elements. The SDE quantifies spatial distribution characteristics by means of the migration trajectory of the center of gravity, changes in azimuth, comparison between long and short axes, and density. The area inside the standard deviation ellipse is the main body of the geographic element distribution [34]. SDE was used to analyze the spatial differences and evolution characteristics of the "Belt and Road" aviation community networks in terms of geographic center, distribution range, direction, and shape.

(1) The migration trajectory of the center of gravity (average center) reflects the regional balance of the spatial distribution, as shown in the following equation:

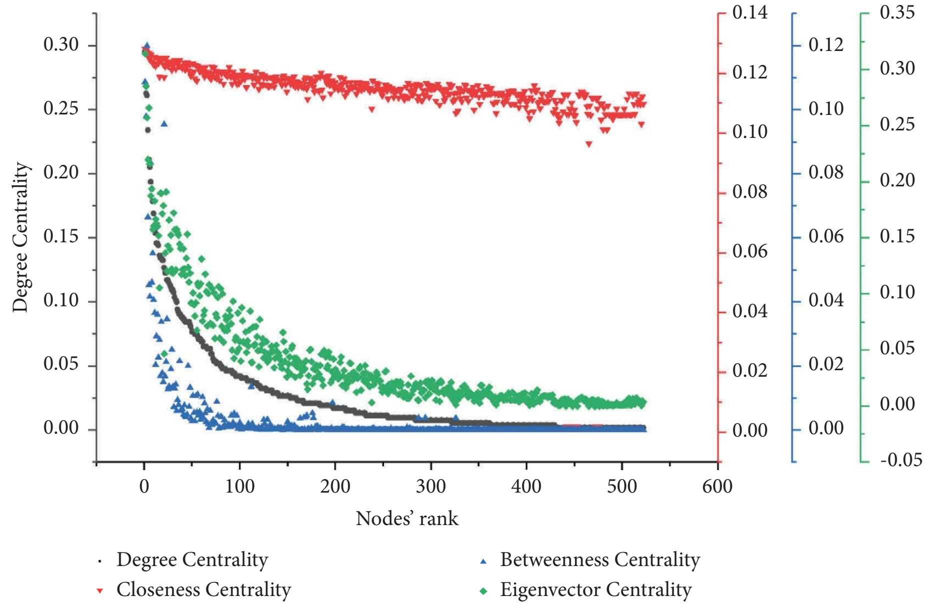

Figure 3: Position-scale distribution diagram of centrality indicators.

Table 1: The "Belt and Road" aviation community networks' scale and geographical division.

Community number	Size	Geographic division
1	141	West Asia and North Africa (88), South Asia (44), Southeast Asia (7), Northeast Asia (2)
2	89	Northeast Asia (71), Central Asia (9), West Asia and North Africa (6), South Asia (2), Central and Eastern Europe (1)
3	154	Central and Eastern Europe (89), Central Asia (26), West Asia and North Africa (20), Northeast Asia (19)
4	136	Southeast Asia (66), Northeast Asia (63), South Asia (7)

$$\overline{x} = \frac{\sum_{i=1}^{n} x_i}{n},\quad \overline{y} = \frac{\sum_{i=1}^{n} y_i}{n}, \tag{3}$$

where x_i, y_i are the longitude and dimension of node i. $\overline{x}$, $\overline{y}$ represents the average center of all nodes, and $\tilde{x}_i = x_i - \overline{x}$, $\tilde{y}_i = y_i - \overline{y}$.

(2) The comparison of changes in the azimuth angle ($\tan\theta$) can quantitatively analyze the differences in the main directions (long-axis direction).

$$\tan\theta = \frac{\left(\sum_{i=1}^{n}\tilde{x}_i^2 - \sum_{i=1}^{n}\tilde{y}_i^2\right) + \sqrt{\left(\sum_{i=1}^{n}\tilde{x}_i^2 - \sum_{i=1}^{n}\tilde{y}_i^2\right)^2 + 4\sum_{i=1}^{n}\tilde{x}_i^2\tilde{y}_i^2}}{2\sum_{i=1}^{n}\tilde{x}_i^2\tilde{y}_i^2}. \tag{4}$$

(3) A comparison of changes between the long axis X and the short axis Y can reveal the shape difference of the spatial distribution of geographic elements, that is, the difference between the main distribution direction and the secondary distribution direction.

$$X = \sqrt{\frac{\sum_{i=1}^{n}\left(\tilde{x}_i\cos\theta - \tilde{y}_i\sin\theta\right)^2}{\mathrm{n}}},\quad Y = \sqrt{\frac{\sum_{i=1}^{n}\left(\tilde{x}_i\sin\theta - \tilde{y}_i\cos\theta\right)^2}{\mathrm{n}}}. \tag{5}$$

Statistics on the geographical distribution indicators of the four communities of the "Belt and Road" aviation network are shown in Table 2. The area of each community network standard deviation ellipse is sorted from large to small: Russian Community, West Asia and North Africa Community, China and Southeast Asian community, and Central and Eastern European community. Except for the communities in China and Southeast Asia, which are distributed in a north-south direction, the other three communities are distributed in an east-west direction.

The standard deviation ellipse visualization of the four communities in the "Belt and Road" aviation network is shown in Figure 5. Community distribution and

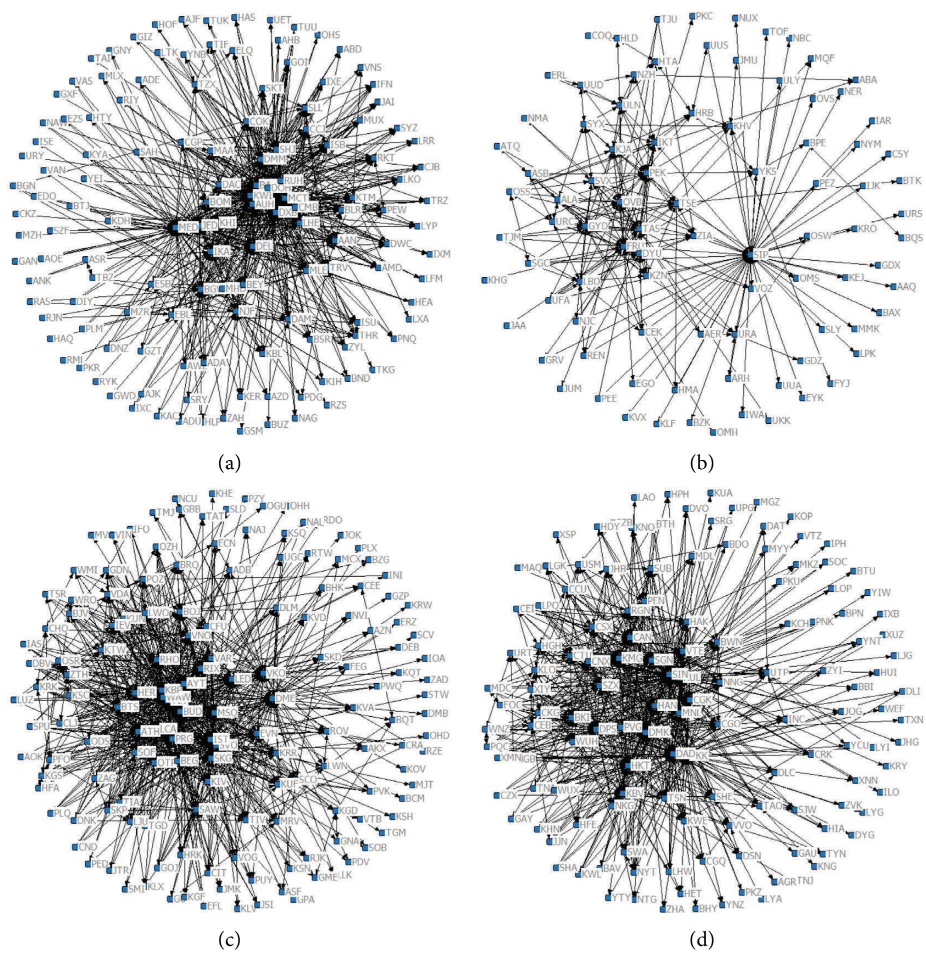

Figure 4: The 4 community of the "belt and road" aviation network: (a) West Asia and North Africa community network, (b) Russian community network, (c) Central and Eastern European community network, and (d) China and Southeast Asian community network.

Table 2: Ellipse standard deviation parameters of the community.

Community	Shape length	Shape area	Center X	Center Y	X	Y	Rotation azimuth
West Asia and north Africa community	145.73	1329.68	58.81	26.42	31.04	13.64	109.93
Russian community	193.58	1733.40	75.64	50.67	44.60	12.38	92.34
Central and Eastern European community	115.75	735.24	33.65	45.17	25.73	9.10	90.69
China and Southeast Asian community	108.85	894.24	109.56	19.59	13.97	20.38	14.14

geographical division showed great overlap, and the geographical distribution of communities showed good continuity. In West Asia and North Africa, 64.2% of airports are located in West Asia and North Africa, 29.2% are located in South Asia, and 6.6% are located in Northeast Asia and Southeast Asia. In Russian community, 79.8% of the airports are in China, Russia, and Mongolia, and 10.1% of the airports are in Central Asia. In the Central and Eastern European Community, 57.8% of the airports are located in the Central and Eastern European region, and 42.2% of the airports are located in Russia in Northeast Asia, West Asia and North Africa, and Central Asia. China and Southeast Asian communities have 63 airports in Northeast Asia (46.3%), of which 62 airports belong to China, one airport is in Russia, 48.5% of airports in the community are in Southeast Asia, and 5% of airports are in South Asia.

5. Node Locations in the "Belt and Road" Aviation Community Network

5.1. Definition of Key Nodes. Finding key nodes in a network is one of the most important applications in community detection [35]. Overlapping node and bridging node play key roles in the communications and interactions among different communities and server as "messengers." The method to detect two types of nodes based on local flow conservation in electrical circuits was proposed [36]. Based on the internal and external structural characteristics of

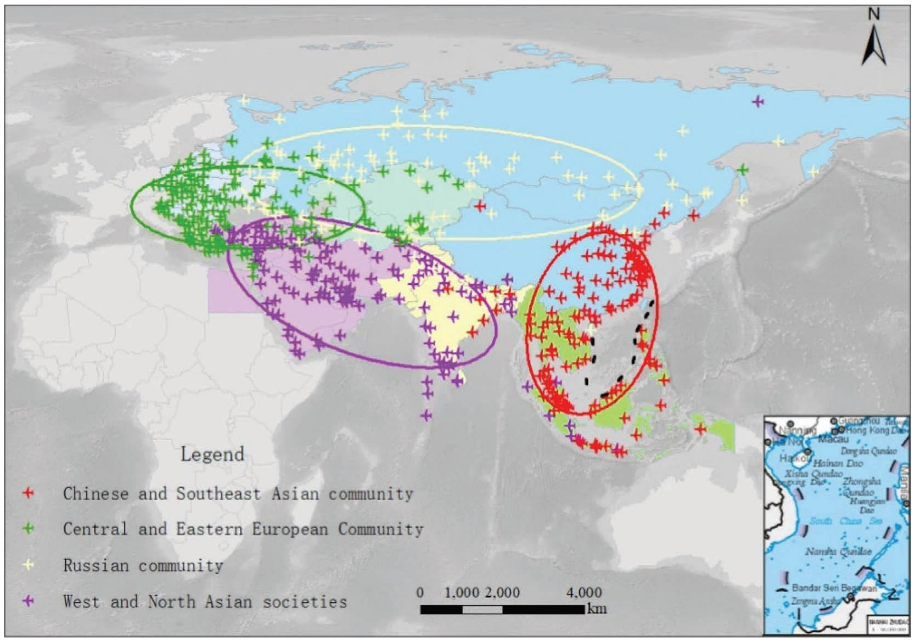

Figure 5: Geographical distribution of communities.

a community network, an influence maximization algorithm based on the structure of the community was proposed, which has an important reference value for this study [37]. The community structure of complex networks provides a new approach for identifying key nodes in aviation networks.

Based on the internal and external structural characteristics of the community network, this study identifies the key nodes of the "Belt and Road" aviation community network. Important hub nodes within the community constitute the core node set, and important boundary nodes connecting the two communities constitute the core boundary node set. The two sets together constitute the key node set of the "Belt and Road" aviation community network. The key node set is defined as follows:

$$|\mathrm{Key}| = U_1^M\left(\left|F_{C_i}\right| + \left|B_{C_i}\right| - R_{C_i}\right), \tag{6}$$

where F_{Ci} represents the core node set within each community network, B_{Ci} represents the core boundary node set that plays an important role in connecting two community networks, and R_{Ci} represents the overlapping part of the two node sets. This study used the k-core decomposition method to study the internal hierarchical structure and core nodes of the "Belt and Road" community network.

When an edge exists between a given node and the nodes of other communities, the node is called the boundary node of its community. There are mainly three indicators to measure the importance of core boundary nodes: (1) the number of connected communities. If node v has connections to many communities, node v has the opportunity to spread information or resources to these communities. (2) The importance of each connection between the communities also differed. For example, for communities C_1 and C_2, u_1 is a point in C_1, v_1 and v_2 are points in community C_2, and $k_1 = 1$ and $k_2 = 12$. Obviously, edge (u_1, v_2) is more important. Because v_2 is closer to the core of C_2 than v_1, edge (u_1, v_2) is connected to the core of C_2, which activates more nodes of C_2. (3) The size of C_2 should be considered. The larger the size of the connected community, the more nodes the edge can activate and the more important the edge is.

5.2. Core Nodes

5.2.1. K-Core Decomposition. The basic idea of k-core decomposition is that a core node in community networks should not only be connected with a sufficient number of nodes, but also with a certain number of adjacent nodes that are as important or more important as this node. Compared with other methods to study the network structure, k-core decomposition helps us understand the node locations and hierarchical characteristics inside the "Belt and Road" community network more clearly and directly.

(1) k-Core network: By repeatedly deleting all nodes with degrees lower than k and their connected edges, the degree of all the nodes in the k-core network is not lower than k.

(2) k-Core values of node: If a node exists in the k-core network but is eliminated from the $k+1$ core network, the k-core value of this node is k. The k-core value of a node reflects its core depth in the network, which is generally used to evaluate the connectivity of a node. The smaller the k-core value, the worse the connection degree of this node.

(3) The k-core decomposition process extends from the outer layer to the inner layer. Therefore, the nodes with the smallest k-cores are generally in the outermost layer of the network, and the nodes with the

largest k-cores are generally in the innermost layer. The purpose of k-core decomposition is to identify specific subsets of the network, thus providing a new perspective for studying regional and organizational properties. Through k-core decomposition, the hierarchical structure of the network, from the outermost layer to the innermost layer, was revealed.

5.2.2. The Hierarchy of the Four Community Networks. Ucinet software was used to obtain the hierarchical structure after k-core decomposition. Figure 6 shows a schematic diagram of the k-core decomposition of West Asia and the North African community. The maximum k-cores of West Asia and North Africa Community, the Russia Community, Central and Eastern Europe Community, China, and Southeast Asia Community are 14, 7, 14, and 12, respectively. 137 airports of the West Asia and North Africa Community network can be divided into 14 subsets, and the k-core values of the nodes are 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, and 14. 14-core network was the largest connected subgraph. Every node in the 14-core network had at least 14 international air routes with other airports in this layer.

5.2.3. Core Node Sets of Four Community Networks. K-core decomposition can quickly and efficiently find the core of a network, especially for smaller networks. In addition, reducing the size of the network can help improve the accuracy of k-core hierarchical division, making the assessment of node impact by k-core decomposition more accurate. The core layer composed of nodes with the largest number of cores in the network has the largest clustering coefficient, maximum network density, and stronger connection strength [38]. Due to the strong correlation between kernel number and degree centrality and feature vector centrality, this layer node has greater degree centrality and feature vector centrality, playing a greater role in connecting [39]. Due to its larger clustering coefficient and smaller average path length, this layer of network exhibits stronger "small world" characteristics and higher convenience. In addition, the node degree difference of this layer is relatively small and has high stability [40]. The above characteristics indicate that the core layer nodes decomposed by k-core have the characteristics of core nodes. The four community networks of the "the Belt and Road" aviation network are k-core layered, and all nodes in the community network are arranged in descending order of k-value. The core layer node with the largest number of k-cores is selected as the core node set of the "the Belt and Road" aviation community network. Finally, the scale of the core node set of West Asia and North Africa Community, Russian Community, Central and Eastern European community, and China and Southeast Asia community was 29, 15, 28, and 33, respectively. The core node set members are listed in Table 3.

5.3. Core Boundary Nodes

5.3.1. Boundary Hub Degree. The influence of a boundary node is mainly evaluated by the number and importance of

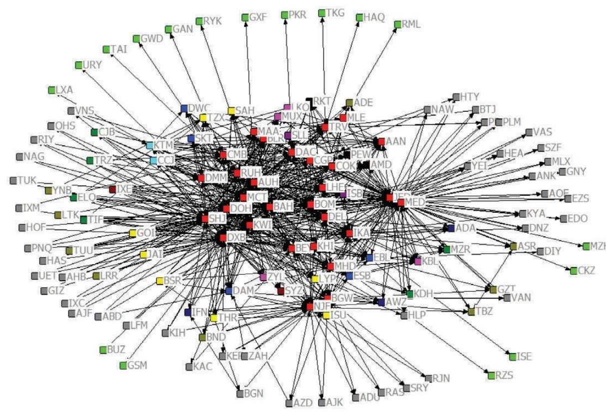

Figure 6: K-core decomposition of West Asia and North Africa community.

the nodes' connections between the two communities. If two nodes are located in two different communities, the edge between them only has the effectiveness of connecting the two communities when both nodes have high k-core values. These two nodes are called effective nodes, and the edge between them is called effective edge.

Definition 1. Effective nodes. If any node is $v \in C_i$, $k_v \geq k_{C_i\,\max}/2$, then v is an effective node in community C_i, and S_{Ci} represents the set of all effective nodes of community C_i.

Definition 2. Effective edges. Both endpoints are effective nodes of different communities, and $T(i, j)$ represents the number of effective edges between C_i and C_j.

Definition 3. The tightness of the connection between any two communities is given by the following equation:

$$H(i, j) = \frac{T(i, j)}{|C_i|}. \tag{7}$$

Definition 4. The unified standard for the size of the community size$_j$ where another endpoint of the connection is given by the following equation:

$$\text{Size}_j = \frac{|C_j|}{\sum_1^M |C_i|}. \tag{8}$$

Definition 5. Edge weights $w(v, u)$. Edge weight of the connection (v, u) between C_i and C_j is not only related to the connection degree $H(i, j)$ but also to the size of the community C_j where another endpoint u is located.

$$\mathbf{w}(v, u) = H(i, j) + \text{Size}_j. \tag{9}$$

Definition 6. Boundary hub degree $Link(v)$ represents the ability of the boundary node to connect all other communities, $Link(v)$ is as follows:

Table 3: The core node set of the community network.

Community	$k_{\max}$	Core node sets
West Asia and North Africa community	14	BAH, CGP, DAC, BLR, BOM, COK, DEL, MAA, TRV, IKA, MHD, BGW, NJF, KWI, BEY, MLE, MCT, KHI, LHE, DOH, DMM, JED, MED, RUH, CMB, AAN, AUH, DXB, SHJ
Russian community	7	GYD, PEK, SYX, URC, ALA, TSE, FRU, ULN, IKT, KJA, KZN, OVB, SVX, DYU, TAS
Central and Eastern European community	14	MSQ, BOJ, SOF, VAR, ZAG, LCA, PRG, ATH, CFU, HER, RHO, SKG, BUD, TLV, RIX, VNO, KIV, WAW, OTP, DME, LED, SVO, VKO, BEG, BTS, AYT, IST, KBP
China and Southeast Asia community	12	BWN, CAN, CGO, CKG, CSX, CTU, HAK, HGH, KMG, NNG, PVG, SZX, WUH, XIY, CGK, DPS, VTE, BKI, KUL, PEN, RGN, CEB, KLO, MNL, SIN, BKK, CNX, DMK, HKT, KBV, DAD, HAN, SGN

$$\text{Link}(\text{v}) = \sum_{1}^{M} \sum w(v,u). \tag{10}$$

5.3.2. Core Boundary Node Set of Four Community Networks. Figure 7 shows the Pareto analysis of the boundary hub degree of the "Belt and Road" aviation community network. It can be observed that the proportion of nodes with a high boundary hub degree in the four communities is small. The West Asia and North Africa Community, Central and Eastern European Community, China, and Southeast Asian Community have a larger number of effective nodes than the Russian Community, and the boundary hub degrees of the three communities show a long-tailed distribution.

The nodes are determined whose cumulative number is 10%–15% and whose cumulative value of the boundary hub degree accounts for 40%–60% as the core boundary nodes of the community network. Nodes with a cumulative number of 15%–25% and the cumulative value of the boundary hub degree accounting for 25%–35% are determined as the quasicore boundary nodes. The nodes with a cumulative number of 60%–70% and the cumulative value of the boundary hub degree accounting for less than 25% are determined as the edge boundary nodes. Based on the above classification criteria, this study selected 17, 11, 21, and 18 nodes from four communities as the core boundary nodes of the "Belt and Road" aviation community network, shown in Table 4.

6. Key Node Sets of the "Belt and Road" Aviation Community Network

6.1. Key Node Sets

Definition 7. Key node repetition rate (R_{Si}). It is expressed as the ratio of the number of repeated nodes, R_{Ci}, to the total value of the internal core nodes and core boundary nodes of the community. R_{Si} is given by the following equation:

$$R_{S_i} = \frac{R_{C_i}}{\left|F_{C_i}\right| + \left|B_{C_i}\right|}. \tag{11}$$

Repeatability analysis showed that (1) in West Asia and North Africa Community, 16 airports, including Bahrain, Dhakasha, Muscat, Doha, Jeddah, Riyadh, Colombo Bandaranaike, Abu Dhabi, and Dubai, belong to the k-core, and the decomposed core node set also belongs to the core boundary node set. (2) In Russian Community, 10 airports, including Bakubina, Beijing Capital, Urumqi Diwopu, and Almaty, belong to both the core node set and the core border node set. (3) In Central and Eastern European Community, Minsk, Larnaca, Prague Havel, Eleftherios Venizelos, Macedonia, Liszt Franz, Tel Aviv Jafa Tel Aviv, Warsaw Chopin, etc. 16 airports belong to both the core node set and the core boundary node set. (4) In China and Southeast Asian communities, there are 12 airports: Bandar Seri Begawan, Guangzhou Baiyun, Zhengzhou Xinzheng, Chongqing Jiangbei, Changsha Huanghua, Chengdu Shuangliu, Haikou Meilan, Hangzhou Xiaoshan, Kunming Changshui, Nanning Wuwei, Shanghai Pudong, and Shenzhen Baoan that belong to both the core node set and the core boundary node set. These airports are not only at the core of the community to which they belong but also as key boundary nodes connecting with the other three communities.

In this study, 118 key nodes were obtained from the key node identification research based on the "Belt and Road" aviation network community structure, as shown in Table 5. Airports without superscripts represent the core nodes inside the key node set. The superscript "$*$" indicates the core boundary nodes in the key node set, and "$**$" indicates that the key nodes are both internal and core boundary nodes. West Asia and the North African Community (size = 137) had 30 key nodes, including 29 internal community core nodes and 17 core boundary nodes, and $R_{S1} = 0.35$. The Russian Community (size = 89) has 16 key nodes, including 15 internal core nodes and 11 core boundary nodes, $R_{S2} = 0.39$. The Central and Eastern European Community, with a network size of 154, has 33 key nodes, including 28 internal core nodes and 21 core boundary nodes, with-$R_{S3} = 0.33$. China and Southeast Asian communities (size = 136) had 39 key nodes, including 33 internal core nodes and 18 core boundary nodes, $R_{S4} = 0.24$.

From Table 5, it can be seen that the key nodes of West Asian and North African communities, the Russian Community, and Central and Eastern European communities have a high repetition rate. The scale of China and Southeast Asian communities ranks third among the four communities, but it has the most key nodes and the lowest repetition rate; therefore, the international air routes in China and Southeast Asian communities are more complex. Most core boundary nodes had the highest k-cores of the community. However, some core boundary nodes are not part of the core

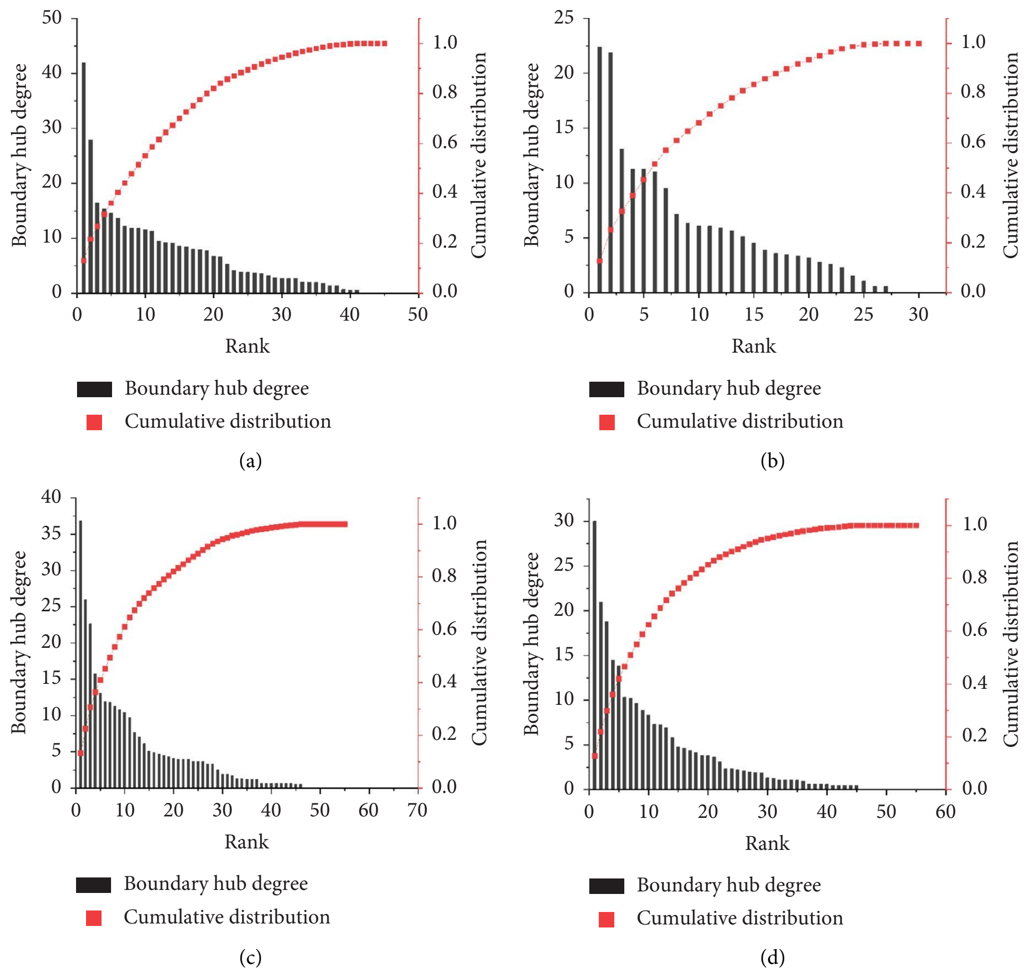

Figure 7: Pareto analysis diagram of boundary hub degree: (a) boundary hub degree of West Asia and North Africa community, (b) boundary hub degree of Russian community, (c) boundary hub degree Central and Eastern European community, and (d) boundary hub degree of China and Southeast Asian community.

node set. These nodes play the role of bridges between communities and are the "representatives" of the community's external contacts, but these nodes do not play a central role in the community network. Therefore, strengthening the connection of such nodes within the community can promote it to the status of a hub and further improve the degree of connection with other communities.

6.2. Correlation Analysis. Analyzing the characteristics of community key nodes in the overall network is helpful for further understanding the role of the community in the overall network. Therefore, this study analyzes the correlation between the k-core, boundary hub degree, and centralities in the "Belt and Road" aviation network. The analysis results are shown in Figure 8, where the X coordinate represents the k-core, the Y coordinate represents the boundary hub degree, and the Z coordinate represents four types of centralities.

The correlation between the k-core and centralities was weak, but the overall relationship was positive. The correlation between the boundary hub degree and centralities is much higher. Except for the Russian Community (Pearson = 0.745), the Pearson correlation coefficients of the border hub degree and centralities were all higher than 0.86, and the correlation with the eigenvector was the most significant. It can be seen that the node with higher boundary hub degree is more likely to have a long-term influence on the "Belt and Road" aviation network. When selecting important nodes in a network, the boundary hub degree index based on the community structure should be considered.

6.3. Geographical Distribution of Key Nodes. In Figure 9, purple, yellow, green, and red represent the key nodes in the four communities. The 30 key nodes of West Asia and North Africa Community are mainly distributed in the United Arab Emirates (5), Qatar (1), Lebanon (1), Saudi Arabia (4), Twitt (1), Bahrain (1), Oman in North Africa and West Asia (1), Iraq (2), Iran (2), and South Asia in Bangladesh (2), India (6), Maldives (1), Pakistan (2), and Sri Lanka (1). The airports represented by the key nodes have a total of 1,400 direct international air routes, of which 940 are with other airports in the West Asia and North Africa Community, and 64, 173,

Table 4: The boundary core nodes of the 4 communities.

Community	Number/size	Core boundary node sets
The West Asia and North Africa community	17/45	BAH, DAC, BOM, DEL, IKA, KWI, BEY, MLE, MCT, DOH, JED, RUH, CMB, AUH, DWC, DXB, SHJ
Russian community	11/30	GYD, PEK, URC, ALA, TSE, FRU, KZN, OVB, SVX, ASB, TAS
Central and Eastern European community	21/64	EVN, MSQ, LCA, PRG, ATH, SKG, BUD, TLV, WAW, OTP, DME, KRR, KUF, LED, SVO, VKO, AYT, DLM, IST, SAW, KBP
China and Southeast Asian community	18/55	BWN, CAN, CGO, CKG, CSX, CTU, FOC, HAK, HFE, HGH, KMG, KWE, NGB, NKG, NNG, PVG, SHE, SZX

Table 5: Key node identification results of community network.

Community	Key node sets
The West Asia and North Africa community	BAH**, CGP, DAC**, BLR, BOM**, COK, DEL**, MAA, TRV, IKA**, MHD, BGW, NJF, KWI**, BEY**, MLE**, MCT**, KHI, LHE, DOH**, DMM, JED**, MED, RUH**, CMB**, AAN, AUH**, DXB**, SHJ**, DWC*
Russian community	GYD**, PEK**, SYX, URC**, ALA**, TSE**, FRU**, ULN, IKT, KJA, KZN**, OVB**, SVX**, DYU, TAS**, ASB*
Central and Eastern European community	MSQ**, BOJ, SOF, VAR, ZAG, LCA**, PRG**, ATH**, CFU, HER, RHO, SKG**, BUD**, TLV**, RIX, VNO, KIV, WAW**, OTP**, DME**, LED**, SVO**, VKO**, BEG, BTS, AYT**, IST**, KBP**, EVN*, KRR*, KUF*, DLM*, SAW*
China and Southeast Asian community	BWN**, CAN**, CGO**, CKG**, CSX**, CTU**, HAK**, HGH**, KMG**, NNG**, PVG**, SZX**, WUH, XIY, CGK, DPS, VTE, BKI, KUL, PEN, RGN, CEB, KLO, MNL, SIN, BKK, CNX, DMK, HKT, KBV, DAD, HAN, SGN, FOC*, HFE*, KWE*, NGB*, NKG*, SHE*

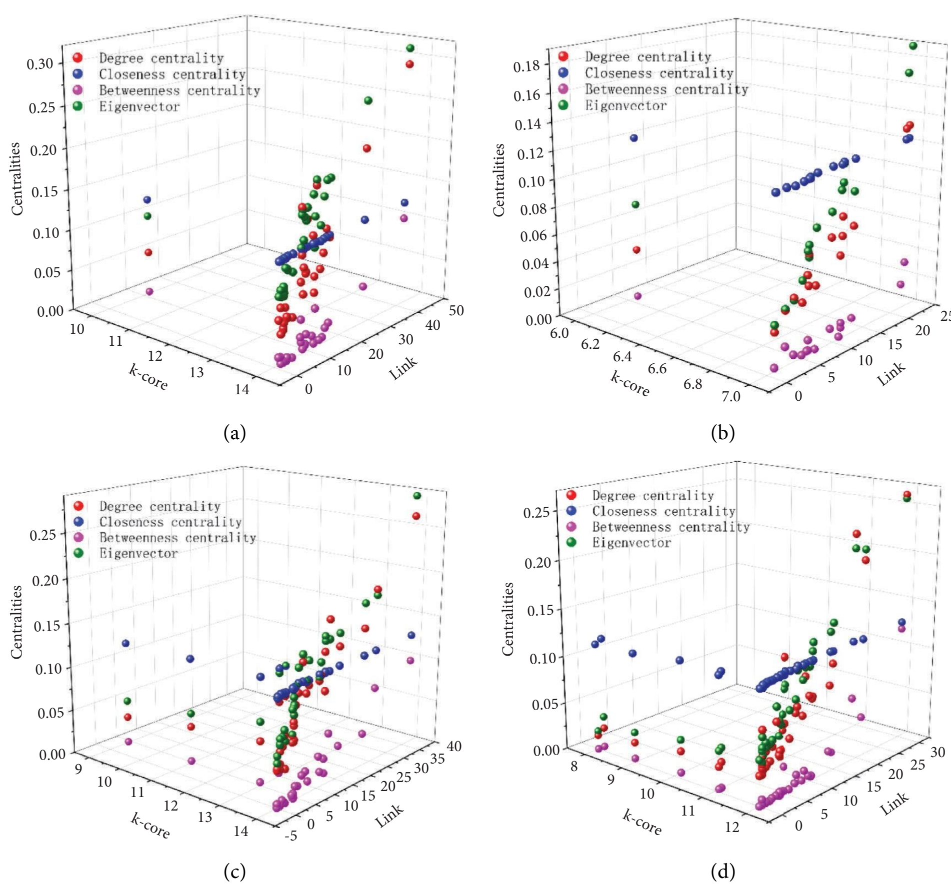

Figure 8: Correlation analysis of key nodes in the communities: (a) correlation analysis of West Asia and North Africa community, (b) correlation analysis of Russian community, (c) correlation analysis of Central and Eastern European Community, and (d) correlation analysis of China and Southeast Asian Community.

and 223 routes have airports in the Russian Community, Central and Eastern European Community, China, and Southeast Asian Community, respectively. Airports extensively connected to key nodes in the West Asian and North African communities are Dubai, Sharjah Baja, Abu Dhabi, Doha, Jeddah, Medina Mohammed, and Tehran Imam Khomeini.

As shown in Figure 10, the 16 key nodes of the Russian Community are distributed in China (3), Russia (5), Mongolia (1) in Northeast Asia, Azerbaijan (1), Syria (1) in North Africa and West Asia, and Central Asia (1), Uzbekistan (1), Kazakhstan (2), Kyrgyzstan (1), and Turkmenistan (1). There are 501 direct international air routes, of which 214 are between airports within the Russian Community, and 80,

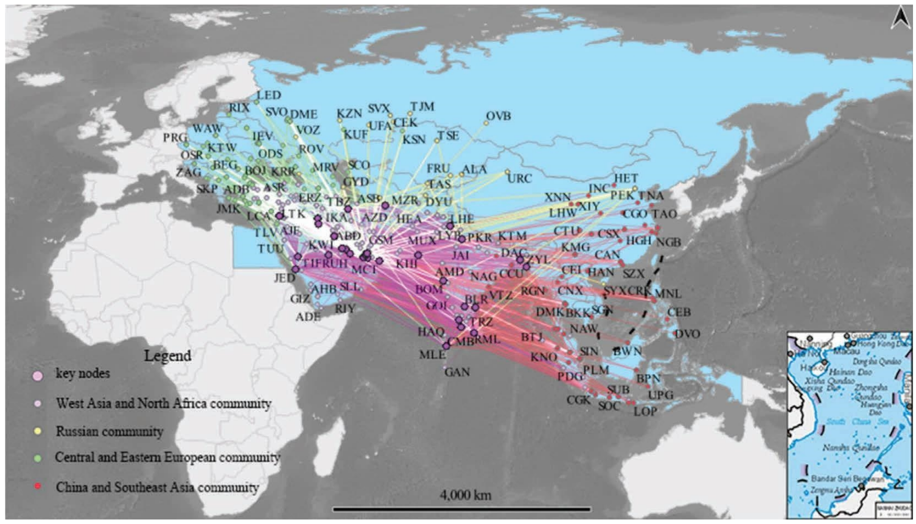

Figure 9: International routes of key node set in West African and North Asian community.

133, and 74 are between airports in the West Asian and North African Community, Central and Eastern European Community, and China and Southeast Asian Community, respectively. Airports have close flight connections with the key nodes of the Russian Community include Beijing Capital, Bakubina, Tashkent, Novosibirsk, and Yekaterinburg Koltsovo.

As shown in Figure 11, the 33 key nodes of the European Community are mainly distributed in Turkmenistan (1) in Central Asia, the Czech Republic (1), Belarus (1), Poland (1), Cyprus (1), and Greece (1) in Central and Eastern Europe (5), Hungary (1), Serbia (1), Latvia (1), Romania (1), Bulgaria (3), Slovakia (1), Lithuania (1), Moldova (1), Croatia (1), North Africa and Turkey (4), Israel (1), and Armenia (1) in West Asia, and Russia (6) in Northeast Asia. There are 1513 international air routes, of which 1069 are connected with other airports within the Central and Eastern European Community, and 196, 173, and 75 are connected with airports in the West Asian and North African Community, Russian Community, and China and Southeast Asian Community, respectively. Airports extensively connected to key nodes in Central and Eastern European Community are Istanbul, Moscow Domodedovo, Moscow Sheremetyevo, St. Petersburg Pulkovo, Antalya, Tel Aviv Yafo Tel Aviv, Prague Havel, etc.

As shown in Figure 12, the 39 key nodes of China and the Southeast Asian Community are distributed in Brunei (1), Indonesia (2), Laos (1), Malaysia (3), Myanmar (1), the Philippines (3), Singapore (1), Thailand (5), Vietnam (3), and China (19) in Northeast Asia. The airports represented by these key nodes have 1,327 international air routes, of which 1,002 are between other airports in China and the Southeast Asian Community, and 201, 66, and 58 routes are between the airports in the West Asian and North African Community, Russian Community, and Central and Eastern European Community, respectively. Airports with close flight connections to the key nodes of China and Southeast Asian Community are Bangkok Sovarnabhumi, Changi, Kuala Lumpur, Bangkok Don Muang, Guangzhou Baiyun, Kunming Changshui, Shanghai Pudong, Phuket, Jakarta Soekarno Hatta, and Bali Deng Bassa Uralai.

7. The Scheme for Chinese Airports to Deeply Integrate into the "Belt and Road" Aviation Community Network

7.1. Deep Integration Idea Based on Communities' Key Node Sets. Airports represented by key nodes have numerous international routes and play a core connection role. Therefore, airports belonging to key node sets are called hub airports of the "Belt and Road" aviation community network. The deep integration of the key node set with other nodes in the same community network can amplify the international air transport radiation capability of hub airports, further exerting the transport resource advantages of hub airports. The deep integration between key nodes and key node sets in other communities can weaken the limitation of the community structure on network transmission capacity and enhance the overall operational efficiency of the network. Strengthening the international air connection of hub airports within the community at first, and then strengthening the connection between hub airports and other community hub airports, realizes the goal of deep integration in the "Belt and Road" community aviation network.

There are 75 Chinese airports out of 522 airports in the Belt and Road aviation network. Among Chinese airports, 62 belong to the China and Southeast Asian Community, 11 belong to the Russian Community, and Lhasa Gonggar belongs to the West Asian and North African Community. The Chinese airports have 834 international air routes. Countries with more international connections with Chinese airports include Thailand (218), Russia (123), Vietnam (75), Malaysia (66), Indonesia (62), the Philippines (47), Singapore (41), India (20), the UAE (19), Laos (15), Myanmar (14), Saudi Arabia (14), Kazakhstan (12), Maldives

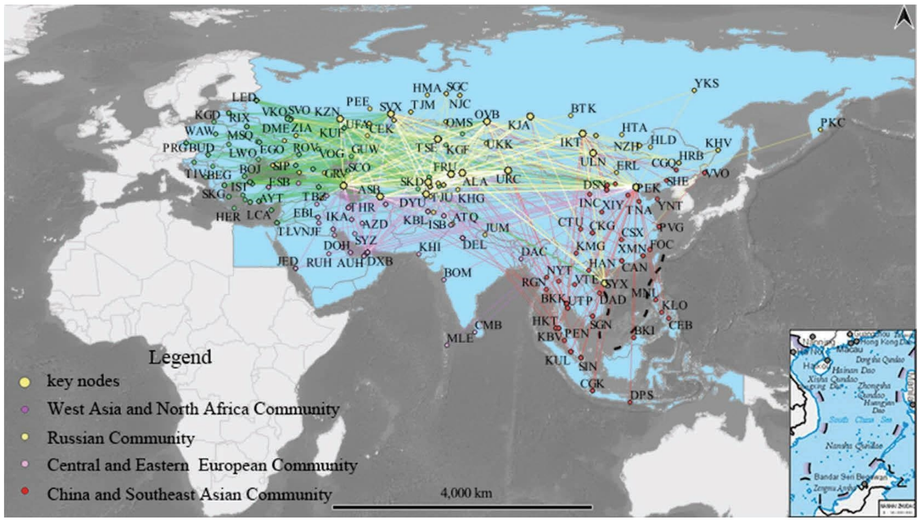

Figure 10: International routes of key node set in Russian community.

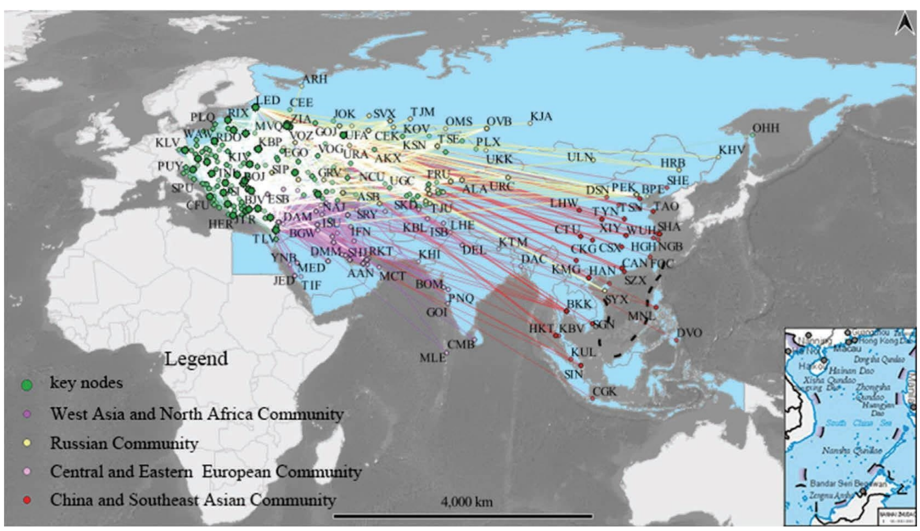

Figure 11: International routes of key node set in Central and Eastern European community.

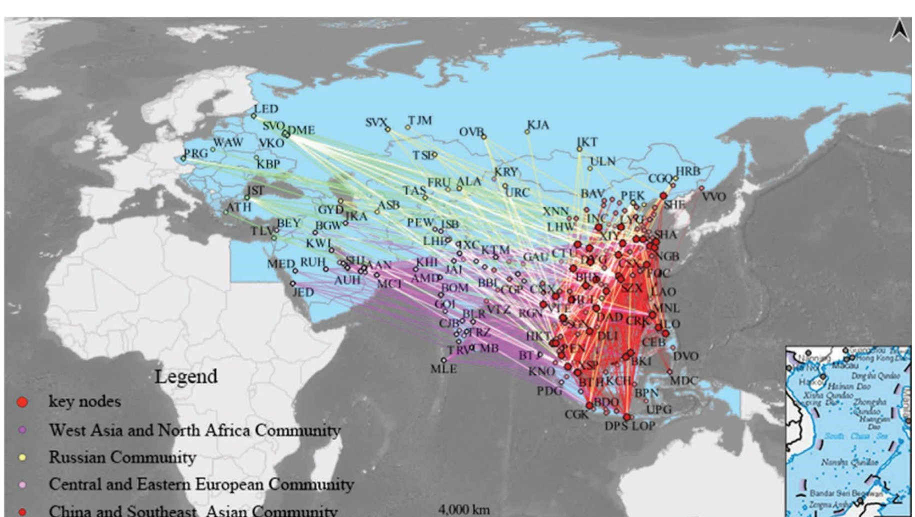

Figure 12: International routes of key node set in China and Southeast Asian community.

(12), and Mongolia (10). From a regional perspective, the international route conditions were as follows: Southeast Asia (564), Northeast Asia (133), West Asia and North Africa (66), South Asia (37), Central Asia (22), and Central and Eastern Europe (12). Based on community structure, 22 Chinese hub airports have 582 international air routes, and 29.3% of Chinese airports have 69.8% international routes. It can be seen that Chinese hub airports undertake a large part of Chinese international air transportation tasks. Combined with the community distribution of Chinese airports, the deep integration of Chinese airports mainly starts from the key node sets of the Russian Community, and China and Southeast Asian communities.

In the process of deep integration of Chinese airports into the "Belt and Road" aviation community network, the following principles are followed:

(1) All Chinese hub airports belonging to the key node set of community C_i are connected to at least $K(C_i)_{\max}$ other airports in the set
(2) If Chinese airports meet the following conditions: k-core $= K(C_i)_{\max} - 1$ and k-core $= K(C_i)_{\max} - 2$, then there are $K(C_i)_{\max}$ international routes between them and key nodes in the same community
(3) Deep integration within the community is preferentially connected to the airport with the highest k-core and boundary hub degree link (v), and the priority decreases in turn
(4) There are at least $K(C_j)_{\max}$ international routes between 1/3 of the Chinese hub airports and the key node set of other community C_j
(5) The deep integration of key node sets between two communities preferentially adds international routes with airports that have the highest boundary hub degree and k-core, and the priority decreases in turn

(1) and (2), respectively, represent the method for Chinese hub airports and general airports to integrate deeply into the key node sets of the community network where they are located. (3) indicates the priority for selecting a node to increase the route during the integration process. For example, Fuzhou Changle Airport (k-core = 11) belongs to the key node set of the Russian Community, so it increases the international route with Brunei-Ban Seri Begawan Airport, which is the airport with the highest k-core and boundary hub degree among airports that do not have international routes with Fuzhou Changle Airport.

7.2. Schemes for Deeply Integrating into the Key Node Set of the Same Community. Beijing Capital, Sanya Phoenix, and Urumqi Diwopu are the key node set members of the Russian Community, and they all meet the condition that k-core = 7. The 19 airports of Guangzhou Baiyun, Zhengzhou Xinzheng, Chongqing Jiangbei, Changsha Huanghua, Chengdu Shuangliu, Fuzhou Changle, Haikou Meilan, Hefei Xinqiao, Hangzhou Xiaoshan, Kunming Changshui, Guizhou Longdongbao, Ningbo Lishe, Nanjing Lukou, Nanning Wuwei, Shanghai Pudong, Shenyang Taoxian, Shenzhen Baoan, Wuhan Tianhe, Xi'an Xianyang are key node set members of China and Southeast Asia community (k-core = 12). The k-cores of Fuzhou Changle, Hefei Xinqiao, Guizhou Longdongbao, Ningbo Lishe, Nanjing Lukou, and Shenyang Taoxian were 11, 8, 9, 10, 11, and 8, respectively. The boundary hub degrees are 10.22, 8.838, 7.27, 6.959, 5.811, and 4.358, respectively. In accordance with principle (1), the Chinese hub airports that are deeply integrated into the key node set of the same community are presented in Table 6. The "rank" column in the table represents the number of the community network.

According to principle (2), this study selects the general airports whose k-core value in community C_i is in the range of $[K(C_i)_{\max} - 2, K(C_i)_{\max} - 1]$ as potential community key nodes. In the "Belt and Road" aviation community network, potential community key nodes in China are Harbin Taiping in the Russian Community and the three airports of Jinan Yaoqiang, Tianjin Binhai, and Xiamen Gaoqi in China and the Southeast Asia Community. Scheme 2 for potential Chinese airports for deep integration into the key node set of the same community is shown in Table 7.

In Figure 13, the blue lines represent the existing international air routes, and the red lines represent new routes in the deep integration scheme. Scheme 1 adds routes between six Chinese hub airports (Fuzhou Changle, Hefei Xinqiao, Guizhou Longdongbao, Ningbo Lishe, Nanjing Lukou, and Shenyang Taoxian) and hub airports in Brunei, Laos, Indonesia, and Myanmar in Southeast Asia. After integration, these airports are not only the core boundary nodes responsible for connecting other communities but also new members of the core node set in China and the Southeast Asian Community.

After adding international air routes with Bakubina, Yekaterinburg Koltsovo, and Tashkent, the Chinese Harbin Taiping Airport has become a new key node for the Russian Community. After adding new routes with hub airports in Southeast Asia, Jinan Yaoqiang, Tianjin Binhai, and Xiamen Gaoqi 3 airports have become key nodes for China and the Southeast Asian Community. In the plan of deep integration into the communities that Chinese airports belong to, there are mainly new routes with hub airports in Southeast Asian countries.

7.3. Scheme for Deeply Integrating into the Key Node Sets of the Other Communities. The process of deep integration of Chinese airports into the key node sets of other community networks follows Principle (4). Considering that the boundary hub degree reflects the strength of the connection between a node and other communities, key nodes with a high boundary hub degree are preferentially selected. All Chinese airports are sorted according to the boundary hub degree from largest to smallest, and seven hub airports of Beijing Capital, Guangzhou Baiyun, Shanghai Pudong, Kunming Changshui, Chengdu Shuangliu, Wuhan Tianhe, and Shenzhen Baoan are selected for integration into the key node sets of other communities.

Scheme diagram of Chinese airports deeply integrated into the other communities is shown in Figure 14. Red lines

Table 6: Scheme 1 for deep integration into the key node set of the same community.

Rank	From	Country	k-core	Link	Rank	To	Country	k-core	Link
4	FOC	China	11	10.22	4	BWN	Brunei	12	30.01
4	HFE	China	8	8.84	4	BWN	Brunei	12	30.01
4	HFE	China	8	8.84	4	CGK	Indonesia	12	2.00
4	HFE	China	8	8.84	4	VTE	Laos	12	1.15
4	HFE	China	8	8.84	4	RGN	Myanmar	12	1.09
4	HFE	China	8	8.84	4	BKI	Malaysia	12	1.09
4	KWE	China	9	7.27	4	BWN	Brunei	12	30.01
4	KWE	China	9	7.27	4	CGK	Indonesia	12	2.00
4	KWE	China	9	7.27	4	VTE	Laos	12	1.15
4	NGB	China	10	6.96	4	BWN	Brunei	12	30.01
4	NGB	China	10	6.96	4	CGK	Indonesia	12	2.00
4	NGB	China	10	6.96	4	VTE	Laos	12	1.15
4	NGB	China	10	6.96	4	RGN	Myanmar	12	1.09
4	NKG	China	11	5.81	4	BWN	Brunei	12	30.01
4	NKG	China	11	5.81	4	CGK	Indonesia	12	2.00
4	SHE	China	8	4.36	4	BWN	Brunei	12	30.01
4	SHE	China	8	4.36	4	CGK	Indonesia	12	2.00
4	SHE	China	8	4.36	4	VTE	Laos	12	1.15
4	SHE	China	8	4.36	4	RGN	Myanmar	12	1.09

Table 7: Scheme 2 for deep integration into the key node set of the same community.

Rank	From	Country	k-core	Link	Rank	To	Country	k-core	Link
2	HRB	China	5	3.57	2	GYD	Azerbaijan	7	21.88
2	HRB	China	5	3.57	2	TAI	Russia	7	13.09
2	HRB	China	5	3.57	2	TGD	Uzbekistan	7	11.27
4	TNA	China	10	3.81	4	HRB	Malaysia	12	20.98
4	TNA	China	10	3.81	4	KUN	Philippines	12	10.34
4	TNA	China	10	3.81	4	SGN	Indonesia	12	10.22
4	TNA	China	10	3.81	4	HRB	Vietnam	12	7.27
4	TSN	China	11	3.64	4	KUN	Philippines	12	10.34
4	TSN	China	11	3.64	4	HRB	Vietnam	12	7.27
4	XMN	China	10	2.12	4	HRB	Vietnam	12	7.27
4	XMN	China	11	2.12	4	HRB	Thailand	12	6.96

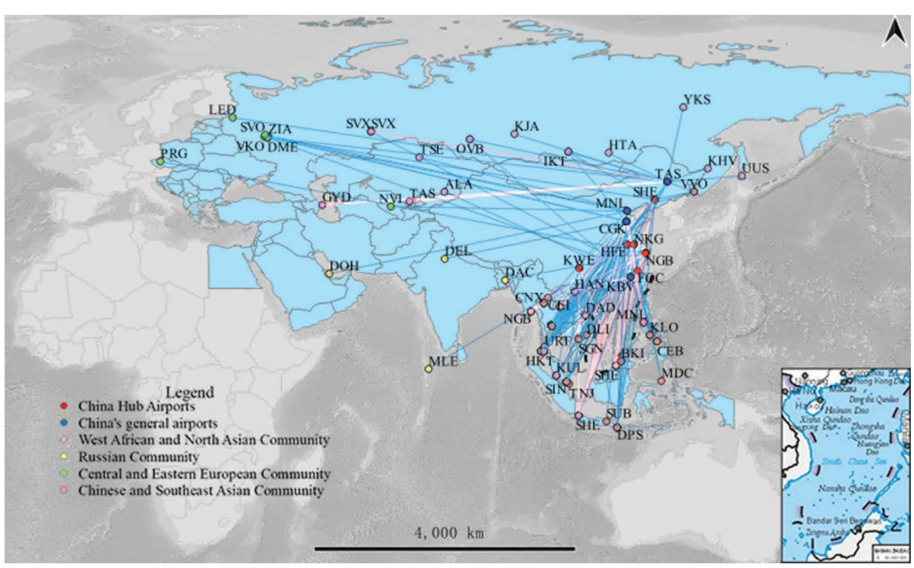

Figure 13: Scheme diagram of Chinese airports deeply integrated into the communities where they belong.

represent new routes in the plan, and blue lines represent existing routes. The new routes in scheme 3 are obviously more complex than scheme 1 and 2 for Chinese airports to deeply integrate into communities where they belong. A prominent feature is that there are many new routes with airports in West Asia and North Africa.

7.3.1. Beijing Capital Airport. Beijing Daxing Airport was officially opened to traffic on September 25, 2019, which was later than the data collection period; therefore, this study selected Beijing Capital Airport. In the "Belt and Road" aviation network, Beijing Capital Airport has a total of 70 international routes, connecting airports in 34 countries in 6 major regions along the "Belt and Road." Affiliated to the Russian Community, Beijing Capital Airport has 16, 21, 12, and 21 international routes with hub airports of the West Asian and North African Community, Russian Community, Central and Eastern European Community, China, and Southeast Asian Community, respectively. Two new international air routes were added from the Beijing capital to Antalya in Turkey and Istanbul Sabiha Gokcen. Beijing Capital Airport will have routes no less than the $k_{\max}$ of other communities.

7.3.2. Guangzhou Baiyun Airport. Affiliated to the Chinese and Southeast Asian Community, Guangzhou Baiyun Airport has 58 international routes connecting 25 countries in six regions. Guangzhou Baiyun Airport has 16, 3, 5, and 34 international air routes with hub airports of the West Asia and North Africa Community, Russia Community, Central and Eastern Europe Community, China, and Southeast Asia Community, respectively. New international air routes have been added from Guangzhou Baiyun Airport to hub airports in Central Asia, Central and Eastern Europe, West Asia, North Africa, and Russia in Northeast Asia.

7.3.3. Shanghai Pudong Airport. There are 11, 6, 6, and 24 international air routes between Shanghai Pudong Airport and the key node sets of West Asia and North Africa Community, Russia Community, Central and Eastern Europe Community, China, and Southeast Asia Community, respectively, covering 22 countries in six regions. There are 12 new routes to Shanghai Pudong Airport, including new international routes connected to hub airports in some countries in West Asia and North Africa, some countries in Central Asia, and Russia in Northeast Asia.

7.3.4. Kunming Changshui Airport. Kunming is located in the joint position of China, Southeast Asia, and South Asia and is an important airport of China facing Southeast Asia and South Asia in the "Belt and Road" strategy. Kunming Changshui Airport belongs to the Chinese Southwest Airport group and is one of the ten China major Chinese international hubs. The Kunming International Aviation Hub Strategic Plan" points out that it is necessary to strengthen international aviation routes to Southeast Asian and South Asian countries.

There are 46 international routes between Kunming Changshui Airport and the hub airports of the "Belt and Road" aviation community network, covering 20 countries in four regions: Southeast Asia, South Asia, Northeast Asia, West Asia, and North Africa. Affiliated to China and the Southeast Asian Community, Kunming Changshui Airport has international air routes connected to hub airports in West Asia and North Africa (12), Russia (1), Central and Eastern Europe (2), and China and Southeast Asia (31). There are 19 new routes connecting Kunming Changshui Airport with hub airports in West Asia and North Africa, including Iran, the United Arab Emirates, Azerbaijan, Turkey, and Armenia.

7.3.5. Chengdu Shuangliu Airport. Chengdu Shuangliu Airport belongs to the Southwest Airport Group of China. In 2019, Chengdu issued relevant aviation policies in line with the Civil Aviation Administration's policies, proposing the development of Chengdu into an international aviation hub along the "Belt and Road" and opening more than five new international direct routes every year. In addition, Chengdu Shuangliu Airport should focus on cultivating intercontinental routes that connect Europe and ASEAN.

There are 37 international routes between Chengdu Shuangliu Airport and the hub airports of the "Belt and Road" aviation community network, covering 16 countries in 6 regions. Twenty international air routes connect Chengdu Shuangliu Airport to other hub airports, with the largest number of new routes in West Asia and North Africa, including hub airports in Turkey, Iran, Lebanon, Saudi Arabia, the United Arab Emirates, Kuwait, Azerbaijan, and Armenia.

7.3.6. Wuhan Tianhe Airport. There are six, three, and nineteen international routes between Wuhan Tianhe Airport and the hub airports of West Asia and North Africa Community, Central and Eastern Europe Community, China, and Southeast Asia Community, respectively, covering 11 countries in four regions. Wuhan Tianhe Airport has a total of 20 new routes, with the largest number of new routes in West Asia and North Africa, similar to the new routes at Chengdu Shuangliu Airport. Other new routes have been added to connect the Wuhan Tianhe Airport to hub airports in Central Asia and Central and Eastern Europe.

7.3.7. Shenzhen Bao'an Airport. Shenzhen Bao'an Airport has four, one, two, and 27 international routes to the hub airports of West Asia and North Africa Community, Russia Community, Central and Eastern Europe Community, China, and Southeast Asia Community, respectively, covering 13 countries in four regions. Shenzhen Bao'an International Airport has 27 new routes, with the largest number of new routes between it and hub airports in West Asia and North Africa (14). Thirteen new routes connect hub airports in Central Asia, Central and Eastern Europe, and Northeast Asia.

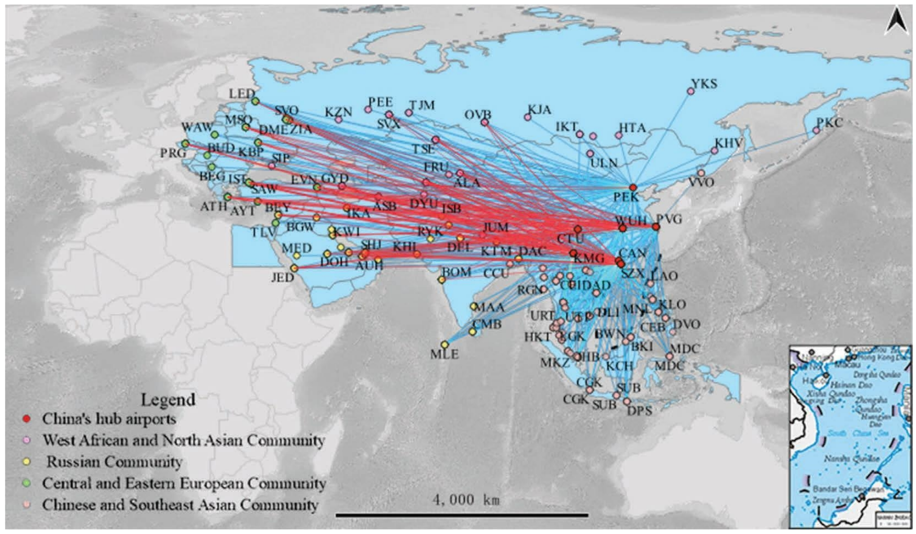

Figure 14: Scheme diagram for deeply integrating into the key node sets of other communities.

8. Conclusion

In Sections 1 and 2, this paper studies the community structure characteristics of the "Belt and Road" aviation network using complex network theory, the Louvain algorithm, and geographic statistical analysis methods. In Section 3, a network key node identification model considering the internal and external structural characteristics of the community is constructed. In Section 4, a deep integration method based on the community key node set is proposed, and an empirical analysis is conducted with Chinese airports. The main conclusions are as follows:

(1) The "Belt and Road" aviation network has the characteristics of a "small world" and is scale-free. Large-scale nodes in the "Belt and Road" aviation networks have a strong long-term influence and transfer ability.

(2) The 522 airport nodes of the "Belt and Road" aviation network are mainly divided into four large-scale communities: West Asia and North Africa, Russia, Central and Eastern Europe, China, and Southeast Asia.

(3) A total of 118 key nodes were identified. The scale of the key node set of the Chinese and Southeast Asian communities, which contains most of the Chinese airports, ranks third among the four communities but has the most key nodes and the lowest key node repetition rate. Therefore, the international air connection between China and Southeast Asian Community is more complex.

(4) The nodes with a higher degree of boundary hubs in the community network are more likely to have a long-term influence on the network. When selecting important nodes in the "Belt and Road" aviation network, the airports with high boundary hub degree should be considered.

(5) In the scheme for Chinese airports to deeply integrate into their communities, there are mainly new routes connecting with hub airports in Southeast Asian countries. In the scheme for Chinese airports to integrate deeply into other communities, a prominent feature is that there are many new routes connecting hub airports in West Asia and North Africa.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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