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Do you need cobalt ore? Estimating potential trade relations through link prediction

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ABSTRACT

Cobalt is an important metal resource in supporting the development of strategic emerging industries. Recently, it has been widely used in the field of new energy. Cobalt ore and its concentrates are the main sources of cobalt raw materials in various countries. These countries' international trade relations will affect the stability of the cobalt resource supply, so it is particularly important to predict the future trade relationships for cobalt ore. This study first selects international trade data on cobalt ore from 2009 to 2018 and calculates the stability of the trade network. Then, the potential international trade relationships for cobalt ore are evaluated by building a link prediction analysis model including the role of trade countries for cobalt ore and identifying the overall utilization level of national cobalt sources in combination with the international trade of cobalt waste and scrap. The results show that trade instability has increased in the past three years. The Netherlands and China, Germany and China, the United States and China, Morocco and the Netherlands, the Republic of Korea and the United States are most likely to trade cobalt ore in the next three years; China and India, China and the Czech Republic, and the Netherlands and South Africa are most likely to trade cobalt ore in the next five years. According to the predicted results, governments can find more new trading partners and expand the diversification of cobalt source countries. In addition, cobalt resource utilization needs to be improved.

1. Introduction

As an emerging strategic mineral resource, cobalt has been widely used in military, aviation, petrochemicals and other fields (Hayes and Mccullough, 2018). In recent years, with the advancement of technology and the rise of smartphones and tablets, cobalt has become an essential raw material for rechargeable batteries. At the same time, the battery industry has become the most important consumption area for cobalt (Hong-Tao, 2015). In 2018, the battery industry used 78,000 tons of cobalt, accounting for 60.9% of the global cobalt consumption (U.S. Geological Survey, 2019). However, cobalt has strong migration ability and low content in the earth's crust. It is generally difficult to form an independent economic mineral deposit. Cobalt exists mainly in the form of copper cobalt and nickel cobalt-associated resources, and cobalt resources are relatively rare (Harvey, 2018). Since 2009, cobalt ore and its concentrates have dominated the international trade of cobalt and have become the main sources of cobalt raw materials in various countries. Additionally, the recycling rate of cobalt resources in various countries is generally low (20% on average) (Sun et al., 2019). And the ores exported from the major cobalt resource holder and supplier, DRC, are not stable (Sun et al., 2019). From the perspective of the supplier of cobalt resources, the instability of its supply capacity will affect the normal use of cobalt by the demander. With this in mind, the supply stability of cobalt ore and its demand forecasts have become the focus of research in various countries (Tisserant and Pauliuk, 2016; Hao et al., 2017). Therefore, it is of great practical significance to predict the potential cobalt ore trade relationship that the two countries may establish in the future, which will help the government find new partners in advance in the face of the breakdown of trade relations and ensure the diversification of trading partners. In summary, this study will explore the potential trade relations in the international trade of cobalt ore, cobalt waste and the overall utilization level of cobalt raw materials.

Most of the previous studies on exploring trade relations have applied traditional gravity model method, which have been used to study the existing potential trade flows of certain types of products. For example, Buongiorno and other scholars predicted the trade flow of forest products among countries by developing the gravity difference model of bilateral trade flow (Buongiorno, 2016). Other scholars used

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the gravity model to explore the general trade relationship between countries or regions (Ravishankar and Stack, 2014), the influencing factors of export flow changes among trading partners (Eita, 2016), and the factors of air travel demand between cities (Hazledine, 2017). In these studies, gravity model is a good model to predict the current trade flow based on specific country variables (GDP, population, etc.) and bilateral relationship variables (distance, boundary conditions, etc.). However, when assessing potential trade relations between countries that do not exist yet but may appear in the future, the effectiveness of the model is not satisfactory (Marco and Fagiolo, 2013; Gómez-Herrera, 2013), and even has some limitations. The purpose of this study is to find new partners for all countries, so a new method is needed. Link prediction based on complex networks (Clauset et al., 2008) provides an effective way to explore the potential trade relations that do not exist at present but may appear in the future. The basic principle is to treat the research objects as nodes, the relationships between the research objects as edges, and construct nodes and edges into a network. Then, by exploring the essence of the formation of network structures, we can better understand the law of network evolution, thus mining the potential relationship and ultimately realize the simulation and prediction of the network. This method was originally widely used to study the interaction between proteins (Lei and Ruan, 2013), recommend friends or commodities in the recommendation system (Li and Chen, 2013), and search for possible cooperative scientists (Lichtenwalter et al., 2010). In recent years, it has been extended to predict international trade relations such as oil (Guan et al., 2016), liquefied natural gas (Feng et al., 2017), and bauxite (Liu and Dong, 2019), providing ideas for the analysis in this paper. However, these predictions are based only on undirected trade networks and lack the exploration of directed trade networks. To fill this gap, this paper improves the above algorithms and predicts trade relations based on directed trade networks.

In addition, at an early stage, most previous studies on cobalt have not fully considered the international field and are limited mostly to certain countries or regions, and the research time span is generally a short period of time. For example, Harper developed the first cobalt life cycle for China, Japan, the United States and the whole planet in 2005 (Harper et al., 2012). Other scholars have studied the global flow of cobalt; for example, Nansai tracked the global flow of cobalt, neodymium and platinum in 2005 (Nansai et al., 2014). Zeng and Li established the flow cycle of cobalt in China from 2005 to 2013 and predicted the potential demand for cobalt in 2030 (Zeng and Li, 2015). Sun used a raw material flow analysis to study the cobalt flow during the 1995–2015 period (Sun et al., 2019). After that, with the increasing adoption of new and advanced technologies, including electric vehicles and jet aircraft, global demand for cobalt has continued to accelerate. Scholars gradually expand their research scope to the world. Gulley et al. studied the domestic and foreign influence of China in the global cobalt supply chain (Gulley et al., 2019). Although these studies have revealed the global movement of cobalt and its related drivers, supply impacts, etc., it is still hard to know which countries have potential trade relations with each other under the unstable international trade environment.

In view of the above problems, this study establishes a direct complex network of the international trade of cobalt ore and predicts the international trade relations of cobalt ore. To make the evaluation more practical and accurate, this paper also establishes a link prediction analysis model, which includes dividing the role of cobalt ore trading countries and identifying the overall utilization level of national cobalt sources based on the international trade of cobalt waste and scrap. The highest-potential trade relations are estimated from the link prediction results. The rest of the paper is arranged as follows: the second part introduces the data and methods used in the study. The third part introduces the research results. The fourth part gives the conclusion and policy implications.

2. Data and methods

2.1. Data

The import and export data on cobalt ore and its concentrates (hereinafter referred to as cobalt ore) and cobalt waste and scrap (hereinafter referred to as cobalt waste) are downloaded from UNcomtrade. The HS codes are 260500 and 810530, respectively, and the time span is 10 years, from 2009 to 2018. Whether it is from the perspective of trade network evolution or from the perspective of data volume and research methods, it is sufficient to select ten years of trade data. The original data include classification, year, trade flow code (including imports and exports), reporter code, partner code, commodity, quantity unit code, trade value (US$), net weight (kg), and so on. According to the needs, the year, reporter code, trade flow code (including imports and exports), partner code and net weight (kg) were selected as the research data.

To ensure the integrity of the data, the annual data we download has both import and export data, so there will be duplication. This paper deletes these data when the trading country codes cannot represent the partnership of specific countries, as well as when the reporter and partner represent the partnership of the same country. In addition, some exporting countries report different trade volume from the importing countries. This paper chooses to delete the smaller trade volume, because the smaller trade volume may be caused by statistical negligence.

2.2. Methods

2.2.1. Construct the cobalt ore international trade network

Based on the complex network theory, taking the countries involved in the trade of cobalt ore as a node, taking the actual trade relationship between countries as the edge, and taking the trade volume (kg) of cobalt ore between countries as the weight, the directed weighted network and the directed unweighted network of international trade of cobalt ore are constructed respectively. For a total of ten years of data, two networks can be built each year, so a total of 20 cobalt ore international trade complex networks are obtained. Fig. 1 is a schematic diagram of the international trade network of cobalt ore in 2018. The directed weighted network is on the left, and the directed unweighted network is on the right.

Fig. 1 shows the trade relations of cobalt ore among countries, and some important trading countries have been identified. The size of the nodes in the figure is divided according to the number of trading partners. The larger the node is, the more trading partners of the country correspond to the node. The thickness of the edges between the nodes is divided according to the amount of trade between the two countries. The thicker the edge is, the greater the trade volume between the two countries.

2.2.2. Calculate the stability of a complex network of cobalt ore international trade

An important factor to measure the stability of complex networks is the change in nodes in the network. In this paper, the autocorrelation function $Z_f(t)$ (Palla et al., 2007) is used to calculate the stability coefficient of the complex network nodes of cobalt ore international trade in different years. The calculation equation is shown in (1).

$$Z_f(t) = \frac{Q_t \cap Q_{t-1}}{Q_t \cup Q_{t-1}} \tag{1}$$

where $Z_f(t)$ represents the stability coefficient of network nodes from year $t-1$ to year t. Q_t represents the node set of all countries in the international trade network for cobalt ore in year t. Q_{t-1} represents the node set of all countries in the international trade network for cobalt ore in year $t-1$. $Q_t \cap Q_{t-1}$ represents the common set of national nodes in

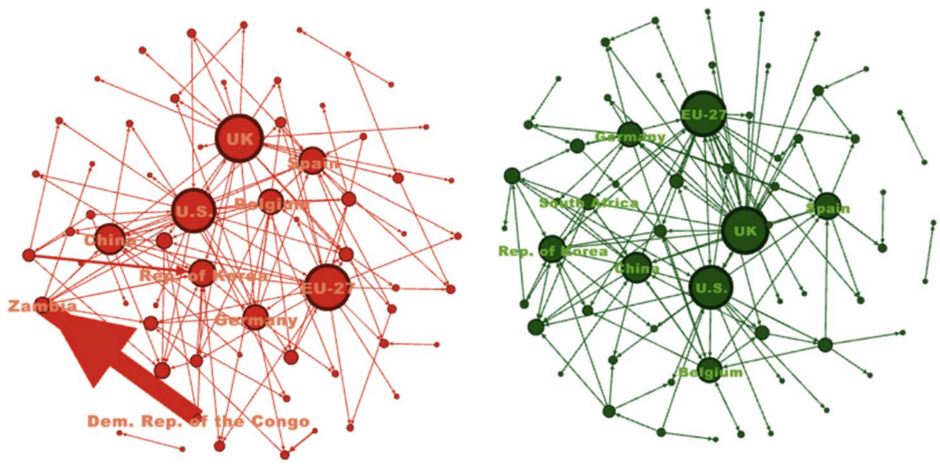


Fig. 1. The directed networks of cobalt ore international trade in 2018 (left weighted, right unweighted).

year t and year $t-1$. $Q_t \cup Q_{t-1}$ represents the set of national nodes that appear in year t and year $t-1$. Equation (1) shows that the larger the value of $Z_f(t)$ is, the higher the stability of the national nodes in the cobalt ore international complex trade network.

It can be seen from Fig. 2 that the stability coefficient of the cobalt ore international trade network in the past 9 years is less than 0.5, and the change in the past three years is relatively large. Trade instability has increased in the past three years, which shows that the stability of the international trade network of cobalt ore is poor, and trade instability has increased in the past three years. If a cobalt ore trading country continues to trade cobalt ore in existing trade relations, it may result in improper trade choices due to trade uncertainty, thus leading to unnecessary trade losses. Therefore, to reduce trade losses, it is necessary to further explore the implicit trade relationship based on existing trade relations.

2.2.3. *Construct a link prediction model*

Although some valuable information can be obtained directly from the existing network structure, there are still some information in the form of "hidden information", which cannot be obtained directly from the data. Link prediction is just a method for evaluating potential link relationships in networks, and has been widely used in recent years (Shi et al., 2015; Sherkat et al., 2015; Li et al., 2018). In detail, link prediction is to predict the possibility of a link between two nodes in the network that have not yet produced a connected edge by using information such

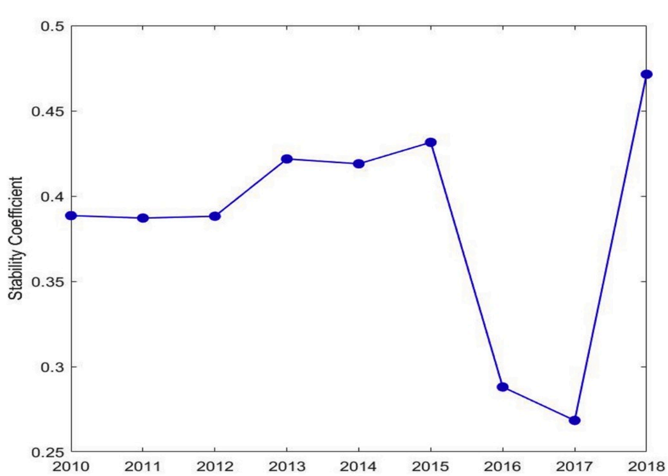


Fig. 2. Stability coefficient of the cobalt ore international trade network from 2010 to 2018.

as known network nodes and network structure. It mines the essence of network formation from the perspective of topology. Network predictions can be achieved through four main steps: the definition of the evaluation index, the division of the test set, the evaluation of unknown edges and the accurate evaluation of the index. The schematic process is shown in Fig. 3.

The six nodes for the network above are {A,B,C,D,E,F}. The network contains 10 existing edges, which are E(Links) = {AB,AC,AE,AF,BD,BE, BF,CD,CF,EF}, and it is represented by the black solid line. First, all possible edges of the network are calculated and expressed in U, U = {AB,AC,AD,AE,AF,BC,BD,BE,BF,CD,CE,CF,DE,DF,EF}. We randomly selected 10% of the existing edges as the test set (E^T), E^T = {AB}, represented by the red dotted line. Then, find the edge set that does not exist: E^I = U-E = {AD,BC,CE,DE,DF}, represented by a red dotted line. Finally, the scores of the above test set and the non-existent link set U-E + E^T = {AD,BC,CE,CF,DF,AB} are calculated according to the four mainstream algorithms, and the accuracy of each algorithm is calculated. Through the above calculation, the prediction of network connections can be realized.

Based on the above process, the specific steps of this study are as follows:

Step 1: Select the optimal algorithm

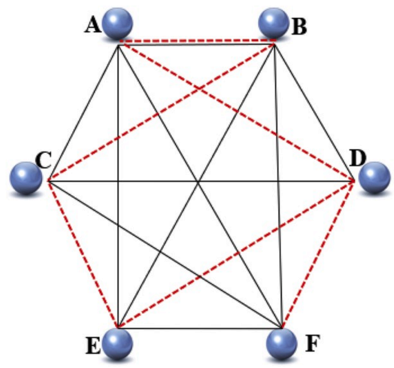
Because the characteristics of the relationships between different trade networks are different, it is necessary to select the optimal algorithm from the current four mainstream algorithms: Common Neighbor (CN), Adamic Adar (AA), Resource Allocation (RA), and Preference Attachment (PA). The following is an introduction to the four algorithms.

(1) Common Neighbor algorithm

If two nodes have more common neighbor nodes, the two nodes are similar. There are two equations for the CN algorithm. One is an unweighted algorithm that does not consider the trade volume, such as equation (2), and the other is a weighted algorithm that considers the trade volume, such as equation (3).

$$P_{xy}^{CN} = |\Gamma_{out}(x) \cap \Gamma_{in}(y)| \tag{2}$$

Combined with the meaning of the cobalt ore international trade network, x and y represent two countries involved in the international trade of cobalt ore. $\Gamma_{out}(x)$ represents the export trade country set of x. $\Gamma_{out}(x) \cap \Gamma_{in}(y)$ represents the number of countries that import from x and export to y. According to the algorithm, the more trading countries that two countries have in common, the more likely they are to trade.



Rank	Link	CN	Link	AA	Link	RA	Link	PA
1	BC	3	BC	6.64	BC	1.00	AB	16
2	AD	2	AD	3.76	AD	0.58	BC	12
3	CE	2	DF	3.76	DF	0.58	CE	9
4	DF	2	AB	3.76	AB	0.58	AD	8
5	AB	2	CE	3.32	CE	0.50	DF	8
6	DE	1	DE	1.66	DE	0.25	DE	6

Fig. 3. Schematic diagram of link prediction.

$$P_{xy}^{CN} = \sum_{z \in \Gamma_{out}(x) \cap \Gamma_{in}(y)} \frac{w(x,z) + w(z,y)}{2} \tag{3}$$

Combined with the meaning of the cobalt ore international trade network, z represents the common trading partner of cobalt ore that import from x and export to y. $w(x,z)$ represents the volume of trade between x and z.

(2) Adamic Adar algorithm

The principle of the algorithm is that the contribution of the common neighbor node with a small degree is greater than that of the common neighbor node with a large degree.

$$P_{xy}^{AA} = \sum_{z \in \Gamma_{out}(x) \cap \Gamma_{in}(y)} \frac{1}{logk_z} \tag{4}$$

$$P_{xy}^{AA} = \sum_{z \in \Gamma_{out}(x) \cap \Gamma_{in}(y)} \frac{w(x,z) + w(z,y)}{\log(1 + P(z))} \tag{5}$$

Combined with the meaning of the cobalt ore international trade network, k_z represents the number of countries that have direct trade links with country z. Among them, $P(z) = \sum_{i \in \Gamma_{out}(z)} w(z,i)$, i represents the country that has direct trade links with country z.

(3) Resource Allocation algorithm

This algorithm was proposed by Zhou Tao. Its principle is similar to that of AA. However, in the RA algorithm, two countries $x$and y without direct trade relations are specially considered. Therefore, the common neighbors are seen as a medium of communication between the two trading countries. Similarly, the RA algorithm is divided into two cases that consider trade volume and do not consider trade volume.

$$P_{xy}^{RA} = \sum_{z \in \Gamma_{out}(x) \cap \Gamma_{in}(y)} \frac{1}{k_z} \tag{6}$$

$$P_{xy}^{RA} = \sum_{z \in \Gamma_{out}(x) \cap \Gamma_{in}(y)} \frac{w(x,z) + w(z,y)}{P(z)} \tag{7}$$

(4) Preference Attachment algorithm

Under this algorithm, the possibility of establishing trade relations between two country nodes is directly proportional to the product of the number of import trade partners and the number of export trade partners of each country. The specific calculation equations are shown in (8) and (9).

$$P_{xy}^{PA} = |\Gamma_{out}(x)| \times |\Gamma_{in}(y)| \tag{8}$$

$$P_{xy}^{PA} = \sum_{j \in \Gamma_{out}(x)} w(x,j) \times \sum_{q \in \Gamma_{in}(y)} w(y,q) \tag{9}$$

Combined with the meaning of the cobalt ore international trade network, in equation (9), j represents the country that import from country x, and q represents the country that export to country y.

Step 2: Divide the training set and test set

Randomly select 10% of the existing trade links (E) in the current trade network as the test set and record it as E^T. Select the remaining 90% of trade links as the training se (Lü and Zhou, 2011) and record it as E^R.

$$E = E^T + E^R \quad and \quad E^T = 10\% * E \tag{10}$$

Step 3: Find links that do not exist

"Implicit trade relationship" refers to a relationship that does not exist in the current trade network. If we want to predict the future trade relations, we should first find out the "implicit trade relationship". Assuming that there are n countries involved in the international trade of cobalt ore, then all the trade link relations U in the current trade network can be calculated using equation (11). Therefore, the relationship that does not exist in the current trade network can be calculated using equation (12).

$$U = \frac{n^*(n-1)}{2} \tag{11}$$

$$E^I = U - E \tag{12}$$

Step 4: Sort the scores of the non-existent relationship set

Through the four mainstream algorithms of CN, AA, RA, and PA, the scores of each trade relationship in the non-existent relationship set can be obtained, and the scores are sorted from high to low. The higher a link's ranking is, the more likely it is to become a real link in the future, that is, the country corresponding to this link is more likely to have a trade relationship in the future.

Step 5: Evaluate algorithm accuracy

Generally, the area under the receiver operating characteristic curve (AUC) is regarded as a common index to measure the accuracy of the link prediction algorithm, which can measure the accuracy of the algorithm as a whole. In addition, the main purpose of this paper is to predict the occurrence of international trade relations of cobalt ore from the whole trade network, so AUC can be used as the accuracy evaluation index of the algorithm. AUC can be calculated using equation (13). It can be understood that the comparison is repeated n times, and each time randomly selects an edge from the test set and the non-existing relationship set, respectively. If the score of the test set edge is higher than the score of the edge of the non-existent relationship set, then 1 is added, and this situation accumulates $n^{'}$ times. If the scores on both sets are equal, then add 0.5 points, and this situation accumulates $n^{''}$ times (Fawcett, 2005). If all scores are generated randomly, then AUC≈0.5. Therefore, as AUC exceeds 0.5, the more accurate the corresponding algorithm is.

$$AUC = \frac{n^{'} + 0.5n^{''}}{n} \tag{13}$$

2.2.4. Cobalt ore link prediction analysis model

To obtain a more accurate prediction of trade relations, this paper constructs a cobalt ore link prediction analysis model.

Step 1: Classify the countries that are successfully predicted

By comparing the potential links and the actual links, we can test the validity of the link prediction model and find the successfully predicted country pairs and the country pairs that need further analysis. To further explore the potential trade link rules, we classify the countries that appear in the top ten and are successfully predicted into different categories: (1) country pairs that establish trade relations rapidly. (2) Country pairs that establish trade relations slowly. (3) Country pairs that fluctuate to establish trade relations.

Step 2: Divide the role of country trade

According to the trade data for cobalt ore and sand, all countries appearing in the top ten potential trade links are divided into net importing countries and net exporting countries. The division rules are as follows:

$$R_t = \begin{cases} E_t, & E_{Pt} - I_{Pt} > 0 \\ I_t, & E_{Pt} - I_{Pt} < 0 \end{cases} \tag{14}$$

where t represents the year and R_t represents that a country is divided in the t-th year. When a country exports more cobalt ore than imports in year t, it will be a net exporter in this year; otherwise, it will be a net importer. When the difference between imports and exports is 0, it will not be given the role of a net import or net export country, but it can be regarded as a different role from an import and export country.

Step 3: Identify the overall utilization level of cobalt raw materials in trading countries

At present, the main source of cobalt supply in the world is cobalt ore and reclaimed cobalt. Therefore, the difference between the import and export of cobalt ore and cobalt waste can reflect the overall utilization level of cobalt raw materials in a country from a trade perspective. Table 1 summarizes the main trading commodities and cobalt grades of cobalt raw materials. According to the cobalt ore, cobalt waste trade data, and its cobalt grade, define the overall utilization level of the country's cobalt raw materials. The calculation rules are as follows:

$$U_t = \begin{cases} High\ utilization\ level, & (\alpha I_{Pt} + \beta i_{Pt}) - (\alpha E_{Pt} + \beta e_{Pt}) < 0 \\ Low\ utilization\ level, & (\alpha I_{Pt} + \beta i_{Pt}) - (\alpha E_{Pt} + \beta e_{Pt}) > 0 \end{cases} \tag{15}$$

where t represents the year and U_t represents the overall utilization level of cobalt raw materials in a country in the t year. I_{Pt} represents the import volume of cobalt ore in a certain country, E_{Pt} represents the export volume of cobalt ore in a certain country, i_{Pt} represents the import volume of cobalt waste in a certain country, and e_{Pt} represents the export volume of cobalt waste in a certain country. α represents the grade coefficient of cobalt ore, and β represents the grade coefficient of cobalt waste. When $U_t < 0$, it means that the inflow of cobalt raw material in a certain country is less than the outflow of cobalt raw material, indicating that the overall utilization level of cobalt raw material is high; when $U_t > 0$, it indicates that the overall utilization level of cobalt raw material in a certain country is low.

Table 1
Main trade commodities of cobalt raw materials and their grades.

Detail	Ore Mining	Waste Cycle
Main category	Cobalt ores and concentrates	Cobalt waste and scrap
HS code	260500	810530
Main commodity	Cobalt ores and concentrates (non-gold value part)	Cobalt alloy scrap、Samarium cobalt permanent magnet scraps、Tungsten chromium cobalt alloy powder scraps、Cobalt waste
Cobalt grade of each commodity	6.5465%	40%、52%、61.7%、99%
Average cobalt grade	6.547%	63.175%

3. Results

3.1. Algorithm evaluation and optimal algorithm selection

It was shown in section 2.2.3 that the more AUC is greater than 0.5, the higher the accuracy of the corresponding algorithm is. Therefore, the potential trade relationship can be predicted by comparing the accuracy index AUC corresponding to the four algorithms and then selecting the optimal algorithm.

Fig. 4 shows the AUC scores for the four algorithms. To minimize random errors, the AUC score here is 10 experimental average results, and the annual data are randomly divided into a 10% test set and a 90% training set in the 10 experiments. $\alpha = 0$ means that the impact of trading volume is not considered, and $\alpha = 1$ means that the impact of trading volume is fully considered. The redder the color in the graph is, the higher the AUC score, and the higher the accuracy of the corresponding algorithm. Through comparison, it can be found that the AUC color of the PA algorithm is reddest when $\alpha = 0$ in ten years, indicating that the algorithm is optimal. Therefore, in this paper, we will select the PA algorithm based on the directed and unweighted complex network when we predict the cobalt ore trade relationship. That is, the PA algorithm is the optimal algorithm in this study. In addition, Table 2 shows the detailed AUC scores of the four algorithms under weighted and unweighted conditions.

In summary, in the new trade relationship predicted by the directed and unweighted PA algorithm, countries with a large trade volume and countries with a small trade volume have the "equal importance" phenomenon, and the product of the number of trade partners of the two participating countries in cobalt ore trade plays an important role in the formation of their trade relationship.

3.2. Classification of countries that have been successfully predicted

In the case of directed and unweighted, the PA algorithm is the optimal algorithm for predicting potential trade links in this study. This paper uses the PA algorithm to calculate the possibility of a trade relationship between the test set and the non-existent relationship set through the complex network of cobalt ore. This section sorts the test set and the non-existent relationships by PA value. Then, select the non-existent relationship ranked in the top ten of each year and define it as a "potential trade link". In order to find the characteristics of the countries that have been successfully predicted, these countries need to

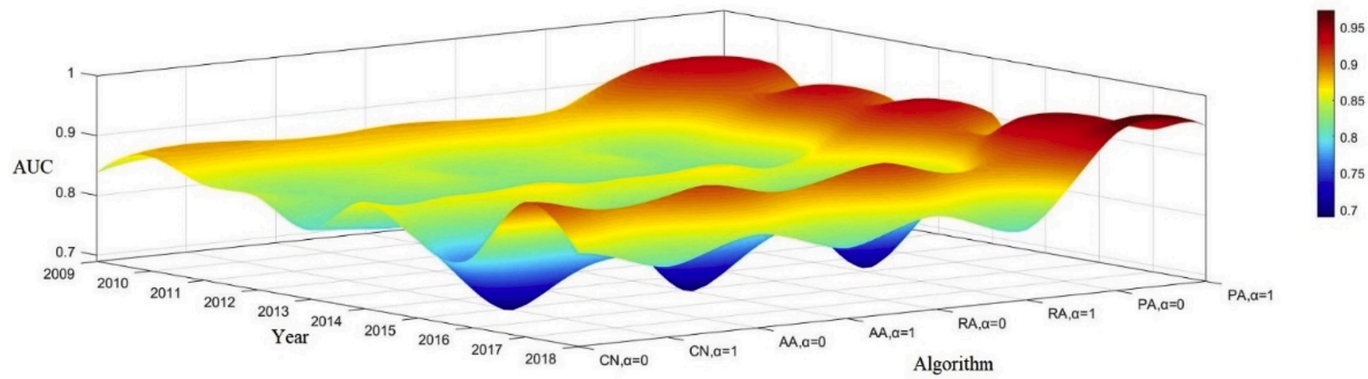


Fig. 4. Evaluation of four algorithms from 2009 to 2018.

Table 2
The AUC score of the four algorithms.

	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
CN(α = 0)	0.837	0.881	0.849	0.845	0.805	0.868	0.819	0.805	0.915	0.845
CN(α = 1)	0.851	0.885	0.827	0.822	0.794	0.858	0.690	0.804	0.889	0.807
AA(α = 0)	0.837	0.881	0.849	0.845	0.805	0.869	0.819	0.788	0.912	0.846
AA(α = 1)	0.851	0.885	0.827	0.822	0.794	0.858	0.690	0.804	0.888	0.807
RA(α = 0)	0.838	0.881	0.849	0.845	0.807	0.869	0.820	0.819	0.919	0.845
RA(α = 1)	0.853	0.887	0.830	0.824	0.795	0.858	0.698	0.804	0.889	0.807
PA(α = 0)	0.916	0.924	0.904	0.927	0.915	0.932	0.902	0.940	0.932	0.953
PA(α = 1)	0.884	0.923	0.857	0.905	0.848	0.907	0.773	0.907	0.927	0.949

be further classified.

Theoretically, select the top 10 pairs of countries in the PA every year, and there should be 100 pairs of countries in total in ten years. However, because some "potential trade links" were repeated in the top ten in different years, a total of 55 pairs were obtained within the 10 years. Because of the lack of data after the year 2018, the 6 pairs of forecasting countries that will generate trade relations predicted by the 2018 data are excluded (which will be further analyzed in Section 3.4) and 49 pairs of forecasting countries left. Of these 49 pairs of countries, 34 pairs (70%) successfully established trade relations after their appearance in the top 10 ″potential trade links". According to the speed of establishing trade relations, 34 pairs of countries are divided into three categories.

The first category is the country pairs that quickly establish the trade relationships for cobalt ore.

As shown in Fig. 5, for each row, the blue color blocks represent the leftmost country pair in the top ten "potential trade links" of PA value in the corresponding year of this column, but they did not establish a cobalt ore trade relationship in that year. The yellow color blocks represent the leftmost country pair that has successfully established trade relations

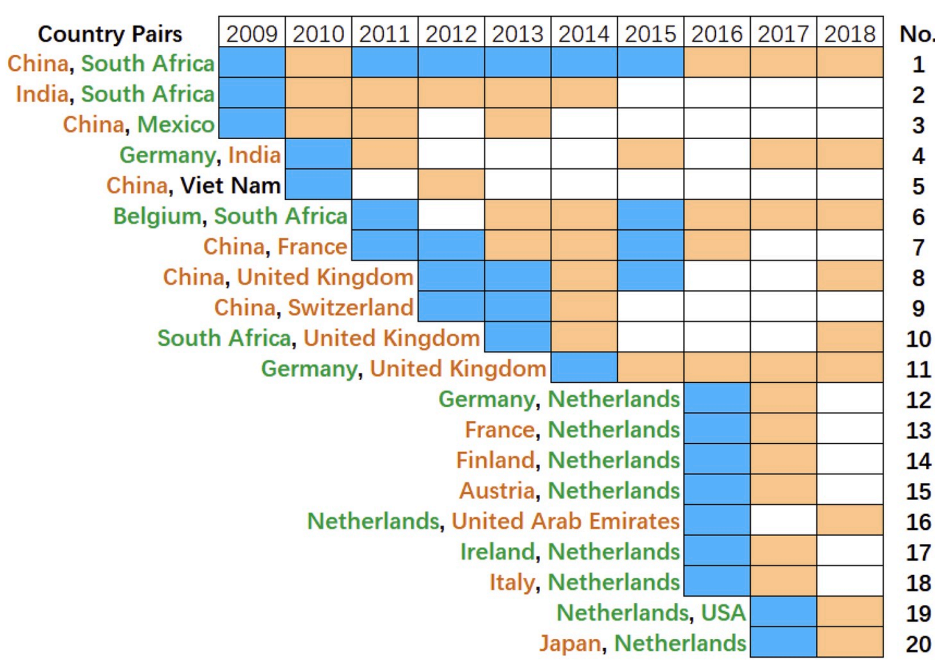


Fig. 5. Country pairs that quickly establish the trade relationships for cobalt ore.

with cobalt ore in the corresponding years in this column. The numbers in the far-right column represent the pairs of countries in the figure. This category includes 20 pairs of trade relations countries headed by "China-South Africa", and these country pairs have successfully established trade relations within two years after they were first predicted as potential trade links. In addition, the different colors of country names indicate different roles, which will be further analyzed and explained in Section 3.3.

The second category is the country pairs that slowly establish trade relationships for cobalt ore.

As shown in Fig. 6, this category contains 8 pairs of countries. According to the characteristics of these countries, they are successfully established trade relations either after being predicted as potential trade links many times or two years after they were predicted as potential trade links for the first time. Compared with the first category, countries in this category have a longer time from being predicted as potential trade links to successful trade, so they are classified as countries that are slow to establish cobalt ore trade relations.

The third category is the country pairs that fluctuate to establish trade relationships.

As shown in Fig. 7, compared with the first two categories of country pairs, these six pairs of countries have experienced a repeated process from "being predicted" to "successfully building relations" and then "being predicted". The characteristics of successful trade relations are different from those of the first group of countries and the second group of countries, and whether these six pairs of countries can successfully establish trade relations after the last prediction is uncertain and therefore requires an in-depth analysis. Therefore, they are classified as a separate group.

From the above classification, it can be seen that not all pairs of countries appearing in "potential trade links" can quickly establish trade relations, which shows that even though the link prediction based on physical topology network has a high algorithm accuracy (AUC score), there are some defects in practice. The predicted countries also show different characteristics of the speed of successfully establishing trade relations. In order to improve the accuracy, it is necessary to perfect the prediction results based on the consideration of the physical topology of the network and the characteristics of the trade countries of cobalt ore. Therefore, the following will conduct in-depth analysis through the division of trade roles.

3.3. Analyze the trade role of cobalt ore trading countries and summarize the trade rules

This section will explore trade rules by observing the role of the trading countries that have been successfully predicted. The country role is divided according to equation (14). Using the downloaded trade data, if a country's total imports are higher than its total exports within a year, the country is classified as a net importer, and its country name is marked in yellow. Otherwise, it is classified as a net exporter, and its country name is marked in green. As shown in Fig. 5, in the first pair of countries, China is marked in yellow as a net importer, and South Africa is marked in green as a net exporter. When the volume of imports and exports is equal, the country is not classified into any category, and its country name remains in the original black, for example, Vietnam in the fifth pair of countries in Fig. 5.

Observe the above three categories of countries that are successfully predicted to have trade relations. The longest time to successfully establish trade relations is within five years after the last appearance among the top ten potential trade links. In addition, there are 20 pairs of countries in the first category, of which 13 pairs (65%) are composed of net importing and net exporting countries. Three pairs are composed of net importing countries, and each pair includes China. Four pairs are composed of net exporting countries, including Germany, the United States, South Africa and the Netherlands. The second category consists of 8 pairs of countries. Four of them (50%) are composed of net importing and net exporting countries. Four pairs are composed of net importing countries, including China, the United Kingdom and South Korea. The third category consists of 6 pairs of countries. Three of them (50%) are composed of net importing and net exporting countries, 2 of them are composed of net importing countries, and both include China. One pair consists of net exporting countries, including Germany and South Africa.

From the above analysis, we summarize the trade rules applicable to this study. It should be noted that these rules are to choose the most potential trade links from the links proposed by the structural motivation of cobalt ore trade network. Therefore, the trade countries selected through these rules are more likely to trade cobalt ore than other countries, but it does not mean that there will be no trade relationships between the other countries. The rules are as follows:

(1) If a pair of cobalt ore trading countries appears in potential trade links and the two countries play different trade roles, their speed of establishing trade relations will accelerate.
(2) If the pair of countries appearing in the potential trade link is composed of two net importers and one of them is China, the speed of its successful establishment of trade relations will occur on a relatively slow basis.
(3) If the country pair that appears in the potential trade link is composed of two net exporters, the process of successfully establishing a trade relationship is relatively fluctuant; however, if it involves Germany or South Africa, it may succeed in establishing trade relations within five years.
(4) If a pair of countries does not successfully establish a trade relationship within the next five years after the last occurrence of the top ten potential trade links, the possibility of establishing trade relations later is slim.

It is known from section 3.2 that 34 (70%) of the 49 pairs of countries have successfully established trade relations after appearing in the top ten "potential trade links", while the remaining 15 pairs of countries have not established trade relations, although they have appeared in the top ten "potential trade links", as shown in Fig. 8. According to trade rule (4), the 1–4 pairs of countries did not successfully establish trade relations for more than five years after their last appearance among potential trade links, so the likelihood that they will establish trade

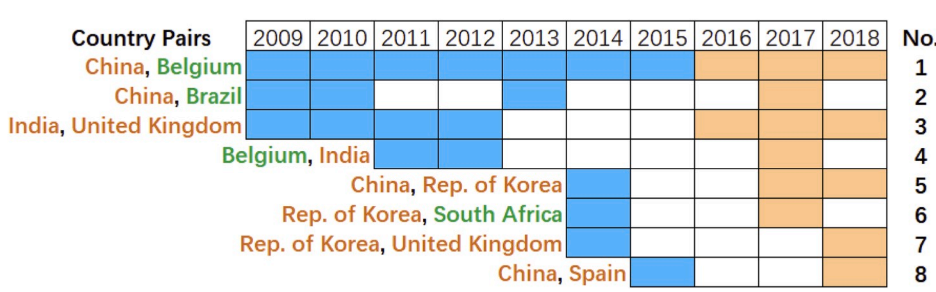


Fig. 6. Country pairs that slowly establish trade relationships for cobalt ore.

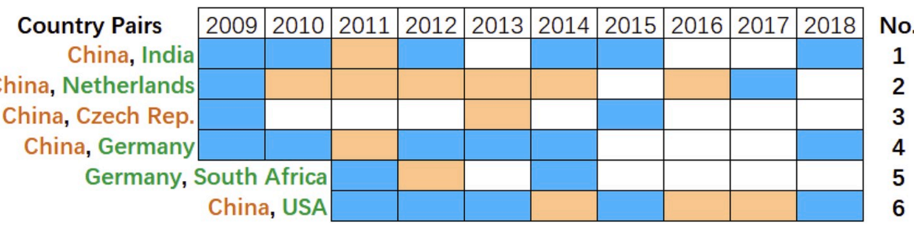


Fig. 7. Country pairs that fluctuate to establish trade relationships for cobalt ore.

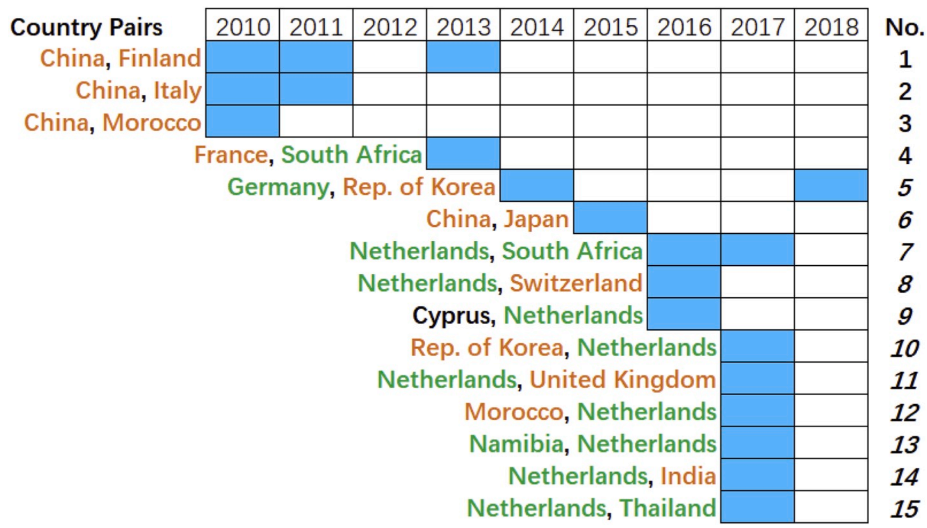


Fig. 8. Country pairs that have not yet successfully established trade relations.

relations is slim. Because 5–15 country pairs appeared among the potential trade links for the last time in the past 3 years, it is necessary to conduct an in-depth analysis of these countries (the names of the countries are given in italics, a total of 11 pairs) in the next part to find the countries that are most likely to successfully establish trade relations in the future.

3.4. Prediction of cobalt ore trade countries based on the overall utilization level of cobalt raw materials

To find the most likely countries to establish trade relations and realize the prediction of international trade relations of cobalt ore, this part will further study the 23 $(7+6+11)$ pairs of countries that need in-depth analysis in combination with the characteristics of countries that have successfully established trade relations, the role of trading countries and the overall utilization level of cobalt raw materials.

These 23 pairs of countries are divided into two categories according to whether the two countries have the same trade roles or not.

The first category includes pairs of countries that have the same trade roles, as shown in Fig. 9. Because the countries in the 1st to 6th pairs play the role of net importers of cobalt ore (country names marked in yellow), the speed of their successful establishment of trade relations is relatively slow. The 1st to 3rd pairs involve China; according to formula (15), the overall utilization level of cobalt raw materials in China is low, which will lead to an increase in cobalt ore imports. The overall utilization level of cobalt raw materials in India and Czech Rep. is increasing, which will lead to a decrease in cobalt ore imports. Therefore, among the countries with net imports role (with their serial numbers marked in red), China and India and China and the Czech Republic are most likely to establish trade relations in the next five years. The 7th to 10th country pairs play the roles of net exporters of cobalt ore (country names marked in green), thus causing their successful establishment of trade relations to be relatively fluctuant. However, due to the overall utilization level of cobalt raw materials in the Netherlands, the 8th trading country, has

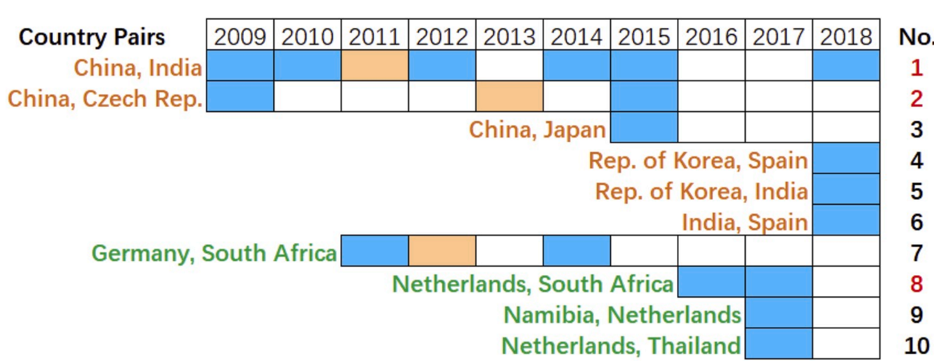


Fig. 9. Countries with the same trade role.

changed from low to high in recent years, and its cobalt ore exports will increase. In contrast, South Africa's overall utilization level of cobalt raw materials is becoming lower and lower, when it needs more supply, the demand for diversified sources of supply will increase, which will promote the establishment of trade relations with it. Therefore, among the countries that are net exporters of cobalt ore and sand, the Netherlands and South Africa are most likely to establish trade relations in the next five years (numbered in red).

The second category is country pairs consisting of different trade roles, as shown in Fig. 10. Because of their different trade roles, the speed of being predicted to successfully establish trade relations will shorten from five years to three years. In the 1st to 3rd pairs, China is a net importer of cobalt ore whose overall utilization level of cobalt raw materials is low. Therefore, it is necessary to import more cobalt ore to ensure the utilization of cobalt resources, which will lead to an increase in the import of cobalt ore. While the Netherlands, Germany and the United States are net exporters of cobalt ore, their overall utilization level of cobalt raw materials is increasing, which will lead to an increase in cobalt ore exports. Therefore, the 1st to 3rd pairs of countries are likely to establish trade relations in the next three years. Similarly, Morocco and Netherlands (the 9th pair), Republic of Korea and the United States (the 13th pair) are the same.

To sum up, China and India, China and Czech Rep., Netherlands and South Africa are the most likely to establish trade relations in the next five years; Netherlands and China, Germany and China, USA and China, Morocco and Netherlands, Rep of Korea and USA are the most likely to establish trade relations in the next three years.

4. Conclusions and policy implications

Strategic mineral resources are essential for each country, to find new trade partners in advance and maintain the security of cobalt supply, it is particularly important to calculate the stability of the current cobalt ore trade network and predict the future international trade relations of cobalt ore. Given this background and based on the complex network topology of the international trade of cobalt ore, this paper uses the link prediction method to find the most likely potential trade relationships by building the prediction model. According to the prediction results, the following conclusions and policy implications are drawn.

(1) Seeking diversified international trade partnerships

Cobalt is a vital resource for electronic products and rechargeable batteries for electric vehicles. As the sales of electric vehicles grow, the demand for cobalt will continue to increase (Gulley et al., 2018). However, by measuring the stability of the cobalt ore international trade complex network, we find the stability of the international trade network of cobalt ore has been poor (Sun et al., 2019). If we rely excessively on the existing trade relationships for cobalt ore, it may lead to the improper selection of trading countries and unnecessary trade losses due to trade instability. For example, the mining law issued by the DRC in March 2018 caused a shock to the international new energy market. The law defined the rich cobalt resources in the DRC as "strategically significant" minerals and accordingly raised the proportion of royalties from the previous 3.5%–10%. The law caused the most direct impact on cobalt resource use in Switzerland and China. Therefore, governments should appropriately strengthen the diversity of trading partners, actively seek more potential trading partner countries, and expand the diversification of cobalt sources.

(2) Estimating the partner countries most likely to establish international trade relations of cobalt ore

Through link prediction, it is found that the possibility of establishing trade relations between two country is directly proportional to the product of the number of import trade partners and the number of export trade partners, and if the predicted trading partner countries have two distinct roles – a net importer and a net exporter– the rate of establishing a successful trade is generally faster. Thus, this paper predicts that the Netherlands and China, Germany and China, the United States and China, Morocco and the Netherlands, and the Republic of Korea and the United States are the most likely to establish trade relationships in the next three years. These pairs of countries feature different trading country roles. For the cobalt ore importing countries, on the one hand, to ensure the healthy development of the mobile phone and new energy battery industries, the high-speed growth of the cobalt-consuming power battery field has led to the increased need for cobalt ore in recent years. On the other hand, from the perspective of cobalt trade, the low overall utilization of raw materials has also increased the import demand for cobalt ore. In contrast, the total utilization level of cobalt raw materials in these cobalt ore exporting countries is gradually increasing. For example, in the United States, cobalt is listed as a key mineral resource, and the utilization rate of cobalt resources is gradually increasing. The annual recovery rate of cobalt resources is approximately 20%–25%, which is high (Sun et al., 2019). All the reasons mentioned above promote the establishment of a new trade partnership between countries with two different roles. This paper also predicts that China and India, China and Czech Republic, and the Netherlands and South Africa are the most likely pairs to establish cobalt ore trade relations in the next five years. Even if these pairs are made up of the same trade country roles, the forecast time is longer. However, considering

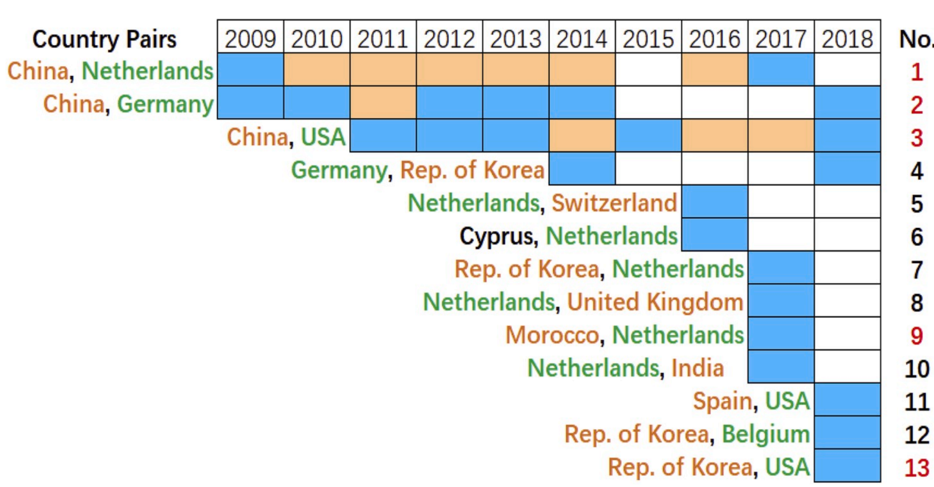


Fig. 10. Countries with different trade roles.

the overall utilization level of cobalt raw materials, the possibility of successfully establishing trade relations is relatively high. For example, as the world's largest producer of refined cobalt, China's overall utilization level of cobalt raw materials is low (Sun et al., 2019), and it needs to import a large amount of cobalt ore to meet the export demand of refined cobalt. On the other hand, the shortage of cobalt resources is seriously affected by the unstable political situation of raw material importing countries and the policy of raw material export restrictions, which encourage an increase in China's imports of cobalt ore and the establishment of more trading partners.

(3) Improve the utilization rate of cobalt resources

From the prediction results, the overall utilization level of cobalt resources has a greater impact on the prediction effect. However, from the perspective of cobalt recovery, the overall recovery efficiency of each country is low (Cullen and Allwood, 2013; Cullen et al., 2012). Thus, countries need to know more about their own cobalt consumption, develop recycling technologies for different products to increase the recovery rate of cobalt resources. Additionally, they can establish a recycling system for cobalt end products and improve the recycling rate of cobalt-containing waste products (such as batteries, alloy products, and catalysts). Moreover, the excess capacity of lithium batteries is a serious problem (Natalia et al., 2017), which reduces the utilization rate of cobalt resources. Countries should optimize the production process of lithium batteries, decompose the processing stage of lithium batteries, and improve the utilization rate of cobalt from different stages of production. Finally, countries should introduce relevant policies, laws and regulations to encourage the development of a recycling economy in the field of renewable cobalt resources as soon as possible, vigorously develop a recycling economy, and implement policies supporting the renewable metal industry. In addition, they should improve the comprehensive recovery and utilization level of cobalt resources, and promote the healthy and sustainable development of the cobalt industry.

In this paper, a new method, link prediction, is used to evaluate the future cobalt ore trade partnership. Although the topological structure of international trade-oriented network, the role of trading countries and the overall utilization level of cobalt raw materials are considered comprehensively, there are still some unsolved problems. For example, there is a lack of a global cobalt resource database that takes geographical, political and other factors into account. Therefore, further research is needed to predict the international trade relations of cobalt ore more accurately.

CRediT authorship contribution statement

Sen Liu: Conceptualization, Resources, Methodology, Investigation, Software, Writing - original draft, Writing - review & editing. **Zhiliang Dong:** Conceptualization, Supervision, Project administration, Funding acquisition. **Chao Ding:** Software, Validation. **Tian Wang:** Formal analysis. **Yichi Zhang:** Data curation.

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