


Research Article

Influential Nodes in the OBOR Fossil Energy Trade Network Based on D-S Theory: Detection and Evolution Analysis

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The structure formed by fossil energy trade among countries can be divided into multiple subcommodity networks. However, the difference of coupling mode and transmission mechanism between layers of the multirelationship network will affect the measurement of node importance. In this paper, a framework of multisource information fusion by considering data uncertainty and the classical network centrality measures is build. Then, the evidential centrality (EVC) indicator is proposed, by integrating Dempster–Shafer evidence theory and network theory, to empirically identify influential nodes of fossil energy trade along the Belt and Road Initiative. The initial result of the heterogeneity characteristics of the constructed network drives us to explore the core node issue further. The main detected evidential nodes include Russia, Kazakhstan, Czechia, Slovakia, Egypt, Romania, China, Saudi Arabia, and Singapore, which also have higher impact on network efficiency. In addition, cluster analysis discovered that resource endowment is an essential factor influencing country's position, followed by geographical distance, economic level, and economic growth potential. Therefore, the above aspects should be considered when ensuring national trade security. At last, the rationality and comprehensiveness of EVC are verified by comparing with some benchmark centralities.

1. Introduction

Fossil fuel is an essential resource for economic and social development. It has a vital bearing on the national economy and human survival. Although more and more voices are emphasizing low-carbon fuels, in particular, solar PV and wind, the dominant position of fossil energy cannot be eliminated over a short period, due to the fact that 100% renewable energy must go through a process [1, 2]. Therefore, the issue of fossil energy-related carbon emission reduction is still rigorous towards the current carbon neutrality target. In 2019, for instance, global energy-related CO₂ emissions reached 33.4 Gt, with 14,798 Mt in coal, 11,344 Mt in oil, and 7,250 Mt in natural gas, respectively [3].

As the embodiment of international division of labor, trade is a significant factor in explaining the change in carbon emissions in many countries [4]. Especially for

developing countries, international trade is an important way to achieve their energy supply-demand balance and supply security. As the world's largest carbon emitter, China's continued dependence on imported crude oil and natural gas as well as its growing fossil energy demand is also expanding its influence on world energy markets. Simultaneously, China's pivotal role in international fossil energy trade market has only increased since the Belt and Road Initiative (BRI) in 2013.

Fossil energy trade is at the core of the BRI due to unevenly distributed resources. After seven years of construction, the initiative has become new solutions to improve global governance in the new era [5]. "China's Trade and Investment Cooperation under the Belt and Road Initiative" published by the Shanghai Academy of Social Sciences showed that exported-oriented fuel and mineral resources are the most common trading type along the "One

Belt One Road” (OBOR) nations which accounts for nearly 40 percent [6]. The remaining proved reserves for oil and gas under OBOR account for 58.7% and 77.7%, respectively. The production of oil and gas exceeds 50% of the world’s [7]. In addition, seven of the world’s top 10 oil and gas exporters are concentrated in the OBOR. As a result, it is beneficial for China to promote the construction of the initiative by clarifying the fossil energy trade patterns. Furthermore, it is necessary to better understand the pattern changes of fossil energy trade in OBOR countries to achieve national energy transition and carbon neutrality targets.

The trade relationship of fossil energy among the OBOR countries is firstly a system, involving a large number of countries and intricate links between countries. Secondly, each country plays a different role in trade, such as oil exporter, gas importer, coal net exporter, and oil and gas net importer. Thirdly, due to the influence of uncertainties including multienergy complementarity, energy structure adjustment, clean energy transitions, limitation by increasing aggregate demand, and renewable energy substitutability, countries in various roles or relationships are expected to interact with each other and evolve over time. Importantly, the participators are likely been influenced heterogeneously owing to their unique energy structure and trade structure. Thus, a comprehensively and systemic study by considering uncertainties is needed. Ultimately, the potential impact of uncertainties on fossil energy trade among OBOR countries is embedded into the model as “cognitive uncertainty” in this paper, because it is difficult and sometimes proves impossible to accurately judge what the impacts of these uncertainties are.

The primary contributions of this study can be summarized as follows:

- (i) First, the constructed network is the first such measure to consider uncertainty in modeling fossil energy trade relationships.
- (ii) Second, the proposed evidential centrality has benefits in terms of measurement, which allow it to provide a more comprehensively calculation from the perspective of local, global, and uncertainty.
- (iii) Third, the top-ranked countries for fossil energy trade under OBOR are identified, and the possible underlying driving forces are exposed empirically.

The rest of this paper is organized as follows: Section 2 reviews the literature on fossil energy trade network and uncertainty analysis methods. Section 3 introduces a trace of preliminaries and describes the details of the proposed evidence-based method for identifying the influential nodes. Section 4 presents the data sources. Section 5 illustrates the empirical results. Finally, Section 6 draws the conclusions.

2. Literature Review

Most of the existing studies related to fossil energy trade are focusing on the world level and most developing countries. Moreover, developing countries are the main consumers, who have obvious contradiction between resource shortage

and economic development, while the OBOR is an important group in global trade. With the increasing importance of regional trade, literature studies on OBOR countries and their trade relations is not rare. Exemplarily, Zhang revealed the status and prospects of the oil and gas trade among the OBOR countries and discovered that the general trading relationship between China and the other participating countries was closely related to their gas and oil trade [8].

On the other hand, complex network analysis has been proposed for exploring the patterns of fossil energy trade. Table 1 lists the recent ones that used complex network theory in the study of international fossil energy trade. In all, the existing studies typically addressed single-layer networks in fossil energy trade, such as separate oil network, natural gas network, or coal network. Certainly, a few researchers consider fossil fuels as a whole, but the data used represent a linear sum of the observed values between countries. For example, Gao et al. [17] constructed the international coal, oil, and natural gas network models by gathering nodes into a single plane, without considering the influence of uncertainty factors. That is, most literature studies just provide an intuitive description of the volume between two countries’ trade. Few scholars have paid attention to incorporating uncertainties as parameters when constructing the network model formed by all three (coal, oil, and natural gas) layers. In addition, research on the OBOR energy trade using complex network analysis is scarce.

Researchers have demonstrated that both global and local information of the fossil energy trade relations can fully unfold in influential nodes. Hence, influential node detection has become the focus of existing literature. It can be seen from Table 1 that the commonly adopted centrality indicators include degree centrality (DC), betweenness centrality (BC), and closeness centrality (CC). However, these evaluation methods are based on node’s structural characteristics; that is, their importance is evaluated based on the structural parameters of nodes themselves. For example, degree centrality only considers node’s influence capability from local information. It does not make an in-depth quantification of their surrounding environment, such as target node’s position and neighborhood attributes within multisteps [21–23]. BC and CC are both based on the shortest distance between node pairs, reflecting the control force of network flow. But, they have high time complexity of $O(N^3)$ which is not suitable for large-scale networks [24, 25]. As mentioned above, it is still an open issue providing a new and comprehensive method, to identify influential nodes with high accuracy and low time complexity [26].

However, in the existing network models of energy trade, the influence of uncertainty factors, such as trade strategy, policy implementation, and data uncertainty, is still not adequately taken into account [27]. The impact of uncertainty can be roughly divided into two categories: one is external, such as financial crisis and geopolitics, and the other is the linkage effect of trade structure within different kinds of fossil energy caused by substitution and price. How do we evaluate the influential nodes integrally as well as the complexed interactions among them? How will the

TABLE 1: List of fossil energy trade network studies in recent years.

Authors (year)	Modeling	Type of network	Category	Scope and time	Evaluation indexes
Peng et al. (2021) [9]	$G = (V, E, W)$	Transportation	LNG	World, 2013–2017	DC, L, CC, C,
Bu et al. (2020) [10]	$G = (V, E, W)$	Consumption	Gas	China, 2005–2017	DC, BC, CC, LMDI
Wang and Li (2019) [11]	$G = (V, E, W)$	Transportation	Coal	China, 1997–2016	DC, BC, L, CC,
Wang et al. (2019) [12]	$G = (V, E, W)$	Trade	Coal	World, 1996–2015	DC, BC, C
Xi et al. (2019) [13]	$G = (V, E, W)$	Trade	Oil	OBOR, 2009–2016	DC, BC, CC
An et al. (2018) [14]	$G = (V, E, W)$	Trade	Oil	World, 2014–2017	PMI, C
Guan and An (2017) [15]	$G = (V, E)$	Trade	Oil, coal, gas, PV	World, 2014	BC, ND, RankS, LP
Zhong et al. (2017) [16]	$G = (V, E)$	Trade	Coal, oil, gas	World, 2000–2013	C, NMI
Gao et al. (2015) [17]	$G = (V, E, W)$	Trade	Coal, oil, gas	World, 2002–2013	DC, C, NMI
Ji et al. (2014) [18]	$G = (V, E)$	Trade	Oil	World, 2010	EI, DC, CC, C, NMI
Zhong et al. (2014) [19]	$G = (V, E, W)$	Trade	Oil	World, 2002–2011	C, NMI
An et al. (2014) [20]	$G = (V, E, W)$	Trade	Oil	World, 1993–2012	DC, CC, C, stability

Note. DC: degree centrality, L: shortest path length, CC: closeness centrality, C: community structure, BC: betweenness centrality, NMI: normalized mutual information, LMDI: logarithmic mean Divisia index, PMI: pointwise mutual information, ND: network density, RankS: ranking score, LP: link prediction, and EI: export intensity.

influential nodes affect the efficiency of network operation? Of course, it is not straightforward to incorporate these factors into the model. In this paper, we will introduce the multisource information fusion technology that has an extensive practicality, effectiveness, and applicability, to solve the uncertainty problem mentioned above. As an effective uncertain information processing method, it has been well developed, such as GIQ [28], CaFr [29], evidence theory [30], D numbers theory [31], Z numbers [32], and entropy-based approaches [33].

As one of the most effective tools of uncertainty reasoning, Dempster–Shafer (D-S) evidence theory uses multievent hypothesis to express a nondetermination state directly [34]. Besides, the D-S evidence theory has the advantages of expressing “uncertain” and “unknown” directly and has great application value in classification and information fusion, which provides strong support for the evaluation of complex uncertain systems. Furthermore, it has been widely applied in lots of fields, including but not limited to reliability analysis, classification, quantum information decision, and fault diagnosis [35, 36]. Moreover, it has the ability to combine observations from different sources, so as to reduce system uncertainty effectively.

In this paper, the trade data for coal, oil, and natural gas can be seen as multisource information. Due to the factors such as multienergy complementarity and energy structure adjustment, the existing energy trade networks are insufficient to consider these kinds of information, so that some information would be lost during the modeling and processing of data. Therefore, the fusion method of evidence theory can be used in multirelationship energy trade network studies.

3. Methodology

3.1. Preliminaries

3.1.1. *D-S Evidence Theory.* The D-S evidence theory-based method is among the alternative algorithmic approach to

multisensor data fusion that tries to achieve refined estimates of “uncertainty” [37–39]. It employs a reliability function rather than probability to measure uncertainty, and it is widely used in the field of information and decision-making. It provides a favorable Dempster combination rule for information fusion, which has the superiority such as the commutative law and the associative law and can realize fusion between evidence without the support of prior probability. The basic framework of multisource information fusion based on D-S theory is shown in Figure 1. The basic concepts and definitions used in this paper are shown as follows. Much more detail is provided in references [40–42].

Definition 1 (frame of discernment). Let $\Theta = \{\theta_1, \theta_2, \dots, \theta_N\}$ be a finite nonempty set, and let 2^Θ be the power set of Θ ; thus, $2^\Theta = \{\emptyset, \theta_1, \dots, \theta_N, \{\theta_1, \theta_2\}, \{\theta_1, \theta_3\}, \dots, \Theta\}$.

Definition 2 (basic probability assignment (BPA)). For a frame of discernment Θ , BPA is a mapping $m: 2^\Theta \rightarrow [0, 1]$, satisfying

$$m(\emptyset) = 0 \quad (1)$$

and

$$\sum_{\emptyset \subseteq 2^\Theta} m(\theta) = 1, \quad (2)$$

where \emptyset is an empty set and θ is any element of 2^Θ . $m(\theta)$ reflects the exact degree of trust in the proposition θ , namely, the probability assigned. Condition (1) reflects no confidence in the null set; condition (2) reflects the sum of the basic probability assignment of all propositions equal to 1.

Definition 3 (Dempster combination rule). Suppose m_1 and m_2 are independent BPAs from different evidence resources, respectively. The fusion result of m_1 and m_2 , denoted by $m = m_1 \oplus m_2$, under Dempster’s rule of combination is defined as follows:

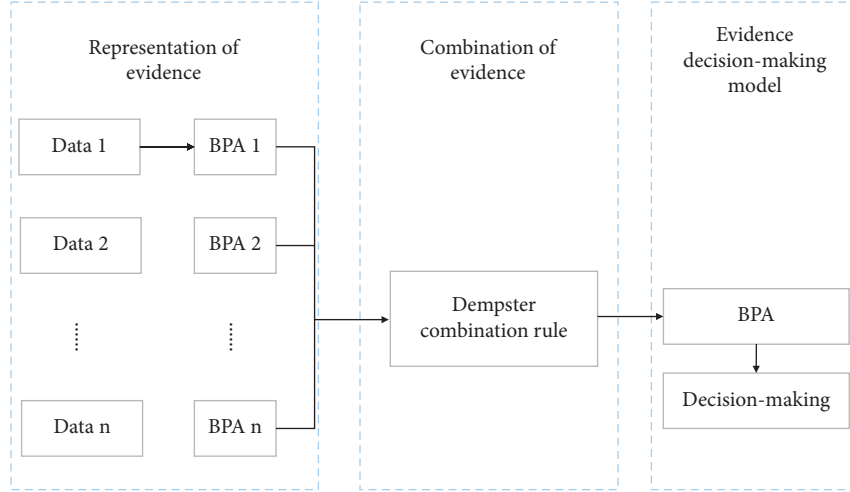


FIGURE 1: Framework of multisource information fusion based on D-S theory.

$$m(\theta) = [m_1 \oplus m_2](\theta) = \begin{cases} 0, & \theta = \emptyset \\ \frac{\sum_{B \cap C = \theta} m_1(B)m_2(C)}{1 - \sum_{B \cap C = \emptyset} m_1(B)m_2(C)}, & \theta \neq \emptyset \end{cases}, \quad (3)$$

where θ , B , and C are the elements of 2^Θ . Thereinto, \oplus is an orthogonal operator.

3.1.2. Benchmark Centrality Measures for Influential Nodes

Definition 4 (degree centrality (DC)). The DC of node i , denoted as d_i , is defined as

$$d_i = \sum_{j=1}^N a_{ij}, \quad (4)$$

where N is the total number of nodes in the network and $a_{ij} = 1$ if node i is connected to node j and $a_{ij} = 0$ otherwise [43, 44].

Definition 5 (betweenness centrality (BC)). The BC of node i , denoted as b_i , is defined as

$$b_i = \sum_{j,k \neq i} \frac{g_{jk}(i)}{g_{jk}}, \quad (5)$$

where g_{jk} denotes the total number of shortest paths between nodes j and k and $g_{jk}(i)$ is the number of those paths that go through node i [45, 46].

Definition 6 (closeness centrality (CC)). The CC of node i , denoted as c_i , is defined as the reciprocal of the sum of geodesic distances to all other nodes and calculated by the following formula:

$$c_i = \left[\sum_{j=1, j \neq i}^N d_{ij} \right]^{-1}, \quad (6)$$

where d_{ij} is the geodesic distance between nodes i and j [47, 48].

Definition 7 (eigenvector centrality (EC)). The EC of node i , denoted as e_i , is defined as

$$e_i = \lambda_{\max}^{-1} \sum_{j=1}^N a_{ij} e_j, \quad (7)$$

where λ_{\max}^{-1} is the maximum eigenvalue of the adjacent matrix and its corresponding eigenvector is $e = [e_1, e_2, \dots, e_N]^T$. $a_{ij} = 1$ if node i is connected with node j , and $a_{ij} = 0$, otherwise [49, 50].

Definition 8 (PageRank centrality (PC)). Let $E(u)$ be some vector over the Web pages that corresponds to a source of rank. Then, the PageRank of a set of Web pages is an assignment R' to the Web pages which satisfies

$$R'(u) = c \sum_{v \in B_u} \frac{R'(v)}{N_v} + cE(u), \quad (8)$$

such that c is maximized and $R'_1 = 1$ [51, 52].

3.2. A Relevance Matrix-Based BPA Method. The relevance matrix can be obtained by converting the multiproduct trade matrixes with certain processing approaches. The correlation among nodes in the network can be fully reflected in the construction of BPA. The primary question is how to build an effective BPA, which is also the critical step. The detailed subsequent steps are as follows (see Figure 2).

Step 1. The representation of evidence. Firstly, we build a weighted matrix for each fossil energy trade $W^k \equiv (w_{ij}^k)_{n \times n}$ ($i = 1, 2, \dots, n; j = 1, 2, \dots, n$) with elements of w_{ij}^k , where $k = 1, 2, 3$ represents coal, oil, and natural gas, respectively. w_{ij}^k represents the trade volume from node i to node j (unit in USD). Then, we can build the relevance matrix for each energy $S^k \equiv (s_{ij}^k)_{n \times n}$, where $s_{ij}^k = w_{ij}^k / w_{\max}^k$ is

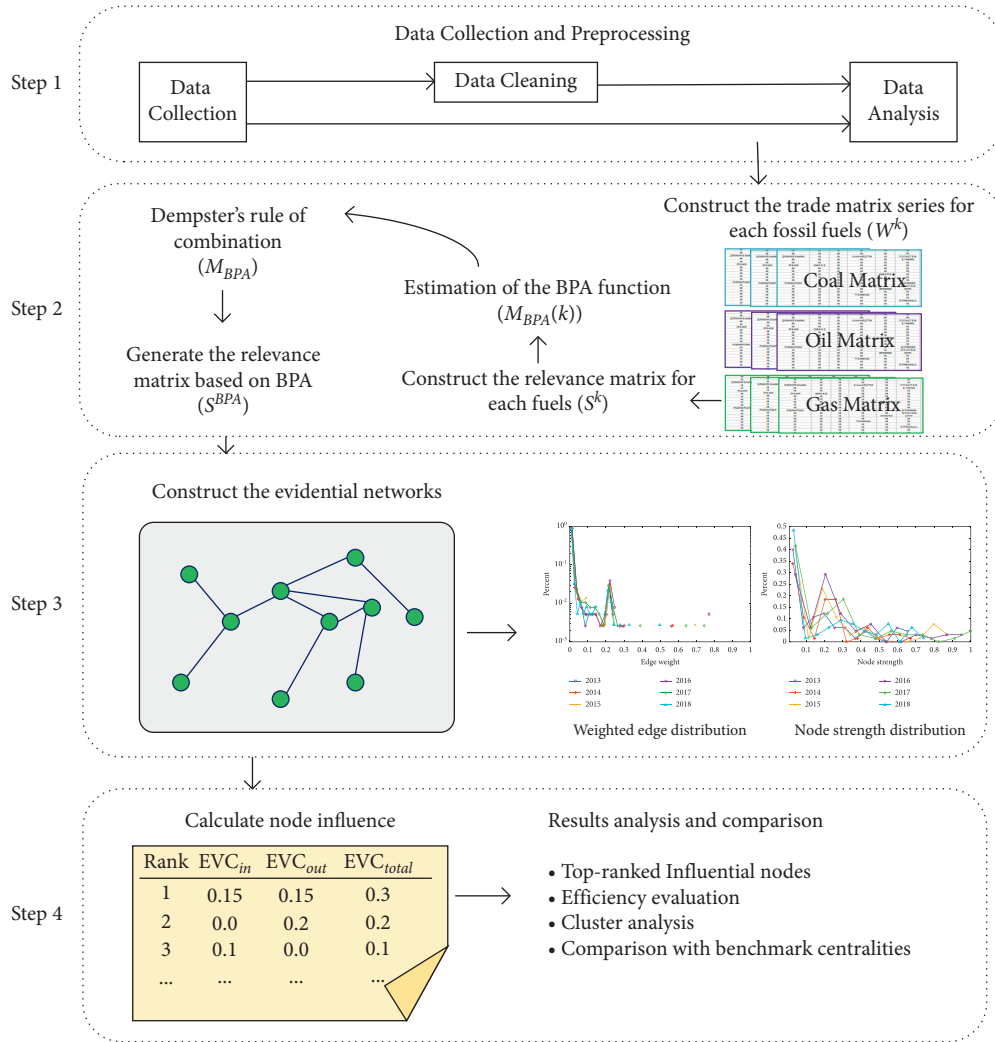


FIGURE 2: Flowchart of the proposed D-S based network method.

proportional to node strength and w_{\max}^k is the maximum of elements in W^k . However, existing studies have verified that the distribution of fossil energy trade displayed power-law characteristics [9]. In order to avoid too many small values to reflect variability, we adopt $s_{ij}^k = w_{ij}^k / w_{\text{local-max}}^k$, where $w_{\text{local-max}}^k$ is the maximum in the local connected networks of node i and j .

Step 2. Estimation of the BPA function. Each element in the relevance matrix S^k can be transformed to the elements in the BPA matrix of $M_{BPA} \equiv (m_{ij}(Y), m_{ij}(N), m_{ij}(Y, N))_{n \times n}$. The elements in the BPA matrix M_{BPA} are defined as follows:

$$m_{ij}(Y) = \frac{|s_{ij} - \min(S)|}{\text{summ}}$$

$$m_{ij}(N) = \frac{|s_{ij} - \max(S)|}{\text{summ}}, \quad (9)$$

$$m_{ij}(Y, N) = \frac{|s_{ij} - (\max(S) + \min(S))/2|}{\text{summ}}$$

where $\text{summ} = |s_{ij} - \max(S)| + |s_{ij} - \min(S)| + |s_{ij} - (\max(S) + \min(S))/2|$ and $m_{ij}(Y) + m_{ij}(N) + m_{ij}(Y, N) = 1$. In this paper, each single-layer matrix of coal, oil, and

natural gas corresponds to a BPA matrix, defined as $M_{\text{BPA}}(c) \equiv (c_{ij})_{n \times n}$, $M_{\text{BPA}}(o) \equiv (o_{ij})_{n \times n}$ and $M_{\text{BPA}}(g) \equiv (g_{ij})_{n \times n}$, respectively.

Step 3. Dempster's rule of combination. Let $M_{\text{BPA}} \equiv (l_{ij})_{n \times n}$ be the BPA matrix of total fossil energy, where

$$\begin{aligned} l_{ij} &= [l_{ij}(Y), l_{ij}(N), l_{ij}(Y, N)] \\ &= c_{ij} \oplus o_{ij} \oplus g_{ij}. \end{aligned} \quad (10)$$

If $t_{ij} = c_{ij} \oplus o_{ij}$, then $l_{ij} = t_{ij} \oplus g_{ij}$.

$$t_{ij} = [t_{ij}(Y), t_{ij}(N), t_{ij}(Y, N)], \quad (11)$$

where

$$\begin{aligned} t_{ij}(Y) &= \frac{c_{ij}(Y) * o_{ij}(Y) + c_{ij}(Y) * o_{ij}(Y, N) + c_{ij}(Y, N) * o_{ij}(Y)}{1 - (c_{ij}(Y) * o_{ij}(N) + c_{ij}(N) * o_{ij}(Y))}, \\ t_{ij}(N) &= \frac{c_{ij}(N) * o_{ij}(N) + c_{ij}(N) * o_{ij}(Y, N) + c_{ij}(Y, N) * o_{ij}(N)}{1 - (c_{ij}(Y) * o_{ij}(N) + c_{ij}(N) * o_{ij}(Y))}, \\ t_{ij}(Y, N) &= \frac{1}{1 - (c_{ij}(Y) * o_{ij}(N) + c_{ij}(N) * o_{ij}(Y))} (c_{ij}(Y, N) * o_{ij}(Y, N)). \end{aligned} \quad (12)$$

Step 4. Probabilistic conversion and decision-making. We transform the BPA matrix for total fossil energy into the relevance matrix again and make final decision judgement. Let the relevance matrix for total fossil energy be $S^{\text{BPA}} \equiv (s_{ij}^{\text{BPA}})_{n \times n}$, and

$$\begin{aligned} s_{ij}^{\text{BPA}} &= l_{ij}(Y) + \frac{l_{ij}(Y, N)}{|Y, N|} \equiv \text{Bet}P_{l_{ij}}(Y), \\ |Y, N| &= 2, \end{aligned} \quad (13)$$

$$\text{Bet}P_m(Y) = m(Y) + \frac{m(Y, N)}{|(Y, N)|}.$$

3.3. Network Construction and Node Influence. In this paper, the network can be constructed as a directed weighted network. The model of the directed weighted network is given as a triple $G = (V, E, W)$, where $V = (v_1, v_2, \dots, v_n)$ represents the set of nodes and $E = (e_1, e_2, \dots, e_m)$ represents the set of edges. Here, each link of a graph has an associated numerical value, called a weight. $W = (w_{ij})_{n \times n} = (s_{ij}^{\text{BPA}})_{n \times n}$ is the weighted matrix of connected edges, where $w_{ii} = 0$ and $w_{ij} \geq 0$ and $w_{ij} (i \neq j)$ represents the weight of edge from node v_i to node v_j . Then, a time series of the influence network, which is called evidential network (EN), among OBOR countries is build.

Normally, when two nodes have high relevance, then nodes' influences will increase automatically. Given a network $G = (V, E, W)$, for any node $i \in V$, the incoming and outgoing influence capability of node i , denoted as $\text{EVC}_{\text{in}}(i)$ and $\text{EVC}_{\text{out}}(i)$, are given by

$$\begin{aligned} \text{EVC}_{\text{in}}(i) &= \sum_{j \in \Phi(i)} w_{ji}, \\ \text{EVC}_{\text{out}}(i) &= \sum_{j \in \Phi(i)} w_{ij}, \end{aligned} \quad (14)$$

where $\Phi(i)$ is the set of nearest neighbors of node i .

The total evidence centrality ($\text{EVC}_{\text{total}}$) measures the sum of the total incoming influence of all inlinks and the total outgoing influence by all outlinks, which can be calculated as follows:

$$\text{EVC}_{\text{total}}(i) = \text{EVC}_{\text{in}}(i) + \text{EVC}_{\text{out}}(i), \quad (15)$$

where $\text{EVC}_{\text{total}}(i)$ is the total influence of node i . The greater the total evidence centrality value of a node, the more influential the node.

4. Data Description

The data for the three kinds of fossil energy trade were downloaded from the United Nations Commodity Trade Statistics Database (UN COMTRADE). HS codes are 270100, 270900, 271111, and 271121, respectively. In the original data sources, natural gas consists of two categories: gasified natural gas and liquefied natural gas. In addition, the data presented in the UN COMTRADE are unit in both US dollars (trade value) and kilograms (trade volume). We finally select the data for trade value due to serious data lack of trade volume.

More importantly, the statistical data are from both importing and exporting countries. However, there exist data errors between them, as shown in Figure 3. Due to space constraints, only part of the country names is marked in

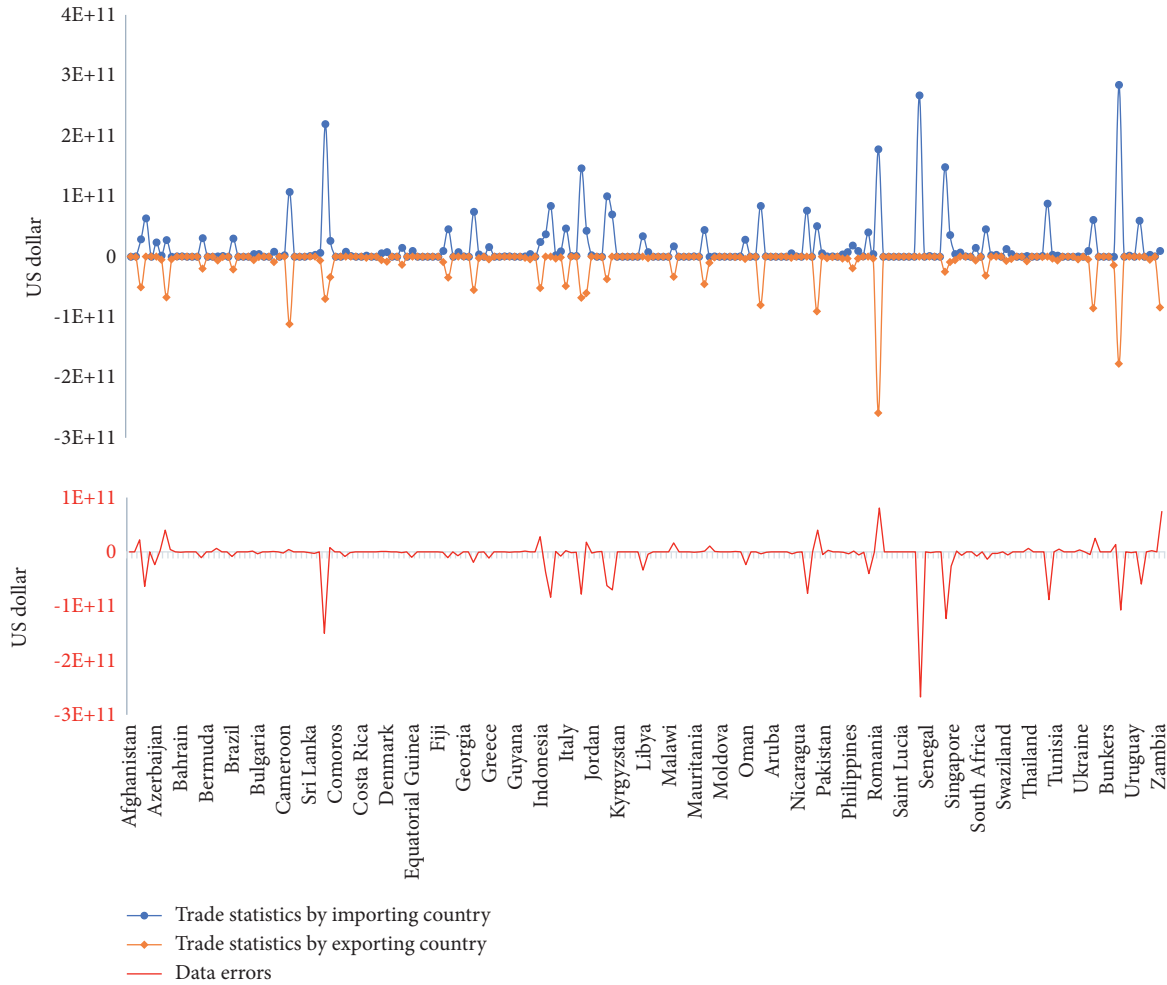


FIGURE 3: Data uncertainty example of oil export in 2013.

Figure 3. Consistent with most existing studies, we use the trade data released by exporting countries ultimately. In fact, the errors existing here can be seen as one kind of data uncertainty.

Nest, we conducted statistical analysis on the evolution and proportion of fossil energy trade within the countries under OBOR, as shown in Figure 4. Although the trade volume of OBOR countries accounted for less than 20 percent, its proportion has been increasing since the BRI was put forward, from 8 percent in 2013 to 14 percent in 2018. This indicates that the status of fossil energy trade for countries in the OBOR route has increased in the international market. This also proves the necessity of studying such issues.

5. Result Analysis

5.1. *Topological Structure Analysis of Evidential Networks.* According to Sections 3.2 and 3.3, we can obtain the fossil energy trade evidential networks during 2013–2018. Then, the network structure is drawn by using Gephi, a general network analysis visualization software tool, as depicted in Figure 5. In Figure 5, node size is proportional to node degree—the number of links incident to the node. The

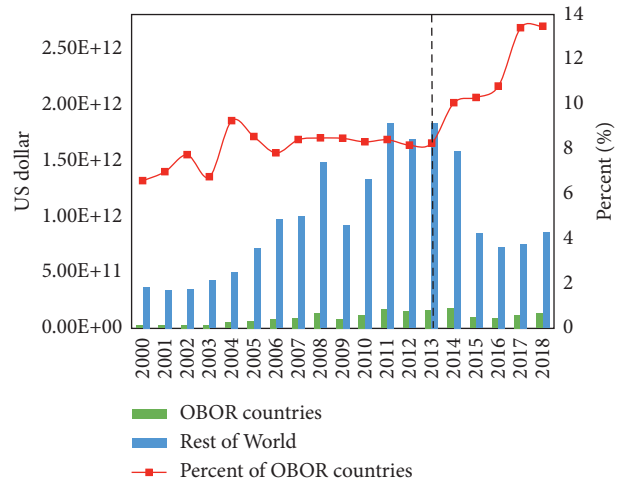


FIGURE 4: Changes in volume and share of fossil energy trade under OBOR since 2000.

thickness of link indicates the connection weight between the two countries, and the thicker the link, the greater the connection, and vice versa.

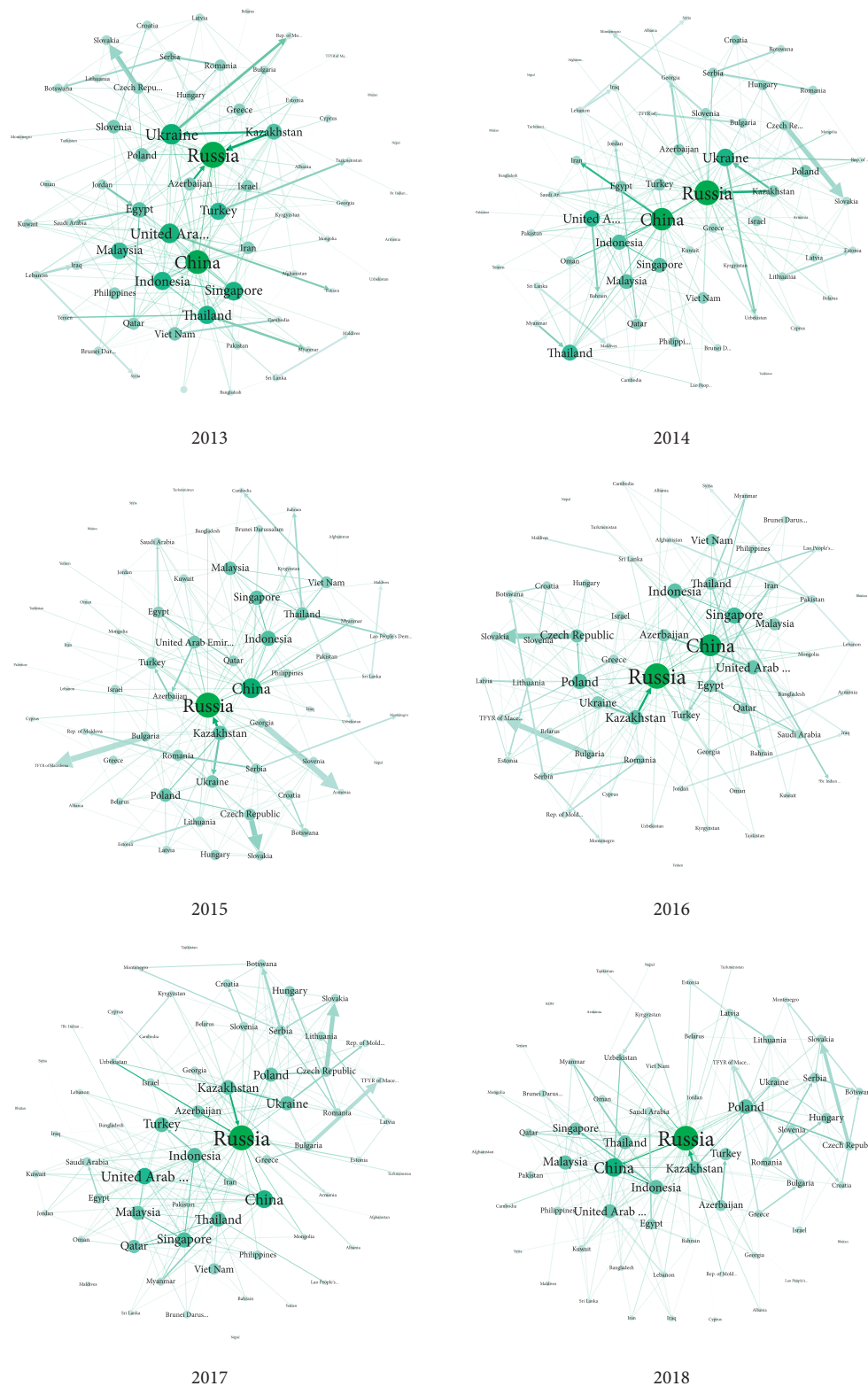


FIGURE 5: Structure of the evidential networks during 2013–2018.

From Figure 5, firstly, Russia dominated the system in terms of node degree. In other words, Russia has the largest number of partners owing to its abundant energy resources. Russia’s top three trading partners are concentrated in

Kazakhstan, China, and Azerbaijan. It can be seen that resource advantage dominates a country’s position. Secondly, as the world’s largest energy consumer, China’s top five trading partners include the United Arab Emirates,

Kazakhstan, Azerbaijan, Iran, Singapore, and Indonesia. Of course, Russia is also an important trading partner for China. With the construction or undergoing construction of oil and gas pipelines in the Far East, the energy relation between China and Russia has become increasingly close. Both countries are committed to build an energy security system conducive to each other and expected to form an energy community with a shared future. There are also some notable countries, namely, Ukraine, United Arab Emirates, Kazakhstan, Azerbaijan, Singapore, Indonesia, and Turkey, whose positions were not very much changed over time.

Furthermore, Figure 5 shows that the connecting links between most countries are thin, while those between a few country pairs are thick. That is, the weights gather on a very few connections, which can be depicted from the weighted edge distribution (Figure 6(a)). Figure 6(a) shows that the distribution of weighted links in all years presents similar power-law heterogeneity, which is similar to the results of most existing studies. Namely, the proposed method in this paper does not change system heterogeneity when considering uncertainty.

In addition, we further analyze how strength is distributed across nodes in a similar way to the weighted edge distribution, as shown in Figure 6(b). Node strength is the total of the edge weights in the network incident to the node. In fact, node strength is the measure of total EVC proposed in Section 3.3. Similar to the result of Figure 6(a), heterogeneity exists in node strength distribution. In other words, the distribution of strength values across nodes is based on power-law; many nodes have a lower EVC while a smaller number of key nodes take the lion's share of centrality, making them as hubs that facilitate integration across the network. In the following sections, we will explore these critical nodes in detail.

5.2. Influential Nodes Identification. Figure 7 depicts the time evolution of the ranking of various countries during the study period according to nodes' total EVC. The results show that countries' rankings have changed markedly since the BRI. In 2013, for example, Russia, Thailand, and Ukraine were the top three countries according to their total EVC, while in 2018, Czechia, Slovakia, and Bulgaria were the top three. Meanwhile, affected by the development of global trade internationalization, the total influence value of each country is also changing which makes the analysis considerably more complicated.

Thus, the average EVC for all countries and standard deviation (SD) are used to present the ranking characteristics of sample countries in the evidential networks. Figure 8 scatters all OBOR countries and their corresponding total EVC, incoming EVC, and outgoing EVC values. In Figure 8(a), for instance, the abscissa represents the average EVC value for each of the 65 countries, the ordinate represents their SD during 2013–2018, and the imaginary lines represent the means of EVC and SD for all countries, respectively. Countries with larger values along the abscissa but smaller values along the ordinate indicate stabilized higher influence.

It can be seen from Figure 8(a) that Russia and Kazakhstan in the lower right corner dominate the centrality. Of course, the total EVC values for Czechia and Slovakia are larger than those for Russia and Kazakhstan. But, the SD values for Czechia and Slovakia are also higher. That is, these may only be the values in a particular year supporting this result, which cannot be considered as influencer roles. For resource exporters of Russia and Kazakhstan, their positions are firmly in the top 10 with little volatility (see Figure 7). It can be seen that resource advantages play an absolute role in the influence of a country's trade. Energy dependence is central to Russia's economic structure. According to the data of the Russian State Statistics Bureau, in the export commodity structure from 2015 to 2017, the proportion of raw materials such as oil and natural gas has always remained at about 60%. Therefore, it can be seen that energy export is still the main driving force of Russia's economic recovery. Besides, Kazakhstan, Turkmenistan, and Uzbekistan are major oil producers in Central Asia. Kazakhstan has the largest crude oil reserves (about 1.7% of the world's total). Turkmenistan has the largest natural gas reserves (about 9.9% of the world's total), but the country's natural gas resources are far from being fully exploited. This is also why Turkmenistan's centrality in the export structure is not obvious (see Figure 8(b)).

In addition, Ukraine, Egypt, Romania, China, Singapore, Qatar, Saudi Arabia, and Indonesia are also essential countries due to their lower SD and higher EVC values (Figure 8(a)). Another possible reason is that these countries have a high export influence, or a high import influence, such as China, Thailand, Egypt, and Saudi Arabia (Figures 8(b) and 8(c)).

After the BRI, China's influence rose briefly in 2014 and then increased sharply since 2017 after a period of stability. In 2017, China's oil import volume from countries along the Belt and Road Initiative was 141.71 billion US dollars, nearly ten times of its export. That is, China runs a large oil trade deficit, accounting for 77% of its total import. Although China is the proposer of the BRI, it can be seen that its influence in fossil energy trade is at a medium level. Possible reasons are as follows: first, China is focusing on developing renewable energy; second, Kazakhstan, Russia, and other countries are important fossil energy resource exporters. However, China's EVC value (0.608) surpassed Russia's (0.60) in 2017, indicating that the increasingly active oil and gas activities of Chinese companies in Central Asia will challenge Russia's energy monopoly.

5.3. Evaluating the Impact of Top-Ranked Influential Nodes.

In this section, the impact of the identified top-ranked influential is evaluated by comparing their efficiency. Damage resistance is to evaluate the variation of network efficiency at risk nodes to observe the system's ability to maintain stability in the face of risk disturbance. In this paper, the value of network efficiency when a node disappears is used as a quantitative evaluation index to measure the efficiency of the removed node. Efficiency refers to the aggregation degree of paths within the system [53, 54]. It can measure the ability of

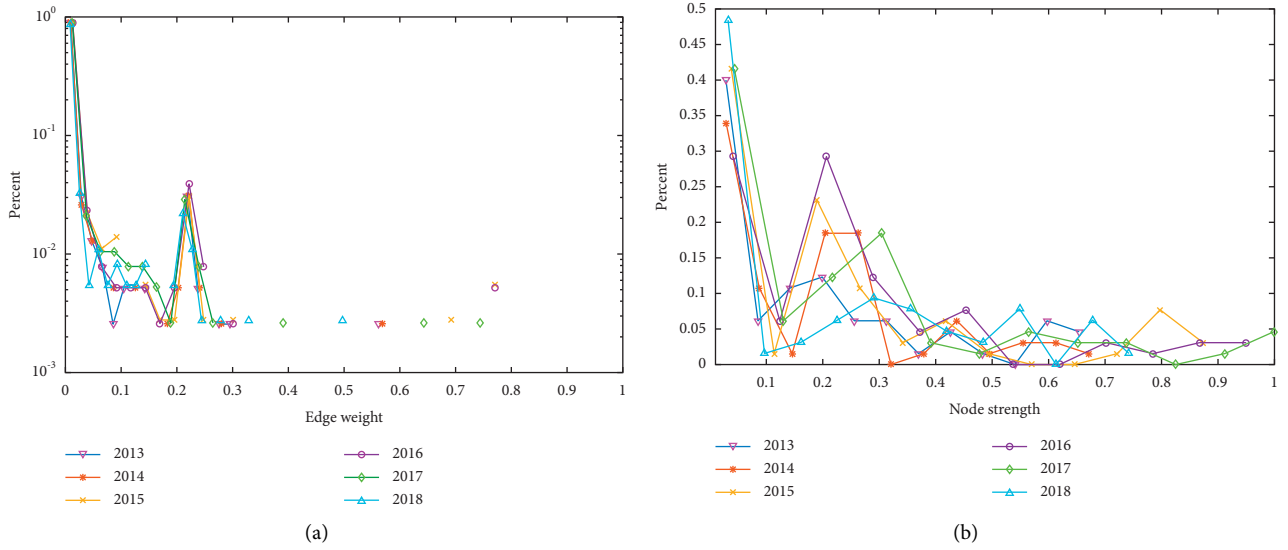


FIGURE 6: Weighted edge distribution and node strength distribution. (a) Edge weight. (b) Node strength.

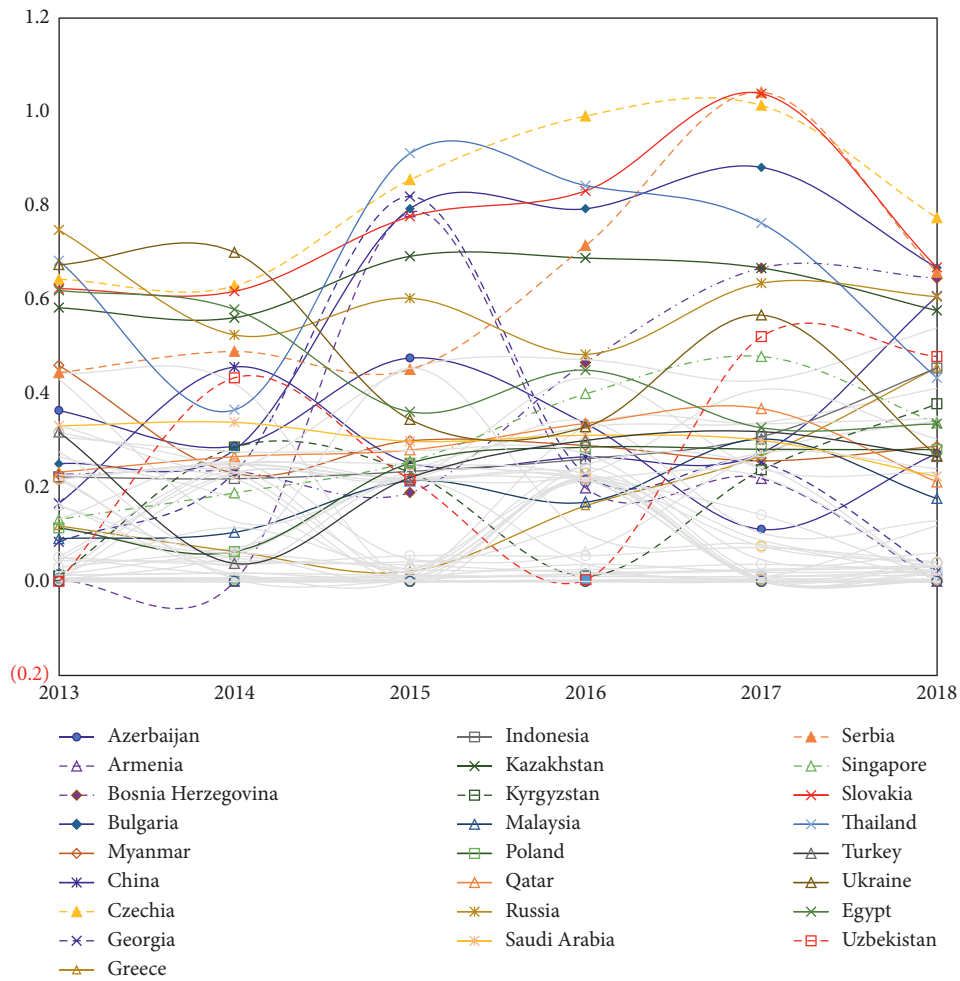


FIGURE 7: Evolution of the ranking of various countries by total EVC.

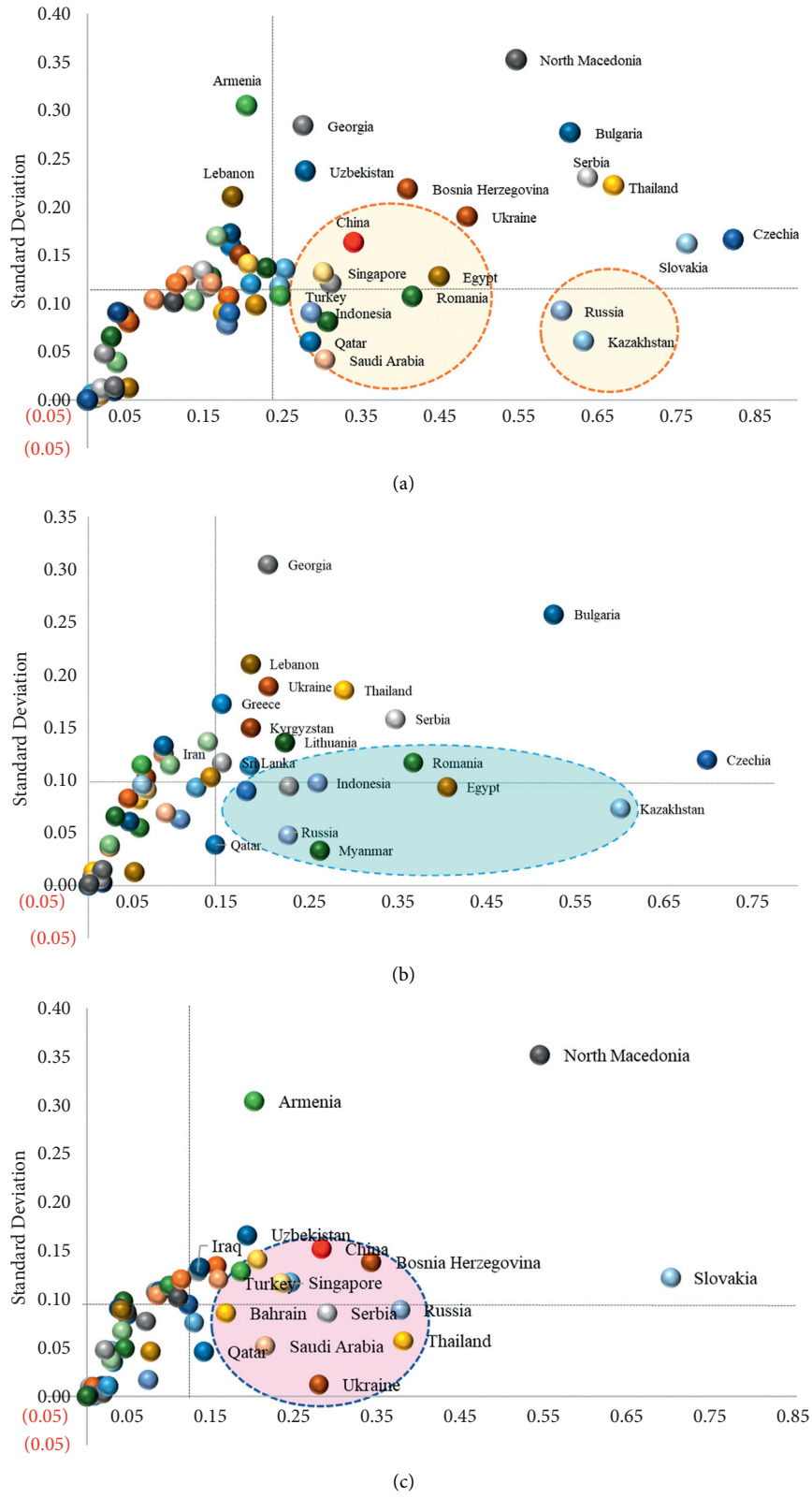


FIGURE 8: Scatter of EVC and SD for the Belt and Road countries. (a) Total EVC. (b) EVC_out. (c) EVC_in.

TABLE 2: Influences of removing the top nodes on the network efficiency when using the EVC ranking.

2013		2014		2015		2016		2017		2018	
Removed node	EffC (k)	Removed node	EffC (k)	Removed node	EffC (k)	Removed node	EffC (k)	Removed node	EffC (k)	Removed node	EffC (k)
Russia	0.134	Ukraine	-0.042	Thailand	0.052	Czechia	-0.025	Serbia	-0.048	Czechia	0.044
Thailand	0.038	Czechia	-0.030	Czechia	-0.008	North Macedonia	-0.054	Slovakia	-0.022	Slovakia	0.037
Ukraine	-0.044	Slovakia	-0.032	Georgia	-0.047	Thailand	0.036	Czechia	-0.016	Bulgaria	0.022
Czechia	-0.041	Egypt	-0.055	North Macedonia	-0.057	Slovakia	-0.022	Bulgaria	-0.037	Serbia	0.012
Slovakia	-0.036	Kazakhstan	-0.015	Bulgaria	-0.048	Bulgaria	-0.038	Thailand	0.041	Bosnia herzegovina	0.017
Egypt	-0.064	Russia	0.058	Armenia	-0.056	Serbia	-0.053	North Macedonia	-0.049	China	0.104
Kazakhstan	-0.016	Serbia	-0.060	Slovakia	-0.011	Kazakhstan	-0.032	Bosnia herzegovina	-0.049	Russia	0.185
Myanmar	-0.017	China	0.132	Kazakhstan	-0.012	Russia	0.133	Kazakhstan	-0.049	Kazakhstan	0.034
Serbia	-0.066	Uzbekistan	-0.060	Russia	0.055	Romania	-0.036	Russia	0.111	North Macedonia	0.012
Lebanon	-0.067	Lebanon	-0.061	Azerbaijan	-0.010	Bosnia herzegovina	-0.054	Ukraine	-0.025	Romania	0.032
Moldova	-0.066	Thailand	0.011	Viet Nam	-0.034	Egypt	-0.034	Uzbekistan	-0.017	Uzbekistan	0.050
Azerbaijan	-0.013	Saudi Arabia	-0.069	Romania	-0.035	Lithuania	-0.044	Singapore	0.026	Greece	0.025
Saudi Arabia	-0.081	Azerbaijan	-0.024	Serbia	-0.057	Singapore	-0.003	Romania	-0.031	Indonesia	0.072
Romania	-0.043	Kyrgyzstan	-0.060	Egypt	-0.049	Estonia	-0.054	Montenegro	-0.049	Thailand	0.088
Turkey	-0.057	Bulgaria	-0.059	Ukraine	-0.039	Qatar	-0.024	Qatar	-0.008	Croatia	0.017

nodes to transfer information in the network after the occurrence of risks, using the information theory-based network flow analysis. Here, we adopt the average mutual information to define the efficiency of weighted network G :

$$E[G] = \sum_{i,j} \frac{T_{ij}}{T_{..}} \log \frac{T_{ij} T_{..}}{T_{i.} T_{.j}}. \quad (16)$$

Here, T_{ij} represents a flow from node i to node j , $T_{i.} = \sum_j T_{ij}$ represents the total flow leaving node i , $T_{.j} = \sum_i T_{ij}$ represents the total flow entering node j , and $T_{..}$ represents the sum of all flows in the system.

The efficiency for node k in a weighted network is defined as

$$\text{EffC}(k) = \frac{\Delta E}{E} = \frac{E[G] - E[G'(k)]}{E[G]}, \quad k = 1, \dots, N, \quad (17)$$

where $G'(k)$ is a subgraph of G with $N-1$ nodes and $P-Q$ edges obtained by removing node k and its neighbor edges. The greater the efficiency value, the higher the influence of a node.

Table 2 shows the effect of removing the top fifteen countries on the network efficiency when using the EVC ranking. According to Table 2, the influences of the top-15 listed countries are different and vary with ongoing time. To sum up, however, most of them have relatively high efficiency values, such as Russia, China, and Thailand. Without these nodes, the network efficiency will decline obviously. The efficiency value of Russia is the maximum of all nodes, although its ranking dropped significantly from 2014. In fact, it is intuitional that Russia is a pivotal node in the network

because it connects to most nodes. The results show that the node evaluation index proposed in this paper has a greater impact on network performance. In other words, the failure of these nodes will make the network show more fragile damage resistance or robustness.

5.4. Hierarchical Cluster Analysis. In this section, we also conduct hierarchical clusters further, as shown in Figure 9. The clusters, depicted by the dendrogram, result from the Unweighted Pair Group Method with Arithmetic Mean (UPGMA). UPGMA is a generally used clustering technique that uses the arithmetic average approach to construct a phylogenetic tree from a distance matrix. It has been used most frequently in ecology and systematics [55] and in numerical taxonomy [56]. For detailed algorithm, please see reference [57].

According to Figure 9, the OBOR countries can be roughly divided into the following five categories: Cluster 1 contains the largest number of countries, but most of them are from underdeveloped regions although their annual GDP growth has increased in recent years. Besides, those countries are relatively concentrated geographically, such as Tajikistan, Kyrgyzstan, Kazakhstan, Afghanistan, Pakistan, and other Central Asian countries. It can be seen that geographical distance is one of the factors affecting fossil energy trade, which involves the cost of transportation. Cluster 2 includes resource countries such as Iraq, Qatar, and Saudi Arabia. This category has typical characteristics, that is, except Bahrain and Maldives, and the GDP of all countries in this category was higher than the average level

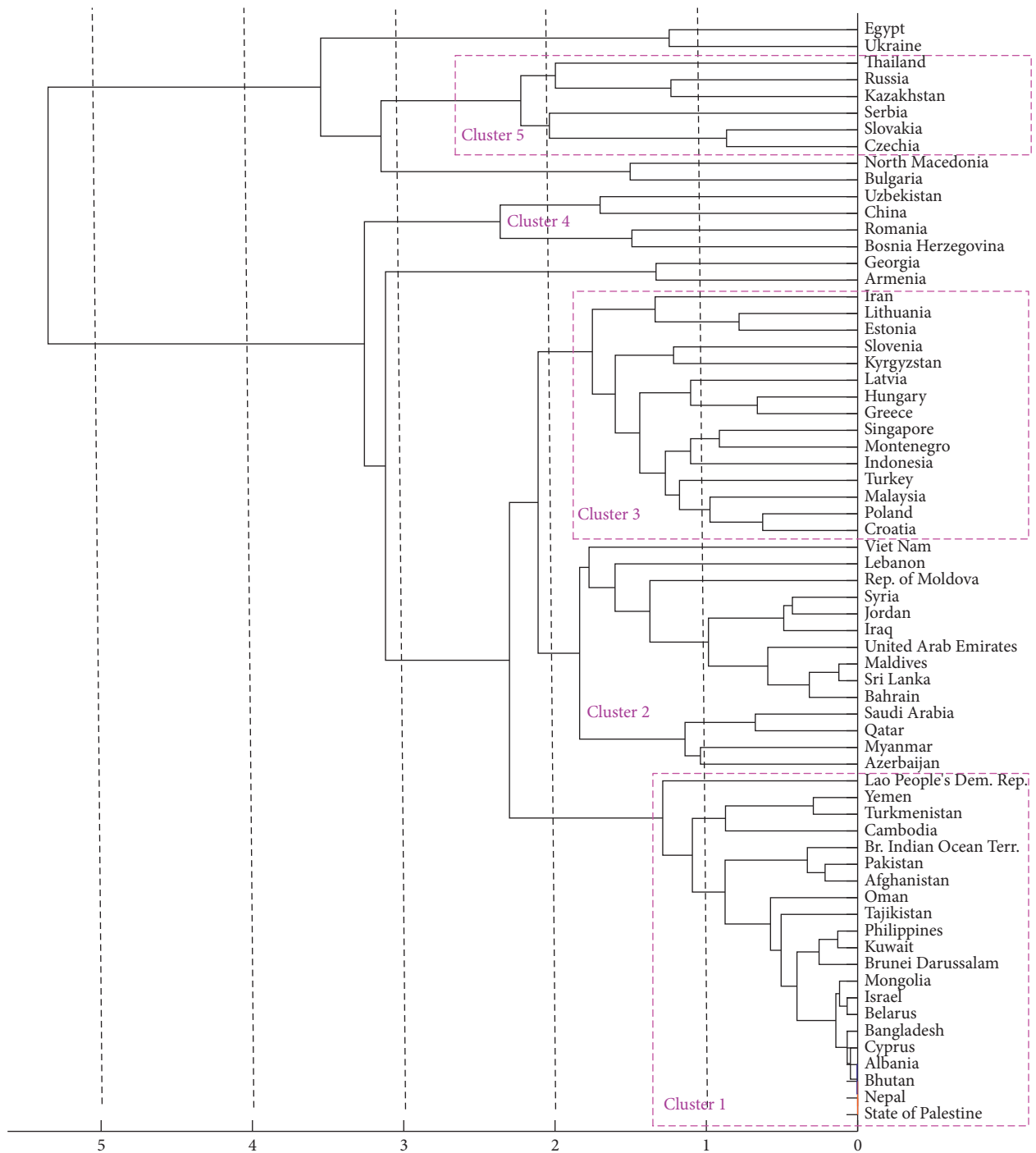


FIGURE 9: Dendrogram of cluster analysis.

of the OBOR countries in the year of 2018. Cluster 3 includes Turkey, Greece, Iran, Poland, Singapore, Hungary, and other emerging economies with relatively high annual GDP growth and GDP per capita simultaneously. Cluster 4, represented by China, has a high level of GDP income and annual GDP growth. However, the GDP per capita of these countries is

lower than the average level. Cluster 5 includes Russia, Kazakhstan, Czechia, Slovakia, and Serbia with high GDP level, but their annual GDP growth and GDP per capita are not high.

By comparing the sorting results of the above EVC scatter plot with the classification results of cluster analysis, it can be seen that the classification of most countries is

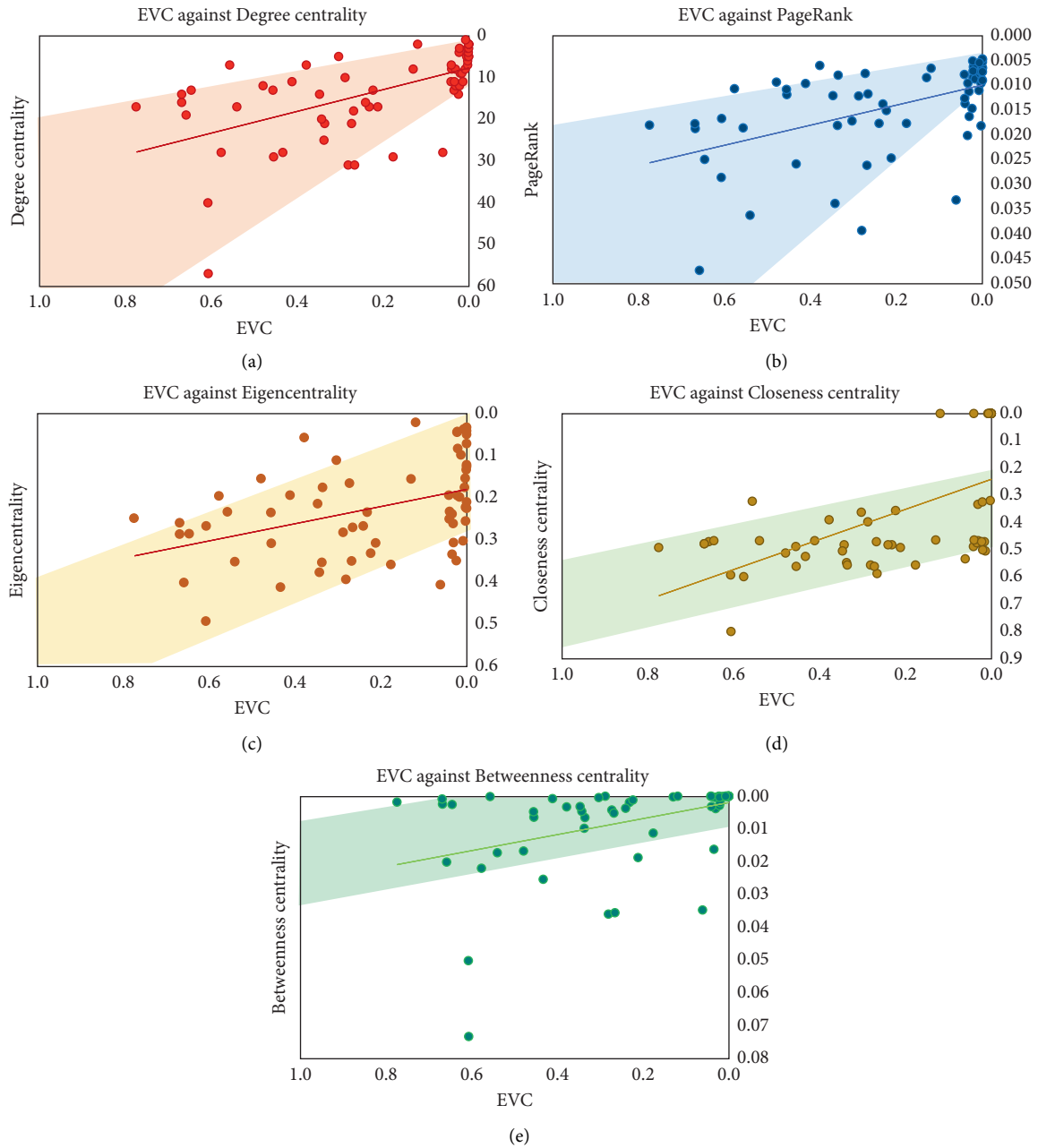


FIGURE 10: Scatterplots of EVC values against another centrality measure. EVC against (a) degree centrality, (b) PageRank centrality, (c) eigencentrality, (d) closeness centrality, and (e) betweenness centrality.

consistent. In all, in addition to geographical distance, economic development level, economic growth potential, and per capita national income are all potential influencing factors of fossil energy trade.

5.5. Comparison with Benchmark Centralities. Finally, in order to evaluate the performance of the proposed method, we pay attention to the correlation between EVC ranking list and five classical centrality measures, i.e., degree centrality, PageRank centrality, eigenvector centrality, closeness centrality, and betweenness centrality, as depicted in Figure 10. It is obvious that each node's EVC are highly correlated with

other centrality indicators. This shows that the method proposed is reasonable and comprehensive in identifying influential nodes.

6. Conclusions

In this paper, we propose a novel evidential ranking method based on complex network analysis and evidence theory. The combination of local structure, global structure, and uncertainty is taken into consideration in the construction of evidence centrality. Then, a performance analysis is conducted on fossil energy trade along the OBOR. We utilize the network efficiency to simulate the influence of top-ranked

nodes and demonstrate the superiority of EVC. At last, various classical centrality measures are also analyzed to identify the advantages of the proposed method.

The results of node centrality based on D-S theory show that the distribution of weighted edges has obvious heterogeneity which is superior to node strength distribution. That is, only a few pairs of countries have high relevance relationships, while most pairs of countries have low relevance relationships. For influential countries, along with the increase of average EVC values, the volatility also increases. But, some countries with higher average EVC tend to be driven by one or two specific years, such as Czechia and Slovakia. Relative to these countries, Russia, Kazakhstan, and other resource-based and export-oriented countries maintain the core positions. Finally, the clustering results show that geographical distance, income level, GDP per capita, and GDP growth rate are the potential driving forces of fossil energy trade.

Data Availability

All relevant data are publicly available at <https://comtrade.un.org/>, <https://data.worldbank.org/>, and <https://www.oecd.org/>.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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