Journal of Energy and Economic Development,
Niroo Research Institute.
Vol. 1, Issue. 2, Autumn 2022 , Pages 1-15
Journal homepage: https://jeedev.nri.ac.ir

A Survey of the Global Electricity Trade Network Structure

Leila Mirtajadini*[1], Shamsollah Shirin Bakhsh[2], Mir Hossein Mousavi[3]

1. PhD, Department of Economics, Social Sciences and Economics Faculty, Alzahra University, Tehran, Iran,

2. Associate professor, Department of Economics, Social Sciences and Economics Faculty, Alzahra University, Tehran, Iran,

3. Associate professor, Department of Economics, Social Sciences and Economics Faculty, Alzahra University, Tehran, Iran

Original Article

Abstract. This study tries to analyse the global electricity trade network by considering nations as nodes and trade among them as links. The data were derived from electricity export and import time series for the period 2010-2018. Network Theory is the basic approach to analyse the relationship between different countries. There are some metrics to scrutinize the global electricity trade network structure; namely node degree, betweenness centrality, cluster coefficient, dominating sets, and link prediction. Also, community detection helps us understand the position of each country in its sub-network. This analysis examines the main players in the electricity trade market. Dominating sets identify a group of nodes that play an active part in facilitating trade. As a result of link prediction analysis, it is very easy to identify missing links in the network. It is a very innovative method of estimating possible links among nodes and predicting the future of trade relations.

Keywords: *Electricity Trade, Network Analysis, Community, Centrality Measures, Link Prediction*

INTRODUCTION

Monopoly has always dominated some economic sectors more than others (like electricity) have, but has had no negative effect on growing trade among countries. Statistics indicate that in 2011, the electricity sector accounted for 19 percent of energy use in the world. Electricity trade increases the efficiency of energy generation, enhances the stability of the electricity system, and provides countries with trade benefits. Electricity is a homogeneous good that can only be stored at a high cost, and output may be produced by a wide range of different technologies. Demand and supply conditions vary considerably on both the short-time scales of a day and the long-time scale of a season or year (Jan and Sebastian, 2016). Unlike other commodities, electricity cannot be stored and supply must meet demand instantly. As a result, when electricity demand fluctuates, especially during peak hours, it is difficult for supply to keep up. To resolve the supply shortage problem, countries can import the difference. This is the importance of international trade in addressing the problem of the electricity market (Antweiler, 2016).

Corresponding author E-mail addresses: leilamirtajadini@gmail.com
Received Date: 2022-09-02 ; Revised Date:2022-10-08; Accepted Date:2022-12-06
https://doi.org/10.30503/jeedev.2022.360245.1017

Consequently, the possible problem with the electricity supply for consumers would be solved. The main goal of liberalizing the electricity market is to achieve more cost-efficient production and lower electricity prices (Lise et al., 2006).

This study tries to analyse the global electricity trade network by considering nations as nodes and trade among them as links. This network analysis helps us to understand the different aspects of the trade network. This study focuses on network fundamental features while introducing some innovations and indices to interpret the network. Using trade values as links, it examines the period 2010-2018 (focusing on the network in 2018). For community detection, we discuss how to find the most effective method to get better results. In addition, new metrics for network analysis have been introduced, like assortative and dominating sets. Finally, link prediction is added to get a comprehensive result.

This paper starts with a small review of historical data and some studies in section 1. Section 2 explains the method and data, which have been used to get the results. The results are then explained in the next section. Included in it are the main features of the global network, community structure, network assortative, betweenness centrality and clustering coefficients, dominating sets, and link prediction analysis. The final section is dedicated to the conclusion and discussion.

1. LITERATURE: ELECTRICITY TRADE

There is a growing electricity trade all over the world. Based on IEA's Electricity Information for 2019, OECD member's imports increased from 89 TWh in 1974 to 490 TWh in 2018 (by an annual growth rate of 4.0%) compared to the 2.1% growth in overall electricity supply. These imports account for 4.4% of the electricity supply in 2018. OECD exports of electricity grew from 81 TWh in 1974 to 480 TWh in 2018. There is substantial electricity trade between Russia, Kyrgyzstan, Turkmenistan, Ukraine, and other countries of the former Soviet Union. There is a significant amount of trade in the southern part of Africa. In Asia, India and China have transitioned from being net importers to major power exporters in the region (Electricity information: overview, 2019). The importance of trade can be estimated in different regions. South Asia is a relevant example as it is lagging behind many regions in regional electricity trading despite the huge potential for trade. The unrestricted electricity trade provision would save $226 billion in electricity supply costs over the period (Timilsina and Taman, 2016). Srinivasan (2013) investigates the role of electricity as a primary export and evaluates the impact on the terms of trade. He concludes that in the medium term, an electric power exporting economy would be better off developing its manufacturing sector. This would diversify its exposure and protect its trade interests. Li et al. (2003) scrutinizes some scale-free features of the world trade web (WTW), where the United States is the 'biggest' node in the weighted degree sense. To study the economic synchronization on the WTW, real GDP data of the 1975–2000 period for 21 developed countries were analysed based on their correlations with the US. The conclusion is that 18 developed countries indeed show significant synchronization of economic cycles with the USA.

Ji et al. (2016) examines the global electricity trade. The global electricity trade network is composed of nations as nodes and trade volumes as links. As the largest sub-network, they used the Eurasian sub-network to identify critical nations in the global electricity trade network using various metrics. In Europe, the cross-border electricity trade is intensive. Germany, France, and the Czech Republic are the largest electricity exporters. Russia, Ukraine, China, and Azerbaijan have more central positions as measured by the betweenness centrality. From an overall perspective, these countries play an imperative role in the security of the Eurasian sub-network. Liu et al. (2018) survey trade facilitation in the Belt and Road Initiative (BRI) by focusing on the top two trade relations networks to illuminate the structure and evolution of trade relations.They conclude, since the future impacts of China's BRI will depend on the degree of integration of the connected regions, some countries with stable and high centrality indices (e.g., Russia, Singapore, Serbia, Greece, Turkey, Iran, Poland, Hungary, and Romania) could be selected by China as strategic regional partners, and countries with a strategically significant geographical position but weak trade links (e.g., Myanmar, Pakistan, and Belarus) should be prioritized. These studies conclude based on the network analysis in their defined framework. There are some other studies on trade network analysis with the same attitude, like Fang et al. (2018), Fair et al. (2017), Giudici et al. (2019), and Wang et al. (2019).

2. DATA AND METHODS

Electricity export and import data (HS code 27160000) for the period 2010-2018 have been used. Most of the data were collected from comtrade.un.org; but for some of the missing data of high importance to our community analysis, other sources have been employed. There are some conflicts in trade reports among countries, that is, there are two numbers for a single trade flow (export or import). In this study, we only considered the larger of the two, although the differences were usually not significant. Trade values are represented in US dollars. In the network, for simplicity, the names of the countries are shown in ISO 3-digit codes. This study explores the main features of the global electricity trade as a network and represents the properties of the global electricity trade network. In addition, it provides an analysis of the global electricity trade network by its different communities, focusing on the 2018 trade network.

3. RESULTS: GLOBAL TRADE NETWORK

3.1 Global Trade Network: Main Features

The global electricity trade network is composed of nations as nodes and trade flow as links. Links are weighted; meaning that each nation has a value of electricity trade which is directed (i.e., trade from A to B means export from A to B and differs from that of B to A). There are some metrics to scrutinize the global electricity trade network structure such as centrality measures (like node degree and betweenness centrality), dominating sets, and group centralities. In addition, community detection helps us understand the position of each country in its sub-network. The node degree of a nation is measured by the total number of links from or to other nations. Node strength is an extended version of node degree that adds the weights of links and measures the total weight of its connected links.

At present, the electricity trade network is flourishing. Nodes and links (trade flows) increased from 10 and 9 in 1990 to 114 and 400 in 2010 (Ji et al., 2016). It implies a substantial increase in electricity trade. Fig. 1 illustrates changes in the number of nodes and links for the period 2010-2018. After the drastic increase during 1990-2010, there has not been a significant change. For four years (2012-2015), the number of links exceeded 500. Although the number of connected nations slightly increased from 2010 to 2015, the value of trade decreased after 2012, as shown in the right figure.

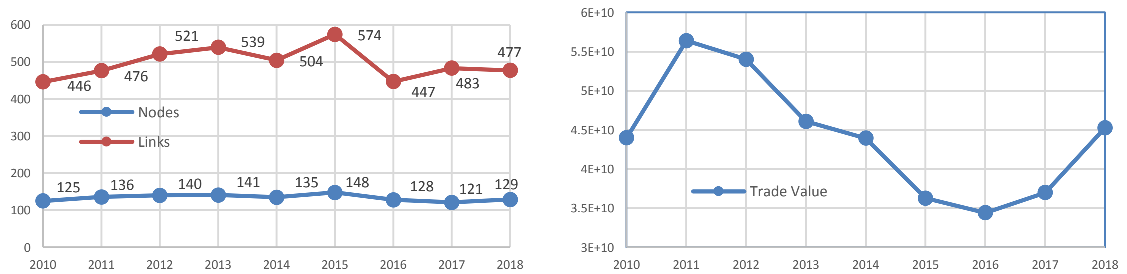

Fig. 1. Dynamics of the global electricity trade network, 2010-2018.

The main properties of the global electricity trade network are presented in Table 1. As we can see from the table, the number of nodes changed from 148 in 2015 to 121 in 2017. The links reached a maximum of 575 in 2015, with the lowest amount being 446 in 2010. The Largest In-Degree index shows the number of links to a certain node or its import node degree. In the same way, the Out-Degree index shows the number of exports links. Here the weights are not taken into account. The largest In- and Out-Degree node of the period belongs to the Netherlands with respectively 29 and 87 both in 2015. Although the Netherlands appears among the top ten nations just twice (based on the node degree) in 2015 and 2017, interestingly enough, it is the largest node in both years (Table 2).

Table 1. Main Features of the global network, 2010-2018.

	2010	2011	2012	2013	2014	2015	2016	2017	2018
No. Nodes	125	136	140	141	135	148	128	121	129
Edges	446	477	522	539	565	575	447	483	478
Largest In-Degree	20	22	23	22	21	29	20	36	23
Largest Out-Degree	18	21	39	55	26	87	21	33	33
Largest Node Degree	37	43	44	55	39	116	41	69	43
Largest Node Weight (billion$)	12.8	17.1	17.2	9.3	8.4	7.5	5.3	5.7	7.5
Total Trade Value (billion$)	44.0	56.4	54.0	46.1	43.9	36.3	34.4	37.0	45.3
Largest Trade Value (billion$)	1.2	3.5	3.8	2.4	2.7	2.5	2.2	2.3	2.2
Mean Electricity Value (billion$)	0.11	0.12	0.10	0.08	0.08	0.06	0.08	0.08	0.09

The biggest numbers in total electricity trade value in the whole period are 56.4 and 54 billion dollars in 2011 and 2012 respectively. The highest Electricity Value index represents the largest trade value each year. The biggest links in the first three years were Germany to Switzerland in both 2010 and 2012, and Switzerland to Germany in 2011. For the rest of the period (2013-2018), the largest trade flow was Canada to the USA. The highest node strength represents the total trade value of a certain node with its neighbours. In our data, Germany had the most significant node strength each year. In 2011 and 2012, its strength exceeded 17 billion dollars.

Four countries (Slovenia, the Czech Republic, Germany, and Switzerland) were among the top ten nations in terms of node degree for the whole period. Italy and Serbia also appeared on the list, except for the years 2012 and 2010, respectively. Greece missed out in 2013 and 2014, and Bulgaria had the same situation in the first two years. Spain also did not appear in the last three years. Croatia was among the top ten for only the first five years of the period. Eight nations (highlighted in Table 2) were present among the top ten for at least 8 years of the total 10 years of the examined period.

Table 2. Top ten countries with the largest node degrees, 2010-2018**.**

	2010	2011	2012	2013	2014	2015	2016	2017	2018
1	SVN	CZE	SVN	JAM	CZE	NLD	CZE	NLD	CZE
2	CZE	SVN	CZE	CZE	BUL	CZE	BUL	CZE	UZB
3	DEU	DEU	THA	SVN	DEU	SVN	DEU	SVN	BUL
4	AUT	AUT	DEU	DEU	ITA	BUL	ITA	BUL	SVN
5	CHE	GRC	ESP	ESP	SVN	DEU	SRB	DEU	DEU
6	GRC	SRB	CHE	ITA	ESP	ESP	SVN	ITA	GRC
7	ESP	CHE	GRC	CHE	HRV	CHE	CHE	GRC	ITA
8	HRV	HRV	BUL	SRB	CHE	ITA	RUS	CHE	SRB
9	HUN	ITA	HRV	BUL	THA	GRC	BIH	HUN	CHE
10	ITA	ESP	SRB	HRV	SRB	SRB	GRC	SRB	DNK

3.2 Centrality Measures

Betweenness Centrality (BC) quantifies the number of times a node acts as a bridge along the shortest path between two other nodes. This is one of the most significant indices that has been used to analyse the importance of the nodes in our network. This metric is measured with the number of the shortest paths (between any couple of nodes in the graphs) that pass through the target node u (denoted σv,w(u)). This score is moderated by the total number of the shortest paths existing between any pair of nodes in the graph (denoted σv,w). The target node would have a high betweenness centrality if it appears in many shortest paths (Perez & Germon, 2016).

$$B(u) = \sum_{u \neq v \neq w} \frac{\sigma_{v,w}(u)}{\sigma_{v,w}} \quad (1)$$

Table 3 shows the highest scores for BCs. Russia has the biggest BC followed by China, the UAE, and Uzbekistan. This shows that these countries are crucial nodes in the network and play an invaluable role in easing trade among nations.

Even though it seems there is a relation between this variable and the node degree, examining all the nodes proves that there is no significant correlation between them. As shown in Fig. 2, there is no obvious relationship. Countries with a high BC are necessary for the stability of the network (Ji et al., 2016). Some countries have large node degrees but small BC and vice versa. Countries from Central Asia like Kazakhstan, Kyrgyzstan, and Tajikistan, together with other nations like Mongolia, Guatemala, Myanmar, and Mexico are among the first 30 countries in terms of BC ranking, but they do not have a high position in the node degree ranking. Similarly, countries generally from Europe, like Serbia, Croatia, Macedonia, Slovenia, Bosnia and Herzegovina, and Montenegro have the opposite situation. Kazakhstan, the USA, and Mexico (among the top ten in terms of BC) have node degrees of 7, 6, and 8. While Serbia, Slovenia, and Greece (among the top ten in terms of node degree) have BC scores of almost zero. It means that although Serbia has 23 trading partners, it is not among its community's most prominent trade facilitators.

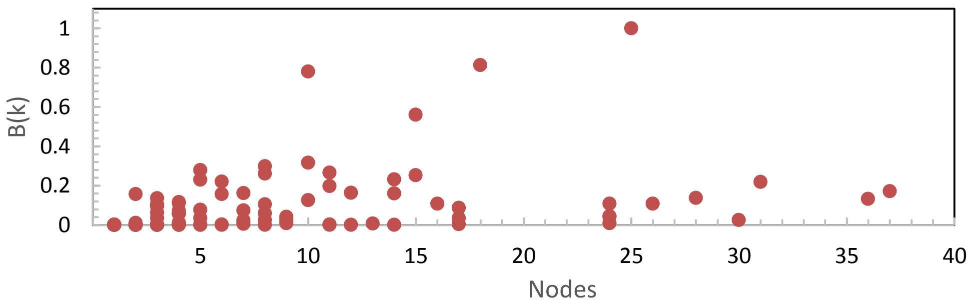

Fig. 2. Node Betweenness (B) against node degree (k)

Table 3. Betweenness Centrality, Top ten in 2018.

	1	2	3	4	5	6	7	8	9	10
Betweenness Centrality	RUS	CHN	UAE	UZB	KAZ	DEU	TUR	MOZ	USA	MEX
	0.04	0.02	0.02	0.02	0.02	0.02	0.01	0.01	0.01	0.01

3.3 Community Structure

A community is defined as a subset of nodes within the graph such that links between the nodes are more solid than the links with the rest of the network (Radicchi et al., 2003). A community, or cluster, is generally defined as a subset of nodes densely interconnected relative to the rest of the network (Newman and Girvan, 2004). It is possible to identify groups of nodes that are heavily connected but sparsely linked to the rest of the network. These interconnected groups are often characterized as communities (Yang et al., 2016). The problem of community detection requires the partition of a network into communities of densely connected nodes, with nodes belonging to different communities being only sparsely connected. Several algorithms have therefore been proposed to find reasonably good partitions in a reasonably fast way (Blondel et al., 2008). This problem has not been satisfactorily solved yet, despite the huge efforts made by different researchers.

The modularity score determines the partition number and the group size automatically without manual intervention. The computed modularity z-score number for each year is shown in Table 4. Some algorithms have higher z-scores, i.e., they can be employed as the main approach to community detection. Among all, Fast greedy (Clauset et al., 2004), Optimal (Brandes et al., 2008), and Louvain (Blondel et al., 2008) methods provide better results. There are some disputes that the modularity z-score is not considered to be the most accurate index. Still, it could be used as a basis for tackling the problem. In our study, we used the Louvain method for community detection.

Table 4. Different Modularity Scores

	Edge_ density	**Edge_ betweenness**	**Walk trap**	**Fast greedy**	**Label_ prop**	**Optimal**	**Louvain**
2010	0.06	0.42	0.58	0.57	0.49	0.57	0.57
2011	0.05	0.35	0.48	0.57	0.54	0.57	0.57
2012	0.05	0.39	0.50	0.55	0.44	0.55	0.55
2013	0.05	0.35	0.54	0.58	0.56	0.59	0.57
2014	0.06	0.46	0.58	0.62	0.60	0.62	0.62
2015	0.05	0.37	0.62	0.64	0.61	0.64	0.64
2016	0.05	0.54	0.64	0.66	0.61	0.66	0.66
2017	0.07	0.52	0.63	0.63	0.60	0.63	0.63
2018	0.06	0.48	0.59	0.64	0.55	0.65	0.63

Louvain is an unsupervised algorithm composed of two phases: Modularity Optimization and Community Aggregation. This method is a greedy heuristic that searches for a maximum modularity partition of the nodes in successive steps. It starts with an initial partition where each node is a community. Then, the method merges the related nodes in successive steps and creates communities that increase the value of modularity. These combinations are made until a local maximum of modularity is achieved (Adam et al., 2018, Rita, 2020). For a weighted graph, modularity is defined as:

$$\Delta Q = \left[\frac{\Sigma_{in}+k_{i.in}}{2m} - \left(\frac{\Sigma_{tot}+k_i}{2m}\right)^2\right] - \left[\frac{\Sigma_{in}}{2m} - \left(\frac{\Sigma_{tot}}{2m}\right)^2 - \left(\frac{k_i}{2m}\right)^2\right] \tag{2}$$

Where Σ_{in} is the sum of link weights in Community (C), Σ_{tot} is the sum of link weights incident to nodes in C, k_i is the sum of link weights incident to node i, $k_{i.in}$ is the sum of link weights from i to nodes in C and m is the sum of weights of all the links in the network (Blondel et al., 2008). Fig. 3 shows the global electricity trade network in 2018. There are 14 sub-communities in the 2018 trade network. There is just one small community of three nations (Columbia, Ecuador, and Peru) that is disconnected from the universal network.

We applied the within-module degree Z-score (Guimerà & Amaral, 2005) to identify network hubs based on their connections with other nodes. This index is a measure of the connectivity of a given vertex to other vertices in its module/community. In Asia, Uzbekistan (2.71), China (2.23), India (1.5), and Iran (1.37) are the most significant countries in their communities. France (2.56), Russia (1.85), Serbia (1.78), and the Czech Republic (1.63) have the highest z-score in the European community. In the African sub-network, Ivory Coast (2.13), South Africa (2.00), and Mozambique (1.67) play crucial roles within the community. El Salvador (1.9), Mexico (0.95), and the USA (0.95) have the same situation in the North American community. In South America, Argentina (1.43), Brazil (0.95), and Colombia (0.58) serve as vital nodes for establishing connectivity among other nodes. Specialized hubs have an influential role in maintaining efficient communication along the network, making their topological properties of high interest (Vargas & Wahl, 2014).

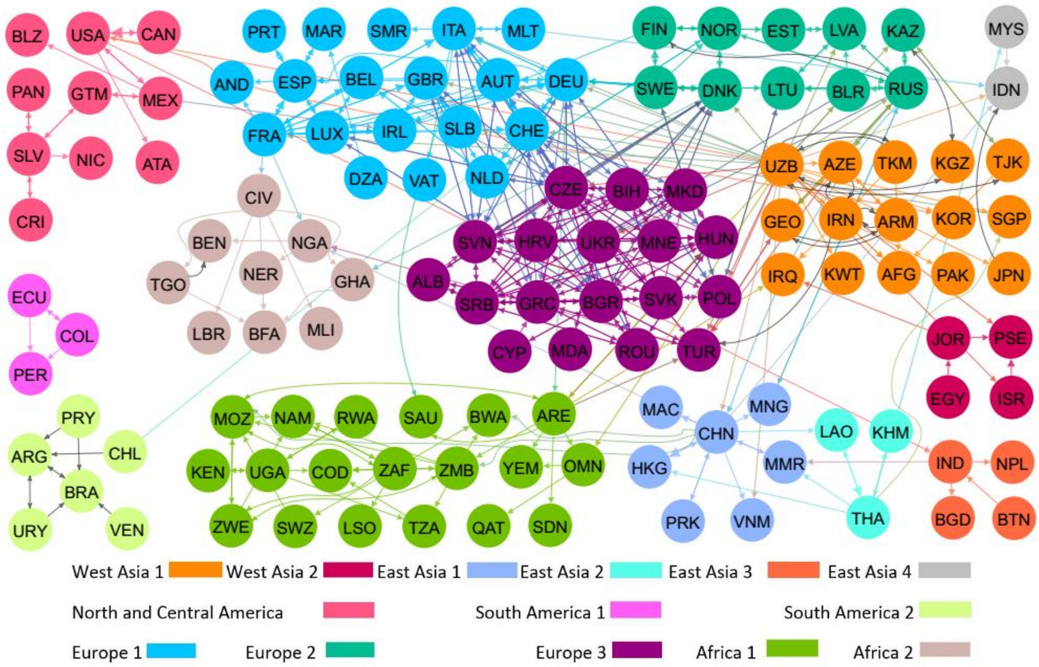

Fig. 3. Global Electricity Trade Network in 2018

Geographic locations and transmission technologies significantly affect the structure of the global electricity trade network. In the 1990s, the correlation between flow and geographical distance was as high as 90% in the electricity trade network. This indicates that geography was the main influencing factor for trade flow. However, the correlation continued to decline, indicating that other factors gradually occupy the main position in influencing trade volume (Wu et al., 2020). Besides geographical distance, other factors like political relations and landscape affect grid construction costs.

Fig. 3 shows the components of Europe, West and Central Asia, Africa, North America, and South America. Europe is the most interconnected region with a large number of Asian partners and links among its nodes. Weights have not been depicted in the graph. We can see the top ten nations in terms of node degree for 2018 in Table 2. On the list, the index ranges from 43 (the Czech Republic) to 21 (Denmark). Table 5 shows the main characteristics of the sub-networks. With some adjustments, communities could compose five major communities: Africa, Asia, Europe, North America, and South America. Compared to the network in 2010, the trade network in 2018 is more connected. In addition, there are connections among communities as well. The most significant sub-network is the European community, consisting of three sub-communities. European nations have a lot of interactions with other community members, especially Asian nations. Nearly 70 percent of all electricity trade takes place in this community. The number of links in a typical community is indicated in the second row of Table 5. Although the number of nodes in the European community is more than the Asian community by a few, the number of links is almost five times as large. This could be an exporting or an importing flow between two nodes of two different communities. Mean node degree and strength are rather high in European nations. The average nation in this group has 12.7 links with its neighbours. Lastly, the mean clustering coefficient is high, indicating a clear tendency among members to form a group. South America is next with 0.53 for the coefficient, which indicates its members tend to cluster together and trade with each other.

Node strength is the total trade value of the node. The most weighted node is Germany, followed by France, Italy, Switzerland, and the Czech Republic. Germany has 7.5-billion-dollar electricity trade with its trading partners. Italy, Germany, and the USA have the most imports and rely heavily on their trade partners. In addition, France, Germany, and China have the most export values with respectively 5.9, 5.1, and 2.3 billion dollars. The results are compatible with practical situations. Although Germany is a net importer of energy (in 2017, it imported 86 percent of its energy supply and exported 52 percent of its energy production), it is a major net exporter of electricity. In 2018, its trade surplus was 2.7 billion dollars. Consequently, it has a significant impact on the trade network with a high node degree. Renewable energy accounts for 16 percent of Slovenia's total primary energy supply. Switzerland, Italy, Bulgaria, and the Czech Republic each have a share of 23, 18, 10, and 10 percent, respectively. Italy is the biggest importer with a deficit of 4.3 billion dollars. France, Germany, China, the Czech Republic, and Canada are the biggest exporters, respectively.[1]

The total traded electricity in 2018 was about 45.3 billion dollars. Table 6 shows the largest links in the network. Among the 30 largest links, there are just 3 trade flows from regions other than Europe. The largest links in other communities are Canada-USA, Paraguay-Brazil, China-Hong Kong, France-Italy, and South Africa-Mozambique, respectively in North America, South America, Asia, Europe, and Africa. In West Asia, the biggest link is Iran-Iraq with a value of 421 million dollars. France and Germany together appear 10 times in the first 20 top exporter links. The Czech Republic and Italy have also been on the list of largest links six times.

The probability density of node degree (PDF) and cumulative density of node degree (CDF) functions are shown in Fig. 4. Both PDF and CDF functions decrease when fitted to the node degree range. The results for these two functions over node strength (instead of node degree) are the same.

Table 5. Main features of the sub-networks, 2018.

	Africa	**Asia**	**Europe**	**North America**	**South America**
No. Nodes	29	35	47	10	9
No. of links (Within the Community)	48	46	208	15	43
No. of links (With other Communities)	15	72	200	4	1
No. of links (Total)	63	118	408	19	52
Total Electricity Value (billion$)	1.6	5.8	321	3.4	2.3
Mean node degree	3.6	3.9	12.7	3.4	2.9
Mean node strength (billion$)	0.1	0.4	1.3	0.7	0.4
Mean clustering coefficient	0.17	0.11	0.33	0.00	0.53

Table 6. Top ten largest links, 2018.

Exporter	**Importer**	**Trade Value (billion$)**
Canada	USA	2.3
Paraguay	Brazil	1.6
China	Hong Kong	1.5
France	Italy	1.5
Switzerland	Italy	1.5
Laos	Thailand	1.4
France	ESP	1.1
France	UK	1.1
Germany	Italy	1.0

[1] The data are extracted from IRENA (International Renewable Energy Agency), country profiles.

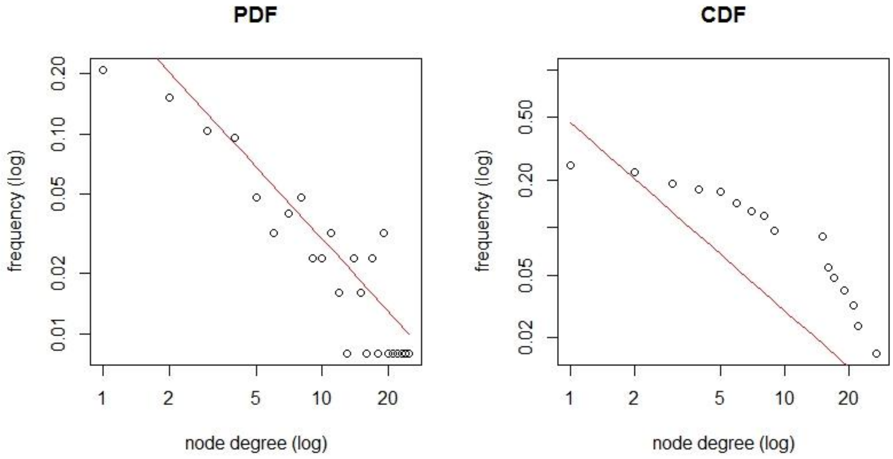

Fig. 4. Probability Density Function (left) and Cumulative Density Function (right), 2018.

3.4 Network Assortativity

Network Assortativity happens when in a network, nodes with high degrees tend to link together. Newman (2003) defined the assortativity coefficient for nominal classes of individuals as:

$$\mathrm{r} = \frac{\sum_i e_{ii} - \sum_i a_i b_i}{1 - \sum_i a_i b_i} = \frac{Tr\ e - \|e^2\|}{1 - \|e^2\|} \tag{3}$$

Where quantity eij is the fraction of edges in a network that connects a vertex of type i to one of the types j. Where ai and bi are the fraction of edges in which the ends of the edges are attached to vertices of type i. In undirected graphs, where the ends of edges are all of the same types, ai = bi, e is the matrix with elements of eij and $\|e^2\|$ (the sum of all elements of the matrix x). On an undirected network, this quantity is symmetric in its indices eij = eji, while on directed networks or bipartite networks, it may be asymmetric. It satisfies the sum rules as follow:

$$\sum_{ij} e_{ij} = 1\ , \sum_j e_{ij} = a_i\ ,\quad \sum_i e_{ij} = b_j \tag{4}$$

This formula gives r = 0 when there is no assortative mixing, as eij = aibj. The coefficient r = 1 when there is perfect assortative mixing, $\sum_i e_{ii} = 1$. If the network is perfectly disassortative, i.e., every edge connects two vertices of different kind, then r is negative. Newman also defines a formula for scalar properties of vertices continuous measures. Assortative mixing by degree can be quantified in exactly the same way as for other scalar properties of vertices. Farine (2014) has derived a weighted version of the continuous assortativity coefficient (To see more, check Newman (2003) and Farine (2014)).

We have implemented these methods in the R package assortnet and obtained the standard error of the assortativity coefficient calculated using the jack-knife method as described by Newman (2003) for the network in 2018; this gives the coefficient value r = -0.15 and the standard error σr= 0.12. It shows our findings of assortative mixing are strongly statistically significant. The computed assortative coefficient shows a low level of assortativity within the network. The assortativity coefficients for other years are in the -0.06 to -0.20 range.

Fig. 5 illustrates the average nearest-neighbour degree (Knn) and the average nearest-neighbour strength (Snn) to evaluate the similarity between connected nodes, another measure known as network assortativity. Table 7 shows the top ten nations with the largest average nearest-neighbour degree. In the table, ND represents the correspondent node degree, and R is the nation's rank based on the node degree among all. We can see that countries with large Knns like Canada, Armenia, and Afghanistan have few treading partners (2, 6, and 4, respectively) and a low position in terms of node degree. Similarly, countries like the Czech

Republic, Bulgaria, and Uzbekistan with high node degrees are ranked 20, 25, and 120 in terms of Knn. Ji et al. (2016) shows that in 2010, there was no obvious correlation between Knn and Snn functions with node degree in the Eurasian sub-network. Our results are the same for the average nearest-neighbour degree and the average nearest-neighbour strength against the node degree. It shows that the electricity trade network in 2018 was disassortative and to some extent, countries with few trading partners were connecting to countries with large nodes.

Table 7. First ten nodes with the largest average nearest-neighbour degree, 2018.

	1	2	3	4	5	6	7	8	9	10
	CAN	ARM	AFG	ARG	ALB	DEU	CHE	AND	BLR	CHN
K_{nn}	37	36	31	30	28	26	25	24	24	24
ND	2	6	4	6	8	29	23	2	5	17
R	88	53	62	49	43	5	8	99	60	16

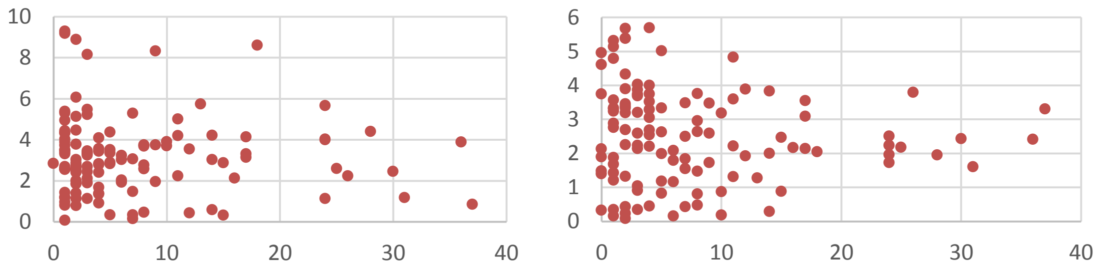

Fig. 5. Average nearest-neighbour node degree Knn against node degree k (Left);

Average nearest-neighbor node strength Snn against node degree k (Right), 2018.

3.5 Dominating Set

A dominating set (DS) of a graph G is a subset S⊂V (nodes) such that for each node in graph (G), it either belongs to S or has at least one neighbour in S. A CDS (Connected DS) is a DS, which induces a connected subgraph. The nodes in the CDS are called dominators or dominates. It is desirable to build a minimum-sized connected dominating set (MCDS) in consideration of reducing more traffic and maintenance (Li et al., 2005). There are several algorithms to extract the most dominating subset of nodes, including the “Greedy”, “Tree Growing”, “Marking”, “k-Local”, and “Largest ID” algorithms. Here we have applied the Greedy algorithm to get the optimal conclusion. The results are provided in Table 8, indicating the first top ten countries with high scores in selected years. There are 29 vertices with different scores that have been identified as dominant nodes in 2018. The number of nodes for 2016, 2014, and 2012 are 30, 29 and 29, respectively. Iran, Spain and China are among the most dominant nodes over the entire considered period, 2010-2018 (even though they do not rank in the top ten countries).

Table 8. Top ten nodes, Dominating Sets, 2018

	2018	2016	2014	2012
1	Uzbekistan	South Africa	South Africa	South Africa
2	USA	Uganda	USA	USA
3	Ukraine	Russia	Ukraine	Ukraine
4	Uganda	Niger	Uganda	Thailand
5	Thailand	Malaysia	Thailand	Slovenia
6	El Salvador	Moldova	Serbia	Russia
7	Oman	Kuwait	Russia	New Zealand
8	Nigeria	Cambodia	New Zealand	Niger
9	Mozambique	Kazakhstan	Nigeria	Morocco
10	Latvia	Jordan	Mozambique	Lithuania

3.6 Link Prediction

Link prediction is a valuable feature of social network analysis. From the observed part of the network, it detects hidden links or predicts future links based on its current structure (Jiang et al., 2015). Most of the researchers focus on the link prediction problem, which is very valuable for solving real-world problems. Generally, the prediction problem can be approached from two angles: (i) network structure and (ii) attributes of nodes and connections (Gao et al., 2015). It is imperative to note that, for all prediction measures, the network should be undirected, simple and connected to all nodes. In order to avoid the problem, a few modifications have been made; for example, some nodes have been deleted each year.

We applied AUC (Area under Curve) scores to evaluate the quality of the results from the tested algorithms. Fig. 6 displays AUC curves for 19 different estimated prediction methods for the network in 2014 (the results for this year are clearer). These results are obtained based on the actual links in 2015. Most of the methods are very efficient, so it is difficult to choose between them. Link prediction scores of some selected approaches are shown in Table 9. These links are the most probable predicted links (or missing links) in 2017.

With $\Gamma(x)$ as the set of all neighbouring vertices of vertex x, Common Neighbour and Jaccard Indices are defined as follows:

$$CN_{xy} = s_{xy} = |\Gamma(x) \cap \Gamma(y)| \ , \ Jaccard_{xy} = s_{xy} = \left|\frac{\Gamma(x)\cap\Gamma(y)}{\Gamma(x)\cup\Gamma(y)}\right| \quad (5)$$

For example, using the Common Neighbour method for each pair of Hungary-Slovenia, Bulgaria-Switzerland, and Bulgaria-Bosnia and Herzegovina, there are 32 common neighbours. Meaning that there is a high chance of these pairs being connected. The Jaccard Index (Jaccard, 1912) measures the proportion of common neighbours in the total number of neighbours. It reaches its maximum if all neighbours are connected to both vertices. Based on this index, there are 13 missing links with the maximum score (1).

Cosine Based L+ index assesses the cosine of the angle between node vectors in a space spanned by columns of the Laplacian matrix (L+).

$$s_{xy} = \frac{l^{+}_{xy}}{\sqrt{l^{+}_{xx} l^{+}_{yy}}} \quad (6)$$

The Katz Index counts all the paths between the given pair of nodes, with shorter paths having larger weights. β is a free parameter. The sum converges when β is lower than the reciprocal of the largest eigenvalue of adjacency matrix. If this condition is satisfied, the Katz Index can be expressed in a matrix form. Where A is the adjacency matrix and I is the identity matrix.

$$s_{xy} = \sum_{i=1}^{\infty} \beta^{l} \left|paths^{<l>}_{xy}\right| = (I - \beta A)^{-1} - I \quad (7)$$

Different methods predicted a big number of missing links.

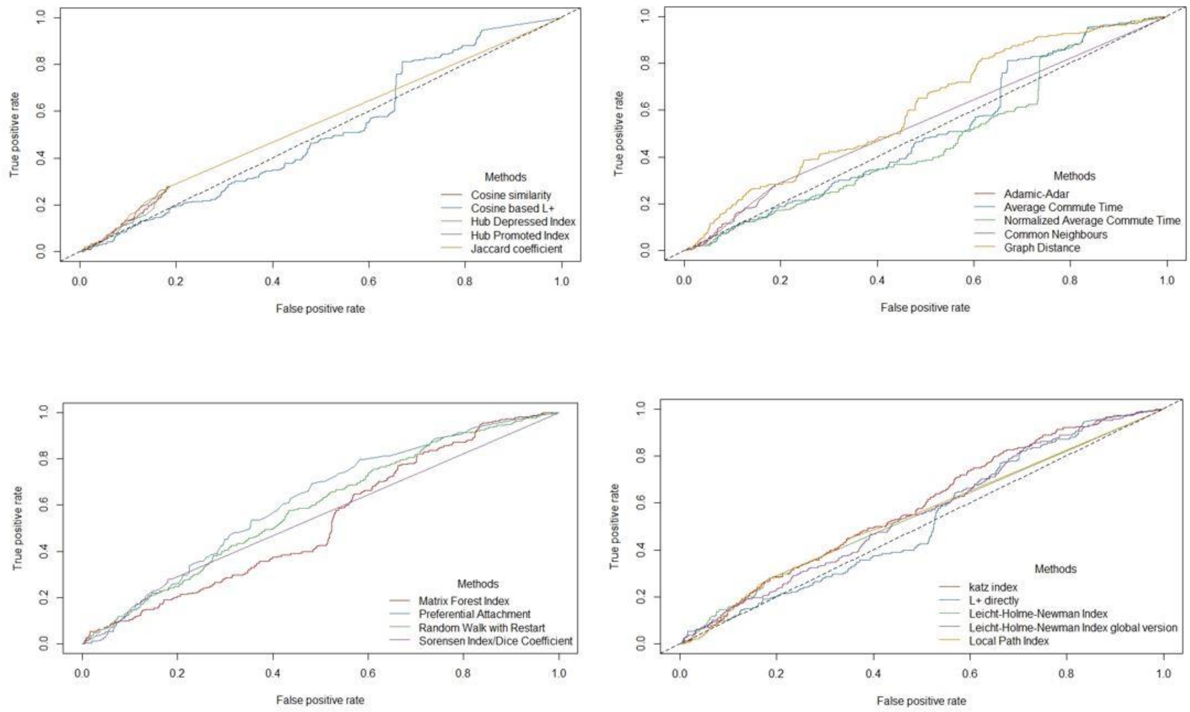

Fig. 6. AUC curves, Link Prediction for the Network of 2015

In general, missing links (including those in Table 9) can be predicted by most prediction methods, although they differ greatly in their scores (probability of existing). For example, direct trade between Hungary and Slovenia is missing from the network (with a high score in all methods) and it could help the interconnectedness and stability of the network. All the missing links in the table are in the same situation.

Table 9- Top 10 Link Prediction Scores, 2017.

	Common Neighbour		**Jaccard**		**Cosine Based L^+**		**Random Walk**		**Katz**	
1	HUN	SVN	SMR	VAT	BRA	PRY	NIC	SLV	HUN	SVN
2	BGR	CHE	PRY	URY	ARG	PRY	BRA	VEN	CZE	HUN
3	BGR	BIH	NIC	PAN	BRA	URY	BGD	IND	SRB	SVK
4	CZE	HUN	MAC	PRK	PRY	URY	KHM	THA	CHE	GRC
5	DNK	SRB	LBR	MLI	FRA	NLD	ATA	USA	MKD	SVK
6	CHE	SRB	KEN	RWA	CZE	FRA	BLZ	MEX	CZE	UZB
7	DNK	ITA	HKG	LAO	BRA	VEN	ARG	PRY	BGR	MNE
8	DEU	GBR	CRI	PAN	PRY	VEN	BRA	PRY	BIH	HUN
9	BIH	GRC	CRI	NIC	AUT	FRA	BRA	URY	DEU	UZB
10	SRB	SVK	BTN	NPL	ARG	VEN	NER	NGA	AUT	LUX

CONCLUSION AND DISCUSSION

This study examines the electricity trade network for the time 2010-2018. The results show that the network size has slowly increased over the studied period. In historical data, however, the number of the nodes and links indicates a massive increase in the size of the network. To analyses a network, it is helpful to divide it to sub-networks that are densely interconnected. Different modularity-based methods and their corresponding scores were compared for community detection. The global network in Fig. 3 shows the components of Europe, West and Centre Asia, East Asia, Africa, North America and South America. Europe is the largest community with 70 percent share of the total trade value and 58 percent of the links in the network. During the 2010-2018 period, Slovenia, the Czech Republic, Germany, Switzerland, Italy, Serbia, Greece, and Bulgaria had large node degrees and were crucial for network stability. France and Germany were the biggest exporters for the whole period; the reliability of their national grids being an imperative aspect for their partners. Switzerland, Canada and the Czech Republic were also in the top 5 in this regard (depending on the year). In addition, in 2018, China became the third biggest exporter. Despite having a node, degree of two, Canada was one of the largest electricity exporters. The largest net importers of electricity in all nine years of the studied period were Italy, Brazil and the USA, raising concerns about the security of energy supply.

Russia, followed by China, UAE, and Uzbekistan had the highest Betweenness Centrality. This indicates that these countries are the key nodes in facilitating trade among other nations. European and Asian nations had the most interactions. For most of the period, the assortativity coefficient was low, indicating that the network was more likely to be disassortative. Furthermore, there was no correlation between average nearest-neighbour degree (or strength) and node degree (strength) in 2018 (and also other years), which implies no similarity between connected nodes, another way to measure network assortativity.

Another criterion for network analysis is dominating sets. South Africa, the USA, Ukraine, Uganda, and Thailand are among the nodes with high presence in dominant sets. Iran, Spain and China were on the list of dominant nodes for the entire period, even though they were not among the top ten countries. Link Prediction is another method of revealing missing links and evaluating the dynamics within a network. The results indicate that in 2018, there should have been a connection between some nodes, like Hungary-Slovenia and Bulgaria-Switzerland. If a researcher focuses on a specific country, this method identifies the most likely potential trading partner in the network. Sometimes, these types of nodes are not connected because of political relations. Additionally, this method does not consider the direction of trade, i.e., two big net exporters (importers) cannot necessarily trade with each other even if they have many common neighbours.

ACKNOWLEDGMENT

We would like to pay our gratitude and our respects to the late Dr. Shamsollah Shirinbakhs. Dr. Shirinbakhs passed away in 2020. He was a dedicated professor in the Social Sciences and Economics Faculty at the University of Alzahra in Tehran.

REFERENCES

Adam, A., Delvenne, J. C. and Thomas, I. (2018). Detecting communities with the multi-scale Louvain method: robustness test on the metropolitan area of Brussels. J. Geogr. Syst. 20, 363–386. https://doi.org/10.1007/s10109-018-0279-0

Antweiler, W. (2016). Cross-border trade in electricity. Journal of International Economics, 101, 42–51.

Barrenas, F., Chavali, S., Holme, P., Mobini, R. and Benson, M. (2009). Network Properties of Complex Human Disease Genes Identified through Genome-Wide Association Studies. PLoS One. Volume 4, Issue 11, e8090, https://doi.org/10.1371/journal.pone.0008090.

Blondel, V. D., Guillaume, J. L., Lambiotte, R., and Lefebvre, E. (2008). Fast unfolding of communities in large networks. J. Stat. Mech, P10008.

Brandes, U., Delling, D., Gaertler, M., Gorke, R., Hoefer, M., Nikoloski, Z., and Wagner, D. (2009). On Modularity Clustering, IEEE Transactions on Knowledge and Data Engineering, 20 (2), 172-188.

Clauset, A., Newman, M. E. J., and Moore, C. (2004). Finding community structure in very large networks, http://www.arxiv.org/abs/cond-mat/0408187.

Fang, J., Wang, S., Zhang, Y., and Chen, B. (2018). The electricity-water nexus in Chinese electric trade system. Energy Procedia, 152, 247–252.

Fair, K. R., Bauch, C. T., and Anand, M. (2017). Dynamics of the global wheat trade network and resilience to shocks. Scientific Reports, 7, 71-77.

Farine, D.R. (2014) Measuring phenotypic assortment in animal social networks: weighted associations are more robust than binary edges. Animal Behaviour, 89, 141-153.

Giudici, P., Huang, B., and Spelta, A. (2019). Trade networks and economic fluctuations in Asian countries. Economic Systems, 43, 100695, 1-17.

Guimera, R. and Amaral, L.A.N. (2005). Cartography of complex networks: modules and universal roles. Journal of Statistical Mechanics: Theory and Experiment, 02, P02001. https://dx.doi.org/10.1088/1742-5468/2005/02/P02001

International Energy Agency. (2020). Electricity information: overview, 2019. Available at: www.iea.org/publications/reports/globalevoutlook2019/

Jan, A., and Sebastian, R. (2016). Cross-Country Electricity Trade, Renewable Energy and European Transmission Infrastructure Policy. Economics working paper series (229).

Ji, L., Jia, X., Chiu, A., and Xu, M. (2016). Global Electricity Trade Network: Structures and Implications, https://doi.org/10.1371/journal.pone.0160869.

Li, D., Thai, M. T., Wang, F., and İk, T-U., Wan, and Du, D-Z. (2005). On greedy construction of connected dominating sets in wireless networks: Research articles. Wireless Communications and Mobile Computing, 5, 927-932, DOI: 10.1002/wcm.356.

Li, X., Jin, Y.Y., and Chen, G. (2003). Complexity and synchronization of the World trade Web. Physica A, 328, 287–296.

Lise, W., Linderhof, V., Kuik, O., Kemfert, C., Stling, R., and Heinzow, TH. (2006). A game theoretic model of the North-western European electricity market—market power and the environment. Energy Policy, 34, 123–126.

Liu, Z., Wang T., Sonn, J. W., and Chen, W. (2018). The structure and evolution of trade relations between countries along the Belt and Road. Journal of Geographical Science, 28, 1233-1248. DOI: doi.org/10.1007/s11442-018-1522-9.

Jiang, M., Chen, Y., and Chen, L. (2015). Link Prediction in Networks with Nodes Attributes by Similarity Propagation.

Newman, M. E. J. (2002). Assortative mixing in networks, Phys. Rev. Lett. 89, 208701 http://arxiv.org/abs/cond-mat/0205405/

Newman, M. E. J. (2003). Mixing patterns in networks. Physical Review, E (67).

Newman, M. E. J. and Girvan., M. (2004). Finding and evaluating community structure in networks. Physical Review, E 69, 026113.

Noldus, R. and Van Mieghem, P. (2015). Assortativity in complex networks. Journal of Complex Networks, Vol 3, 507-542.

Nykamp DQ, “Clustering coefficient definition.” From Math Insight. http://mathinsight.org/definition/clustering_coefficient

Page L., Brin, S., Motwani, R., and Winograd, T. (1999). The Page-Rank Citation Ranking: Bringing order to the web. Technical report, Stanford Info Lab.

Perez, C. and Germon, R. (2016). Chapter 7 - Graph Creation and Analysis for Linking Actors: application to social data. In: Layton R, Watters PA, editors. Automating open-source intelligence. Boston: Syngress; p. 29-103.

Piraveenan, M., Prokopenko, M., and Zomaya, A.Y. (2008). "Assortative mixing in directed biological networks". IEEE/ACM Transactions on Computational Biology and Bioinformatics. 9 (1): 66–78. DOI:10.1109/TCBB.2010.80. PMID 20733240

Radicchi, F., Castellano, C., Cecconi, F., Loreto, V., and Parisi, D. (2004). Defining and identifying communities in networks. PNAS March 2, 101 (9), 2658-2663; https://doi.org/10.1073/pnas.0400054101.

Rita, L., Francisco, A., and Carriço, J., and Borges, V. (2019). Community Finding with Applications on Phylogenetic Networks. 10.1007/978-3-030-31635-8_234.

Rita, L. (2020). Louvain Algorithm: An algorithm for community finding. DOI: https://towardsdatascience.com/louvain-algorithm-93fde589f58c

Srinivasan, S. (2013). Electricity as a traded good. Energy Policy, 62, 1048–1052.

Timilsina, G.R., Toman, M. (2016). Potential gains from expanding regional electricity trade in South Asia. Energy Economics, 60, 6–14.

Vargas, E.R. and Wahl, L.M. (2014). The gateway coefficient: A novel metric for identifying critical connections in modular networks. The European Physical Journal B. 87. 10.1140/epjb/e2014-40800-7.

Wang, Y., Wang, Y., Huang, Y., Yang, J., Ma, Y., Yu, H., Zeng, M., Zhang, F., and Zhang, Y. (2019). Operation optimization of regionally integrated energy system based on the modelling of electricity-thermal-natural gas network. Applied Energy, 251, 1-27.

Wu, Z., Cai, H., Zhao, R., Fan, Y., Di, Z., and Zhang, J. (2020). A Topological Analysis of Trade Distance: Evidence from the Gravity Model and Complex Flow Networks. Sustainability, 12, 3511, 1-17.

Yang, Z., Algesheimer, R. and Tesson, C. J. (2016). A Comparative Analysis of Community Detection Algorithms on Artificial Networks. Scientific Reports, 6:30750, DOI: 10.1038/srep30750.