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Finding Global Liquefied Natural Gas Potential Trade Relations Based on Improved Link Prediction

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Abstract: Unstable factors such as international relations, geopolitics, and transportation routes make natural gas trade complex and changeable. Diversified and flexible sources of liquefied natural gas (LNG) can guarantee the energy supply security of natural gas-consuming countries. Therefore, it is very important to find potential natural gas trade links to help the government find potential partners and prepare strategically in advance. In this paper, the global LNG network is taken as the research object. In order to fully consider the importance of nodes and the influence of economic and political factors, the "centrality degree" and "node attraction degree" are added into the link prediction algorithm, and multifactor coupling is carried out. The reliability of the improved algorithm is verified using the area under the curve (AUC) evaluation index, and the prediction results are analyzed. The results are as follows: Trinidad, Russia, Algeria, Nigeria, Angola, and Equatorial Guinea (Eq. Guinea) are more likely to establish new LNG trading relationships with other countries. For all potential trade relationships, potential relations involving the above countries are more likely to be realized within 5 years, while potential relations involving China, India, Japan, and South Korea are more likely to be realized within 2 years. China, India, and South Korea are more likely to import LNG from Algeria, and Taiwan Province is more likely to import LNG from Algeria, Angola, Eq. Guinea, and America. On the basis of the above study, states and governments can give priority to the above countries and regions when dealing with the possible LNG supply crisis.

Keywords: liquefied natural gas; potential trade; link prediction

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1. Introduction

Environmental pollution and the energy crisis are two major problems in the development of many countries. As a resource-rich, clean, and efficient energy source, the share of natural gas in the energy consumption structure is gradually expanding. In recent years, the increase in proven reserves of natural gas and the improvement of transportation and storage capacity have further promoted the growth of global natural gas trade. However, the distribution of natural gas is extremely uneven. According to British Petroleum's (BP) statistics, the Asia-Pacific region, as the main force of natural gas consumption, imported 70% of the global total demand in 2020, while the proven natural gas reserves in the Asia-Pacific region only accounted for 8.8% of the global total. At the same time, more than 60% of the world's total LNG comes from America, Qatar, Australia, Russia, etc., which means that the dominant power of LNG export is in the hands of a few countries. The influence of investment environment and political laws makes the stable supply of LNG projects face national politics and trade risks.

In addition, in most countries that have issued the goal of "carbon neutrality" at present, natural gas still plays the role of the main force of energy supply, and Asian countries such as China, Japan, and South Korea have also explicitly proposed to achieve the goal around the middle of the 21st century. The Russia–Ukraine conflict, the European energy crisis, the change of natural gas delivery mode, and other changeable situations have further pushed the big natural gas-consuming countries to find more potential trading partners, thus making the trade relations more diversified. Therefore, it is necessary to estimate the potential trade relationship of LNG using a reasonable forecasting method, so as to help the governments to adjust their energy strategies in time and improve the safety of natural gas trade when there are problems in the existing trade relationship.

This paper adopts a novel prediction method to find the potential partnerships in international LNG trade, i.e., the link prediction method. This method can not only distinguish various factors clearly and intuitively by using the quantitative results, but also calculate the accuracy of the prediction method, which plays a very good role in the prediction of trade links [1]. Therefore, this paper builds a global LNG trade network from 2010 to 2020 using the network link prediction method, with the countries or regions participating in LNG trade as nodes and the actual trade relations between countries or regions as links, and then uses the accuracy evaluation index AUC to evaluate the accuracy of the link prediction algorithm. In order to fully consider the importance of nodes in the network and the influence of external factors on the prediction results, node centrality and node attraction are introduced into the algorithm, and the prediction accuracy is further improved using a multifactor coupling algorithm. By comparing the predicted results with the actual trade relations, the possible future trade partnerships of the global LNG demanders can be more accurately explored, and the theoretical basis for ensuring trade security and diversification can be provided.

The main work and novel contributions of this paper are as follows. Firstly, the link prediction index based on the proximity of local information is improved, so that the attribute information of nodes can be used more effectively. Secondly, the information of the network structure is made full use of, and the best algorithm is selected from various link prediction indices to improve the prediction accuracy. Lastly, in the prediction of LNG trade network, according to the actual situation in trade exchanges, the consideration of political, economic, and other practical factors is added to make the prediction results more realistic.

The remainder of this paper is organized as follows: Section 2 reviews the literature in the relevant fields; Section 3 introduces the algorithm steps and indices of link prediction; Section 4 confirms the feasibility of the proposed indices and analyzes the empirical results; Section 5 discusses the results, include making estimations about future trade relations; and Section 6 presents the derived conclusions.

2. Literature Review

2.1. Studies on Global Natural Gas Trade

In recent years, in order to cope with climate change and environmental pollution, countries have accelerated the exploration of clean and low-carbon energy; accordingly, the consumption of natural gas has increased steadily. Due to the uneven distribution of natural gas resources and the seasonal difference between supply and demand, trade flows in regional and global areas have emerged. More and more studies have emerged on natural gas trade in academic circles. Some scholars have studied the present situation and potential of natural gas trade, which provides a reference for the states and governments to formulate long-term and short-term strategies of natural gas trade. Lin (2021) simulated the supply and demand changes of regional LNG market in a low-carbon scenario by 2050 using a partial equilibrium model and provided suggestions for the government and energy companies [2]. Egging (2016) analyzed the capacity investment and trade trend of natural gas in some countries in the face of the Russia–Ukraine conflict, the change of final demand level, and the shale gas supply potential [3]. Guo (2019) used the improved gas game-risk model to predict the changes of the global natural gas market under changes of the China–America natural gas tariff policy and demand level [4]. Kan (2020) analyzed the evolution of international natural gas consumption structure and import and export mode for 11 consecutive years using a time series, providing a basis for the formulation of future natural gas trade policies [5].

In order to further understand the characteristics of natural gas trade, some scholars devoted themselves to mining the key factors that affect natural gas trade. Chen (2019) used the extended logarithmic mean divisor index to identify the distribution of energy flow and natural gas consumption in typical countries, and concluded that energy intensity, economic growth and population drove the increase in natural gas supply and consumption [6]. Farag (2021) explored the determinants of international natural gas trade from the perspective of political economy and suggested that institutional gap and economic sanctions had a great influence on natural gas trade [7]. Rasoulinezhad (2022) analyzed the energy trade pattern of Central Asian economies based on the generalized moment method of transnational trade force method and held that urbanization level and geographical factors are crucial to shaping the energy trade policy of Central Asia [8]. Zhang (2018) concluded that LNG trade is mainly affected by the economic scale of the demand side by identifying the influencing factors of global LNG [9].

With the increasing importance of LNG trade, some scholars have identified the main forces of the LNG competitive market. Magnier (2019) constructed a simplified coarse-grained model based on four variables of LNG demand, liquefaction capacity, utilization rate of liquefaction capacity, and transportation distance, and predicted the LNG import trade relationship between the Asia-Pacific region and Europe in 2030 from the perspective of trade security [10]. Meza (2021) predicted the competition and trade challenges among LNG-trading countries using the agent-based predictive model and held that Qatar would still be the most competitive LNG supplier in 2030, and that United States would be its emerging competitor [11]. Li (2021) considered that the natural gas trade in Southeast Asian countries such as China and India developed at a high speed on the basis of analyzing the evolutionary characteristics of PNG (pipeline natural gas) and LNG network in countries along the BRI (Belt and Road Initiative) [12]. Peng (2020) combined the related indices of complex networks with vessel trajectory data, quantitatively analyzed the global LNG network from the perspective of port scale, and considered that Singapore, Ras Laffan, and Khawr Fakkan played an important role in the LNG network [13].

2.2. Studies on International Trade Prediction and Its Methods

In the past, the gravity model was mostly used to explore international trade relations. Barnes (2015) estimated the relationship between the trade volume of PNG, LNG, and the whole natural gas market and the distance between countries using the gravity model and believed that LNG trade contributed to the de-regionalization of the natural gas market [14]. Emikonel (2022) used the trade gravity model to analyze the trade among ASEAN (Association of South East Asian Nations), APEC (Asia-Pacific Economic Region), and China, and thought that energy trade plays an important role [15]. Bakouan (2022) studied the export, industrial, and agricultural trade of 40 African countries for many years through the spatial autoregressive gravity model and concluded that intra-African trade was mainly influenced by political factors [16]. Chen (2022) embedded the gravity equation into the exponential decomposition equation to explore the impact of bilateral trade on energy consumption in BRICS (Brazil, Russia, India, China, and South Africa) countries, and concluded that trade increased fossil energy consumption by promoting economic development [17].

Although the gravity model relates the international trade flow and its determinants, as well as measures the trade potential between countries from the key factors, its emphasis is still on the study of existing trade relations, and the prediction of potential trade relations is not ideal [18]. Therefore, many scholars used the complex network method to study international trade and found the law of trade evolution by analyzing the overall characteristics, associations and related indicators of the trade network. Du (2017) used complex network method to study the relationship and evolution characteristics of international oil trade from 2002 to 2013 [19]. Wang (2022) used the complex network method to build the global fossil energy trade network from 1998 to 2017 and analyzed the trade volume using the point-wise mutual information method to reveal the fossil energy trade dependence among countries [20]. Chen (2018) identified the global, regional, and national energy flow patterns from the perspective of complex networks based on the environmentally ex-tendered input–output analysis [21]. Chen (2022) built a weighted orientation network of global coal trade to determine the core countries and hub countries of coal trade and developed different competitive strategies for different countries according to the competitive advantage theory [22]. Recently, the more cutting-edge research method of trade relations has been to combine link prediction with complex networks. Link prediction can predict new links through appropriate algorithms on the basis of the structure of existing networks [23]. Guan (2016) took the number of trading partners of countries in the international crude oil unweighted nondirectional trade network in 2014 as the basis for predicting the potential international crude oil trade relationship and divided the relevant countries into different trade roles according to the crude oil import, export, and proven reserves, making the prediction more practical [24]. Zhou (2022) predicted the crude oil competition relationship on the basis of the global crude oil import and export competition network and link prediction method, combined with the analysis of geopolitical, economic, and social emergencies [25]. Zhang (2021) constructed an undirected weighted network of international trade of lithium carbonate by using complex network method and explored the potential cooperation relationship of lithium carbonate resources between small exporting countries and importing countries using the link prediction method based on local information proximity [26]. Liu (2019) selected the best algorithm from four mainstream link forecasting methods based on local information proximity to forecast the international bauxite trade, which provided a new idea for the bauxite trade partnership forecast [27]. Liu (2020) identified the utilization level of cobalt resources in various countries according to the trade data of cobalt ore and cobalt waste and scrap, and then evaluated the potential trade relationship among countries with different utilization levels by link prediction method [28]. Feng (2017) used the AUC evaluation index to select the optimal link prediction algorithm, compared the weighted and unweighted networks of LNG trade and predicted the potential trade relationship of LNG [29]. Filimonova (2022) built a directed network of international LNG trade in 2019 and used the link prediction method to find potential trade routes to provide decision support for countries and their governments [30].

Some scholars proposed that the traditional link prediction algorithm does not fully consider the influence of nodes in the network [31,32]. Zhou (2022) proposed a community adaptive network based on node centrality to measure the different contributions of nodes and their neighbors in the network, effectively utilizing the community structure in the network [33]. Hajarathaiah (2022) proposed the nearest neighbor trust ranking index based on the structural attributes of neighbor nodes to evaluate the importance of each node [34]. Gao (2013) established a bionic centrality measurement model to measure the degree of node influence in link prediction from the biological point of view [35].

In addition, in order to better capture and combine the local, quasi-local, and global characteristics of nodes in the network and improve the accuracy of link prediction, Li (2022) introduced naïve Bayesian algorithm into the weighted link prediction model [36]. Yu (2022) proposed a link prediction method based on multi-order local information [37]. Anand (2022) proposed an improved link prediction algorithm which integrated node centralities, similarity measures, and machine learning classifiers [38]. Zhu (2022) proposed a time network link prediction method combining the network collective influence method, random walk index, and centrality [39]. Zhao (2022) put forward a link prediction method using the induction matrix of node characteristics [40]. It turned out that the accuracy of these models was indeed improved.

Previous studies have promoted the development of the research fields of natural gas trade, trade forecast, etc. Through combing the existing literature, it was found that there is still room for further research. Although many scholars have used the link prediction method to predict the international energy trade, the method remains a classic link prediction algorithm based on the proximity of local information. In spite of its simple program and fast calculation speed, this kind of algorithm has poor performance in node information utilization. Therefore, this paper improves this algorithm, and selects the best among several link prediction algorithms based on local information proximity, path proximity, and random walk proximity, such that the node information can be fully utilized as best as possible. At the same time, although many scholars believe that political, economic, geographical distance, and other factors have a certain influence on natural gas trade, there is no quantitative consideration of these practical factors in the current research of international LNG trade link prediction. Therefore, this paper comprehensively considers the influence of political, economic, geographical distance, and other major factors on the prediction of international LNG trade links through quantitative indicators so as to improve the prediction accuracy.

3. Methods

3.1. Link Prediction Model

For an undirected network $G(V, E)$, the node set V is formed by N nodes in the network, the connected link set E is formed by existing links among these nodes, set U^0 is formed by links that do not exist among these nodes, and set $U = \frac{N(N-1)}{2} = E + U^0$. The link prediction algorithm predicts the missing links and possible links in the set U^0 through the known node set V and connected link set E in the network [23].

The process of link prediction can be divided into the steps below. A brief flowchart is given in Figure 1.

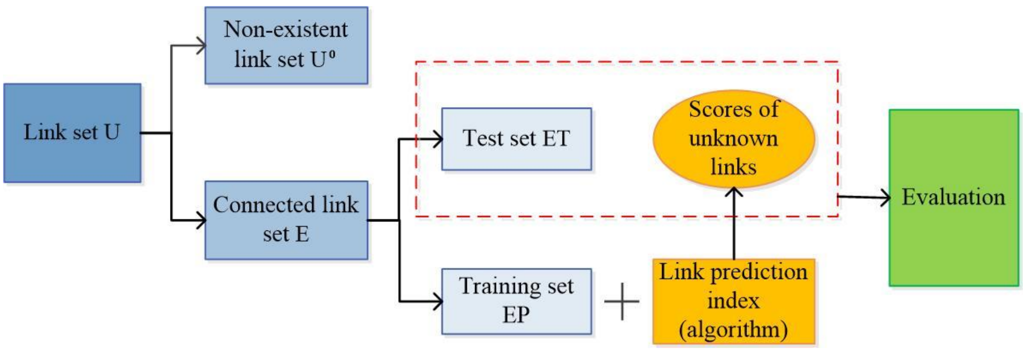

Figure 1. Flowchart of link prediction.

Step 1: Divide the connected link set E randomly.

The connected link set E is randomly divided into training set E^P and test set E^T. The former is used as known information to calculate the score of connected links, and the latter is used to test the accuracy of predicted connected links. Both satisfy the relationship: $E^P \cap E^T = E$, $E^P \cup E^P = \varnothing$. The division ratio is considered to affect the accuracy of calculation results, whereby a higher division ratio of E^P generally leads to higher accuracy of the algorithm. Therefore, $E^P : E^T = 1 : 9$ was established.

Step 2: Calculate the scores of unknown links.

According to step 1, only the structure and information of the links in the training set E^P are known; thus, a link prediction index is selected to calculate the scores of the remaining unknown links according to the known information, and the scores are arranged in descending order. Specific link prediction indices are described in Section 3.2.

Step 3: Evaluate the accuracy of link prediction indices.

It can be considered that a higher score denotes a greater probability that a link will be generated between two nodes. Theoretically, the scores of links in the test set E^T rank high. Therefore, the prediction accuracy of the indices can be evaluated according to the calculated ranking of links in the test set E^T and the set U^0.

The prediction effect of link prediction index can be judged using model evaluation index AUC. AUC is a commonly used model evaluation index in the field of machine learning, and it is also the most commonly used index to measure the accuracy of link prediction. This method can measure the accuracy of the algorithm as a whole, and it can be understood as the probability that the score of a randomly selected connecting link is higher than that of a randomly selected nonexistent connecting link. If the score of the randomly selected link is higher, 1 point is added; otherwise, 0 points are added. Equality is represented by 0.5 points. The algorithm is as follows:

$$\mathrm{AUC} = \frac{n' + 0.5n''}{n}, \tag{1}$$

where n represents the times of independent comparisons, i.e., the times of sampling; n' represents the times in sampling comparison that the score of the links in the test set E^T is greater than that in the non-existent link set U^0, and n'' represents the times that the two scores above are equal. A closer AUC to 1 denotes a more accurate current link prediction index.

Step 4: Calculate the average precision of link prediction indices.

Steps 1–3 are repeated n times, and the average value of AUC is taken as the final accuracy of this link prediction index.

3.2. Common Link Prediction Indices

3.2.1. Indices Based on Local Information Proximity

The link prediction algorithm based on the local information proximity emerged first, and it is widely used because of its simple design and short operation time. This kind of algorithm mainly considers the situation of common neighbors. Among them, the common neighbors index is the simplest and most intuitive index, which only considers the number of common neighbors of two nodes, while the Adamic–Adar, resource allocation and preferential attachment indices also consider the role differences of common neighbors, whereby the degree of common neighbors reflects their contribution in the network.

1. Common neighbors index (CN)

The CN index takes the number of common neighbors of two nodes x and y as the basis to measure the possibility of establishing links between two nodes, whereby more common neighbors between two nodes denotes a greater possibility of creating links. This index is defined as

$$S_{xy}^{\mathrm{CN}} = |\Gamma(x) \cap \Gamma(y)|, \tag{2}$$

where $\Gamma(x)$ and $\Gamma(y)$ represent the set of neighbors of node x and y, respectively, and the set of their common neighbors is $\Gamma(x) \cap \Gamma(y)$.

2. Adamic–Adar index (AA)

The AA index takes the influence of the common neighbors of nodes x and y into consideration, considering the contribution of the common neighbor with a small degree to be greater than that with a large degree. In other words, if the degree of a common neighbor of nodes x and y is larger, the contribution of the common neighbor to these two nodes is smaller. This index is defined as

$$S_{xy}^{\mathrm{AA}} = \sum_{z=\Gamma(x)\cap\Gamma(y)} \frac{1}{logk_z}, \tag{3}$$

where k_z represents the degree of a common neighbor of two nodes x and y.

3. Resource allocation index (RA)

From the perspective of resource allocation, the RA index follows the idea that each node has certain resources, and these resources will be equally distributed to their neighbors. Therefore, the common neighbor of x and y can be regarded as the medium of resource transmission between the two nodes, and the amount of resources allocated reflects the proximity of the two nodes. This index is defined as

$$S_{xy}^{\mathrm{RA}} = \sum_{z=\Gamma(x)\cap\Gamma(y)} \frac{1}{k_z}. \tag{4}$$

4. Preferential attachment index (PA)

The idea of the PA index is that a greater degree of two nodes denotes a greater possibility of interconnection. This index is defined as

$$S_{xy}^{\mathrm{PA}} = k_x k_y. \tag{5}$$

3.2.2. Indices Based on Path Proximity

The link prediction index based on path proximity takes more information into account than the index based on local information, while giving up redundant information that has no or little contribution to the prediction accuracy. This method needs to consider paths of all lengths in the network, which has high complexity and a long operation time.

1. Local path index (LP)

The LP index considers that a shorter path length between two nodes denotes a closer relationship between the two nodes, taking the influence of the second-order and third-order neighbors of the nodes into account. This index is defined as

$$S_{xy}^{\mathrm{LP}} = \left(A^2\right)_{xy} + \alpha\left(A^3\right)_{xy}, \tag{6}$$

where α represents a variable parameter, and A represents an adjacency matrix. $(A^m)_{xy}$ represents the number of paths with a length of m between nodes x and y.

3.2.3. Indices Based on Random Walk

The proximity index based on random walk is transformed from the random walk model, considering the topological information of the whole network; thus, the calculation is very time-consuming.

1. Average commute time index (ACT)

Let the average step length of a random walk particle from node x to node y be m; then, the average commuting time between two nodes is $n(x,y) = m(x,y) + m(y,x) = M(l_{xx}^{+} + l_{yy}^{+} - 2l_{xy}^{+}$. The ACT index follows the idea that a shorter commuting time between two nodes denoted that they are closer. This index is defined as

$$S_{xy}^{\mathrm{ACT}} = \frac{1}{l_{xx}^{+} + l_{yy}^{+} - 2l_{xy}^{+}}, \tag{7}$$

where l_{xy}^{+} represents the element in the row x and column y of the Laplace pseudo-inverse matrix

3.3. Indices of Added Centrality

The link prediction indices based on local information proximity usually only consider the number of common neighbors and the node degree of a node pair, but the information contained by the node degree is relatively little; for example, the closeness and influence of nodes in the network are not taken into account, which cannot comprehensively reflect the proximity of network nodes. Centrality is an important parameter to judge the influence of nodes in complex networks, which mainly includes degree centrality, betweenness centrality, and closeness centrality. Using the centrality value instead of the traditional degree value in link prediction can better reflect the structural characteristics of the network and make the prediction results more accurate. It should be noted that the CN index only takes the number of common neighbors as a measure of the possibility of establishing links between two nodes, but does not consider the contribution difference of common neighbors, i.e., the degree value of common neighbors; therefore, the centrality cannot be used to improve this index. At the same time, in heterogeneous networks such as the international LNG network, because of the high degeneracy of the CN index, the CN values of many candidate links are the same, and the link discrimination is far worse than other indices according to the proximity of local information; therefore, the prediction effect is not good. Accordingly, the CN index is not optimized below.

3.3.1. Definition of Centrality Index

1. Degree centrality

Degree centrality is the most intuitive centrality index in traditional centrality, which shows the importance of a node in the network. It uses the degree of a node to emphasize the individual value of the node. In undirected networks, the degree centrality value is the number of connected links of a single node. More links of a node indicate a closer relationship, a greater audience reached by the information when spread through this node, and a wider spread range. The degree centrality of node i can be expressed by the number of all connected links of the node. The formula is as follows:

$$C_D(i) = \sum_{j=1}^{n} x_{ij}(i \neq j), \tag{8}$$

where x_{ij} is the element of row i and column j in the adjacency matrix A. In the adjacency matrix A, if the nodes i and j are connected, a_{ij} is 1; otherwise, it is 0.

2. Betweenness centrality

Betweenness centrality refers to the proportion of the shortest path of any two nodes through node i to all the shortest paths in a complex network. It emphasizes the betweenness regulation ability of the node in the network. A shorter path through the node results in a higher betweenness centrality, indicating that the node has superior betweenness regulation ability in the network. The formula is as follows:

$$C_B = \sum_{s \neq v \neq t \neq V} \frac{\sigma_{st}(v)}{\sigma_{st}}, \tag{9}$$

where $\sigma_{st}(v)$ represents the number of shortest paths between nodes s and t passing through node v, and σ_{st} represents the number of shortest paths between two nodes.

3. Closeness centrality

Closeness centrality is related to the information flow transmission between nodes, and it is used to indicate the ability of nodes to avoid being controlled by other nodes and transmit information to other nodes in the network. Actually, closeness centrality indicates the proximity of the "distance" between nodes in the whole network, which reflects the reciprocal of the sum of the shortest paths from one node to other nodes. A greater closeness centrality of a node denotes a smaller sum of distances between this node and other nodes, as well as less time taken for the information flow of this node to other nodes in the network, thus reflecting higher efficiency. The closeness centrality of node i can be expressed by the reciprocal of the sum of the shortest distances between node i to other nodes in the network. The formula is as follows:

$$C_c(i) = \frac{1}{\sum_j^n d_{ij}}, \tag{10}$$

where n represents the number of nodes in the network, and d_{ij} represents the number of shortest paths between two nodes i and j.

3.3.2. Indices of Added Centrality

Through comprehensive consideration of the degree centrality, betweenness centrality and closeness centrality, according to the information level provided by the centrality value in evaluating the centrality degree of nodes, the entropy weight method is used to give weight to the three kinds of centrality, and the proximity centrality value of a single node C_K is calculated as follows:

$$C_K = a_1 C_D + a_2 C_B + a_3 C_C. \tag{11}$$

Then, the indices are improved on the basis of local information proximity, while the improved link prediction indices are defined with centrality as CAA, CRA, and CPA indices.

$$S_{xy}^{\mathrm{CAA}} = \sum_{z \in |\Gamma(x) \cap \Gamma(y)|} \frac{1}{logC_{K_z}}. \tag{12}$$

$$S_{xy}^{\mathrm{CRA}} = \sum_{z \in |\Gamma(x) \cap \Gamma(y)|} \frac{1}{C_{Kz}}. \tag{13}$$

$$S_{xy}^{\mathrm{CPA}} = C_{K_x} C_{K_y}. \tag{14}$$

3.4. Node Attraction Index

All the above indices can be considered link prediction indices based on network structure characteristics. However, when predicting the potential links in the network, it is still one-sided to consider only optimizing the network structure characteristics. For example, the indices based on local information proximity only depend on the known topology information in the network, and their prediction results are easily affected by the sparsity of network data. In actual networks, economic development, supply and demand, national policies and other factors affect the links between nodes [41,42]. The complexity of influencing factors makes it impossible to add only a single influencing factor to analyze the characteristics of the whole network system in the prediction process. Therefore, the index "node attraction" [43] is introduced to comprehensively consider the influence of influencing factors on the actual network from many aspects.

Calculation of Mutual Attraction between Nodes

In a network, it can be considered that any two nodes attract each other, but the attraction between different node pairs is strong or weak. When this attraction is strong enough, the two nodes are linked, which shows the LNG trade relationship between two countries or regions in the global LNG trade network. When this attraction is too weak, there is no direct trade activity between the two nodes, and there is no direct link relationship in the topological network, but the two nodes may have indirect trade activity through other nodes.

Accordingly, the concepts of network node attraction and attraction degree are given. Network node attraction is the ability of a node to link with other nodes by virtue of its own advantages. Network attraction degree refers to the difficulty for a node to establish connections with other nodes in the process of network evolution. A greater attraction degree denotes that it is easier to establish links with other nodes [44].

Relevant scholars have identified the key factors in natural gas trade using various methods, suggesting that energy intensity [6], political factors [7,45], geographical location [8], and economic scale [46] have great influence on natural gas consumption and supply. Zhang (2018) [9] analyzed the global LNG trade from multiple dimensions by using the trade gravity model, which further confirmed the above conclusions. According to the above research results, this paper selected the GDP (gross domestic product) of importing countries, LNG consumption of importing countries, political stability of exporting countries, and natural gas output of exporting countries as influencing factors, as well as the distance between countries or regions, as outlined below. The data sources are shown in

Table 1. The entropy weight method was used to assign the above influencing factors and calculate the attraction degree of each country. The formula is as follows:

$$Z_i = 100 \times \sum_{j=1}^{n} r_{ij} W_j, \tag{15}$$

where W_j represents the weight of the influencing factors, and r_{ij} represents the standardized value of the influencing factor j in the country or region i.

Table 1. Data sources of influencing factors.

Variable	Unit	Data Source
GDP	US dollars	World Bank
Natural gas consumption	Billion cubic meters	BP
Natural gas production	Billion cubic meters	BP
Political Stability index	-	WGI
Distance	Kilometers	CEPII

Attraction degree is an attribute of the node itself, just like how every object has a mass, and it is a positive scalar. A greater attraction degree denotes a greater attraction between two nodes. According to Newton's universal gravitation formula, it is extended to calculate the attraction between nodes, and a gravitational model of interaction between nodes is constructed [47]. This model indicates that the attraction between nodes is directly proportional to the product of the attraction degree of two nodes, and inversely proportional to the square of the distance between nodes.

$$F_{xy} = G \frac{Z_x Z_y}{D_{xy}^2}, \tag{16}$$

where F_{xy} represents the mutual attraction between nodes, G represents the node attraction coefficient, Z_x and Z_y represent the attraction degrees of nodes, and D_{xy} represents the distance between nodes x and y.

3.5. Coupling Proximity Index

Whether the nodes in the network are linked or not is by no means determined by a single factor. It is necessary to further couple different types of indices and combine the network structure and node attribute information to comprehensively consider the link mechanism of the network. Firstly, the influence of external political and economic factors on links in the network is considered, and attraction is taken as one of the main coupling factors. Then, two indices with the highest accuracy are selected from the remaining nine link prediction indices based on network structure characteristics for multifactor coupling [48], which can be defined as

$$S_{xy}^{Final} = \lambda_1 F_{xy} + \lambda_2 S_{xy}^1 + (1 - \lambda_1 - \lambda_2) S_{xy}^2, \tag{17}$$

where F_{xy} represents the attraction index, and S_{xy}^n represents a link prediction index based on the characteristics of network structure. The parameter coupling coefficient is $\lambda \in [0, 1]$, $\lambda_1 + \lambda_2 = 1$. The arbitrary step value of λ is 0.1. When λ is 1, the coupling algorithm returns to the initial algorithm with the coefficient of 1. In order to ensure the rationality and accuracy of the coupling algorithm, the proximity matrix parameters of each coupling index are divided by their maximum values, i.e., the coupling calculation is carried out after normalization measures are taken.

4. Experiment and Evaluation

4.1. Accuracy Analysis of Each Link Prediction Index

The global LNG trade data from 2010 to 2020 were collected through the Shipping Intelligence Network (SIN), covering 11 years, involving 60 countries or regions and 2610 pieces of trade data. Then, 11 annual undirected LNG trade networks were built with trading countries as nodes and trade relations between countries or regions as links.

Each link prediction index was used to predict the actual global LNG network in each year. Here, 90% of the links in the link set were included in the training set and 10% were included in the test set. Through MATLAB simulation, 10 independent experiments were carried out, and the average AUC of each year and the average AUC of the 11 years were obtained, as shown in Table 2, where CAA, CRA, and CPA represent the improved link prediction indices after adding centrality.

Table 2. AUC values of link prediction indices.

	CN	AA	RA	PA	LP	ACT	CAA	CRA	CPA
2010	0.669	0.681	0.681	0.928	0.957	0.516	0.685	0.691	0.954
2011	0.659	0.675	0.679	0.927	0.964	0.537	0.677	0.687	0.955
2012	0.705	0.719	0.728	0.920	0.950	0.531	0.721	0.733	0.940
2013	0.798	0.805	0.806	0.932	0.953	0.638	0.817	0.826	0.946
2014	0.813	0.822	0.827	0.916	0.943	0.634	0.831	0.845	0.929
2015	0.772	0.786	0.792	0.914	0.932	0.653	0.791	0.802	0.939
2016	0.720	0.733	0.737	0.869	0.912	0.665	0.733	0.742	0.901
2017	0.718	0.734	0.746	0.886	0.929	0.678	0.738	0.757	0.936
2018	0.689	0.695	0.698	0.865	0.909	0.745	0.697	0.711	0.918
2019	0.604	0.628	0.651	0.853	0.915	0.729	0.629	0.666	0.913
2020	0.593	0.605	0.616	0.829	0.907	0.732	0.606	0.626	0.903
Average	0.704	0.717	0.724	0.894	0.934	0.642	0.721	0.735	0.930

As shown in Table 2, the AUC accuracy was basically above 0.6, and the accuracy of the algorithm was high. Among the indices based on local information proximity, the prediction accuracy of AA, RA, and PA indices was higher than that of the CN index, which is also related to the fact that the contribution of common neighbors was not considered in the CN index, as mentioned above. Among all indices based on network structure characteristics, the LP index had the best prediction effect, with an AUC value of 0.934. The PA index based on local information proximity had the second-best prediction effect, with an AUC value of 0.894, while the ACT index based on random walk had a poor prediction effect, which indicates that it is more appropriate to predict the structural characteristics of the global LNG network from the perspective of network path and local information proximity.

The AUC values of AA, RA, and PA after adding centrality were 0.721, 0.735, and 0.930, respectively, which are higher than the original values of 0.717, 0.724, and 0.894. Among them, the prediction effect optimization efficiency of the CPA index was the highest, with its AUC value increasing from 0.894 to 0.930, and its accuracy improving by 4.0%, as shown in Figure 2. This shows that the centrality of nodes can better reflect the importance of nodes in the network.

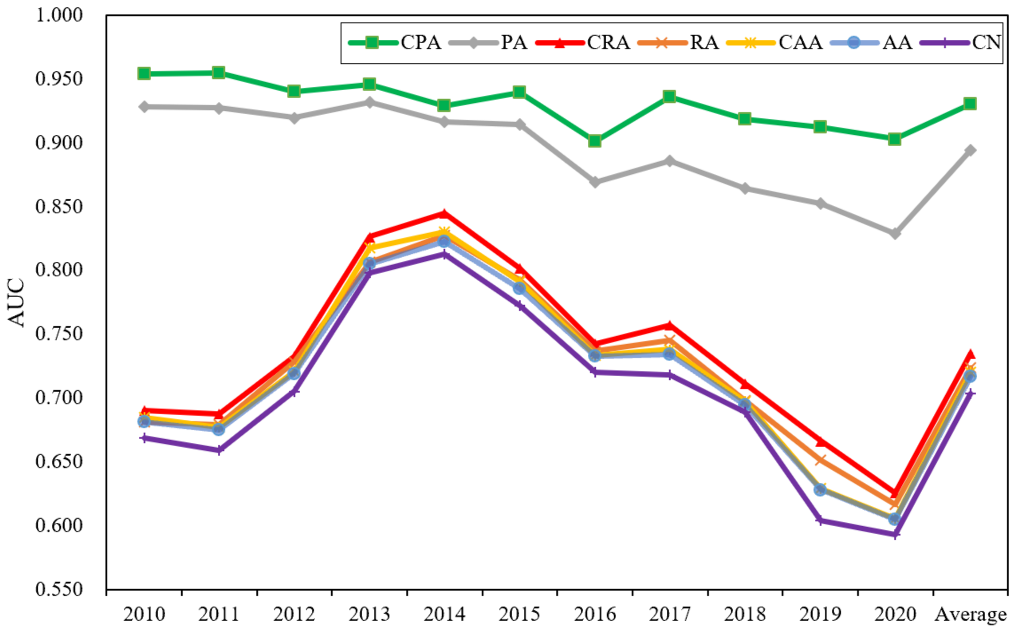

Figure 2. AUC value of indices after adding centrality.

To sum up, the two indices based on network structure with the highest prediction accuracy were the LP index and CPA index.

4.2. Accuracy Analysis of Coupling Index

The attraction index (ATT) was coupled with LP and CPA indices with the highest AUC values, as follows:

$$S_{xy}^{Final} = \lambda_1 F_{xy} + \lambda_2 S_{xy}^{\mathrm{LP}} + (1 - \lambda_1 - \lambda_2) S_{xy}^{\mathrm{CPA}}, \tag{18}$$

where $\lambda \in [0, 1]$, and the step size is 0.1. The AUC calculation steps were repeated to obtain the AUC average of each year and the AUC average of 11 years of the coupling algorithm. Figure 3 clearly shows the changes in the AUC average of the coupling algorithm under different values of λ. With the change in coefficient, the accuracy of the coupling algorithm also changed. When $(\lambda_1, \lambda_2) = (0.1, 0.8)$, the accuracy of the coupling algorithm reached the highest at 0.9397. Specifically, for the coupling algorithm of ATT, LP, and CPA, when the coefficient of the ATT index exceeded 0.1, a larger index coefficient led to a worse effect of the coupling algorithm is (Figure 3b). When the LP index coefficient became larger, the effect of the coupling algorithm was improved (Figure 3c). When the coefficients of the PA index ranged from 0 to 0.8, the effect of the coupling coefficient was good (Figure 3d).

As shown in Figure 4, compared with a single index, the coupling index achieved multi-attribute fusion, and the prediction performance was improved. The average AUC of each year was above 0.9, and the prediction effect was better. Although the coupling algorithm had no obvious improvement in prediction accuracy compared with the LP index and CPA index, this effect could not be ignored compared with other indices. This shows that the coupling index could effectively improve the prediction effect.

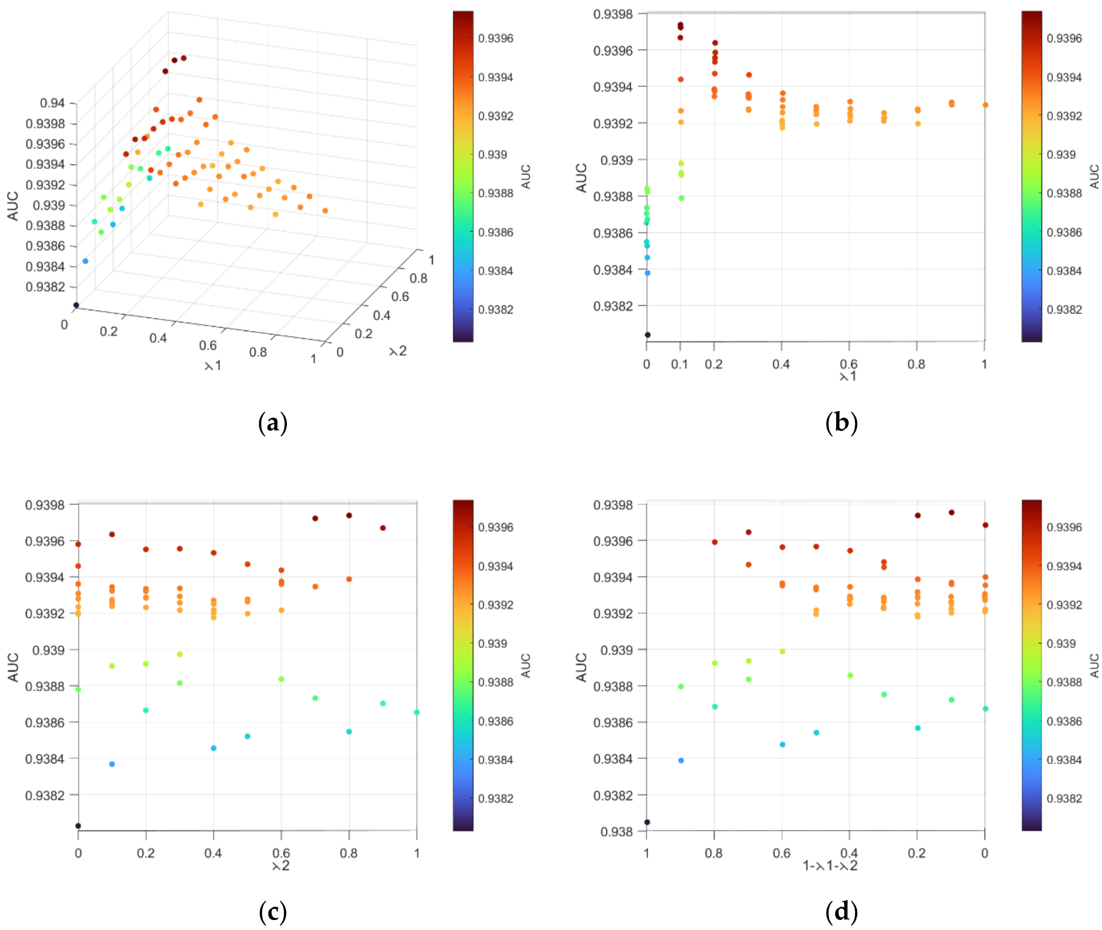

Figure 3. Changes in coupling algorithm accuracy with coefficient. (**a**) Influences of Coefficient λ_1, λ_2, and $(1 - \lambda_1 - \lambda_2)$ in coupling algorithm accuracy; (**b**) Influences of Coefficient λ_1 in coupling algorithm accuracy; (**c**) Influences of Coefficient λ_2 in coupling algorithm accuracy; (**d**) Influences of Coefficient $(1 - \lambda_1 - \lambda_2)$ in coupling algorithm accuracy.

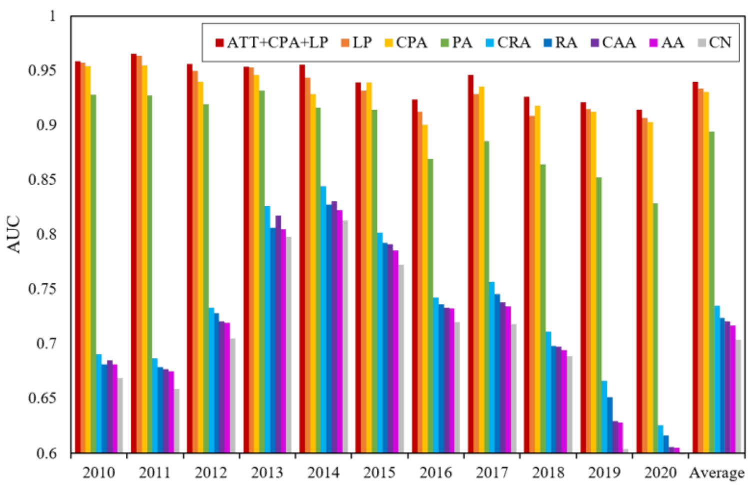

Figure 4. AUC value of coupling index.

4.3. Comparison between Potential Trade Links and Actual Situation

The coupling index of ATT, LP, and CPA was used to predict the potential trade relationship in the natural gas trade network. In the proximity ranking list, a higher ranking indicated a greater likelihood of nonexistent links coming to be true in the future.

The top ten nonexistent links in the 2010–2019 forecast results were extracted every year. As some trade relationship pairs appeared repeatedly in many years, there were 76 potential trade relationship pairs in the final forecast. Comparing the predicted results with the actual trade situation, 52 pairs of potential trade relations predicted in 2010–2019 were converted into actual trade relations before 2020, with a predicted success rate of 67.1%. Among them, 31 pairs were converted into actual trade within 1 year, 43 pairs were converted within 2 years, and 45 pairs were converted within 3 years, accounting for 86.5% of the successfully predicted trade relations. The remaining six pairs all turned into actual trade relationships within 4–5 years, suggesting that improved link prediction coupling algorithms are effective in discovering potential LNG trade relationships. Of the 52 successfully predicted relationships, 35 had actual trade relations before the prediction, accounting for 67.3%, indicating that trading countries are more inclined to re-establish trade relations with their previously familiar trading partners. The remaining 25 pairs of relationships failed to predict, i.e., 25 pairs of potential trade relationships predicted in 2010–2019 did not turn into actual trade relationships before 2020. Table 3 shows all the trade relationship pairs that failed to predict in 2010–2019. The actual trade data from 2010–2020 were taken from the LNG Trade and Transport 2021 report of Clarkson SIN. In Table 3, the light-blue block in each row indicates no actual LNG trade between the corresponding countries or regions in the corresponding year, but that, through the link forecast, the trade relationship is likely to occur after that year. The dark-blue block indicates that LNG trade indeed took place between the corresponding countries or regions in the corresponding year. When the light blue block is followed by a dark blue block, the predicted trade relationship became a reality. The "+" indicates the year in which the actual trade relationship existed before the potential relationship was predicted. Among them, the first 13 pairs of relationships with failed forecasts did not produce trade relations between 2010 and 2020, indicating that it is very unlikely for them to establish new trade relations in the future. However, the "Algeria–Kuwait" pair established trade relations in 2021, although they did not produce trade relations in the 11 years after 2010, which shows that these relationships with failed forecasts are still promising for the future. The last 12 failed pairs had trade relations before the forecast, but they may have terminated their trade relations for some reasons, remaining without trade relations after the forecast. For example, the suspension of the "Qatar–Dubai" trade relationship may have been due to the deterioration and breaking off of relations between Qatar and Bahrain, United Arab Emirates, and other countries headed by Saudi Arabia in 2017. The suspension of the "Trinidad–Japan" trade relationship may have been due to the decrease in demand for LNG caused by the return of nuclear power plants in Japan in 2018. The disappearance of the "Yemen–Spain" pair of trade relations may have been due to the decline in demand for LNG caused by Spain's increased dependence on renewable energy and domestically produced coal, as well as Yemen's domestic political challenges. The disappearance of the "Peru–Brazil" trade relationship may have been due to the fact that Brazil mainly relies on the import of pipeline natural gas. Before 2013, the import of pipeline natural gas in Brazil was more than twice that of liquefied natural gas. After 2013, the import of liquefied natural gas in Brazil increased, but pipeline natural gas still dominates.

Table 3. Relationship pairs that failed to predict in 2010–2019.

		2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Egypt	Brazil											
Nigeria	Chile											
Yemen	Brazil											
Peru	Kuwait											
Yemen	Argentina											
Portugal	Japan											
Algeria	Dubai											
Algeria	Kuwait											

Table 3. *Cont.*

		2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Peru	Egypt											
Peru	Pakistan											
Peru	Dubai											
America	Sweden											
Trinidad	Sweden											
Yemen	Spain	+										
Peru	Brazil	+										
Peru	India						+	+				
Trinidad	Belgium	+	+									
Norway	Dubai							+	+			
Qatar	Dubai	+	+	+	+	+	+	+	+			
Trinidad	Japan	+	+	+	+	+	+	+	+	+		
Angola	Japan				+	+			+	+		
Australia	Pakistan						+	+		+		
Trinidad	Pakistan							+	+	+		
Trinidad	Lithuania								+			
America	Finland											

The light-blue block in each row indicates no actual LNG trade between the corresponding countries or regions in the corresponding year. The dark-blue block indicates that LNG trade indeed took place between the corresponding countries or regions in the corresponding year. The "+" indicates the year in which the actual trade relationship existed before the potential relationship was pre-dicted.

It should be noted that the actual factors considered in the prediction method in this paper mainly came from the identified key factors of natural gas trade in the existing literature [6–9,45,46], such as energy intensity, political factors, geographical factors, and economic scale. However, in the actual natural gas trade, the trade is not only affected by the above factors; some factors, although their influence degree is limited, cannot be ignored sometimes. For example, because of its remote location and scarce natural gas resources, Japan has always been the world's largest importer of LNG (except in 2021). In 2011, due to the Fukushima nuclear power plant disaster in Japan, the demand for LNG increased sharply, while the nuclear power restart plan in recent years caused the demand for LNG to drop, which shows that alternative energy sources have an impact on the demand for LNG to some extent. Furthermore, the price, technical conditions, sudden disasters and other factors also play a certain role in the LNG trade [9]. Therefore, the feasibility of the prediction results is further analyzed in combination with the annual LNG report of the International Gas Union (IGU) and the actual situation of that year.

5. Discussion

5.1. Analysis of Global Potential Trade

According to the analysis of the relationship of successful prediction in Section 3, the prediction time limit of the prediction method used in this paper was 3–5 years. Therefore, 28 pairs of relationships predicted in 2016–2020 were selected and analyzed in combination with the World LNG Report in 2017–2022 of IGU, so as to accurately identify potential trade relationships (Table 4). It should be noted that since the Russia–Ukraine conflict at the end of February 2022, the price fluctuation and the change in supply and demand of LNG caused by Russia's reduction in pipeline gas supply to Europe and Europe's "gas grabbing" behavior in the international energy market have had a significant impact on the global LNG pattern [49]. The below analysis is made in connection with this incident. Among the 28 relationship pairs, 10 pairs of forecasting relationships were related to Norway. Considering that, since 2016, Norway's LNG export has basically shown a downward trend, and the strong demand for Norway's natural gas in the European market, coupled with the tight supply of European natural gas caused by the recent Russia–Ukraine conflict and the shortage of European natural gas reserves, Norway has hardly exported LNG to other regions since 2019. Therefore, it is unlikely that the other countries involved in the above prediction will establish new LNG trading relationships with Norway in recent years. Four pairs of forecasting relationships were related to Trinidad. It can be seen from the forecast that three of them had frequent LNG trade since 2010 and had actual trade transactions in the past 2 years. The LNG trade of "Trinidad–South Korea (S. Korea)" was interrupted only once in 2016, maintaining stable trade relations in other years. Therefore, it can be considered that it is more likely to establish a new LNG trade relationship with Trinidad. Three pairs of forecasting relationships were related to France, which focuses on LNG re-export trade. In recent years, France ranked first in the list of LNG re-export countries, and the above three pairs of trade relations all turned into reality from 2016 to 2020. For re-export trade, the price difference of different river basins makes arbitrage an important and profitable monetization strategy. However, considering the recent rising price of LNG in Europe, the cutoff supply of Russian PNG is causing Europe to excessively hoard imported LNG, and the bids are usually higher than those of Asian buyers. The LNG trade relationship with France in the future depends on the changes in natural gas prices in Europe and Asia, and there may be hope when the European gas supply crisis eases. Belgium's LNG re-export trade may also be delayed for the same reason. Two pairs of forecasting relationships were related to Russia. In recent years, Russia has maintained the status of the fourth largest exporter of LNG, and its LNG output is considerable. In addition, with the reduction in supply to the European market, Russia's gas is likely to flow to other regions. Therefore, it is very likely that other countries will establish new LNG trade relations with Russia. Egypt's import and export market is unstable, and its energy import and export strategies are mainly influenced by domestic natural gas supply and international natural gas pricing. Africa's liquefied natural gas is mainly exported to Europe and Asia. Algeria, Nigeria, Angola, and Equatorial Guinea have unstable export volumes due to raw gas supply or technical problems. However, in 2021, Africa's proposed liquefied capacity was 123.9 MTPA (million tons per annum), and Africa may become an important LNG export region in the future. Therefore, African countries still have great potential in LNG export.

Table 4. Potential relationships that may be realized in the future.

		2010	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
Norway	Japan											
Norway	Malaysia				+							
Norway	Jordan											
Norway	Japan											
Norway	Taiwan	+	+	+								
Norway	America	+	+	+	+	+	+	+				
Norway	Kuwait											
Norway	China											
Norway	S. Korea	+		+	+	+						
Norway	Jamaica									+		
Trinidad	S. Korea	+	+	+	+	+	+					
Trinidad	Portugal	+		+	+	+	+					
Trinidad	Dubai		+	+			+	+	+			
Trinidad	Malaysia											
France	S. Korea											
France	China											
France	Taiwan							+				
Belgium	S. Korea	+	+	+	+	+	+					
Russia	Turkey											
Russia	Dubai											
Egypt	S. Korea	+	+	+	+	+						
Egypt	Taiwan	+	+	+	+							
Algeria	China			+	+	+	+					
Algeria	Egypt				+		+					

Table 4. *Cont.*

		2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Algeria	S. Korea								+			
Nigeria	Thailand		+	+	+	+	+	+	+	+		
Angola	Taiwan											
Eq. Guinea	Taiwan	+	+	+	+	+	+	+				

The light-blue block in each row indicates no actual LNG trade between the corresponding countries or regions in the corresponding year. The dark-blue block indicates that LNG trade indeed took place between the corresponding countries or regions in the corresponding year. The "+" indicates the year in which the actual trade relationship existed before the potential relationship was pre-dicted.

5.2. Analysis of Potential Trade of Countries or Regions with High Dependence on Foreign Countries

Since 2014, the LNG trade has been growing continuously, and the Asia-Pacific region has been the largest LNG import region in the world. In this region, mature natural gas markets such as China, India, South Korea, Japan, and Taiwan Province have been the strong driving forces for the import growth. In Japan, South Korea, and Taiwan Province, the remote geographical location and scarcity of natural gas resources drive the LNG import, while the inability of natural gas production to keep up with the demand growth is the main reason for China and India importing LNG. According to the GIIGNL (International Group of Liquefied Natural Gas Importers) survey, in 2021, the LNG imports of the above countries and regions accounted for 65.6% of the total global LNG imports, ranking in the top five for global LNG import. For these countries or regions, the source of LNG is highly dependent on foreign countries. Ensuring the safety of LNG supply is the most important thing. Reasonable prediction of potential trade relations can help these countries or regions to find potential LNG trading partners, as well as provide a reference for the diversification of LNG imports and the safety of energy trade. Further analysis is presented below.

The links related to China, India, Japan, and South Korea in the forecast results are shown in Table 5. As can be seen, from 2010 to 2020, there were a total of 27 links involving China, India, Japan, and South Korea, of which 85.2% were successfully predicted, and 95.7% of potential trade relations turned into actual trade relations within 2 years.

Table 5. Potential Relationships among China, India, Japan and South Korea from 2010 to 2020.

		2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Norway	Japan											
Peru	Japan											
America	Taiwan											
Portugal	Japan											
Algeria	Taiwan			+								
France	S. Korea											
Belgium	Japan	+	+	+								
Norway	Taiwan	+	+	+								
Norway	China											
Norway	India		+	+	+							
France	China											
Belgium	China											
Peru	S. Korea	+	+		+							
Norway	S. Korea	+		+	+	+						
Algeria	India		+	+	+	+						
Trinidad	S. Korea	+	+	+	+	+	+					
Algeria	China			+	+	+	+					
Belgium	S. Korea	+	+	+	+	+	+					
Peru	India						+	+				
Eq. Guinea	Taiwan	+	+	+	+	+	+	+				
Angola	Taiwan											

Table 5. *Cont.*

		2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Egypt	S. Korea	+	+	+	+	+						
Egypt	Taiwan	+	+	+	+							
Algeria	S. Korea								+			
France	Taiwan							+				
Trinidad	Japan	+	+	+	+	+	+	+	+	+		
Angola	Japan				+	+			+	+		

The light-blue block in each row indicates no actual LNG trade between the corresponding countries or regions in the corresponding year. The dark-blue block indicates that LNG trade indeed took place between the corresponding countries or regions in the corresponding year. The "+" indicates the year in which the actual trade relationship existed before the potential relationship was pre-dicted.

Although most potential trade relations were realized several years after the forecast, there were still some trade relations ranked in the top 10 in the forecast results, for which no real trade relations were generated after the forecast. In order to predict the future potential trade relations more accurately, it is necessary to further analyze all the successful and unsuccessful links to summarize the rules.

Taking 2016 as the dividing line, among the potential trade relations in China, India, Japan, and South Korea predicted in 2010–2016, only the "Portugal–Japan" pair was not realized before 2020. This pair of relations was predicted once in 2012, but these countries had no actual trade relations in 2010–2021. On the one hand, the increase in nuclear and renewable energy generation in Japan reduced the demand for gas power generation. On the other hand, Portugal is mainly positioned as an importer of liquefied natural gas, and only engages in a small amount of re-export trade. Recently, the European energy crisis caused by the Russia–Ukraine conflict made it almost impossible for the predicted relationship to become an actual trade relationship in the future. Among the remaining 17 pairs of successfully predicted trade relations, 16 pairs of potential trade relations developed into actual trade relations within 2 years after the prediction. At the same time, these successfully predicted trade relations often lasted for several years, among which 10 pairs of links generated actual trade relations for three consecutive years. Therefore, it can be considered that, in this forecast of trade relations among China, India, Japan, and South Korea, the forecast is valid for 2 years. If the potential trade relations between China, India, Japan, and South Korea are not established within 2 years after the first forecast, the possibility of establishing trade relations in the future is small; however, once trade relations are established, China, India, Japan, and South Korea are more inclined to establish long-term and stable trade relations. Of the nine pairs of potential trade relations among China, India, Japan, and South Korea predicted in 2017–2019, three were not realized before 2020. The "Trinidad–Japan" and "Angola–Japan" pairs of predicted relations had actual trade before 2018, but the trade relations disappeared after 2019. This was probably due to the restart of Japan's nuclear energy reducing domestic LNG demand. At the same time, whether these two pairs of forecasting relationships were realized or not can only be verified from the results in 2020, negating the forecast being valid for two years, and these two pairs of forecasting relationships may still produce actual trade relations. The relationship of "Peru–India" may be due to the unstable supply of raw materials and the decline in natural gas production caused by technical problems in Peru.

At the same time, among the 23 successfully predicted trade relations, 15 (65.2%) had trade relations before the first forecast. It can be understood that China, India, Japan, and South Korea are more inclined to re-establish trade relations with countries or regions that have previously had trade relations. Among the four pairs of trade relations that were not successfully predicted, three pairs had trade relations for more than two consecutive years before the prediction; hence, it is still possible to establish trade relations again in the future.

The other predicted successful relationship pairs were mainly related to some countries in Europe, Africa, and America, but the recent Russian–Ukrainian conflict is likely to hinder the export and re-export trade of LNG in Europe. Considering that Norway only exported LNG to China and India, the only two non-European countries, in 2019, it is very likely that "Norway–China" and "Norway–India" trade relations will be re-established in the future. Furthermore, the potential trade relations among China, India, Japan, and South Korea and some countries in Africa and America may continue in the future, such as "America–Taiwan", "Peru–S. Korea", and "Algeria–China".

6. Conclusions

As a clean and efficient energy source, LNG plays an important role in the global low-carbon transformation process. The low-carbon requirement and energy transformation have led to the LNG trade increasing continuously since 2015. How to ensure the stability and safety of domestic LNG supply in the complex and changeable market environment has become a concern of LNG importers. In this paper, the improved link forecasting method was used to study the international LNG trade relations. While discovering the potential trade relations according to the topological attributes of each country, it also provides a further perspective, taking geographical, economic, and political factors into account, thus further improving the forecasting accuracy. This paper attempted to find potential partnerships for natural gas-importing countries through the improved link prediction algorithm, aiming to help these countries realize the diversification of LNG trade and ensure the safety of LNG supply. Combining the optimization of the link prediction method and the analysis of prediction results, the main conclusions are as follows:

(1) For the global natural gas trade network, among the single forecasting indices, the LP index based on path proximity had the highest forecasting accuracy; for the indices based on local information proximity, the prediction accuracy of the index could be improved by replacing the traditional node value with the centrality value. Economic and political factors also had a certain influence on the prediction results, and the prediction accuracy of multi-factor coupling indices was obviously better than that of single indices.

(2) The correct rate of link prediction cannot reach 100% because changes in political relations, newly promulgated policies of the state, and sudden epidemics all have certain influences on trade relations. Therefore, it is a normal phenomenon for some predicted links to fail. For example, the shale revolution of the United States led to the country becoming a big exporter of LNG, instead of a net importer whose natural gas production could not keep up with the demand growth as originally predicted by the International Gas Union. For LNG trade, the price difference between river basins, the change in domestic output, the competition with alternative energy, the geopolitical situation, the change in natural environment (temperature, climate, etc.), and the relevant restrictions of COVID-19 all have certain influences. At the same time, the main influencing factors are also different for different countries. For example, they are different for France, Belgium, and other countries engaging in re-export trade, where the price difference between river basins is the main factor affecting LNG trade relations.

(3) For those successful predicted trade relationships, in terms of prediction timeliness, it generally took 3 years for a potential global LNG trade relationship to change from the first prediction to an actual trade relationship. For countries or regions such as China, India, Japan, and South Korea with high dependence on foreign countries, this timeframe was generally 2 years. At the same time, previous trade cooperation relationships led to countries re-establishing trade relations, whereby most countries tended to establish trade relations with those countries they are familiar with.

(4) Trinidad, Russia, Algeria, Nigeria, Angola, and Equatorial Guinea are more likely to establish new LNG trade relations with other countries. Trinidad and Portugal, Trinidad and Dubai, Trinidad and Malaysia, Russia and Turkey, Russia and Dubai, Algeria and Egypt, and Nigeria and Thailand are more likely to establish trade relations in the next five years. The shortage of natural gas supply in European

countries caused by the Russia–Ukraine conflict may temporarily restrict their export and re-export trade. The forecast of the IEA (International Energy Agency) also shows that African countries will be the biggest driving force of global natural gas production growth in the next 5 years, which proves the accuracy of the link forecast results to some extent.

(5) At present, about 90% of the LNG imported by China, India, Japan, and South Korea comes from Australia, Qatar, Malaysia, and Indonesia. Considering the security of energy supply, Algeria, Angola, Equatorial Guinea, Trinidad, the United States, Peru, and Norway may become future partners. China, India, S. Korea, and Taiwan Province are more likely to import LNG from Algeria in the next 2 years. In addition, Angola and Taiwan Province, Eq. Guinea and Taiwan Province, Trinidad and S. Korea, Peru and Japan, Peru and S. Korea, and America and Taiwan Province are more likely to establish trade relations in the next 2 years.

Although the link prediction algorithm was improved in this paper, which effectively improved its prediction accuracy, the LNG trade market is complex and changeable, and the formation of trade is affected by many factors. The research carried out in this paper still has certain limitations and room for improvement, as discussed below:

(1) In this algorithm, only the key factors affecting the LNG trade precipitated from the existing literature were quantitatively considered, such as the price of LNG, the competition of alternative energy, and the change in technology, but not quantified. In the future, the potential factors affecting the global LNG trade can be comprehensively studied through methods such as the trade gravity model [9] and incorporated into the link prediction algorithm to make the algorithm more realistic.
(2) The data used in the link prediction algorithm in this paper were national statistical data with a unit of 1 year, but the temporal resolution of the data is still insufficient. Therefore, the response to unexpected events (e.g., Russia–Ukraine conflict) and the characteristics of real-time LNG trade cannot be well reflected. In the future, the scale and research timescale of the research object can be further refined by obtaining ship history and real-time data [13].
(3) In the future, countries can be further classified according to the main factors that affect the LNG trade to analyze the international trade relations; then, then combined with the factors such as trade volume and trade direction, the potential trade relations can be predicted more accurately and evaluated more deeply.

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