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CLUSTERING BASED ON BETWEENNESS CENTRALITY IN PERIOD: TRANSFORMATION OF CORRELATION COEFFICIENT VALUE INTO DISTANCE IN MATRIC SPACE

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ABSTRACT

The main information of this research is the transformation of the correlation coefficient value for stock price into the distance. It is done to create a representation in metric space that can be used in cluster analysis on the correlation network, which is a dynamic network. The dynamic network is generated from the weighted edges in the form of distances in each period. Finding the cluster members of the network can be analyzed using a simple technique called a minimum spanning tree. The central cluster member is the vertex betweenness. Vertex betweenness represents banking companies with a high degree of proximity and correlation. It means that the banks that are members of the central cluster are banks with high investment value. Clustering based on betweenness centrality in the case study of stock price correlation becomes useful when transforming the value of the correlation coefficient to distance. The effort to build a network with the edge weight being the distance makes the minimum spanning tree a simple, valuable method for cluster analysis on bank stock prices. In particular, the benefit to investors, i.e., it can reveal which assets are closely correlated, indicating that they may respond to market events in a similar way and make decisions in stock purchases

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1. INTRODUCTION

The stock price data of banks at any time is very easy to obtain information. It is important information for potential investors in the banking sector in Indonesia. The correlation of stock prices between banks in Indonesia can provide an overview of how strong the relationship of stock price movements between one bank and another. Investors and analysts often use this correlation to assess the risk and diversification of investment portfolios in the banking sector [1]. Correlation analysis is usually used to calculate the correlation coefficient between bank stock prices, which measures the linear relationship between two variables.

In the case study in this research, the bank is represented as a node or vertex. Correlation is represented as an edge, a form of vertices interaction [2]. Furthermore, the correlation between vertices is represented as a connected graph or network. Some references explain that the connected graph, in this case, is called a correlation network [3] [4]. Graphs with edge weights representing correlation coefficients are one way of visualizing networks between variables using graph concepts. In the context of stock prices between banks, vertices represent banks, and edges connecting two vertices represent the correlation level between the two banks' stock prices. The edge weights in the network are correlation coefficient values that range from -1 to 1, which will then be transformed into distances in the metric space.

The transformation of correlation coefficient values into Euclidean distances creates a representation in metric space that can be used in cluster analysis. Since the correlation coefficient ranges from -1 to 1, while the Euclidean distance is always non-negative, we need to perform some transformation. The Euclidean distance of the transformation can be used to find vertex betweenness. This method ensures that we are working in a metric space that matches the properties of the distance, i.e., non-negative and symmetric values.

We can build a graph with edge weights showing the Euclidean distance between bank stock prices. The smaller the distance, the closer the relationship between the stock prices after converting the correlation coefficient value into a distance value. The larger the distance, the more distant the relationship. Next, we will look for vertices with the slightest edge weights, which are used to determine vertex betweenness. Minimum Spanning Tree (MST) is used to determine vertex betweenness.

MST is a graph structure that includes all vertices in a connected graph with a path of minimum total weight without any cycles [5] [6]. Although MST is usually used to find the minimum path in a connected network, it is not a direct method to calculate vertex betweenness. However, both can be used together in network analysis, especially to find essential elements in graphs or community structures [7] [8]. There are several other methods that have the same use as MST, but the advantage of MST is that the algorithm used is very simple; see [2] [4] [6] [7]. Since the networks to be clustered are dynamic, it needs the simplest approach to clustering to minimize time.

Vertex betweenness measures how often a vertex is on the shortest path between two other vertices [9]. It indicates the importance of a vertex in facilitating flow through the network [10]. So, the relationship between MST and vertex betweenness is that MST provides the minimum path connecting all vertices in the graph and thus provides insight into how vertices are efficiently connected. Vertex betweenness focuses on how vital a vertex is in facilitating connectivity in the network.

This research's contribution is to determine the technique of clustering members of bank companies with important positions by looking at the level of correlation between banks. Some vertex betweenness from the dynamic network can be used as cluster members.

2. RESEARCH METHODS

2.1 Correlation Analysis

The goodness of fit of the stock price data from each bank in **Figure 1** shows that the data does not follow a normal distribution. Furthermore, the correlation analysis will use Spearman rank or Spearman's ρ. On the other hand, the reason for choosing Spearman rank is that it does not require the assumption of linear correlation between research variables and the assumption of data normality. This is because the stock price data from each bank tends to be different and change every time. Before looking for the correlation coefficient value, the data is first standardized with a Z-score in **Equation (1)**,

$$Z_i = \frac{X_i - \bar{X}}{s}, \tag{1}$$

where s is the standard deviation. After obtaining the z_i value, the next step is to find the correlation coefficient value with the **Equation (2)**,

$$\rho = \rho_{XY} = 1 - \frac{6\sum d_i^2}{n(n^2-1)}, \tag{2}$$

where n is the number of observations, and $d_i = R[X_i] - R[Y_i]$ is the difference between the two ranks of each observation. **Equation (2)** is used for Spearman's ρ when no similar observation values are found. If a similar observation value is found, **Equation (3)** is used,

$$\rho_{XY} = 1 - \frac{\sum X^2 + \sum Y^2 - \sum d^2}{2\sqrt{\sum X^2 \sum Y^2}}, \tag{3}$$

where $\sum X^2 = \frac{n(n^2-1)}{12} - \sum \frac{t(t^2-1)}{12}$, $\sum Y^2 = \frac{n(n^2-1)}{12} - \sum \frac{t(t^2-1)}{12}$, and t is the number of similar observations.

Spearman's ρ can range from -1 to 1, with the coefficient sign indicating a negative or positive monotonic relationship. A positive correlation is when one variable increases and the other tends to increase, and a negative correlation is when one variable increases and the other tends to decrease. Values close to -1 and 1 indicate a stronger relationship, while values close to 0 indicate a weaker relationship. The statistical test used is the t statistic in **Equation (4)**, with the null hypothesis being the two independent variables; there is no correlation.

$$t = t_{statistical} = \rho\sqrt{n-1} \tag{4}$$

2.2 Network and Minimum Spanning Tree

In mathematics, a network is a connected graph. A graph $\mathrm{G} = \mathrm{G}(V, A)$ with $V = \{v_0, v_1, \dots, v_n\}$ as vertices, and $A = \{(v_i, v_j): i, j \in V, i \neq j\}$ as edges **[11]**. A graph $\mathrm{G} = \mathrm{G}(V, A, g)$ is called a weighted graph G on V, i.e., a pair (V, A, g) where g is a function that maps pairs of each element of V to a non-negative real number $g: V \times V \to \mathbb{R}_{\geq 0}$ **[12] [13]**. In this case, banks are represented as vertices, while correlations are represented as edges. The weight of the edge is the distance value derived from the transformation of the correlation coefficient value. The network with the vertex is the bank, and the edge is the correlation, presented in **Figure 1**.

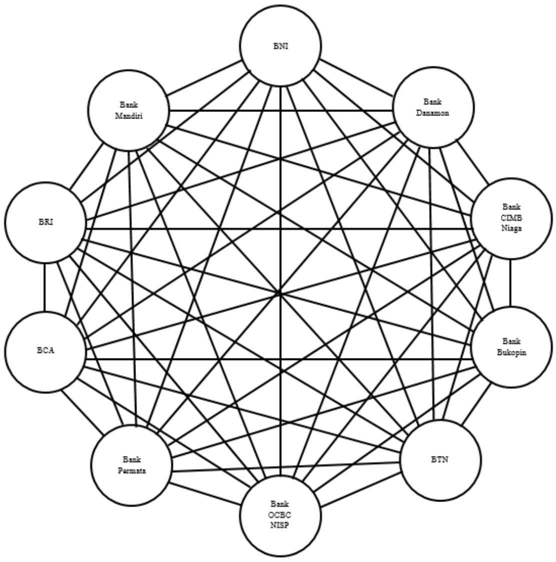

Figure 1. Network with Bank Name as Vertex and Correlation as Edge

The network in **Figure 1** will be a dynamic network, which is a network with weights that change over a period.

MST is a graph theory concept that plays a significant role in optimization problems, especially network design and optimization problems. In network optimization, before a problem is solved, it is represented or visualized first so that the actual problem structure can be known. It is called network design. In network design, the concepts most often used to illustrate or represent problems are concepts from graph theory.

A *spanning tree* is a subnetwork that is formed without containing cycles in it. At the same time, the MST is a construction tree with the minimum number of arc weights [6]. If given a network G, then the MST of G is the spanning tree with the smallest number of weights. Betweenness centrality is the setting of the centrality of a vertex or edges. Betweenness can be visualized as a symbol of the strength or influence of a vertex or edge in the network [9] [10] because the vertex or edge is a link to another vertex or edge.

Furthermore, vertex betweenness is the setting of the centrality of a point. Using MST can give an initial idea of the critical structure of the network. However, to calculate the complete vertex betweenness, it is necessary to use a specific algorithm such as Brandes' algorithm, which calculates all shortest paths in the graph, not just the paths in MST. The steps to calculate vertex betweenness using shortest paths for MST using Kruskal's method are presented in Algorithm 1 [6]. The vertex's betweenness score increases whenever a vertex is on the shortest path between two other vertices.

Algorithm 1. Determining the MST that generates vertex betweenness

Step 1: Create a weighted graph G.

Step 2: Find the MST by removing all edges of G and sorting the edges of G from most negligible to most considerable weight. Based on the order, we add edges to avoid the formation of cycles. The next stop is if a spanning tree with minimum edge weights is formed.

Step 3: Calculate vertex betweenness: To calculate betweenness, determine all the shortest paths between all vertex pairs. Algorithms like Brandes allow us to calculate betweenness centrality efficiently.

3. RESULTS AND DISCUSSION

3.1 Data Description

The data used are bank stock prices per day for 20 months (January 2018-August 2019), taken from www.investing.com. The bank data consists of 10 bank companies, namely Bank Bukopin, Bank Danamon, Bank Mandiri, Bank Permata, Bank CIMB Niaga, Bank OCBC NISP, Bank BCA, Bank BNI, Bank BRI, and Bank BTN. Furthermore, the data and line plot are presented in **Figure 2**.

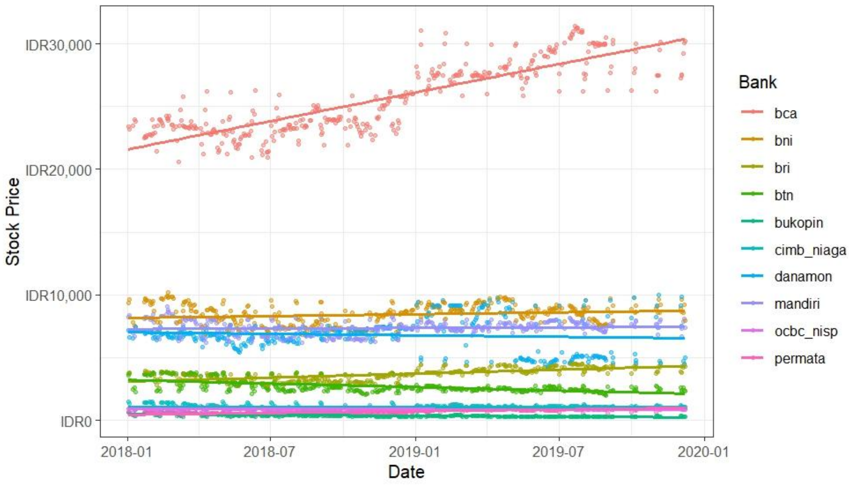

Figure 2. Plot Data and the Line Plot

3.2 Transformation of Correlation Coefficient Value into Distance

The weight of the edges of the network is obtained by converting the correlation coefficient value into the Euclidean distance in metric space. Defined $d(x,y)=\sqrt{2(1-\rho_{XY})}$, it will be shown that $d(x,y)$ is a metric.

Definition 1. Metric [14]

Let A be a non-empty set, a metric on A is a function $d: A\times A\to[0,\infty]$ such that for every pair $(x,y)\in A\times A$ holds: (a) $d(x,y)\geq 0$ for every $x,y\in A$; (b) $d(x,y)=0$ for $x,y\in A$ with $x=y$; (c) $d(x,y)=d(y,x)$ for every $x,y\in A$; and (d) $d(x,y)\leq d(x,z)+d(z,y)$ for every $x,y,z\in A$.

Let **D** be a correlation coefficient matrix of size $m\times m$ whose elements express the pairwise correlation coefficient values of m vectors in $\mathbb{R}^n$. Then, we have a correlation

$$\rho_{XY}=\frac{Cov(X,Y)}{\sqrt{Var(X)Var(Y)}} \tag{5}$$

Take any $x,y\in A$ so as to obtain ρ_{XY} with $-1\leq\rho_{XY}<0$, e.g. $\rho_{XY}=-a, a\in(0,1]$ such that

$$\begin{aligned} d(x,y)&=\sqrt{2(1-\rho_{XY})}\\ &=\sqrt{2\big(1-(-a)\big)}\\ &=\sqrt{2(1+a)}\\ &=\sqrt{2+2a}>0. \end{aligned}$$

For $0\leq\rho_{XY}\leq 1$, e.g. $\rho_{xy}=a, a\in[0,1]$,

$$\begin{aligned} d(x,y)&=\sqrt{2\big(1-\rho_{xy}\big)}\\ &=\sqrt{2(1-a)}\\ &=\sqrt{2-2a}\geq 0, \end{aligned}$$

so, $d(x,y)\geq 0$.

Take any $x,y\in A, x=y$ so as to obtain $\rho_{XY}=1$, such that

$$\begin{aligned} d(x,y)&=\sqrt{2(1-\rho_{XY})}\\ &=\sqrt{2(1-1)}\\ &=0 \end{aligned}$$

so $d(x,y)=0$.

Take any $x,y\in A$ so as to obtain ρ_{xy}. Based on correlation matrix **D**, we have $\rho_{XY}=\rho_{YX}$, such that

$$\begin{aligned} d(x,y)&=\sqrt{2(1-\rho_{XY})}\\ &=\sqrt{2(1-\rho_{YX})}\\ &=d(y,x) \end{aligned}$$

so $d(x,y)=d(y,x)$.

Take any $x,y,z\in A$

$$\begin{aligned} \rho_{XY}&=\frac{Cov(X,Y)}{\sqrt{Var(X)Var(Y)}}\\ &=\frac{E[(X-E[X])(Y-E[Y])]}{\sqrt{(E(X-E[X])^2)(E(Y-E[Y])^2)}}\\ &=\frac{E[(X-E[X])(Y-E[Y])]}{\sqrt{(E(X-E[X])^2)(E(Y-E[Y])^2)}}\\ &=\frac{E[XY]-E[X]E[Y]}{\sqrt{(E(X-E[X])^2)(E(Y-E[Y])^2)}}\\ &=\frac{E[XY]-\mu_X\mu_Y}{\sigma_X\sigma_Y}. \end{aligned}$$

Because the data has been standardized, the data has $\mu = 0, \sigma^2 = 1$ we have

$$\rho_{XY} = \frac{E[XY] - 0}{1} = E[X, Y] = \frac{1}{n}\langle X, Y \rangle.$$

Suppose we have a squared Euclidean distance,

$$\begin{aligned} d^2(x, y) &= \sum (x_i - y_i)^2 \\ &= \sum (x_i^2 - 2x_i y_i + y_i^2) \\ &= \sum x_i^2 + \sum y_i^2 - 2\sum x_i y_i \\ &= n + n - 2\langle X, Y \rangle \\ &= 2n - 2\langle X, Y \rangle \\ &= 2n(1 - \rho_{XY}) \\ &= \sqrt{2n(1 - \rho_{XY})} \\ &= \sqrt{n}\sqrt{2(1 - \rho_{XY})}. \end{aligned}$$

So, the equation form $\sqrt{n}\sqrt{2(1-\rho_{XY})}$ is equivalent to Euclidean distance, and Euclidean distance is a metric [15]. Thus, if $d(x, y)$ is the Euclidean distance, then the product of the constant n with $d(x, y)$ is the Euclidean distance. Then, we have $\sqrt{2(1-\rho_{XY})} \leq \sqrt{2(1-\rho_{XZ}\ )} + \sqrt{2(1-\rho_{ZY})}$, such that $d(x, y) \leq d(x, z) + d(z, y)$.

3.3 Minimum Spanning Tree for Network G

The data used is bank stock prices per day for 20 months (January 2018 to August 2019), divided into 32 periods. So, the vertex betweenness is obtained from 32 networks. The spanning tree of the network G in the period 01/22/2018 to 06/27/2018 obtained from the network in Figure 1 is presented in Figure 3. The **D** matrix for this period is presented in Table 1, and the distance matrix is in Table 2.

Table 1. Matrix D in the Period 01/22/2018 to 06/27/2018

Variables	BCA	Bank Bukopin	BNI	BRI	BTN	Bank Danamon	Bank Mandiri	Bank Permata	Bank CIMB Niaga	Bank OCBC NISP
BCA	1	0.736	0.784	0.789	0.776	0.576	0.836	0.607	0.679	0.117
Bank Bukopin	0.736	1	0.889	0.916	0.896	0.697	0.893	0.864	0.896	0.122
BNI	0.784	0.889	1	0.939	0.884	0.689	0.951	0.820	0.909	0.070
BRI	0.789	0.916	0.939	1	0.954	0.794	0.962	0.858	0.903	0.248
BTN	0.776	0.896	0.884	0.954	1	0.716	0.932	0.777	0.828	0.343
Bank Danamon	0.576	0.697	0.689	0.794	0.716	1	0.735	0.759	0.729	0.368
Bank Mandiri	0.836	0.893	0.951	0.962	0.932	0.735	1	0.846	0.891	0.173
Bank Permata	0.607	0.864	0.820	0.858	0.777	0.759	0.846	1	0.901	0.045
Bank CIMB Niaga	0.679	0.896	0.909	0.903	0.828	0.729	0.891	0.901	1	-0.018
Bank OCBC NISP	0.117	0.122	0.070	0.248	0.343	0.368	0.173	0.045	-0.018	1

Table 2. Transformation of Coefficient Correlation Value to Distance from Table 1

Variables	BCA	Bank Bukopin	BNI	BRI	BTN	Bank Danamon	Bank Mandiri	Bank Permata	Bank CIMB Niaga	Bank OCBC NISP
BCA	0	0.73	0.66	0.65	0.67	0.92	0.57	0.89	0.80	1.33
Bank Bukopin	0.73	0	0.47	0.41	0.46	0.78	0.46	0.52	0.46	1.33
BNI	0.66	0.47	0	0.35	0.48	0.79	0.31	0.60	0.43	1.36
BRI	0.65	0.41	0.35	0	0.30	0.64	0.27	0.53	0.44	1.23
BTN	0.67	0.46	0.48	0.30	0	0.75	0.37	0.67	0.59	1.15
Bank Danamon	0.92	0.78	0.79	0.64	0.75	0	0.73	0.69	0.74	1.12
Bank Mandiri	0.57	0.46	0.31	0.27	0.37	0.73	0	0.55	0.47	1.29
Bank Permata	0.89	0.52	0.60	0.53	0.67	0.69	0.55	0	0.44	1.38
Bank CIMB Niaga	0.80	0.46	0.43	0.44	0.59	0.74	0.47	0.44	0	1.43
Bank OCBC NISP	1.33	1.33	1.36	1.23	1.15	1.12	1.29	1.38	1.43	0

All correlation coefficient values that are not significant based on the t statistical test in **Equation (4)** are not considered the edge weights of network G. It means that there is no correlation between vertices. Hence, the distance between vertices is zero.

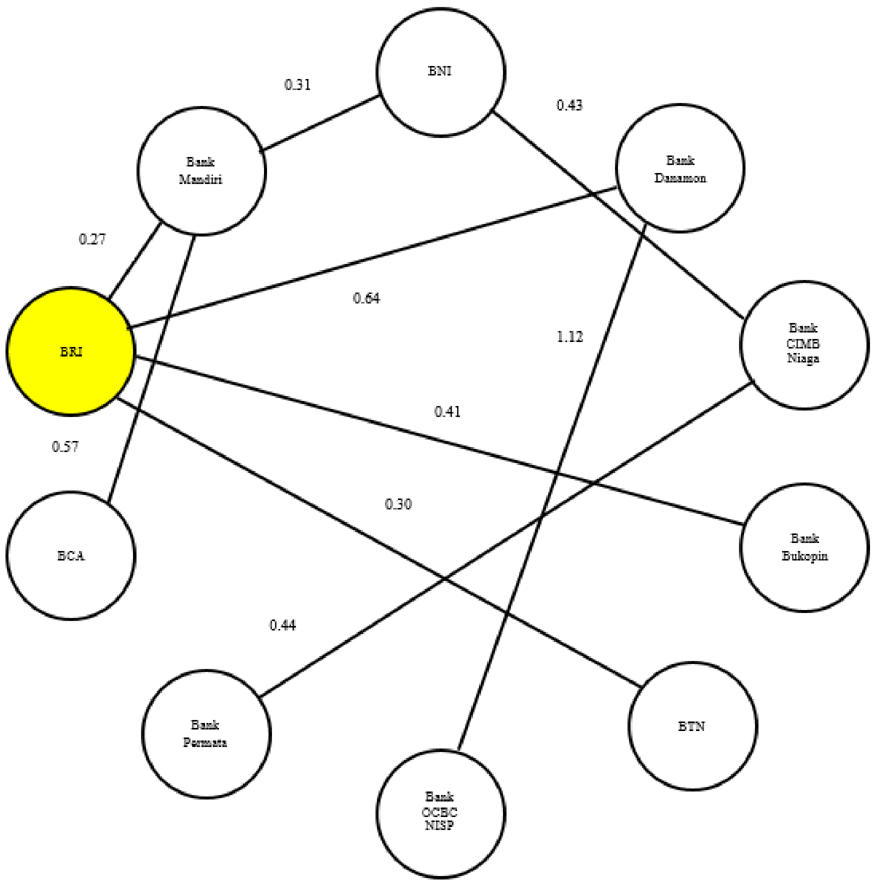

Figure 3. Spanning Tree with Vertex Betweenness in Period 1

In **Figure 3**, the vertex with blue color is the betweenness vertex. The correlation coefficient matrix and the distance transformation results in all periods are not presented in this paper. However, the spanning tree of all periods can be seen in **Figure 4**, while the vertex betweenness can be seen in **Table 3**.

Table 3. Vertex Betweenness Based on Time Period

	Period	Vertex Betweenness		Period	Vertex Betweenness
1	01/22/2018 to 06/27/2018	BRI	17	09/10/2018 to 02/04/2019	Bank Danamon
2	02/05/2018 to 07/11/2018	BRI	18	09/25/2018 to 02/19/2019	Bank CIMB Niaga, BNI
3	02/20/2018 to 07/25/2018	BRI, Bank Mandiri	19	10/09/2018 to 03/05/2019	Bank CIMB Niaga, BNI
4	03/06/2018 to 08/08/2018	Bank Mandiri	20	10/23/2018 to 03/20/2019	Bank OCBC NISP
5	03/20/2018 to 08/24/2018	BRI, Bank Mandiri, BTN	21	11/06/2018 to 04/04/2019	Bank Permata
6	04/04/2018 to 09/07/2018	Bank Mandiri, Bank CIMB Niaga, BTN	22	11/21/2018 to 04/22/2019	Bank CIMB Niaga, BNI
7	04/18/2018 to 09/24/2018	Bank Mandiri	23	12/05/2018 to 05/07/2019	Bank CIMB Niaga, BNI
8	05/03/2018 to 10/08/2018	BNI, Bank CIMB Niaga	24	12/19/2018 to 05/21/2019	BNI, Bank Bukopin
9	05/18/2018 to 10/22/2018	Bank CIMB Niaga	25	01/08/2019 to 06/12/2019	Bank Bukopin
10	06/05/2018 to 11/05/2018	Bank CIMB Niaga	26	01/22/2019 to 06/26/2019	Bank Bukopin, Bank Mandiri
11	06/28/2018 to 11/19/2018	Bank CIMB Niaga, BRI	27	02/06/2019 to 07/10/2019	Bank Bukopin, Bank Mandiri
12	07/12/2018 to 12/04/2018	BRI	28	02/20/2019 to 07/24/2019	Bank Bukopin, Bank Mandiri
13	07/26/2018 to 12/18/2018	Bank CIMB Niaga	29	03/06/2019 to 08/07/2019	Bank Bukopin, BRI
14	08/09/2018 to 01/07/2019	Bank CIMB Niaga, BRI	30	03/21/2019 to 08/21/2019	BNI, BRI
15	08/09/2018 to 01/07/2019	Bank CIMB Niaga, BNI	31	04/05/2019 to 08/30/2019	Bank Bukopin, BNI
16	08/09/2018 to 01/07/2019	Bank Danamon, BCA	32	04/23/2019 to 08/30/2019	Bank Mandiri

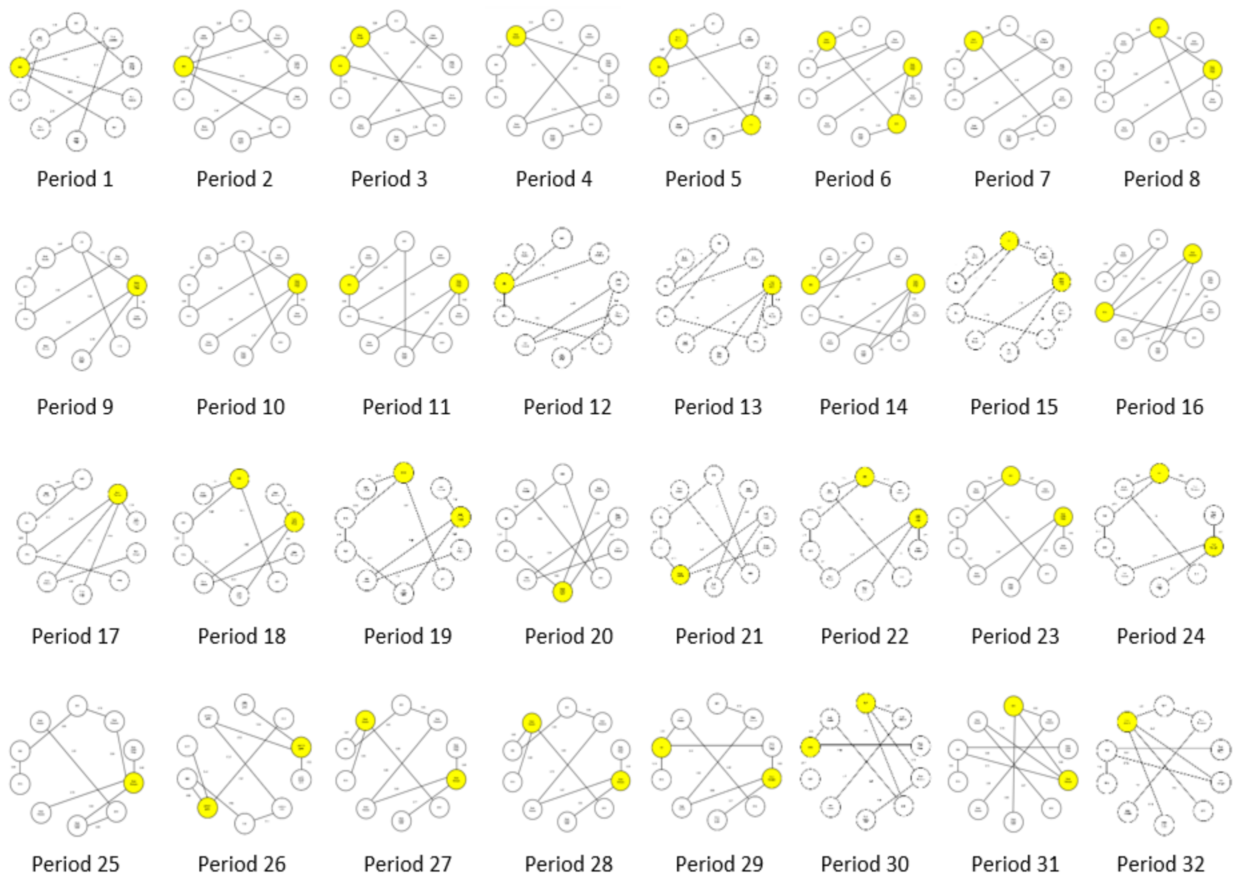

Figure 4. Spanning Tree with Vertex Betweenness in Periods

The information obtained from **Figure 4**, there is a change in the vertex betweens of each network in different periods. This means that the position of banks that influence other banks changes dynamically over a period of time. These changes are caused by stock price fluctuations. For this case, we divide the clusters based on four periods; the cluster members are presented in **Table 4**.

Table 4. Cluster member

Period	Cluster 1 (Vertex Betweenness)	Cluster 2
1 to 8 (22/01/2018-08/10/2018)	BRI, Bank Mandiri, BTN, Bank CIMB Niaga, BNI	BCA, Bank Bukopin, Bank Danamon, Bank Permata, Bank OCBC NISP
9 to 16 (18/05/2018-07/01/2019)	Bank CIMB Niaga, BRI, BNI, Bank Danamon, BCA	Bank Bukopin, BTN, Bank Permata, Bank Mandiri, Bank OCBC NISP
17 to 24 (10/09/2018-21/05/2019)	Bank Danamon, Bank CIMB Niaga, BNI, Bank OCBC NISP, Bank Permata, Bank Bukopin	BCA, BRI, BTN, Bank Mandiri
25 to 32 (08/01/2019-30/08/2019)	Bank Bukopin, Bank Mandiri, BRI, BNI	BCA, BTN, Bank Danamon, Bank Permata, Bank CIMB Niaga, BNI, Bank OCBC NISP

Cluster 1 members in **Table 4** are vertex between banks, meaning they are close to other banks. The bank's role was vital during that period. It can also be said that cluster member 1 is a bank with significant influence on other banks.

The findings of this research provide helpful information for investors when buying and selling bank stock. Based on this information, investors should buy bank stock by looking at the bank's condition, which is the vertex betweenness in these periods.

4. CONCLUSIONS

This study produces several conclusions, namely:

1. Clustering based on betweenness centrality in a case study of stock price correlation is useful when converting correlation coefficient values into distances. Efforts to build a network with edge weights as distances make minimum spanning trees a simple and valuable method for cluster analysis of bank stock prices.
2. The main contribution of this study is a new procedure in determining the technique of grouping banking companies with important positions by looking at the level of correlation between banks.
3. Several betweenness vertices obtained from dynamic networks with the minimum spanning tree method make banking companies members of clusters that greatly influence other banks.

Useful information from the findings of this study is for investors in the field of buying and selling bank shares to make decisions about buying bank shares.

Actually, the method used in this research is suitable for small data as well as big data with complex networks. However, simulations about it have not been carried out. This research's limitation is that it has yet to present a method for predicting cluster conditions in the next period based on historical periods. So, for future research, this clustering method will be combined with predictive distribution to predict **[13] [16]**, and also correspondence analysis for categorical data as variables in the research **[17] [18]**. Predictive distribution helps determine cluster members (vertex betweenness) based on previous periods. Next, the method can also be applied to decompose traffic jams. The problem of vehicle volume on each road can be correlated as long as the roads are connected, so it can be represented as a connected network.

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