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Measuring the Influence of Efficient Ports using Social Network Metrics

Regular Paper

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Abstract

Data envelopment analysis (DEA) is known as a useful tool that produces many efficient decision-making units (DMUs). Traditional DEA provides relative efficient scores and reference sets, but does not influence and rank the efficient DMUs. This paper suggests a method that provides influence and ranking information by using PageRank as a centrality of Social Network analysis (SNA) based on reference sets and their lambda values. The social network structure expresses the DMU as a node, reference sets as link, and lambda as connection strengths or weights. This paper, with PageRank, compares the Eigenvector centrality suggested by Liu, et al. in 2009, and shows that PageRank centrality is more accurate.

Keywords Data Envelopment Analysis (DEA), Social Network Analysis (SNA), PageRank centrality, Eigenvector centrality

1. Introduction

Data Envelopment Analysis (DEA), which was introduced by [1] and expanded by [2], measures the performance of DMUs, and is recognized as a valuable decision support tool for managerial controls and organizational diagnosis. The basic two models provide information of whether the DMU is efficient or inefficient, but not for discriminant or rank information among two or more efficient DMUs, as represented by $\theta=1$ (θ means efficiency score). The cause of this problem is the inappropriate assignment of optimal weight for input and output factors. In order to remedy the problem, researchers have explored ways such as weight restrictions [3], the Cross efficiency model [4, 5, 6, 7], and the Recursive Data Envelopment Analysis [8].

Most recently, [9] and [10] suggested a network-based method that uses reference sets of DEA results. They made many reference sets from DEA analysis with all possible combinations of input and output variables, and then constructed a social network that expresses the DMU as node and reference sets as link. By using Eigenvector centrality of SNA measures, they determined the rank of efficient DMUs. Their study made a great contribution towards discriminating efficient DMUs, but it has some weak points. The study may impair co-relationship between the input and output variables by combining all possible cases and may distort reference sets. The second is the usage of eigenvector centrality, which not only considers the connection strength, but node's influence. This may mean that the eigenvector centrality of efficient DMUs is lower than that of inefficient DMUs. In other words, inefficient DMUs, referring to many efficient DMUs, may have higher eigenvector centrality because they have more connections than those of efficient DMUs.

Therefore, this paper aims to propose a method to determine the influence and rank of efficient DMUs by using PageRank centrality for considering both connection strengths and the node's power of social network analysis measures. The social network of the study is a directed and valued network with reference sets and Lambda (λ) values. PageRank centrality developed by [11] measures the influence of node by considering the neighbouring node's influence. The centrality was first used to measure the importance of web pages in web structure links through hyperlinks. Today, this is used extensively as the centrality measure of social network analysis.

The remainder of the paper is organized as follows. Based on a review of previous studies, the paper briefly reviews one basic model of the CCR and BCC, and the Eigenvector and PageRank centrality concept in the social network analysis in Section 2 and 3, respectively. Section 4 describes the research methodology and data collection. Section 5 builds and analyses reference sets network with 35 ports. Finally, the study concludes with discussions on the contributions and limitations of the network-based approach.

2. Data Envelopment Analysis (DEA)

Today, DEA is well known as a productivity analysis tool for assessing the performance on a homogeneous set of DMUs, which are described by their multiple input and output measures. The DEA model was first coined by Charnes, Cooper and Rhodes (CCR) model in 1978 and was expanded by Banker, Charnes, and Cooper (BCC) model in 1984. The two most widely used models deserve greater attention. The CCR model assumes constant returns to scale (CRS) so that all observed production combinations can be scaled up or down proportionally. The BCC model, on the other hand, allows for variable returns to scale (VRS) and is graphically represented by a piecewise linear convex frontier [12].

Formally, let input variables be $X_k = (x_{1k}, x_{2k}, \ldots, x_{Mk}) \in R^M$ to produce output variables $Y_k = (y_{1k}, y_{2k}, \ldots, y_{Nk}) \in R^N$. The row vectors, x_k and y_k, form the kth rows of the data matrices X and Y, respectively. Let $\lambda = (\lambda_1, \lambda_2, \ldots, \lambda_K) \in R^K$ be a non-negative vector. The output-oriented models where DMUs are deemed to produce with given amount of inputs, the highest possible outputs are also dealt with in this section. The primal CCR model with row vector v for input multipliers and row vector u as output multipliers is described as:

$$\begin{aligned} &\text{Maximize } uy_k \\ &\text{Subject to } vx_k = 1 \\ &uY - vX \leq 0 \\ &u, v \geq 0 \end{aligned} \tag{1}$$

The dual problem of the CCR model above is described by:

$$\begin{aligned} &\text{Minimize } \theta \\ &\text{Subject to } Y\lambda - y_k \geq 0 \\ &Y\lambda - y_k \geq 0 \\ &\lambda \geq 0 \end{aligned} \tag{2}$$

The BCC model is described as:

$$\begin{aligned} &\text{Minimize } \theta \\ &\text{Subject to } X\lambda - x_k \leq 0 \\ &\theta y_k - Y\lambda \leq 0 \\ &e\lambda = 1 \\ &\lambda \geq 0 \end{aligned} \tag{3}$$

3. Social Network Analysis (SNA)

In this paper, the reference sets network is abstracted as a connected network, $G = (V, E)$ by $V = \{V_i : i = 1, 2, \ldots, n\}$, n is number of vertices (DMUs), and $E = \{e_i : i = 1, 2, \ldots, m\}$, m is the number of edges (reference sets). To represent the network, a connectivity adjacency matrix, $A_{n \times n}$ is created such that an element $a_{ij} = \lambda_{ij}$ (connection strength), when reference sets exist between DMU i and j, and $a_{ij} = 0$ otherwise. Edges may be directed, undirected, or of mixed type. Furthermore, vertices and edges may have various attributes encoded, e.g., the type of actors or relations as well as the strength of relations [13].

Social network analysis concentrates on the study of two sets of properties of networks: structural properties and relational properties. Relational properties focus on the contents and the form of the relationships between network members. Structural characteristics of networks are explored with respect to the level of granularity on the analysed objects: node-level, network-level, and group-level. Node-level measures analyse properties of individual nodes and edges, such as importance (centrality). Group-level measures determine specific subsets of nodes. These measures include the computation of densely connected groups (clustering) and the computation of structural roles and positions (block modelling or role assignment). Network-level measure is focused on global properties of the network, such as density, degree-distributions, transitivity, or reciprocity. This paper focuses on two types of node-level metrics—eigenvector and PageRank centrality. Two reasons exist as to why two types of centralities should be considered. First, the eigenvector centrality considers the number of neighbour nodes links. Second, PageRank centrality reflects the number of neighbour nodes links and the resulting impact.

3.1 Eigenvector Centrality

Where degree centrality gives a simple count on the number of connections a node has, the eigenvector centrality acknowledges that not all connections are equal. In general, connections to people who are themselves influential will influence a person more than connections to less influential counterparts. If we denote the centrality of node i by x_i, then we can allow for this effect by making x_i proportional to the average of the centralities of i's network neighbours:

$$x_i = \frac{1}{\lambda} \sum_{j \in M(i)} x_j = \frac{1}{\lambda} \sum_{j=1}^{N} a_{ij} x_j \tag{4}$$

where λ is a constant. Having a large number of connections still counts for something, but a vertex with a smaller number of high-quality contacts may outrank one with a larger number of mediocre contacts. The eigenvector centrality turns out to be a revealing measure in many situations.

3.2 PageRank Centrality

This is based on (and essentially identical to) PageRank as computed by Google's original algorithm [11, 14]. It iteratively computes the influence of the entire network for each node over time. It can operate on either an individual daily graph, or on an average graph, constructed as a weighted composite of a few social networks. The original PageRank algorithm provides a ranking for the importance of web pages based on the link structure of the web created by the hyperlinks between the pages, by using the following model:

$$PageRank(i) = \frac{(1-\alpha)}{n} + \alpha \sum_{j \in G(i)} \frac{PageRank(j)}{OutDegree(j)} \tag{5}$$

where $j \in G(i)$ if there is a link originating from node j to node i (meaning that node j is a network neighbour of node i) and Out-Degree(j) is the total number of links originating from node j. 'n' is the number of nodes in network and α is a probability to be linked with the node. PageRank is usually used as a network-based measure of page importance, but can also be interpreted as a measure of centrality, or the extent to which a network structure influences a page. The advantage of the centrality measures the influence of node by considering both degree and the neighbouring node's influence. Figure 1 shows the example of computing PageRank centrality without α. (a) shows the influence and connection of each node, and (b) PageRank centrality in long run steady state.

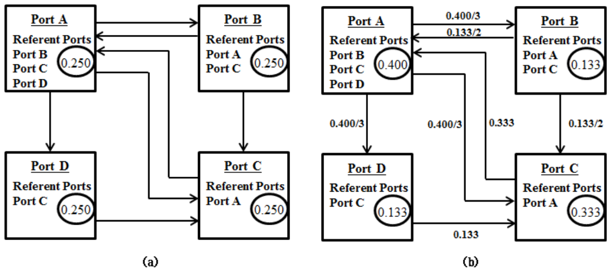

Figure 1. Example of PageRank Centrality

4. Research Method and Data Collection

The research method consists of three stages, as shown in Figure 2, to determine the influence and rank of efficient DMUs. The first stage is to select the input and output variables for analysing DEA, and then to collect the data for ports to measure efficiency. This study selects 35 ports in Asia and the Pacific area out of top 100 worldwide ports based on throughputs in 2010, and uses the number of berths, sea depth, and number of cranes as input variables and throughput as output variables. These variables that impact efficiency are mostly used in previous studies for measuring port productivity (see Table 1). The data of each port for input and output variables were collected in the Containerization International Yearbook in 2010.

The second stage is to measure the efficiency of ports using DEA Excel Solver. This study uses an output-oriented BCC model. Efficiency scores, reference sets and Lambda values for each DMU are given results of DEA analysis.

The third stage is to build and analyse the social network by using reference sets and their lambda (λ) value. Hereby, the paired dataset between DMUs and reference sets are organized by using Microsoft Excel 2007.

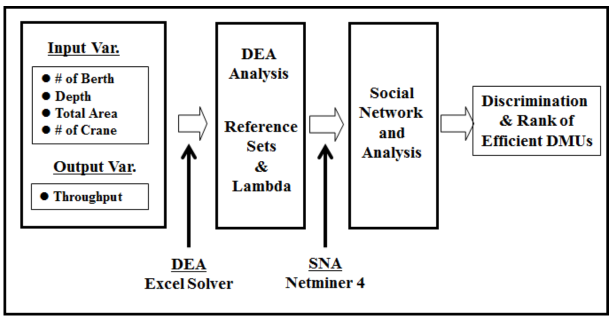

Figure 2. Research Framework

The social network is built and analysed with the paired data (edge list) using Netminer 4.0, which is the software used to compute the various measurements of social network analysis. In building the social network, the node is set to point to its referring DMUs as suggested by DEA. The corresponding lambda values for these referent DMUs are taken as the strength of the network link.

Paper	Analysis Areas (year)	Inputs	Outputs
[15]	The world's major 30 container ports for 2003	Quay Length (m) Terminal Area (ha) Quayside Gantry (number) Yard Gantry (number) Straddle Carrier(number)	Throughput (TEU)
[16]	Ports of two European countries, Greece and Portugal during the 1998-2000 periods	Number of Employees Book Value of Assets	Number of Ships Tons of Freight Moved Tons of Cargo Handled Tons of Containers Handled
[8]	16 Ports in Asia Pacific Region (1996)	No. of Cranes, No. of Container Berths No. of tugs Terminal Area (m2) Delay Time (h) Labour (units)	TEUs Handled Ship Rate
[17]	25 leading container ports (2005)	Quay Length (m) Terminal Area (ha) Quayside Gantry (number) Yard Gantry (number) Straddle Carrier (number)	Container Throughput
[18]	104 European container Terminals (2003)	Total Berth Length Terminal Area Equipment Costs	TEUs Handled
[19]	Italian 24 seaports for the 2002-2003 period	Number of Employees Investment Operating Costs	Liquid Bulk Dry Bulk Number of Ships Number of Passengers Number of Containers Number of Container Total Sales
[20]	41 ports from eleven European countries (2003-2005)	Operational Expenses Capital Expenses	Conventional General Cargos Containerized Cargos Ro-ro Cargo Dry Bulk Cargo Liquid Bulk Cargo Passengers
[21]	22 seaports in the Middle East and East African region for six years (2000–2005)	Berth Length (m) Storage Area (m2) Handling Equipment	Ship Calls (Units) Throughput (Tons)

Table 1. Input and Output measures used in Previous Works

5. Analysis and Results

5.1 DEA Analysis

This study analyses the productivity of 35 ports selected in the previous section by using output-oriented BCC. The results, as shown in Table 2, indicate that the efficient ports are Shanghai, Hong Kong, Shenzhen, and Lianyungang, and all other ports are inefficient. Any with an efficient score of $\theta = 1$ cannot be discriminated and ranked. In order to remedy the problem, one of the social network centralities, the PageRank centrality of equation (5), is used.

5.2 Creation and Analysis of Social Network

The social network structure expresses the DMU as a node, reference sets as link, and lambda as connection strength or weight (called 'reference sets network hereinafter). The size of the circle (stands for DMU) in Figure 3 indicates its influence as frequency when referenced by inefficient DMUs. The width of the line (link) indicates the size of the lambda value as connection strength. In reference sets network, the number of nodes and links are 35 and 96, respectively. The average degree (2.629) shows that the efficient DMUs refer to an average (2.60) of efficient DMUs as a benchmarking target.

The circle sizes of four efficient DMUs are different to each other, as shown in Figure 3. Shenzhen and Lianyungang have the largest circles, and Shanghai and Hong Kong are smaller than Shenzhen and Lianyungang.

The reason for this is that Shanghai and Hong Kong are less referenced than Shenzhen and Lianyungang by inefficient DMUs. All inefficient DMUs are the same circle sizes because the sum of lambda in the reference sets is always '1'. PageRank centrality quantifies and ranks influential levels of efficient DMUs, as shown in Table 3.

DMU	Score	Rank	Ref_1	Lambda_1	Ref_2	Lambda_2	Ref_3	Lambda_3	Ref_4	Lambda_4
Los Angeles	0.3173	12	Shanghai	0.5361	Shenzhen	0.4244	Lianyungang	0.0395		
Long Beach	0.2415	17	Shanghai	0.4045	Shenzhen	0.5955				
New York/New J	0.2260	18	Shanghai	0.5396	Shenzhen	0.3482	Lianyungang	0.1122		
Savannah	0.1980	21	Shanghai	0.0679	Shenzhen	0.4852	Lianyungang	0.4469		
Oakland	0.1207	30	Shanghai	0.1911	Shenzhen	0.6417	Lianyungang	0.1672		
Virginia	0.1765	25	Shanghai	0.1096	Shenzhen	0.2927	Lianyungang	0.5976		
Seattle	0.1003	32	Shanghai	0.0357	Shenzhen	0.7879	Lianyungang	0.1764		
Tacoma	0.0912	34	Shanghai	0.0436	Shenzhen	0.8518	Lianyungang	0.1045		
Houston	0.2017	20	Shanghai	0.0499	Shenzhen	0.3147	Lianyungang	0.6354		
Charleston	0.1000	33	Shanghai	0.1483	Hong Kong	0.0185	Shenzhen	0.4062	Lianyungang	0.4270
Port Everglades	0.2636	14	Lianyungang	1.0000						
Miami	0.0655	35	Shenzhen	0.6111	Lianyungang	0.3889				
Kaohsiung	0.6961	8	Shanghai	0.0494	Shenzhen	0.5399	Lianyungang	0.4108		
Keelung	0.1840	23	Hong Kong	0.0023	Shenzhen	0.3621	Lianyungang	0.6356		
Taichung	0.1688	27	Shenzhen	0.3889	Lianyungang	0.6111				
Busan	0.5649	11	Shanghai	0.3739	Hong Kong	0.1387	Shenzhen	0.4874		
Gwangyang	0.1577	28	Shenzhen	0.5556	Lianyungang	0.4444				
Incheon	0.2464	16	Shenzhen	0.2222	Lianyungang	0.7778				
Tokyo	0.2612	15	Shanghai	0.0729	Hong Kong	0.0715	Shenzhen	0.5697	Lianyungang	0.2859
Yokohama	0.1869	22	Shanghai	0.1613	Hong Kong	0.0365	Shenzhen	0.5087	Lianyungang	0.2935
Nagoya	0.1559	29	Shanghai	0.0747	Hong Kong	0.0666	Shenzhen	0.5051	Lianyungang	0.3536
Kobe	0.1781	24	Shanghai	0.1173	Hong Kong	0.0923	Shenzhen	0.3516	Lianyungang	0.4388
Osaka	0.1734	26	Shanghai	0.0883	Hong Kong	0.0293	Shenzhen	0.3374	Lianyungang	0.5450
Shanghai	1.0000	1	Shanghai	1.0000						
Hong Kong	1.0000	1	Hong Kong	1.0000						
Shenzhen	1.0000	1	Shenzhen	1.0000						
Qingdao	0.6658	9	Shanghai	0.0287	Hong Kong	0.1018	Shenzhen	0.6516	Lianyungang	0.2179
Ningbo	0.9148	5	Shenzhen	0.5556	Lianyungang	0.4444				
Guangzhou	0.7504	7	Shanghai	0.2092	Shenzhen	0.4789	Lianyungang	0.3120		
Tianjin	0.5717	10	Shanghai	0.0362	Hong Kong	0.0692	Shenzhen	0.6668	Lianyungang	0.2278
Xiamen	0.8419	6	Shenzhen	0.1667	Lianyungang	0.8333				
Dalian	0.2938	13	Shanghai	0.1366	Hong Kong	0.0809	Shenzhen	0.5263	Lianyungang	0.2562
Lianyungang	1.0000	1	Lianyungang	1.0000						
Yantai	0.1136	31	Shenzhen	0.6111	Lianyungang	0.3889				
Fuzhou	0.2164	19	Shanghai	0.0357	Shenzhen	0.1212	Lianyungang	0.8431		

Table 2. Reference (Ref.) sets and Lambda

Lianyungang port has the highest PageRank centrality (0.2896), which means that it was referenced more than any other efficient ports according to inefficient ports. The Lianyungang port is also the most influential when considering the neighbouring node's influence and the strength of the network link. Following this port, the Shenzhen port has the second highest PageRank centrality (0.2856). Shanghai port (0.1925) and Hong Kong port (0.0994) are in order. All inefficient ports have the same PageRank centrality (0.0043) because the sum of lambda for the reference sets is 1. Therefore, the efficient ports can be discriminated and ranked by PageRank centrality.

Port Name	This study		Liu, et al.(2009) Approach	
	PageRank	**Eigenvector**	**PageRank**	**Eigenvector**
Lianyungang	**0.2896**	0.4991	**0.6444**	0.7390
Shenzhen	**0.2856**	0.5547	**0.1829**	0.0423
Shanghai	**0.1925**	**0.1123**	**0.0274**	0.0166
Hong Kong	**0.0994**	**0.0250**	**0.0124**	**0.0092**
Los Angeles	0.0043	0.0783	0.0043	0.1059
Long Beach	0.0043	0.0933	0.0043	0.1176
New York/New Jersey	0.0043	0.0769	0.0043	0.1211
Savannah	0.0043	0.1241	0.0043	0.1318
Oakland	0.0043	0.1144	0.0043	0.1318
Virginia	0.0043	0.1174	0.0043	0.1318
Seattle	0.0043	0.1313	0.0043	0.1318
Tacoma	0.0043	0.1315	0.0043	0.1318
Houston	0.0043	0.1235	0.0043	0.1318
Charleston	0.0043	0.1131	0.0043	0.1318
Port Everglades	0.0043	0.1239	0.0043	0.1318
Miami	0.0043	0.1323	0.0043	0.1318
Kaohsiung	0.0043	0.1266	0.0043	0.0894
Keelung	0.0043	0.1286	0.0043	0.1318
Taichung	0.0043	0.1293	0.0043	0.1318
Busan	0.0043	0.0784	0.0043	0.0692
Gwangyang	0.0043	0.1316	0.0043	0.1318
Incheon	0.0043	0.1270	0.0043	0.1318
Tokyo	0.0043	0.1163	0.0043	0.1263
Yokohama	0.0043	0.1111	0.0043	0.1318
Nagoya	0.0043	0.1159	0.0043	0.1318
Kobe	0.0043	0.1066	0.0043	0.1318
Osaka	0.0043	0.1166	0.0043	0.1318
Qingdao	0.0043	0.1182	0.0043	0.0775
Ningbo	0.0043	0.1316	0.0043	0.0724
Guangzhou	0.0043	0.1104	0.0043	0.0730
Tianjin	0.0043	0.1215	0.0043	0.0894
Xiamen	0.0043	0.1262	0.0043	0.1187
Dalian	0.0043	0.1085	0.0043	0.1212
Yantai	0.0043	0.1323	0.0043	0.1318
Fuzhou	0.0043	0.1221	0.0043	0.1318

Table 3. Comparisons of PageRank and Eigenvector

5.3 Results

Efficient ports with $\theta = 1$ of 35 ports are Shenzhen, Lianyungang, Shanghai, and Hong Kong. PageRank centrality analysis shows that Lianyungang has the most powerful influence, followed by Shenzhen, Shanghai, and Hong Kong, respectively.

The rank order of efficient ports are the same as PageRank order, and the inefficient ports with same PageRank centrality are the same as the efficiency score order as shown in Table 4.

Comparisons of this study's results with [9] are suggested in Table 3. According to their method on eigenvector centrality, Lianyungang port has the highest centrality, but the other three efficient ports have lower centrality than inefficient ports. The reason for this result is that the inefficient DMUs that refer to many efficient DMUs have more connections than those of efficient DMUs. The method provides rank information for efficient ports, but this is inappropriate because the rank of some efficient ports is lower than that of the inefficient ports.

However, the result of PageRank centrality with all possible combinations of input and output variables shows that four efficient ports have centrality values of the following order: Lianyungang Shanghai, Shenzhen, and Hong Kong. Therefore, PageRank centrality provides more realistic information than Eigenvector centrality.

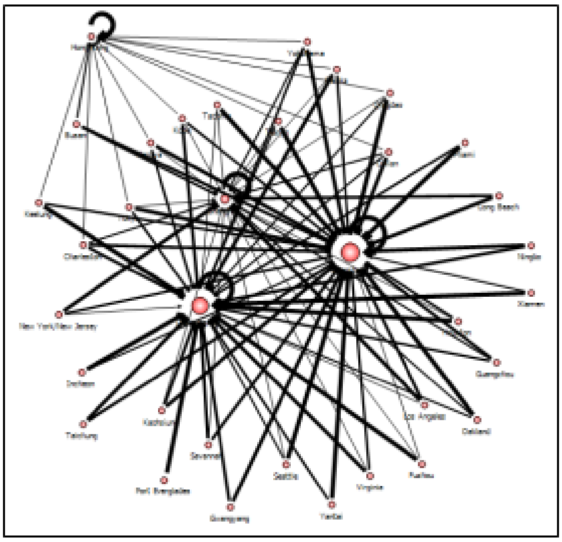

Figure 3. Social Networks by Reference Sets

	Efficiency Score(a)	PageRank(b)	Rank
Lianyungang	1.0000	0.2896	1
Shenzhen	1.0000	0.2856	2
Shanghai	1.0000	0.1925	3
Hong Kong	1.0000	0.0994	4
Ningbo	0.9148	0.0043	5
Xiamen	0.8419	0.0043	6
Guangzhou	0.7504	0.0043	7
Kaohsiung	0.6961	0.0043	8
Qingdao	0.6658	0.0043	9
Tianjin	0.5717	0.0043	10
Busan	0.5649	0.0043	11
Los Angeles	0.3173	0.0043	12
Dalian	0.2938	0.0043	13
Port Everglades	0.2636	0.0043	14
Tokyo	0.2612	0.0043	15
Incheon	0.2464	0.0043	16
Long Beach	0.2415	0.0043	17
New York/New	0.2260	0.0043	18
Fuzhou	0.2164	0.0043	19
Houston	0.2017	0.0043	20
Savannah	0.1980	0.0043	21
Yokohama	0.1869	0.0043	22
Keelung	0.1840	0.0043	23
Kobe	0.1781	0.0043	24
Virginia	0.1765	0.0043	25
Osaka	0.1734	0.0043	26
Taichung	0.1688	0.0043	27
Gwangyang	0.1577	0.0043	28
Nagoya	0.1559	0.0043	29
Oakland	0.1207	0.0043	30
Yantai	0.1136	0.0043	31
Seattle	0.1003	0.0043	32
Charleston	0.1000	0.0043	33
Tacoma	0.0912	0.0043	34
Miami	0.0655	0.0043	35

Table 4. Rankings of all DMUs

6. Conclusions and Limitations

This paper suggests a method that provides ranking information for efficient DMUs by using social network analysis based on reference sets and their lambda. When constructing the network, the node is set to point to its referent DMUs as suggested by DEA. The corresponding lambda for these referent DMUs are considered the strengths of the network link. Thus, this social network is a network with direction and value. This study also provides the influence and rank of efficient DMUs by using PageRank centrality of network centrality metrics.

The result shows that Lianyungang port has the highest PageRank centrality (0.2896), which means that it was referenced much more than any other efficient ports according to inefficient ports. Following this port, Shenzhen port has the second highest PageRank centrality (0.2856). Shanghai port (0.1925) and Hong Kong port (0.0994) are in order. This paper, as compared with the method by [9], finds that PageRank centrality is more realistic than Eigenvector centrality when determining influences and ranks of efficient DMUs.

There are a few limitations to this study. In the case where most DMUs are efficient and some are not a reference to any other inefficient DMU, the DMUs in 'reference sets network' are isolated. The PageRank centrality for all DMUs remains the same, and thus does not provide discriminant or ranking information for them.

7. Acknowledgements

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