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A Proposed Centrality Measure: The Case of Stocks Traded at Bursa Malaysia

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Abstract

In this paper we propose the average of weights of all links adjacent to each stock as a centrality measure. This measure, besides the traditional centrality measures such as degree centrality, betwenness centrality, closeness centrality and eigenvector centrality will be helpful in interpreting the network topology of stocks markets. A case study of 90 stocks market traded at Bursa Malaysia will be presented and discussed to illustrate the advantage of the proposed measure.

Keywords: correlation matrix, distance matrix, Kruskal algorithm, minimum spanning tree, sub-dominant ultrametric

1. Introduction

The stock market has become an increasingly significant subject of the economy and is used by tens of thousands of companies to access equity capital, and tens of millions of investors to pursue opportunities around the world. The behaviour of stock prices is a subject of enduring interest to the investors, policymakers, and economists, and it is widely believed to be the predictor of economic activity (Peek & Rosengren, 1988; Muradoglu et al., 2000). Now days, the researchers from various disciplines i.e. mathematics, financial analysis (Daly & Fayyad, 2011; Da Costa et al., 2005; Zhang et al., 2009) and theoretical physics (Eom et al., 2009; Eom et al., 2010) are given their attention on analyzing the stock behaviour. In general, the behaviour of a stock market will be influenced by the behaviour of others stocks traded in that market. Mathematically, the interrelationships among stocks are customarily represented by the correlations among the logarithm of stock returns. The correlation structure, together with the corresponding stocks, constitutes a complex system in the form of a network. Recently, the network topology of stocks has been introduced in the field of econophysics to understand the interaction among the stocks. Mantegna (1999) presents the complicated relationship between stocks in a topological space by using a visualization mechanism, specifically minimum spanning tree. Since the work of Mantegna, subsequently many studies have confirmed the various properties of stock networks constructed.

To the aid of interpretation, centrality measure can help us to have a better understanding about the information contained in the network as well as to enrich the economic interpretation. The role of importance of each particular stock can be express by the use of centrality measure such as degree centrality, closeness centrality between centrality and eigenvector centrality. However, the problem with those measures is that they take into account only the number of direct and indirect links between two stocks. For that reason, we acknowledge the weight between two different stocks to propose a new measure of centrality which represents the "power" of stock. Later on, to illustrate the role of the propose measure, in this paper we conduct a study on the daily stock price data of 90 stocks traded at Bursa Malaysia from January 1, 2007 until December 31, 2009. For that purpose, those stocks will be viewed as a complex system consisting of 90 stocks as nodes connected by [90-1] *[90]/2=4005 links each of which corresponds to the correlation coefficient between two different nodes.

The nodes and links will be considered as a network or, more specifically, a weighted undirected graph (Jayawant & Glavin, 2009). This point of view is useful in order to visualize, simplify, and summarize the most important information contained in that complex system. The rest of paper is organized as follows. In Section 2 we discuss the analysis of that complex system by using the propose centrality measure as well as the current existing measures. To illustrate the advantage of the proposed measure, a case study on stock market will be presented and discussed in Section 3. At the end of this paper, we will draw attention to a conclusion.

2. Proposed Centrality Measure

In this section we discuss the analysis of a complex system by using network topology approach. This allows us to visualize and simplify a complex system, and to summarize the information contained therein. We show that the centrality measures usually used as the principal tools to summarize the information are not sufficient. This motivates us to propose another measure.

2.1 Network Topology

The essence of a network is its nodes (stocks) and the way how they are linked. Network analysis was originally developed in computer science (De Nooy et al., 2004). Nowadays, it has been used in various fields of study. See, for example, Krichel and Bakkalbasi (2006) in sociology, Mantegna (1999) and Miccichè et al. (2003) in finance, and Park and Yilmaz (2010) in transportation.

In financial industry, network analysis starts with correlation matrix followed by transforming it into a distance matrix (Mantegna & Stanley, 2000). From this matrix we construct a minimum spanning tree (MST) and the corresponding sub-dominant ultrametric (SDU) distance matrix. For this purpose we use Kruskal algorithm (Kruskal, 1956) as suggested in Mantegna and Stanley (2000) and Jayawant and Glavin (2009). MST will then be used to construct network topology of stocks.

The Kruskal algorithm is a graph without a cycle that connects all nodes with links. The correlation coefficient can vary between $-1 < \rho_{ij} < +1$ whereas the distance can vary between $0 < d_{ij} < 2$. Here, small values of the distance imply strong correlations between stocks. This is a simplification of the complex system of stocks and their correlation structure which will be used to summarize the most important information.

The visualization of MST can be made possible by using the open source called 'Pajek' (Batagelj & Mrvar, 2003; Batagelj & Mrvar, 2011; De Nooy et al., 2004). Furthermore, to interpret the MST we use the standard tools, i.e., centrality measures. To make the network topology more attractive and easy to interpret, we use the Kamada Kawai procedure provided in Pajek (Kamada & Kawai, 1989).

2.1.1 Correlation Matrix

The stock network visually displays the significant p-1 links among all possible links, (p-1)* p/2. This is based on the correlation matrix between stocks, using the MST method. The MST, a theoretical concept in graph theory (West, 2000), is also known as the single linkage method of cluster analysis in multivariate statistics (Gower & Ross, 1969; Everitt, 1980).

Let $P_i(t)$ be the stock price of a stock i and $R_i(t)$ be the logarithm of daily stock return at day t in a given period, defined as:

$$R_i(t) = \ln P_i(t+1) - \ln P_i(t) . \tag{1}$$

for all i = 1, 2, … , 90. Equation (1) defines a complex system among stocks in the form of stock networks. To filter the information contained therein, we construct a correlation matrix among those stocks, is a symmetric matrix of size 90×90 where the element in the i-th row and j-th column is,

$$\rho_{ij} = \frac{\langle R_i R_j \rangle - \langle R_i \rangle \langle R_j \rangle}{\sqrt{\left(\langle R_i^2 \rangle - \langle R_i \rangle^2\right)\left(\langle R_j^2 \rangle - \langle R_j \rangle^2\right)}} \tag{2}$$

representing the correlation coefficient between i-th and j-th stocks (Mantegna & Stanley, 2000). That correlation coefficient quantifies the degree of linear relationship between i-th and j-th stocks. By definition, $\rho_{ii} = 1$ for all i and ρ_{ij} can vary from – 1 to 1 for all $i \neq j$ where,

$$\rho_{ij} = \begin{cases} 1 & \text{means perfectly positive linear relationship} \\ 0 & \text{means no linear relationship} \\ -1 & \text{means perfectly negative linear relationship} \end{cases}$$

2.1.2 Distance Matrix

To analyze the network, we transform the correlation matrix into a distance matrix by using the following formula (Mantegna & Stanley, 2000).

$$d_{ij} = \sqrt{2(1-\rho_{ij})} \tag{3}$$

This d_{ij} is a distance between the *i*-th and *j*-th stocks since it satisfies the following three properties; (i) $d_{ij} \geq 0$ and $d_{ij} = 0 \Leftrightarrow X_i = X_j$, (ii) $d_{ij} = d_{ji}$, and (iii) $d_{ij} \leq d_{ik} + d_{kj}$. The first property tells us that two stocks that are perfectly correlated (either positive or negative), $|\rho_{ij}| = 1$, will be represented by a single point in Euclidean space ($d_{ij} = 0$). Moreover, $0 \leq d_{ij} \leq 2$.

The second property is symmetric property; the distance between the *i*-th and *j*-th stocks is equal to the distance between the *j*-th and *i*-th stocks. In other words, the correlation between the *i*-th and *j*-th stocks is equal to the correlation between the *j*-th and *i*-th stocks ($\rho_{ij} = \rho_{ji} \Leftrightarrow d_{ij} = d_{ji}$).

The last property is well known as triangular property. From (2), we conclude that, in general, the higher the correlation coefficient the smaller the distance.

By using Equation (3), we obtain a distance matrix D of size 90×90 with d_{ij} as the element in the *i*-th row and *j*-th column. It is this matrix that we analyze in the rest of the paper.

2.1.3 Kruskal's Algorithm

A spanning tree is a subset of a graph which has no cycles and includes all of the nodes of the original graph, but usually not all the links. A minimum spanning tree is a spanning tree that has smaller (i.e minimum) sum of the weights of its links than any other spanning tree. When the links are weighted where their weights in this paper is representing by the distance, the problem is to find the tree that has minimal distance. In this case, Kruskal's algorithm can help to solve the problem to find the tree that has minimal distance. This is a simple algorithm since the links are selected and included to the tree in increasing order of their weights. But, we have to stop it when it create a cycle or looping.

2.1.4 Information Summarization

To visualize, simplify and summarize the important information contained in the network represented by D, we use the notion MST as discussed in Mantegna and Stanley (2000). Then, we determine MST by using Kruskal algorithm (Kruskal, 1956).

2.2 Centrality Measures

From network analysis view point, the role or degree of importance of each particular node can be analyzed by using its centrality measures such as degree, betweenness, and closeness centralities. These will help us to find the most important nodes in the network structure (Xu et al., 2009; Abbasi & Altmann, 2010; Monárrez-Espino & Caballero-Hoyos, 2010).

Degree centrality indicates the connectivity of nodes. It provides information on how many other nodes are connected with a particular node. On the other hand, betweenness centrality is reflects the extent to which a node lies in relative position with respect to the others (Freeman, 1977). This measure indicates the potentiality of node to influence the others. Closeness centrality measures how close a node is to all other nodes in terms of correlations. Closeness can also be regarded as a measure of how long the information is to spread from a given node to other reachable nodes. Nevertheless, eigenvector centrality, a point centrality measure introduce by Bonacich in 1972. The key idea is to express that an important node is connected to important neighbours (other nodes).

Those measures are computed based on the MST as follows (Borgatti, 1995; Sieczka & Holyst, 2009; Park & Yilmaz, 2010):

(i) Degree centrality of node *i* is $d_i = \sum_{j=1}^{n} a_{ij}$ where $a_{ij} = 1$ if the *i*-th and *j*-th nodes are linked and 0 otherwise.

(ii) Betweenness centrality of node *i*, b_i, is the ratio of the number of path passing through *i* between two different nodes and the number of all possible paths from *j* to *k* for all *j* and *k* where $j \neq i$ and $k \neq i$.

(iii) Closeness centrality of node *i*, c_i, is the ratio of the number of links in the MST, which is equal to (n-1), and the number of links in the path from *i* to *j* for all $j \neq i$.

(iv) Eigenvector centrality of node *i* is, $ev_i = \lambda^{-1} \sum_{j=1}^{n} a_{ij} e_j$ where $(e_1, e_2, ..., e_n)^t$ is the eigenvector of *A* that corresponds to the largest eigenvalue λ.

Degree centrality is the simplest of the node centrality measures by using the local structure around nodes only. In order to identify the role of importance, degree centrality is no longer appropriate to be the best measure. The higher the degree centrality does not reflect to the strength of each particular node.

Due to that limitation of degree centrality, in this subsection we introduce "average of weights" as another measure. It is the average of weights of all links adjacent to each node. This measure reflects the strength of influence of a particular node to the others. Thus, the larger the scores represent the powerful of that particular stock. In all measures, the node that has larger scores is considered to be more central in terms of it influence to the others.

3. A Case Study

We utilized 90 stocks that were traded on the stock market at Bursa Malaysia. The individual stocks that posted daily prices for the last 3 years from January 1, 2007 to December 31, 2009. The 1096 daily data can be retrived from Bloomberg Professional®. Based on the MST issued from Matlab version 7.8.0 (R2009a), we present the top 15 scores of centrality measure discussed previously in Table 1 and Table 2.

Table 1. The top 15 scores of degree and betweeness centrality

Top	Degree		Betweeness	
1	*Genting Bhd*	7	*Wah Seong Corp*	0.708
2	*Wah Seong Corp*	6	*Genting Bhd*	0.594
3	*MMC Corp Bhd*	5	*YTL Cement Bhd*	0.495
4	*Kuala Lumpur Kep*	4	*MMC Corp Bhd*	0.415
5	*Genting Plantation*	4	*Parkson Holding*	0.357
6	*IJM Land Bhd*	4	*WCT Bhd*	0.335
7	*Malaysian Res Co*	4	*CIMB Group Banking*	0.331
8	*WCT Bhd*	4	*AMMB Holding Bhd*	0.308
9	*DRB-HICOM Bhd*	4	*IOI Corp Bhd*	0.287
10	*Supermax Corp*	4	*IJM Corp Bhd*	0.261
11	*CIMB Group Banking*	3	*Genting Plantation*	0.260
12	*IOI Corp Bhd*	3	*Supermax Corp*	0.241
13	*AMMB Holding Bhd*	3	*RHB Capital Bhd*	0.204
14	*RHB Capital Bhd*	3	*Kuala Lumpur Kep*	0.188
15	*IJM Corp Bhd*	3	*Hong Leong Bank*	0.184

Table 2. The top 15 scores of closeness and eigenvector centrality

Top	Closeness		Eigenvector	
1	*Wah Seong Corp*	0.200	*Wah Seong Corp*	0.500
2	*YTL Cement Bhd*	0.190	*Genting Bhd*	0.427
3	*Genting Bhd*	0.184	*MMC Corp Bhd*	0.296
4	*MMC Corp Bhd*	0.179	*Genting Bhd*	0.292
5	*RHB Capital Bhd*	0.170	*RHB Capital Bhd*	0.211
6	*Sunway City Bhd*	0.169	*IJM Corp Bhd*	0.208
7	*CIMB Group Banking*	0.166	*CIMB Group Banking*	0.198
8	*Tanjong PLC*	0.164	*Sunway City Bhd*	0.181
9	*Dialog Group Bhd*	0.164	*Dialog Group Bhd*	0.167
10	*IJM Corp Bhd*	0.163	*Tanjong PLC*	0.167

11	*Parkson Holding*	0.163	*EON Capital Bhd*	0.143
12	*EON Capital Bhd*	0.156	*Multi-Purpose*	0.143
13	*AFFIN Holding*	0.156	*UNISEM(M) Bhd*	0.143
14	*Multi-Purpose*	0.156	*AFFIN Holding*	0.143
15	*UNISEM(M) Bhd*	0.156	*Parkson Holding*	0.141

However, by using Pajek, we can visualize the interrelationship among 90 stocks with more attractively. Therefore, in Figure 1 - Figure 4 we present their network topology with respect to their centrality measure. The size and colour of the node represent the score of centrality measure and the rank of importance for degree centrality, betwenness centrality, closeness centrality, eigenvector centrality and average of weight centrality.

From Figure 1, degree centrality measure, we learn that, the highest number of links in the network belongs to *7-Genting Bhd* (red point). It is followed by *83-Wah Seong Corp* (blue point) and *25-MMC Corp Bhd* (yellow point) are 6 and 5 links, respectively. Each of the fololowing has 4 links: *12-Kuala Lumpur Kep*, *34-Genting Plantation, 61-IJM Land Bhd, 64-Malaysian Res Co, 66-WCT Bhd, 67-DRB-HICOM Bhd, 72-Supermax Corp* (green points). The rests are of 1, 2 and 3 links only. The higher the number of links is the higher the influence of that particular stock to the others.

According to the betweenness centrality, see Figure 2, the most important nodes is *83-Wah Seong Corp* (red point). It has an excellent position compared to the others where the information flow in the network can easily reach others in the network followed by, in order of importance: *7-Genting Bhd* (blue point or the second most important), *73-YTL Cement Bhd* and *25-MMC Corp Bhd* (yellow points or the third most important). This means that those stocks strongly dominance the other stocks, especially the neighbour which is closely to their corner. As example, if come out any shift in the price of *7-Genting Bhd,* the price of the following stocks: *73-YTL Cement Bhd*, *39-Affin Holding*, *38-EON Capital Bhd*, *2-CIMB Group Bhd*, *28-IJM Corp Bhd*, *65-Multi-Purpose*, and *89-UNISEM(M) Bhd* will directly get the impact.

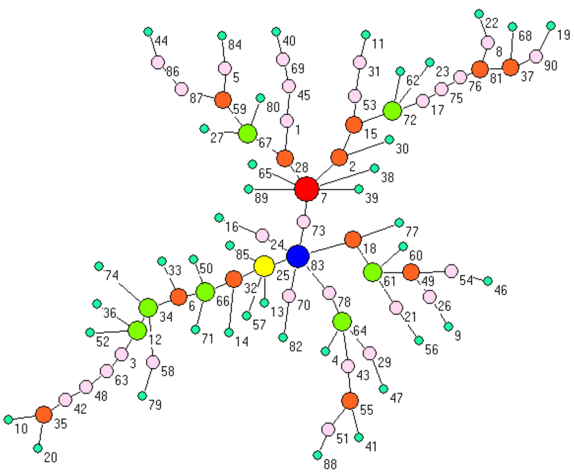

Figure 1. Degree centrality

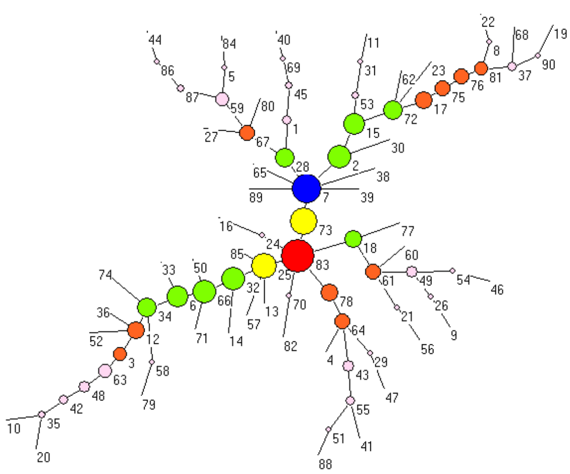

Figure 2. Betwenness centrality

In Figure 3, we present the closeness centrality. The key player in this analysis is represented by *83-Wah Seong Corp* (red point). It plays the most important role in the network and this node is the closest node to the others. The second closest nodes to the others are *7-Genting Bhd*, *73-YTL Cement Bhd* and *25-MMC Corp Bhd* (blue points). The third closest is yellow points; *18-RHB Capital Bhd, 78-Sunway City Bhd, -CIMB Group Banking, 24-Tanjong PLC, 70-Dialog Group Bhd, 28-IJM Corp Bhd, 32-Parkson Holding, 38-EON Capital Bhd, 39-AFFIN Holding, 65-Multi-Purpose, 89-UNISEM(M) Bhd, 13-Genting Malaysia, 57-Star Publication, 85-Lingkaran Trans, 15-AMMB Holding Bhd.*

Based on eigenvector centrality, see Figure 4, *83-Wah Seong Corp* (red point) has the highest scores of centrality measure in the network. This result is similar to betwenness centrality and closeness centrality. The blue points or the second most important are represented by *7-Genting Bhd* followed by third most important stocks; *73-YTL Cement Bhd*, *25-MMC Corp Bhd, 18-RHB Capital Bhd,* and *28-IJM Corp Bhd* (yellow points).

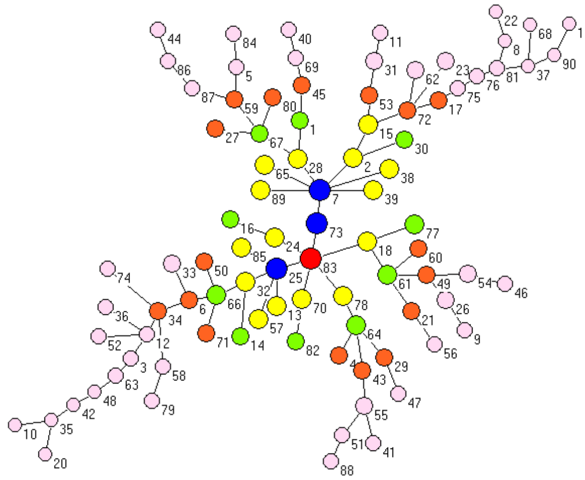

Figure 3. Closeness centrality

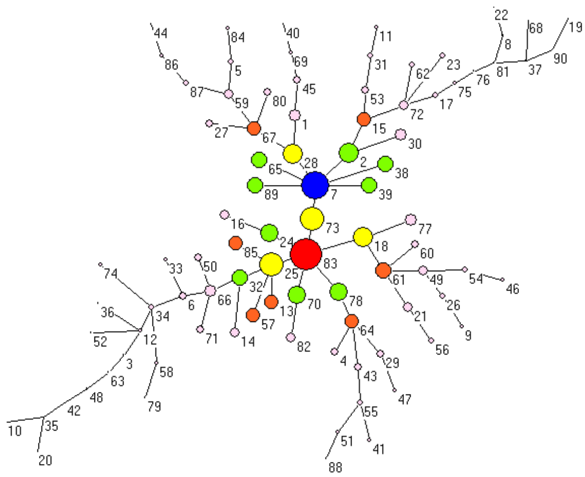

Figure 4. Eigenvector centrality

Average of weight centrality can be used to indicate the average correlations between a particular node and the other nodes adjacent to it. In terms of degree, *7-Genting Bhd* are the most dominance stocks while in terms of average of weights (see Table 3 and Figure 5) the most influential is *20-Telekom* (red point), followed by *19-Brit Amer Tobacc* (blue point) as the second important, and *90-JT International* (yellow point) as the third important. The fourth important stock is *68-KFC Holdings* (green point) followed by the orange points; *33-Berjaya Sports, 35-Berjaya Land, 37- & Neave, 10-DIGI.com, 57-Star Publication, 31-Malaysian Airport, 11-Plus Expressway, 79-NCB Holdings, 50-SHELL Refining,* and *14-YTL Power*. The rest are having small average of weights (pink points).

Table 3. The top 15 scores of average of weights centrality

Top	Average of Weights	
1	*Telekom*	1.065
2	*Brit Amer Tobacc*	1.026
3	*JT International*	0.925
4	*KFC Holdings*	0.815
5	*Berjaya Sports*	0.790
6	*Berjaya Land*	0.739
7	*Fraser & Neave*	0.701
8	*DIGI.com*	0.662
9	*Star Publication*	0.658
10	*Malaysian Aiport*	0.651
11	*Plus Expressway*	0.646
12	*NCB Holdings*	0.618
13	*SHELL Refining*	0.607
14	*YTL Power*	0.600
15	*Boustead Holding*	0.595

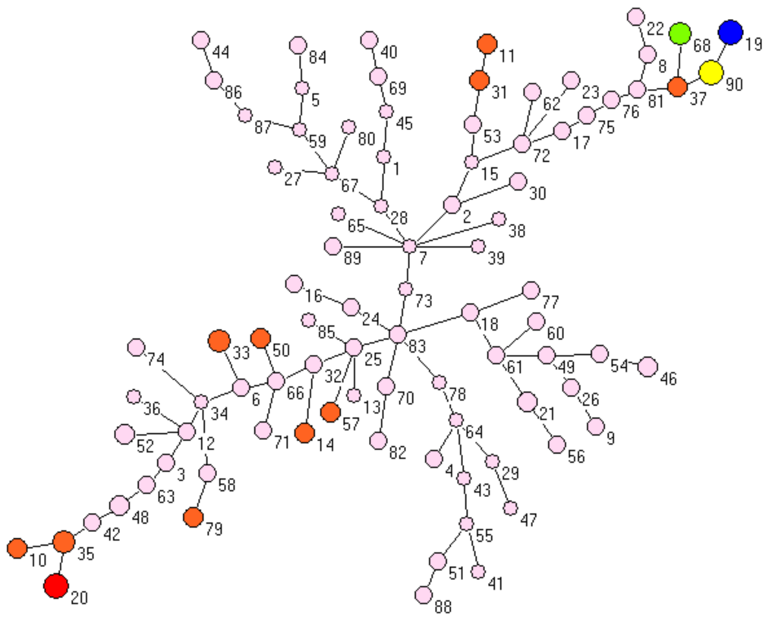

Figure 5. Average of weights centrality

Figure 1 and Figure 5, represent an MST with degree centrality and average of weights, respectively. If degree centrality refer to the number of links adjacent to a node, average of weights is the sum of those links' weight divided by the number of links. The latter measure represent the average influence given by a node to the others adjacent to it. From Table 1, we see its advantage compared to the former and learn that those measures are different.

4. Conclusion

We have introduced "average of weights" as a new centrality measure. The advantage of proposed centrality measure is by considering the weight instead of number of links only. Its advantage is illustrated by using 90 stocks market traded at Bursa Malaysia, together with the other established centrality measures, and could help to enrich the economic interpretation of network topology.

According to the five centrality measures, after using the Pareto analysis based on the top 15 stocks of highest scores in each centrality measures (Table 1), the following six stocks are the most in influencing stocks market; *CIMB Group Banking, Genting Bhd, RHB Capital Bhd, Wah Seong Corp, MMC Corp Bhd* and *IJM Corp Bhd*. These six stocks should be paid more attention by the investors in order to make the investment.

For further research, we render two potential researches. First, we can perform a comparison study on the proposed measure by using difference algorithm for constructing a minimum spanning tree. Furthermore, its applicability to other networks can be performed. Second, we can investigate its mean evolution distribution as well as its variance when involving more than one correlation structure. Many more research idea can be carried out to enrich this topic.

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