Financial Network Approach for Modeling about Company Bankruptcy

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***Abstract*—We construct a financial network that models the complex system representing the bankruptcy effect of a company. In particular, we study the influence of PT Sariwangi AEA and Indorub bankruptcy, which affects at least three banks and four other companies directly. We present the interconnectivity of the banks and other corporations regarding the ownerships and liabilities using graphs. From these resulting graphs, we use techniques in network science to provide several important measurements and statistics, such as the centrality of each network. We successfully constructed a financial network surrounding PT Sariwangi AEA and Indorub. Centrality measures obtained from the graph shows that Rabobank, BCA, Rabobank UA, ICBC, and Interbank are the most important and influential entities in the financial network.**

Keywords—*financial network, network science, PT Sariwangi AEA*

I. Introduction

The high number of creditors in *PT Sariwangi Agricultural Estate Agency* (Sariwangi AEA) bankruptcy case causes concerns over its effects on related parties. Sariwangi AEA and *PT Maskapai Perkebunan Indorub Sumber Wadung* (MP Indorub) owe around 1 trillion *Indonesian Rupiah* (IDR) to around 40 creditors [1]. The financial losses received by the creditors can force them to take action that may cause damage to the financial or economic system. The impacts on related parties need to be analyzed to increase our understanding on bankruptcies.

Parties without direct relation to Sariwangi AEA or Indorub, can experience financial losses due to action taken or effects experienced by parties with direct relation. The spread and the severity of financial losses caused by Sariwangi AEA bankruptcy, especially losses and bankruptcies the case inflicts on banks, increase the chance of loss of public trust and confidence in the economic system [2]. At its worst, loss of trust in banks or the system can cause a financial crisis or hinder economic growth [3], [4].

As Sariwangi AEA and Indorub bankruptcy have the possibility to cause other bankruptcies, we intend to create a financial network surrounding Sariwangi AEA and MP Indorub that can be used to analyze the impacts of the case and find potential scenarios where an outbreak of bankruptcies can happen.

We present the interconnectivity of banks and other corporations using graphs. Relationships between entities or organizations in the graphs are represented as liabilities or ownerships. All relationships that involve movement of assets or money, both current and future are considered liabilities or debts, while ownership represents relations between owners and its companies.

The resulting graphs can be used to create a knowledge base and a contagion simulation. The simulation will be able to identify vulnerable entities that will fail should a contagion of a certain size occur. Combined with the simulation, the graphs should ease the task of tracing the paths the contagion takes and analyze its spread.

The reliability of financial data in news and other social media is questionable due to the old age of data, data copied from similar but different cases, and lack of information on the source. To ensure the reliability of financial data, we primarily gathered them from annual financial reports and news with reliable sources. Annual financial reports are considered reliable as they are regulated by the law of Indonesia, misrepresentation of these reports can inflict legal repercussion [5]. News are considered reliable if the sources of the information are can be held liable for misinformation or the data in the news are consistent on multiple different news outlets. Financial data gathered are synchronized with each other before use, as different reports have different level of transparency and use different economic terms. All financial flows involving unknown bank are redirected to *Interbank* (a system of exchange between banks).

Due to limitations of information on private companies or non-financial companies and simply non-existent of information, the research is limited to public corporation with a focus on financial organization as they are obligated to have financial reports and have a comprehensive report relative to non-financial organizations. The entities in the financial network are limited to those headquartered in Indonesia and foreign entity that have a direct connection to Indonesian companies. For simplicity, this research only uses IDR as currency specified in billions (10^9). The nodes are limited to those whose maximum distance from the center (Sariwangi AEA or Indorub) is three. In other words, there are at most two node in an arbitrary path from the center to any other nodes.

II. Network Science and Financial Network

We build the network by making all related parties and other objects into vertices (nodes) and all relations between them into the edges. All edges are directed and represent forms of liability, these can also be considered as financial flows of the network. Label on nodes represent their net worth or the total value of their assets calculated by (1).

$$W_i = A_i + \sum_{x \in i_{in}} V_{xi} - \sum_{x \in i_{out}} V_{ix} \tag{1}$$

W_i is the net worth of node i, A_i is the total assets owned by node i, i_{in} is the set of all nodes adjacent to i, and i_{out} is the set of all nodes adjacent from i.

In this research, all relationships that involve finance are represented as edges in the graph. While there are many kinds of financial relationship, we simplify them into two classes, liability (or debt) and ownership. Debt edges are considered as flows of financial assets in the network. The categorization of edges that is used in all graph is as follows:

- Debt or liabilities: this type of relationship is shown as red edges in the graph. These are the relationships between debtors (a node who borrows) and their creditors (a node who lend). An edge out of node i and going into node j means that node i borrows money from node j. Labels on these edges represent the amount of debt in the billions IDR.
- Ownership: this type of relationships is shown as purple edges in the graph. These are the relationships between a node owning parts of another node. An edge out of node i and going into node j means that node j owns a certain percentage of node i, and is treated as a debt edge from node i to node j with the value calculated using (2). The labels on these edges means the percentage of ownership, which value is a real number x such that $0 < x < 100$.

$$V_{ij} = S_{ij}(W_i) \tag{2}$$

V_{ij} is the value of the ownership edge in currency, S_{ij} is percentage of node i owned by node j, while W_i is the net worth of node i.

A. Network Centrality

Network centrality is a measure of importance or influence a node has over other nodes in a network. We use Pagerank and eigenvector centrality (eigencentrality) to measure the network centrality. Both methods are chosen because they measure the influence of a node and consider the importance of connected node. Other methods that measure influence such as closeness centrality, does not consider the importance of connected nodes in [6], [7]. We use two centrality scores to have the capability to compare both results against each other. This allows us to identify errors and increase the reliability of resulting centrality.

Eigencentrality assigns scores relative to all nodes in a network. Relative score is used based on the idea that connection to high-scoring nodes gives higher influence to the node in question compared to influence given by low-scoring nodes. This idea means that high-scoring nodes are connected to other high-scoring nodes in the network [8].

$$X_i = \frac{1}{\lambda} \sum_{j=1}^{n} a_{ij} X_j \tag{3}$$

Equation (3) is used to calculate eigenvector score. X_i and X_j are respectively the eigenvector centrality score for node i and j, λ is a constant named eigenvalue, and A_{ij} is the component of the adjacency matrix (of the network) in row i and column j.

Pagerank is a link analysis algorithm that estimates a node's importance based on the importance of the nodes that link to it. It was designed to help search engines and users to quickly find important link in the vast heterogeneity of the World Wide Web [9], [10]. Unlike the original eigenvector, Pagerank is built for directed network and have limited capability to escape an infinite loop.

$$PR_i = \beta \sum_{j \neq i} \frac{a_{ij}}{D_j} PR_j + (1-\beta)\frac{1}{n} \tag{4}$$

Equation (4) is used to calculate Pagerank score, PR_i and PR_j are the Pagerank scores of node i and j respectively, D_j is the total degree of node j, β is a damping factor and a parameter that determine random *hop* to another node to ensure the iteration does not get stuck in a cycle, and n is the number of nodes in the network.

B. Contagion

In economics and financial terms, a contagion or cascading failure can be explained as a situation where a change (shock) experienced by an entity or economic region spreads out and affects or spread to other entities and regions. Contagion can occur on multiple level from the domestic to international level. The primary cause of contagion are interdependence and correlation between different economies and their entities, and as interdependence and correlation increases, so does the possibility of contagion [11].

Contagion can be seen in many systems. Some them are events in financial systems, one such event is the stock market crash in 1997 and financial crisis of 2008 [12]. In the financial crisis of 2008, a financial crisis in the USA cause a worldwide recession.

C. Network Example

In Fig. (1) Label '$A, 6000$' means that a node named A has a net worth of 6000. A's net worth comes from node B, which is 100% owned by A and values of other assets it owns outside the network. We can calculate the value of ownership edges in flat value using equation (2. For example, an ownership edge in Fig. (1) that come from node D to node C will have a value of $V_{DC} = 0.6(3000) = 1600$ and it means node D contribute 1600 billions IDR to the net worth of node C. The graph in Fig. (2) is the result of converting all ownership edges in Fig. (1) into debt edges.

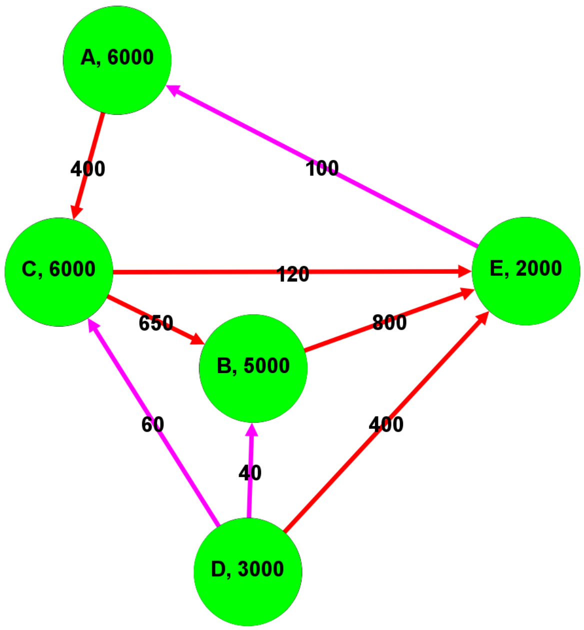

Fig. 1: Example of Financial Network

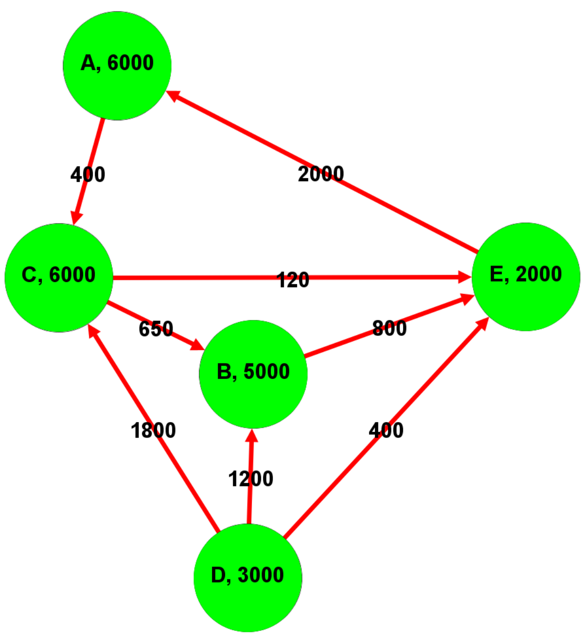

Fig. 2: Example of Debt Only Network

With Fig. 2 and using equation (1), we can calculate assets of nodes that are not shown in the graph. For example, the net worth of node C is $W_C = A_C + 400 + 1800 - 120 - 650 = 6000$ with $A_C = 6000 - 1430 = 4570$ as assets of node C not shown in the graph, and it means that node C have assets worth around 4570 billions IDR outside the graph.

III. Data Analysis and Network Design

Data are gathered from [1], [13]–[16], organization and systems in the data are converted into nodes. The nodes are categorized into three basic classes (categories) which are financial organizations, non-financial organizations, and non-organization. Important organizations such as BI has its own class due to their authorities and connection to the government. Systems get their own class, as they are representation of other networks. The categorization of nodes are as follows:

1) First failures: this type of organization is shown as red nodes in the graph. First failures are organizations designated as first to collapse or bankrupt. First failures are restricted to Sariwangi AEA and Indorub.
2) Banking or financial organizations: this type of organization is shown as blue or cyan nodes in the graph. These are organizations or companies that move in the financial sector such as banks, brokers, and asset managements.
3) Companies: this type of organization is shown as green nodes in the graph. These are non-financial organization or organization with diverse field.
4) Outside: this type of node is shown as pink nodes in the graph. This represents everything unspecified or unknown outside the network, this includes group or individuals who own shares without using the capital market or those that lend privately.
5) Interbank: this system is shown as dark blue nodes in the graph. This is a system or network of bank-to-bank transaction. This node is used to represent the Interbank written in the reports and other banks that are connected to financial organization in the network but not shown in the graph.
6) Indonesian Central Bank (BI): this type of organization is shown as purple nodes in the graph. It is classified as its own in the network due to their government connection and power.

We create aliases for each node based on their original name, since the formal or legal name of the organizations can be too long for use in graphs. A sample of these aliases can be found in Table I.

Fig. 3 is an unfiltered overview of the network. We remove nodes names and edges weight to make the full network comprehensible. To ease understanding of the network, we decided to split the full network into sub-graphs. The full network is filtered into ownership network and debt network, and the debt network is filtered again according to weight of edges.

Availability: The source of graphs in this paper is available at `https://github.com/Georgbart/Sariwangi-Gephi-Graph`

TABLE I: Sample of organizations names, their alias

ID	Formal Name	Label
0	PT Aditirta Suryasentosa	Aditirta S
1	PT Antariksabuana Citanagara	Antariksabuana
2	PT Antarindo Optima	Antarindo O
3	CR Aroma Ltd	CR Aroma
4	PT Fincom Surya Putra	Fincom SP
5	PT Giga Galaxy	Giga Galaxy
6	PT Intidana Wijaya	Intidana
7	PT Mitra Usaha Kencana Sejati	Mitra UKS
8	PT Murni Galaxy	Murni galaxy
9	PT Nirmala Agung	Nirmala
10	PT Perkasa Nusa Guna	Perkasa NG
11	PT Prima Rukun Langgeng	Prima RL
12	PT Ramadewan Winoko	Ramadewan W
13	PT Samudra Anugerah Megah	Samudra AM
14	PT Tjigaru	Tjigaru
15	ANZ Banking Group Ltd, Australia	ANZ Bank
16	ASB Bank Ltd.	ASB Bank
17	PT Bank DKI	Bank DKI
18	PT Bank Pan Indonesia Tbk	Bank Pan
19	Barclays Bank PLC	Barclays
20	PT Bank Central Asia Tbk	BCA
21	PT Bank China Construclion Bank Indonesia Tbk	BCC
22	PT Bank Negara Indonesia (Persero) Tbk	BNI
23	Bank of America, Jakarta	BoA
24	Bank of America, NA	BoA USA
25	Bank of China	BoCh
26	Bank of Communication Co Ltd	BoComm
27	PT Bank Pembangunan Daerah Jawa Barat & Banten Tbk	BPD JWB
28	PT BPR Dampit	BPR Dampit
29	PT Bank Rakyat Indonesia Tbk	BRI IDN
30	PT Bank Sumitomo Mitsui Indonesia	BSMI

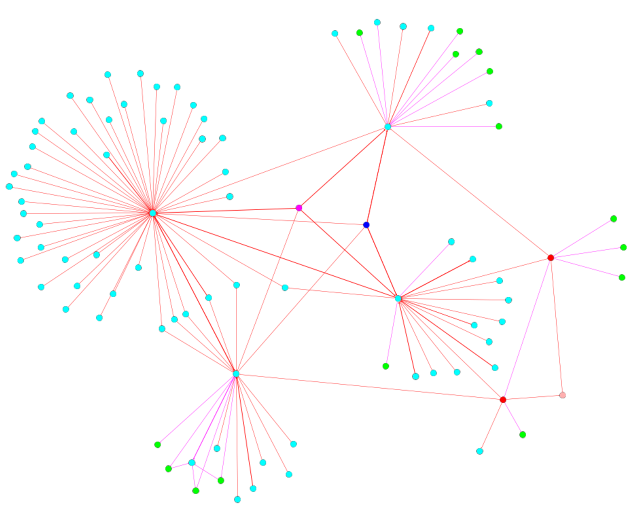

Fig. 3: Unfiltered Network

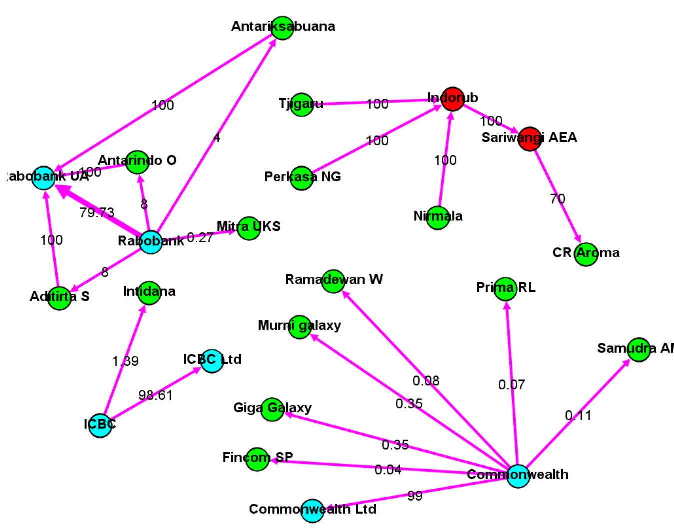

Fig. 4: Network of Ownership

Fig. 4 is a subgraph of the network with all debt edges removed and all nodes without ownership edges removed. Fig. 5 is a subgraph that only shows nodes with one or more debt edges weighted between 0 and 100 billion IDR. Fig. 6 is a subgraph that only shows nodes with one or more debt edges weighted between 100 and 500 billion IDR. Fig. 7 is a subgraph that only shows nodes with one or more debt edges weighted above 500 billion IDR.

TABLE II: Top 33 Pagerank score

Rank	Label	Pagerank Score
1	Rabobank	0.172657
2	BCA	0.168918
3	Rabobank UA	0.078183
4	ICBC	0.049612
5	Interbank	0.028765
6	Commonwealth	0.026587
7	Aditirta S	0.022025
8	Antariksabuana	0.022025
9	Antarindo O	0.022025
10	Mitra UKS	0.022025
11	EU Investment	0.022025
12	Indorub	0.013120
13	Intidana	0.008379
14	BCC	0.008379
15	BPR Dampit	0.008379
16	Citibank	0.008379
17	ICBC AUS	0.008379
18	ICBC CHN	0.008379
19	ICBC Ltd	0.008379
20	Outside	0.007583
21	Sariwangi AEA	0.006481
22	Fincom SP	0.005749
23	Giga Galaxy	0.005749
24	Murni galaxy	0.005749
25	Prima RL	0.005749
26	Ramadewan W	0.005749
27	Samudra AM	0.005749
28	Commonwealth AUS	0.005749
29	Commonwealth Ltd	0.005749
30	Commonwealth SGP	0.005749
31	CR Aroma	0.004796
32	UFJ Lease SGP	0.004796
33	Nirmala	0.003695

IV. Network Analysis

All centrality analysis are performed by Gephi v0.9.2 default statistics algorithm. Analysis is conducted on the network without filter (all nodes and edges) in Fig. 3. Pagerank centrality analysis are performed with $\beta = 0.85$ and $\epsilon = 0.001$ without taking edge weight into account, the values are chosen because they are recommended by [10]. Here ϵ is a variable that controls how many iteration the algorithm perform and how long the convergence will take, the smaller ϵ is, the longer the convergence process. Edge weights are not counted due to multiple categories of edges and the different meanings of edge weight for each categories.

Table II describes the page rank scores of some nodes in Fig. 3. All scores below rank 33 in Table II have the same value of 0.003695. Higher score indicates that node is more important than other nodes in the network. Eigenvector analysis are performed with the directed-graph version of the algorithm and 100 iteration limit as it is recommended by Gephi.

TABLE III: Top 33 Eigenvector Centrality

Rank	Label	eigencentrality
1	BCA	1.000000
2	Rabobank	0.560749
3	Rabobank UA	0.548304
4	Interbank	0.530987
5	ICBC	0.394512
6	Commonwealth	0.271051
7	Aditirta S	0.257861
8	Antariksabuana	0.257861
9	Antarindo O	0.257861
10	Mitra UKS	0.257861
11	EU Investment	0.257861
12	Intidana	0.165853
13	BCC	0.165853
14	BPR Dampit	0.165853
15	Citibank	0.165853
16	ICBC AUS	0.165853
17	ICBC CHN	0.165853
18	ICBC Ltd	0.165853
19	Fincom SP	0.107272
20	Giga Galaxy	0.107272
21	Murni galaxy	0.107272
22	Prima RL	0.107272
23	Ramadewan W	0.107272
24	Samudra AM	0.107272
25	Commonwealth AUS	0.107272
26	Commonwealth Ltd	0.107272
27	Commonwealth SGP	0.107272
28	Outside	0.037227
29	Sariwangi AEA	0.019839
30	CR Aroma	0.017388
31	UFJ Lease SGP	0.017388
32	Indorub	0.014685
33	Nirmala	0.000000

Table III describes the eigenvector scores of some nodes in Fig. 3. All scores below rank 33 in Table III have the same value of 0. Higher score indicates that the node is more important than other nodes in the network. Observation of the score from both centrality analysis methods show that financial organizations who act as creditors to many other nodes attained the highest score in the network.

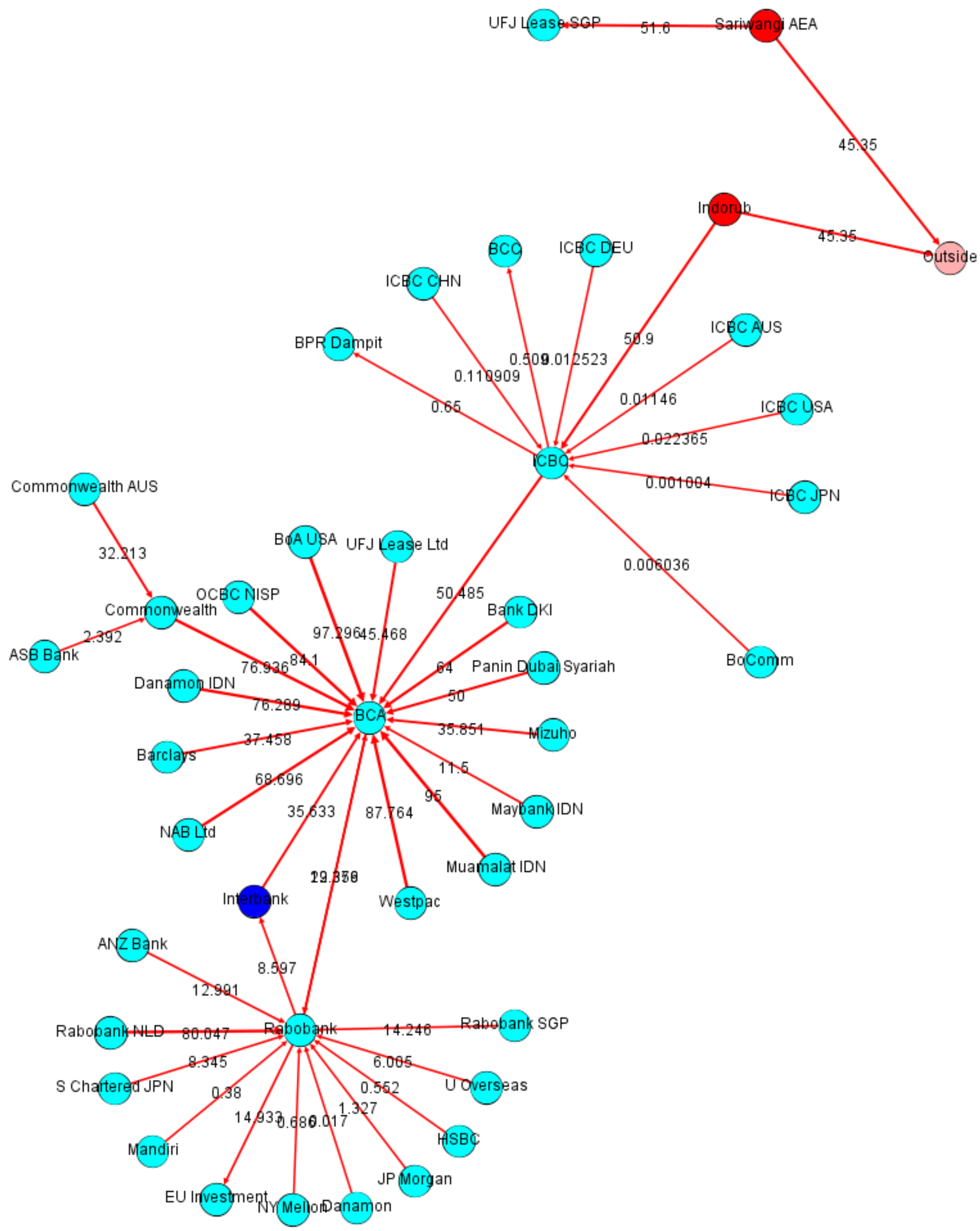

Fig. 5: Network of 0-100 billions IDR debt

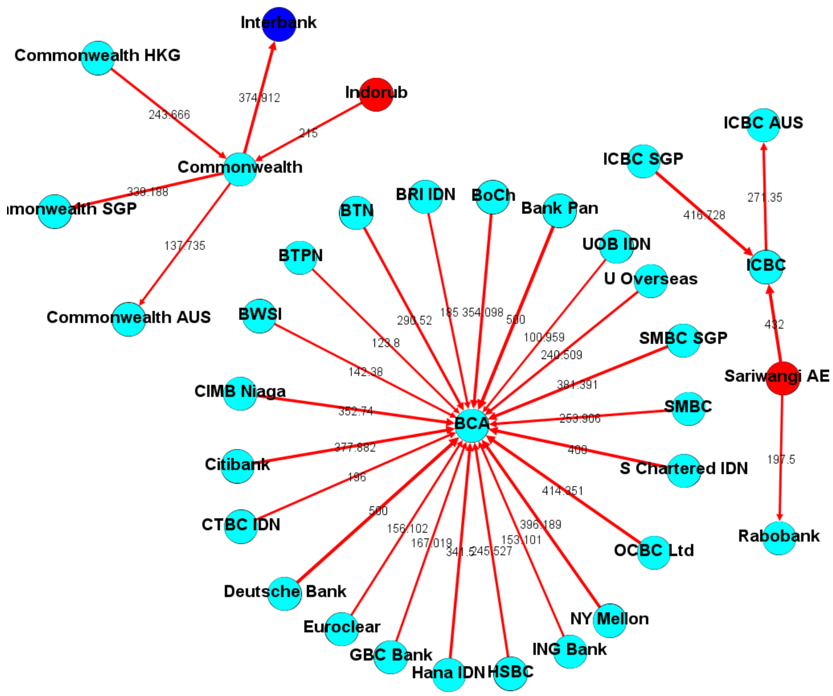

Fig. 6: Network of 100-500 billions IDR debt

TABLE IV: Sample of Prolog Scripts for edge

Source Name	Target Name	Class	Value	Prolog Scripts
ANZ Bank	Rabobank	DebtTo	12.9910	`edge('anz bank', rabobank, debtto, 12.991)`
Sariwangi AEA	ICBC	DebtTo	432.0000	`edge('sariwangi aea', icbc, debtto, 432)`
Wells Fargo	BCA	DebtTo	607.6540	`edge('wells fargo', bca, debtto, 607.654)`
Aditirta S	Rabobank UA	OwnedBy	1.0000	`edge('aditirta s', 'rabobank ua', ownedby, 1)`
ICBC	Intidana	OwnedBy	0.0139	`edge(icbc, intidana, ownedby, 0.0139)`

TABLE V: Sample of Prolog Scripts for Nodes

Node Name	Class	Prolog Script
BCA	Financial	`node(bca, financial)`
Rabobank UA	Financial	`node('rabobank ua', financial)`
Interbank	Interbank	`node(interbank, interbank)`
Rabobank	Financial	`node(rabobank, financial)`
ICBC	Financial	`node(icbc, financial)`

TABLE VI: Sample of Prolog Scripts for Net worth

Node Name	Net Worth	Prolog Scripts
BCA	131402	`net(bca, 131402)`
Rabobank UA	0.000	`net('rabobank ua', 0)`
Interbank	0.000	`net(interbank, 0)`
Rabobank	1802.467	`net(rabobank, 1802.467)`
ICBC	5754.439	`net(icbc, 5754.439)`

V. Knowledge Base Representation

We use the data to create knowledge base for logic programming model. The knowledge base or scripts is written in SWI-Prolog in syntax. The knowledge base can be used to create a program that can simulate a contagion event. Examples of the knowledge base can be seen in Table IV, Table V, and Table VI.

We describe the facts regarding nodes types in the network in Table V. The predicate `node(+Node, +Type)` explain Node `+Node` is of type `+Type`. For example `node(bca, financial)` means node `bca` is of type `financial`.

We describe the facts regarding net worth of nodes in the network in Table VI. The predicate `net(+Node, +Worth)` explain Node `+Node` have a net worth of `+Worth` billions IDR. For example `net(bca, 131402)` means node `bca` is worth `1314021` billions IDR.

Facts regarding edges in the network are described in Table IV. The predicate `edge(+FromNode, +ToNode, +Type, +Weight)` explains an edge from node

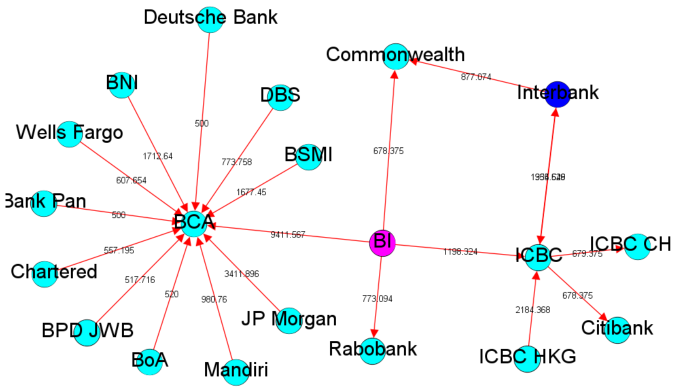

Fig. 7: Network of above 500 billions IDR debt

`+FromNode` going into node `+ToNode` is of type `+Type` and a weight of `+Weight`. For example `edge('anz bank', rabobank, debtto, 12.991)` means that and edge from `anz bank` going to `rabobank` have the type of `debtto` and worth `12.991` billions IDR.

VI. Conclusion and Future Works

We successfully constructed a model representing the effects of company bankruptcy using financial network approach. As a case study, we investigate the influence of the relationships of Sariwangi AEA dan Indorub bankruptcy which may affect numerous banks and institutions.

The network and centrality measure show the importance of each organization to the model. Pagerank centrality yields the five most influential entities within the network—based on their level of influences—are: Rabobank, BCA, Rabobank UA, and ICBC. Meanwhile eigenvector centrality yield the same five most influential entities within the network—based on their level of influences—are: Rabobank, BCA, Rabobank UA, and ICBC. Both measurements show the same five most important entities despite their different levels of influences.

The importance of the five entities means that any event that befall one of them may spread to the entire network. For instance, a collapse of one of these entities may results in cascading failure or contagion of bankruptcy. The network can be used to map possible routes of contagion that originate from PT Sariwangi AEA and Indorub.

While the financial network is capable of showing important nodes, at its current state it cannot simulate a contagion event on its own. The knowledge base can be used as a basis to create a contagion simulation. The simulation can be used to identify vulnerable entities that will fail should a contagion occur. Future work can be performed by extending the network or to include more private companies in the network. Furthermore, we advise to utilize logic programming approach as in [17] to reason the contagion of the network.

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