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Research paper



Behaviours of Bursa Malaysia: a Multidimensional Network Analysis

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Abstract

In current practice, the similarities between two or more univariate time series of stocks are determined by using the Pearson correlation coefficient (PCC). However, the economic information might be misleading if the analysis applies only the univariate time series of stock price, as each stock is denoted by four types of prices. Therefore, multidimensional of stocks are taken into account in this paper. The similarities between two or more multi-dimensional of stocks are quantified by using Random Vector (RV) coefficient. Additionally, an algorithm is proposed due to the computational of RV coefficient is tedious and time-consuming when a large number of stocks are included. In this paper, the Malaysian stock network analysis in univariate and multivariate setting are conducted and analysed by using the PCC, RV coefficient, forest of all possible MSTs and centrality measures. In summary, there is some important economic information could not be brought out by univariate network analysis alone.

Keywords: *Bursa Malaysia; Centrality Measures, Forest of All Possible Msts; Multivariate Analysis; RV Coefficient.*

1. Introduction

In recent times, the stock has turned out to be one of the most essential trading items in the monetary marketplace. Each corporation uses its very own stocks to trade in the stock market through the issue and subscription of shares to increase capital for business growth purposes. The stock market is a place where brokers and investors purchase all the shares of publicly listed corporations on every trading day. More importantly, the stock market is considered as an economic indicator of a country's financial health since it reflects how well all of the listed companies are doing.

Because of the mass of complex interrelationships among the stocks, the stock market is considered as a good example of the complex system. A complex system is about how elements of the system lead to group behaviour and the way the system interacts with its surroundings [1]. In [2], the authors stated that the stock market system is constantly growing through distinct heterogeneous associations among them. Moreover, [3] remarked that the stock market which includes a large quantity of stocks leads the system to excessively carrying superfluous and complicated data. Hence, it is difficult to estimate the behaviours of the entire system if the number of stocks increases [4].

To break down the complex's project data into its component parts and plotting them to show their interrelationships, minimum spanning tree (MST) is introduced by [5]. MST enables the plotting of a network that consists of a set of nodes linked by edges in which the node denote individual stock and the edges represent the similarity among two related stocks. Additionally, the network topology also facilitates the comprehension of the information of the stock market structure and the roles of each stock in the network.

In current practice, the MST built primarily regarding the distance matrix transformed from the Pearson correlation coefficient (PCC) matrix of stocks [3, 5, 6]. The PCC is a common approach in measuring the similarity between two stocks wherein each stock is represented by logarithmic of closed price returns. In the literature, numerous researchers applied the logarithmic of closed price returns in order to quantify the relationships among the stocks as can be seen in [7-11].

However, in real times, the stock is spoken to by four components of prices; which are opening, highest, lowest and closing prices. The authors in [12] stated that there is some possibilities of losing embodying information from different variables if the analysis applies only a single variable. Furthermore, the occurrence of social embeddedness can only be identified by a multivariate approach but not by a univariate approach [13]. As remarked in [14], the closing price transmits only the value that is brought over from the end of the previous trading period to the beginning of the current trading period. Therefore, it is essential to encompass all four features of time series into the analysis to obtain a complete and reliable economic information of the stock market.

The random vector (RV) coefficient introduced by [15] provides the notion of global association in multivariate setting [16]. This method assumes that two sets of vectors are superbly linked if an orthogonal transformation that could affect one sets to agree with the other. RV coefficient is also a unifying tool in multivariate approaches and a theoretical tool to analyse the multivariate techniques [17]. As stated in [3], the RV coefficient can be carried out to assess the interaction between two squared symmetric stocks and quantify the interaction in the form of value. Therefore, RV coefficient is applied to quantify the similarity between two or more stocks wherein every stock is represented as multivariate time series.

Nonetheless, the computational procedure of RV coefficient is difficult, time-consuming and tedious when a large number of stocks are involved. As an example, if 200 stocks are involved in the analysis, it will take 20,100 times to compute the RV coefficient repeatedly to obtain the upper diagonal of RV coefficient

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matrix. This is because the manual computational of RV coefficient only can provide one RV coefficient value at once. To ease and smooth the calculation process of RV coefficient, an algorithm is proposed. The proposed algorithm is capable of measuring the similarities among all pairs of stocks at once.

The purpose of this paper is to investigate the behaviours and interactions among Bursa Malaysia stocks in univariate and multivariate settings by measuring the similarities of the stocks with the use of PCC and the proposed RV coefficient algorithm. In this paper, the 100 most capitalized corporations indexed on Bursa Malaysia with investigation period from January 3, 2016, until January 28, 2018 are selected to depict the benefits of RV coefficient as compared to the PCC in stock network analysis. The rest of the paper is arranged as follows. The following section briefly discusses the methodology of the analysis and section 3 shows the results and discussions. Later on, the conclusions of the study are outlined and highlighted at the end of the paper.

2. Methodology

Assume n stocks are to be analysed in a given portfolio. Let $p_i(t,1)$, $p_i(t,2)$, $p_i(t,3)$ and $p_i(t,4)$ denote as the opening, highest, lowest and closing prices (or briefly known as OHLC prices) for stock i where i = 1, 2, …, n, respectively. Weekly data are considered so as to quantify the synchronization between the stocks. The weekly logarithmic of the m-th price returns of stock i at time t where m = 1, 2, 3, 4 is defined as

$$r_i(t,m) = \ln p_i(t+1,m) - \ln p_i(t,m) \tag{1}$$

For the analysis univariate setting, the similarity between two stocks is measured by the standard approach of Pearson correlation coefficient (PCC) as follow

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

where $\langle r_i \rangle$ is the mean of $r_i(t)$ for all time t. For the analysis in multivariate setting, assume that

$$s_{ij}(m,l) = \langle r_i(m) r_j(l) \rangle - \langle r_i(m) \rangle \langle r_j(l) \rangle \tag{3}$$

where $\langle r_i(m) \rangle$ is the mean of $r_i(t,m)$ for all time t. The covariance between m-th logarithmic price returns of stock i and l-th logarithmic price returns of stock j with m, l = 1, 2, 3, 4 which denoted as O, H, L and C prices and i, j = 1, 2, …, n is represented by $s_{ij}(m,l)$. Covariance matrix which involving all OHLC prices of stock i can be denoted by the matrix $\mathbf{S}_{ii}$ of size (*4* x *4*) and $\mathbf{S}_{ii}$ consists of $s_{ii}(m,l)$ as its component at the m-th row and l-th column where m, l = 1, 2, 3, 4. Besides, $\mathbf{S}_{ij}$ is the covariance matrix of stocks i and j with the size of (*4* x *4*) and contains $s_{ij}(m,l)$ as its component at the m-th row and l-th column.

RV coefficient can be applied to measure the similarity of stocks i and j by using the equation as follow [15],

$$RV_{ij} = \frac{Tr(\mathbf{S}_{ij}\mathbf{S}_{ji})}{\sqrt{Tr(\mathbf{S}_{ii})^2 Tr(\mathbf{S}_{jj})^2}} \tag{4}$$

where Tr(*) is the trace operator on a square matrix *, by implementing the notations stated above. This coefficient has satisfied the following properties;

(i) The RV coefficient matrix is symmetric, i.e. $\mathbf{S}_{ji} = \mathbf{S}_{ij}^T$ for all i and j.

(ii) The range of RV value is between 0 and 1. The RV value is 0 if and only if every price of stock i and all prices of stock j are uncorrelated. Otherwise, if and only if the eigensystem of $\mathbf{S}_{ii}$ is equal to the eigensystem of $\mathbf{S}_{jj}$ except for all zero eigenvalues, the RV value is 1.

(iii) If stocks i and j utilize only their closing prices, then $RV_{ij} = r_{ij}^2$, where r_{ij}^2 is the square of PCC between a pair of stocks.

(iv) If stock i uses only its closing price and stock j is characterized by OHLC prices, then the $RV_{ij} = \frac{1}{2} R_{ij}^2$ where R_{ij}^2 is the coefficient of determination.

In reference to the properties, it can be asserted that RV coefficient is a multivariate generalization of PCC.

As remarked in the earlier paragraph, the computational procedure of RV coefficient is tedious and time-consuming when a large number of stocks are involved. So as to ease the computational complexity and increase the computational efficiency of RV coefficient, an algorithm is set up by referring to equation (4). The following figure is the algorithm's set up to determine all pairs of n stocks at once in the analysis.

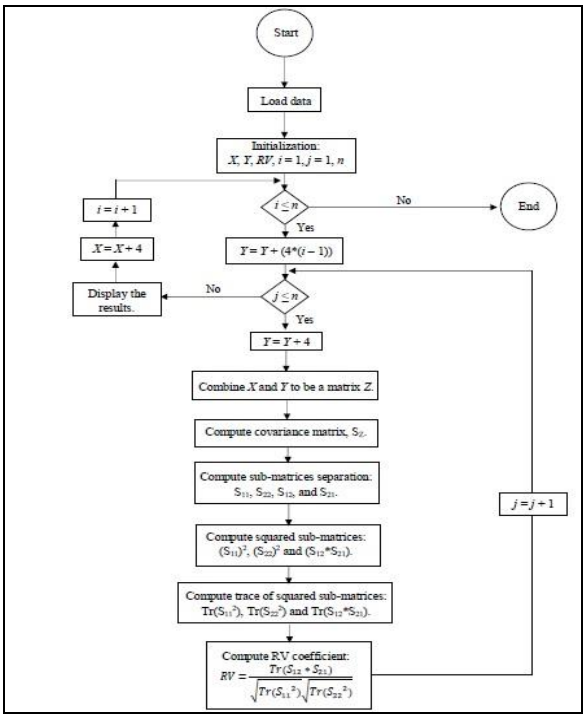

Fig. 1 Flowchart of the proposed RV coefficient algorithm.

The similarities among n stocks are being quantified and numerically compiled into a correlation matrix with the size of (n x n) and ρ_{ij} as the component for the PCC matrix and RV_{ij} as the component of i-th row and j-th column for the RV coefficient matrix.

It is difficult to extract the hidden information by using the correlation matrix since it does not satisfy the axioms that define a metric [5]. Thus, in order to construct the stock network topology, [6] recommended to transform the correlation matrix into a distance matrices, $\mathbf{D_1}$ which consists of d_{ij} as the elements in the matrix and

$\mathbf{D_2}$ which consists of δ_{ij} as the components of *i*-th row and *j*-th column. d_{ij} and δ_{ij} are defined as

$$d_{ij} = \sqrt{2(1-\rho_{ij})} \tag{5}$$

and

$$\delta_{ij} = \sqrt{2(1-RV_{ij})} \tag{6}$$

Respectively, where d_{ij} and δ_{ij} are the distance between two stocks. This edge distance fulfills all the axioms of Euclidean distance as stated in [2]. Regarding equations (5) and (6), the distance matrices $\mathbf{D}_1 = (d_{ij})$ and $\mathbf{D}_2 = (\delta_{ij})$ of size (*n* x *n*) denote the distance network of stocks in univariate setting and multivariate setting, respectively. Distance matrix is applied to decompose the set of *n* items into subsets of closely related items. The hidden economic information contains in distance matrix can be filtered by using forest of all possible MSTs. This is to understand and visualize the topological structure of the stocks in the market.

2.1. Forest of all possible MSTs

As remarked in [18], forest of all possible MSTs is considered as one of the best classification tools in extracting the significant economic information contained in the stock network. If one works within the view of MST, different possible network topologies may exist, but if one works with the Forest, there just exists a single network topology. The MST in distance matrix is considered as unique if and only if the sum of all elements of the adjacency matrix, $\mathbf{\Delta}$ equal to $2(n-1)$. The following steps as shown are applied to construct the forest of all possible MSTs as proposed in [18]:

Step 1: Let *c* = 2, where *c* is the number of times of min-max operation '*' on $\mathbf{D}$.

Step 2: Compute $\mathbf{D}^{*c}$, where $\mathbf{D}*\mathbf{D}^{*(c-1)}$ is a matrix multiplication in the usual sense but multiplication and summation of two real numbers *a* and *b* are defined as max{a,b}and min{a,b} respectively.

Step 3: If $\mathbf{D}^{*c} = \mathbf{D}^{*(c-1)}$, then the subdominant ultrametric (SDU) of $\mathbf{D}$ is $\mathbf{D}^{*c}$ and proceed to Step 4. Otherwise, let *c* = *c* + 1 and then return to Step 2.

Step 4: Compute $\mathbf{\Delta}$ which is defined as follows:

$$u(i,j) = \begin{cases} 1; & \delta(i,j) - \delta^{+}(i,j) = 0 \ \ and \ \ i \neq j \\ 0; & \delta(i,j) - \delta^{+}(i,j) \neq 0 \ \ or \ \ i = j \end{cases} \tag{7}$$

Further details about the forest of all possible MSTs can be referred in [18].

2.2. Centrality measures

Centrality measures help in the finding of most central nodes in the network structure as well as understanding the importance or influence of each stock relative to the others [19]. There are five approaches of centrality measures to be used in this paper which are,

(i) degree centrality

Degree centrality indicates total quantity of direct connections of a stock has in the network [20]. Degree centrality of stock *i* is defined as

$$C_D(i) = \frac{\deg(i)}{n-1} \tag{8}$$

where $\deg(i)$ is the quantity of connections that link to the stock *i*.

(ii) betweenness centrality

Betweenness centrality reflects the potentiality of a stock to control the information flow in the network [20]. Betweenness centrality can be defined as

$$C_B(i) = \frac{2}{(n-1)(n-2)} \sum_{j,k=1}^{n} \frac{d_{(j,k)}(i)}{d_{(j,k)}} \tag{9}$$

where $\mathrm{d}_{(j,k)}$ is the shortest path from stock *j* to stock *k* and $d_{(j,k)}(i)$ is the number of shortest path from stock *j* to *k* that passes through *i*.

(iii) closeness centrality

Closeness centrality determines how close a stock is to all other stocks in terms of total distances of the geodesic path from one stock to the other stocks [20]. Closeness centrality of stock *i*,

$$C_c(i) = \frac{n-1}{\sum_{j=1}^{n} d(i,j)} \tag{10}$$

where $d(i,j)$ is the minimum geodesic distance between stock *i* to stock *j* for all $j \neq i$.

(iv) eigenvector centrality

Eigenvector centrality defines a stock as central if the stock is in relation with other stocks that are central as well [21]. Eigenvector centrality is defined as

$$C_E(i) = \lambda_{\max}^{-1} \sum_j \Delta_{ij} x_j \tag{11}$$

where Δ_{ij} is the component of *i*-th row and *j*-th column of the adjacency matrix, $\mathbf{\Delta}$, $\lambda_{\max}$ is a constant largest eigenvalue and x_j is the eigenvector associated with the largest eigenvalue $\lambda_{\max}$ of the adjacency matrix.

The utilizations of these four standard approaches of centrality measures can be seen in many articles [22-26].

These four centrality measures' values have different roles in indicating the most important stock in the network. Therefore, so as to determine the overall characteristics of each stock, it is important to define an overall centrality [22]. Overall centrality is represented by the Principal Component Analysis (PCA) of the data matrix of size (*n* x *h*) where *h* represents the score of degree, betweenness, closeness and eigenvector centralities, respectively. The score of stock *i* in terms of overall centrality measure is defined by

$$O_i = e_1 C_D(i) + e_2 C_B(i) + e_3 C_C(i) + e_4 C_E(i) \tag{12}$$

where $e = (e_1, e_2, e_3, e_4)^t$ is the eigenvector of covariance matrix $\mathbf{V}$ from the matrix of size (*n* x *h*) and these eigenvectors are associated with the largest eigenvalue [23,25,26].

3. Results and Discussions

This paper investigates the weekly data of 100 most capitalized stocks traded in Bursa Malaysia from January 3, 2016 until January 28, 2018. Nevertheless, because of the limited availability of data within the time frame of investigation, there are only 94 stocks to be analysed. The stocks are coloured according to economic sectors which are trading and services (blue), finance (green), consumer products (yellow), plantation (pink), real estate investment trusts (orange), infrastructure project company (purple),

industrial products (cyan), properties (brown), construction (red), hotels (olive green) and technology (grey). Each stock is labelled by its ticker symbol such as AMMB Holdings Bhd as AMBANK.

Firstly, the 94 stocks with logarithmic closed price returns are applied. The associations among the stocks are measured by using the PCC and the stock network is constructed as can be seen in Figure 2.

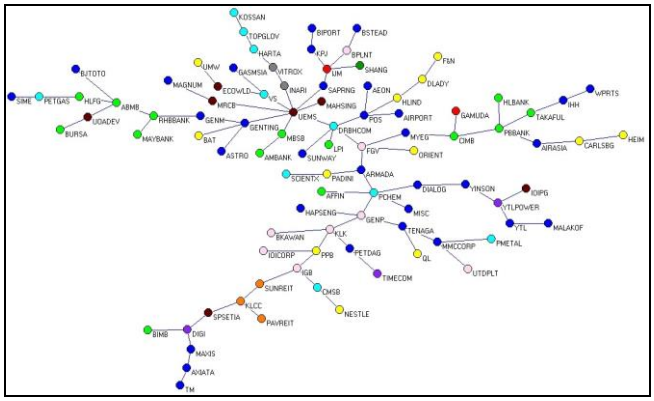

Fig. 2 Forest of Bursa Malaysia based on Pearson correlation coefficient.

Based on Figure 2, UEMS seems to be the dominant stock in the network as it has the highest number of links, followed by DRBHCOM and PCHEM. It is also noticed that all the telecommunication stocks (TM - AXIATA – MAXIS – DIGI) are linked in the network. Moreover, stocks under similar economic sector and have the same economic interests will connect with each other in the network, such as VITROX–INARI, F&N–DLADY and CARLSBG–HEIM. Some intriguing associations between the stocks can also be detected in the network. For instance, GENM–GENTING, BSTEAD–BPLNT, and YTL–YTLPOWER. Each pair of stocks has the subsidiary relationship with the parent company. However, in Figure 2, the financial sector and property sector of stocks are distributed separately in the network.

As remarked in Section 1, some economic information might be unable to be retrieved if the analysis is conducted by using single price only. Therefore, four types of prices are applied and the similarities among the stocks are measured using the RV coefficient algorithm. The forest of the stocks is then constructed as shown in Figure 3. The structure of the network in Figure 3 is quite distinct from the structure in Figure 2.

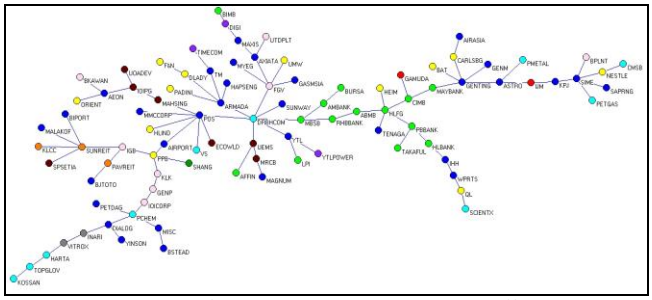

Fig. 3 Forest of Bursa Malaysia based on RV coefficient.

In reference to Figure 3, the most dominant stocks in terms of number of links of a stock to the other stocks are DRBHCOM and POS. Also, in Figure 3, the UEMS is not located in the central hub of the network. It also noticed that majority of the financial and property sectors of stocks congregated together in the network. This is due to stocks under similar economic sector have high similarities as each other. However, this phenomenon cannot be found in Figure 2. Additionally, another economic information not seen from Figure 2 is the association between TM and TIMECOM. As reported in [27], both stocks have a firm relationship. This is because TM and TIMECOM have signed a 20-year agreement on the construction and maintenance of the submarine cable system, Sistem Kabel Rakyat 1 Malaysia (SKR1M), since 2015.

Despite this, another interesting association between the stocks that can be found in Figure 3 but not in Figure 2 is the association between PETDAG, PCHEM and MISC. According to the official website of the parent company, these three stocks are partly-owned by Petroliam Nasional Berhad. However, some of the topological properties in Figure 2 that remain the same in this forest are the telecommunication stocks (DIGI–MAXIS–AXIATA), which still linked to each other and the subsidiary relationships of YTL-YTLPOWER and GENTING-GENM.

The association between DRBHCOM and POS can also be found in both forests. As reported in [28], DRBHCOM and POS have a common chairman, i.e. Datuk Mohammad Zainal Shaari. Thus, any changes occurring in DRBHCOM stock prices, the POS stock prices will be affected as well as both stocks are closely related with each other.

Regarding the two figures, it might indicate that there are some hidden and significant economic information can only be retrieved by using multivariate time series of stock prices in the analysis. In order to understand the significance of a stock relative to the other stocks in the network, centrality measures are applied.

The results of degree centrality measures by using closing price show that UEMS scores the highest with 8 edges (0.0860) in the network. However, in the stock market analysis using multivariate time series of stock prices, the highest number of links connected in the network are DRBHCOM and POS with score of 0.0753 (7 edges). The greater the number of connections of a stock has in the network, the greater the influence power of that particular stock on other stocks. As a result, it can be said that UEMS is the most important stock in the univariate stock network analysis while DRBHCOM and POS are the most significant stocks in the multivariate stock network analysis in terms of degree centrality.

In terms of betweenness centrality measure, FGV scores the highest (0.6103) in the univariate stock network analysis whereas DRBHCOM is the highest scoring stock (0.7139) in the multivariate stock network analysis. The stock with the greatest betweenness centrality value has the greatest role in controlling the information flow of the network. Thus, in the univariate stock network analysis, FGV plays a crucial role in controlling information flow between the stocks; whereas DRBHCOM coordinates the information among the stocks in the multivariate stock network analysis.

The key player in terms of closeness centrality in univariate stock network analysis is FGV with a score of 0.2017, while the key player in the multivariate stock network analysis is DRBHCOM (0.1867). The larger the value of closeness centrality, the quicker the information can be transmitted to other stocks. Hence, this indicates that FGV and DRBHCOM are able to spread the information to the other stocks in a short time in their respective stock network analysis.

In the univariate stock network analysis, UEMS is the highest scoring stock with a score of 0.5930 in terms of eigenvector centrality measure. However, the highest scoring stock in multivariate stock network analysis is DRBHCOM (0.5432) again. The higher value of stock in terms of eigenvector centrality shows that the stock is associated with other imperative stocks in the network.

As remarked in Section 2, it is necessary to determine the most significant stocks with the overall characteristics in the network. This is because each centrality measure has distinct character in explaining the behaviours of the stock market. Therefore, overall centrality measure is applied in this paper.

The proportion in the PCA is the proportion of the variability in the data that each principal component explains. The higher the proportion, the more variability that the principal component can tell [29, 30]. According to the PCA in both univariate and multivariate stock analyses, the first principal component explains much of the percentage of the total variations than the second principal component. A high proportion of the first principal component is crucial and adequate in determining the overall centrality

measure compared to the second principal component. As a result, in the univariate stock network analysis, UEMS scores the highest in terms of overall centrality with 0.5930; whereas DRBHCOM appears to be the top scorer with a value of 0.8886 in the multivariate stock network analysis.

4. Concluding Remarks

As can be seen, similar quantity of stocks with distinct quantity of variables used in the analysis can produce different results. As remarked in [13], the phenomenon of social embeddedness such as the association of PETDAG–PCHEM–MISC can only be identified by using multivariate approach but not by univariate approach. Moreover, there are a few significant economic information that can only be obtained from the analysis that includes all stock prices, such as the association between TM and TIMECOM. Therefore, the economic information retrieved from the multivariate stock network analysis is truly reliable compared to the analysis done by using univariate time series only which is also supported by [2, 3, 12, 23].

As a result, based on the results from the multivariate stock network analysis, DRBHCOM is the most essential and significant stock in Bursa Malaysia within the investigation period, followed by POS, as the second most important stock. Regarding Figure 2, DRBHCOM is positioned at the central hub of the network and displayed a star-like structure in the network. DRBHCOM is one of the nation's largest and most diverse conglomerates [31]. This corporation also owns the nation's icons which include PROTON Holdings Berhad (PROTON) and Motosikal dan Enjin Nasional Sdn. Bhd. (MODENAS) which are widely recognized brands in Malaysia. Additionally, DRBHCOM also has a close relationship with POS from the business point of view in which POS is the nation's postal service provider in Malaysia [32]. With this finding, the related organizations and authorities should put plenty effort on the DRBHCOM or the industrial products sector as this sector might be the steppingstone for Malaysia to achieve the developed economy country by 2020.

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References

[1] New England Complex Systems Institute (2018). Retrieved from http://necsi.edu/guide/

[2] Kazemilari M & Djauhari MA (2015), Correlation network analysis for multidimensional data in stocks market. Physica A 429, 62-75.

[3] Gan SL & Djauhari MA (2013), Multidimensional stock network analysis: An Escoufier's RV coefficient approach. ICMSS 1577, 550-555.

[4] Shabanali R (2017), Definition: What is a complex system? Webmindset. Retrieved from http://webmindset.net/terminology-of-the-complexity-approach.

[5] Mantegna RN (1999), Hierarchical structure in financial markets. The European Physical Journal B 11, 193-197.

[6] Mantegna RN & Stanley HE (2000), An introduction to econophysics: Correlations and complexity in Finance. Physics Today 53, 12, 70.

[7] Jung WS, Chae S, Yang JS & Moon HT (2006), Characteristics of the Korean stock market correlations. Physica A 361, 1, 263-271.

[8] Coelho R, Gilmore CG, Lucey B, Richmond P & Hutzler S (2007), The evolution of interdependence in world equity markets – Evidence from minimum spanning trees. Physica A 376, 455-466.

[9] Bahaludin H, Abdullah MH & Mat Salleh S (2015), Minimal spanning tree for 100 companies in Bursa Malaysia. AIP Conference Proceedings, 1643, 609-615.

[10] Huang F, Gao P & Wang Y (2009), Comparison of Prim and Kruskal on Shanghai and Shenzhen 300 index hierarchical structure tree. International Conference on Web Information Systems and Mining, 237-241.

[11] Tabak BM, Serra TR & Cajueiro DO (2010), Topological properties of stock market networks: The case of Brazil. Physica A, 389(16), 3240-3249.

[12] Brida JG & Risso WA (2009), Multidimensional minimal spanning tree: The Dow Jone case. Physica A, 287, 5205-5210.

[13] Halinen A & Tornroos J (1998), The role of embeddedness in the evolution of business networks. Scandinavian Journal of Management, 14(3), 187-205.

[14] Yamashita Y & Yodahisa H (2012), Similarity measure and clustering algorithm for candlestick valued data. Joint Meeting of Japanese and Italian Classification Societies, 17-20.

[15] Escoufier Y (1973), Le traitement des variables vectorielles. Biometrics 29(4), 751-760.

[16] Josse J, Pages J & Husson F (2008), Testing the significance of the RV coefficient. Computational Statistics and Data Analysis 53, 82-91.

[17] Abdi H (2007), RV coefficient and congruence coefficient. Encyclopedia of Measurement and Statistics, 849-853.

[18] Djauhari MA (2012), A robust filter in stock network analysis. Physica A 391, 5049-5057.

[19] Sharif S, Yussof NS & Djauhari MA (2012), Network topology of foreign exchange rate. Modern Applied Science 6(11), 35-43.

[20] Freeman LC (1979), A set of measures of centrality based on betweenness. Sociometry, 35-41.

[21] Bonacich P (1972), Factoring and weighting approaches to status scores and clique identification. Journal of Mathematical Sociology 2, 113-120.

[22] Gan SL & Djauhari MA (2012), Network topology of Indonesian stock market. Proceedings of International Conference on Cloud Computing and Social Networking, 1-4.

[23] Djauhari MA & Gan SL (2014), Bursa Malaysia stocks market analysis: A review. ASM Science Journal 8(2), 150-158.

[24] Kazemilari M & Djauhari MA (2013), Analysis of a correlation network in world currency exchange market. International Journal of Applied Mathematics and Statistics 44(14), 202-209.

[25] Asrah NM, Djauhari MA & Ebi SS (2014), Work attitude among Malaysian academics in the public universities: A social network analysis. Modern Applied Science 8(5), 9-18.

[26] Lim SY & Salleh RM (2018), Bursa Malaysia performance: Evidence from the minimum spanning tree. AIP Conference Proceedings 1974(1), 1-8.

[27] The Star Online (2015). Retrieved from https://www.thestar.com.my/business/business news/2015/09/02/telekom-malaysia-inks-deal-with-time-dotcom-for-skrlm-cable/

[28] The Star Online (2018). Retrieved from https:/business/business News/2018/04/13/zainal-is-chairman-of-drbhicom-and-pos-malaysia/

[29] Jollife IT, Principal Component Analysis, Springer, New York, (2002), pp: 21-28.

[30] Minitab 18 support (2018). Retrieved from https://support.minitab com/en-us/minitab/18/help-and-how-to/modeling-statistics/multivariate/how-to/principal-components/interpret-the-results/all-statistics-and-graphs/

[31] Drb-Hicom (2018). Retrieved from http://www.drb-hicom.com/ about-us/discover-us/

[32] Pos Malaysia (2018). Retrieved from https://www.pos.com.my/ about-us/corporate-information/?our-heritage