2010 International Conference on Technologies and Applications of Artificial Intelligence

StakeNet: Devise, Study and Utilize Social Networks using Stakeholder Information

Tsung-Ting Kuo*, Jung-Jung Yeh, Chia-Jen Lin, Shou-De Lin
Graduate Institute of Networking and Multimedia
National Taiwan University
Taipei, Taiwan
*d97944007@csie.ntu.edu.tw

Abstract—**Recently, there has been growing interests in exploiting stakeholder information to acquire essential knowledge about stock investments. More and more countries legislate for publicly-issued companies to provide such information. In this paper, we propose a new approach to exploit stakeholder information for constructing stake-based social networks. We devise three types of networks: StakeNet (a company-person network), StakeCompanyNet (a company-company network), and StakePersonNet (a person-person network). We also present a visualization tool to display socio-centric and ego-centric views of the networks. Furthermore, we investigate the static and dynamic properties of the StakeNet, and the results reveal that most of StakeNet's characteristics are similar to those of a typical social network, excluding that the in-degree does not follow a power law distribution. Finally, we show two applications of StakeNet by utilizing it to discover influential companies and business groups. The experiments suggest that our outcomes are highly consistent with the results generated by human experts.**

Keywords-social network analysis; stakeholder analysis; stakeholder management

I. INTRODUCTION

The term "stakeholder" can be defined as "any group or individual who can affect or is affected by the achievement of the firm's objectives" [1]. In the information era, data about the stakeholders (i.e., the chairman, CEO, directors, managers, and shareholders) of publicly traded companies is being made available to investors in an increasing number of countries. For example, in the United States, stock transfers by shareholders who own 10% or more of a company's shares must be made public; and in Japan, information about shareholders that own more than 1% of a company's stock is publicly available. Stakeholder data is important to stock investors because it provides information about individual companies, as well as the relationships between companies.

However, comprehending and utilizing stakeholder data is difficult because of the enormous volume available and the amount of detail involved. For example, two companies without common shareholders might be closely related because their shareholders transfer stocks to one another; or the situation might be more complex if there are 3rd-party mediators transfer stocks between shareholders in both companies. Furthermore, stakeholder data changes over time, and its dynamic nature makes the interpretation and usage of the data even more difficult. As a result, an intuitive and effective way to present, analyze and exploit stakeholder data is highly desirable.

Most machine learning or soft computing studies about stock market focus on predicting the stock price or index [2]. The shareholder relationships have not yet been utilized for prediction, mainly because it is non-trivial to model the dependency between shareholders as features for learning. In the other hand, sociology, economy and business administration researchers provide insights about issues such as stakeholder analysis [3] and management [4]. However, the analyses are conducted manually and they rely to a large extent on the knowledge of domain experts. In this work, we address the presentation, analysis and application of stakeholder data by exploiting social network analysis techniques. It would be of interest to learn how stakeholder data can be utilized to improve the understanding of companies listed on the stock market, and thereby increase the return of investors.

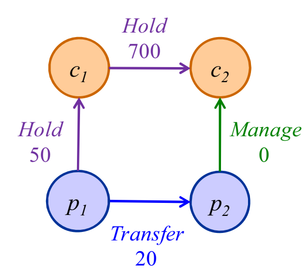

Figure 1. An example of StakeNet in a given time period.

In this paper, we propose a social network called StakeNet, which is constructed using stakeholder data. StakeNet is a directed, weighted, dynamic, and heterogeneous social network, as shown in Figure 1. There are two types of nodes: *companies* and *investors*, and three types of links: *manage*, *hold*, and *transfer* in StakeNet. A *hold* relationship exists if the source node (a company or an individual) holds stock of the target company node, and the weight is the market value of the stocks held; e.g. if a person p_1 holds 10 shares in company c_1 and price of c_1 is 5 dollars per share, then there exists a link from p_1 to c_1 with weight 50. Second, a *manage* relationship exists if a person plays a management role, such as the chairman or CEO of a company; e.g., if a person p_2 is the CEO of company c_2, then there exists a link from p_2 to c_2. Note that the weight of a

We acknowledge CyberLink Education Foundation for financial support of this work.

978-0-7695-4253-9/10 $26.00 © 2010 IEEE
DOI 10.1109/TAAI.2010.25

manage link is zero since it does not imply a stock-holding. Finally, a *transfer* relationship exists if a person transfers stocks to another person; e.g., if p_1 transfers 4 shares of c_1's stock (which is 5 dollars per share) to p_2, then there exists a link from p_1 to p_2 with weight 20. StakeNet allows us to represent and visualize the complicated relationships among companies and stakeholders in the form of a social network. Since StakeNet is dynamic, new relationships can be added over time.

We also investigate three issues for StakeNet. First, we provide a visualization tool that enables investors to view the relationships among companies and stakeholders in an in-depth and efficient manner. The tool can be utilized to examine the relationships of any given company as well as the overall market environment. Second, we represent Taiwan's stock market using StakeNet and perform on top of it both static and dynamic social network measures, such as the degree distribution, clustering coefficient, giant connected component analysis. Finally, we demonstrate the value of StakeNet by using it in two applications: rank important companies, and group companies into intra-related groups. The experiment results show that our system can achieve very high consistency comparing to the results generated by experts in investment companies.

II. STAKENET CONSTRUCTION AND APPLICATIONS

In this section, we discuss the construction and applications of StakeNet.

A. Constructing StakeNet

We define StakeNet as a graph $SN_{t\text{-}t'} = \{V, E\}$, where $V = \{v_1, v_2, \ldots, v_n\}$ is a vertex set, and $E = \{e_{ij}$ = edge from v_i to $v_j| \ 1 \le i, j \le n, i \ne j\}$ is an edge set. For each vertex v_k, type(v_k)∈ {*person, company*}; and for each edge e_{ij}, type(e_{ij}) ∈ {*hold, manage, transfer*}. Weight(e_{ij}) equals the market value of the stocks (i.e., shares multiplied by prices) held or transferred by edge e_{ij} if type(e_{ij}) = *hold* or *transfer.* Recall that the weight is zero if type(e_{ij}) = *manage*.

TABLE I. EDGE AND VERTEX TYPES IN STAKENET.

Type of Edge e_{ij}	**Type of Vertex**	
	From v_i	***To v_j***
Hold	Person or Company	Company
Manage	Person	Company
Transfer	Person	Person

Each type of edge can only occur between certain types of vertex, as shown in Table 1. For example, a *manage* link must connect a person to a company because only people can manage companies. Moreover, for each specific time point, there is a corresponding StakeNet, since relationships can change over time.

Although StakeNet incorporates detailed person-company information, in some cases investors or researchers are more interested in company-company or person-person relationships. For example, consider two companies c_1 and c_3 in a StakeNet, as shown in Figure 2(a). The two companies do not hold one another's stocks (i.e., edge e_{13} does not exist in the StakeNet). However, person p_2 and p_4 manage c_1 and c_3 respectively and they both transfer stocks to p_3. Therefore, the "path" between c_1 and c_3 represents an implicit relationship between them, which might be warrant further investigation (e.g., it might indicate insider trading).

Based on the above observation, we define two kinds of undirected, unweighted, homogeneous stake-based social networks, called StakeCompanyNet and StakePersonNet. Another reason for transforming a heterogeneous StakeNet network into a homogeneous social network is that many social network analysis algorithms can only be applied to homogeneous networks.

A StakeCompanyNet only contains company nodes, and can be constructed from a StakeNet in three steps:

Step 1: Replace directed links in StakeNet with undirected links.

Step 2: For a company pair (v_i, v_j), if there exists a path between them and all the vertices in between are the "person" type, then add a direct edge between (v_i, v_j). For example, in Figure 2(b), edges e_{12} and e_{13} are added, but an edge is not added between c_1 and c_5.

Step 3: Remove all person nodes and the links associated with them.

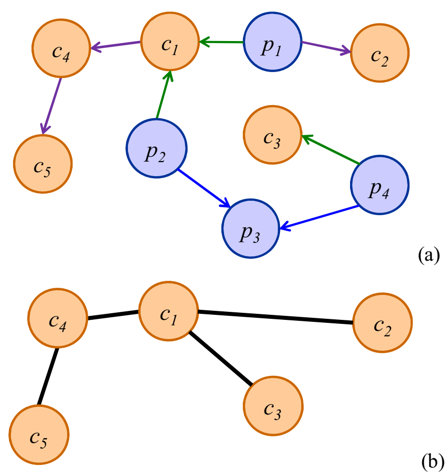

Figure 2. (a) An example of StakeNet (the edge weights are not shown). (b) The StakeCompanyNet constrcuted from (a).

A StakePersonNet can be constructed from a StakeNet in a similar manner. The same procedure is applied, but the roles of the company nodes and person nodes are swapped. All nodes in StakePersonNet are the person type. Note that in StakeCompanyNet and StakePersonNet, the semantics of edges is not *hold*, *manage* or *transfer* anymore, because the edges represent more complex associations between companies.

B. Interrelation Visualization

The three kinds of stake-based social networks (i.e. StakeNet, StakeCompanyNet and StakePersonNet) can be utilized to display complex person-company, company-company, and person-person interrelationships. We have developed a visualization tool that provides two views of a network: a socio-centric (global) view and an ego-centric (local) view. The socio-centric view displays the whole network, and the user can specify a minimum degree to control which vertices are displayed. In the ego-centric view, the user can specify a specific person / company and the level of interested neighbors, and the system will display a subgraph centered at the person / company for further investigation.

C. Social Network Analysis via StakeNet

We apply social network analysis techniques to the three networks. Static techniques, namely, the degree/weight distribution, clustering coefficient and average path length, are applied to gain an in-depth understanding of capital/resource allocation in the stock market. Meanwhile, dynamic techniques, such as changes in the number of links over time, the evolution of giant connected components over time, and the densification power law [5], are measured to determine long-term trends in stock market behavior.

D. Corporate Ranking and Clustering

One potential usage for StakeNet is to rank or group companies based on their stakeholder information. Ranking reveals the importance or centrality of certain companies and clustering allows us to identify potential business groups. Investors can exploit such information to identify vertical/horizontal integration or even prevent possible insider trading. Here we apply centrality analysis (i.e. Weighted PageRank) to rank companies and Edge Betweenness Clustering method [6] for community detection on StakeNet.

III. EXPERIMENT

In this section, we describe the data used to construct StakeNet as well as the results. We use a machine with AMD Opteron 2350 2.0GHz Quad-core CPU and 32GB RAM to run the experiments.

A. Constructing StakeNet

We conducted a survey of the stakeholder information available in seven stock markets. The results, listed in Table 2, show that Japan and Taiwan provide the most comprehensive publicly available stakeholder information. As a result, we took the Taiwan stock market as the data source and gathered stakeholder information from the official website of the Taiwan Stock Exchange (TWSE) [7]. The data covered the period 2002/10 to 2009/10, a total of 85 months. There were 2,026 publicly traded companies registered on the Taiwan stock market during that period.

B. Interrelation Visualization

Figure 3 to Figure 8 are snapshots of our visualization tool for StakeNet constructed from 2008/11 to 2009/10 (12 months). The vertex and edge counts are shown in Table 3. For ease of presentation in the paper, we only show the labels for companies, not people. The weights of the links represent the market value of the stocks held; zero-weighted links represent management relationships. The socio-centric view (i.e., the global view of all nodes) in StakeNet is shown in Figure 3. Due to space limitations, we only show vertices of degree ≥ 30. Figure 4 shows an ego-centric view of ASUSTEK, a well-known computer company [8]. It should be noted that the non-labeled vertices are people.

TABLE II. SURVEY OF STAKEHOLDER INFORMATION IN SEVEN STOCK MARKETS.

Country	Stakeholder Information		
	Hold / Manage	***Transfer***	***Time***
China	Incomplete	Directors only	2004-
Hong Kong	Available (≥ 5%)	Directors only	2003-
Japan	Available (≥ 5%)	Available (≥ 10%)	2006-
Singapore	Incomplete	Directors only	2007-
Taiwan	**Available (≥ 5%)**	**Available (≥ 10%)**	**2002-**
United Kingdom	Available	Directors only	2002-
United States	Incomplete	Available (≥ 10%)	2000-

TABLE III. VERTEX / EDGE COUNT OF STAKENET (2008/11 – 2009/10).

Graph	Statistics		
	Type	***Count***	***Total***
Vertex	Person	34,662	36,688
	Company	2,026	
Edge	Hold	26,508	43,538
	Manage	12,541	
	Transfer	4,489	

TABLE IV. VERTEX / EDGE COUNT OF STAKECOMPANYNET AND STAKEPERSONNET.

Network	Statistics	
	Graph	***Count***
StakeCompanyNet	Vertex	2,026
	Edge	3,102
StakePersonNet	Vertex	34,662
	Edge	39,451

StakeCompanyNet (Figures 5 and 6) and StakePersonNet (Figures 7 and 8) provide summaries that allow users to focus on the relations between companies or individuals. The StakeCompanyNet shown in Figure 5 is constructed from the StakeNet in Figure 4, and contains 2,026 vertices and 3,102 edges (Table 4). Figure 6 shows two levels of ASUSTEK's neighbors. Meanwhile, Figure 7 shows the StakePersonNet constructed from the StakeNet in Figure 4. It contains 34,662 vertices and 39,451 edges, but only those of degree ≥ 10 are shown. Figure 8 shows two levels of neighbors of Jonney Shih, the chairman of ASUSTEK.

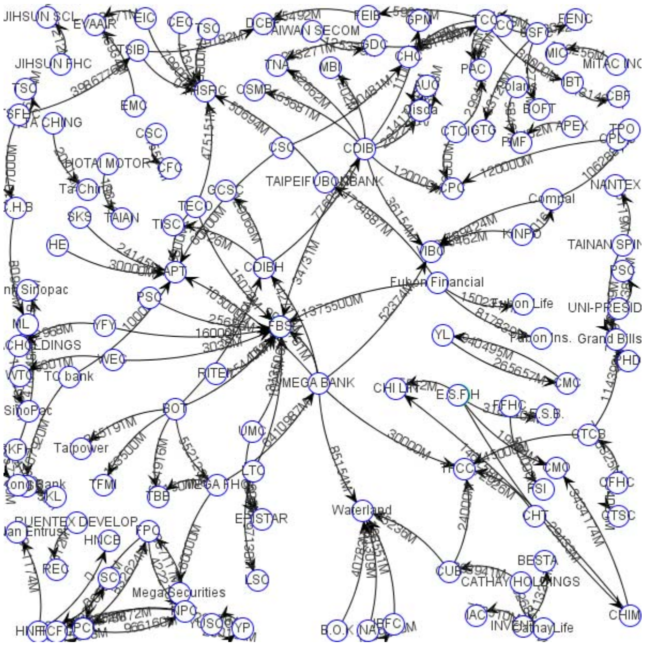

Figure 3. A socio-centric view of the StakeNet built using Taiwan stock market data from 2008/11 to 2009/10. Only vertices of degree ≥ 30 are shown.

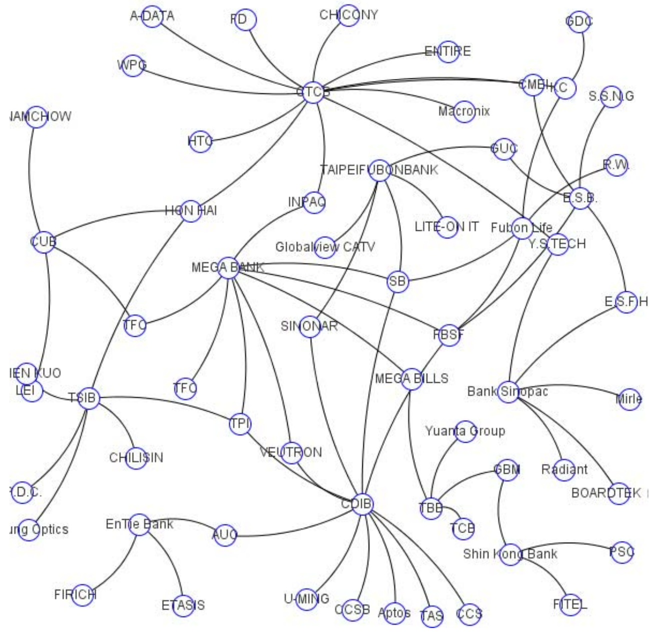

Figure 5. A socio-centric view of the StakeCompanyNet constructed from the StakeNet in Figure 3. Only vertices of degree ≥ 10 are shown.

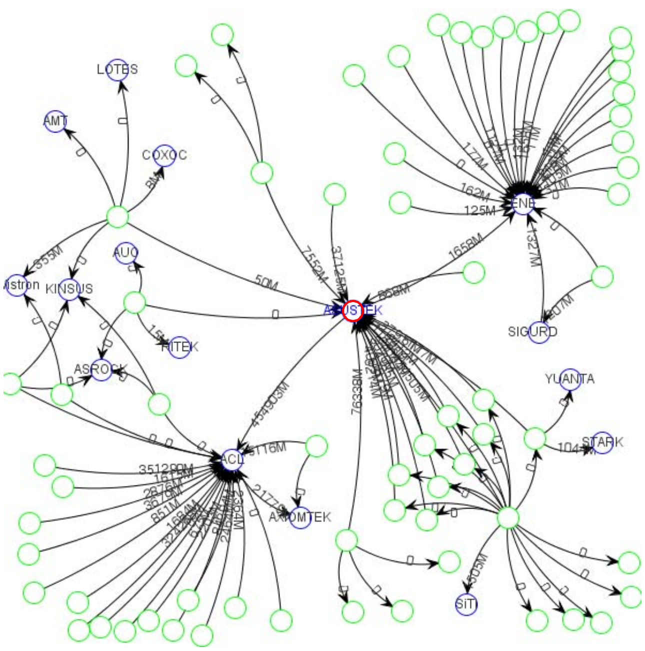

Figure 4. An ego-centric view of the StakeNet in Figure 3, showing two levels of ASUSTEK's neighbors. The non-labeled vertices are people, and the edge with weight zero is a management type.

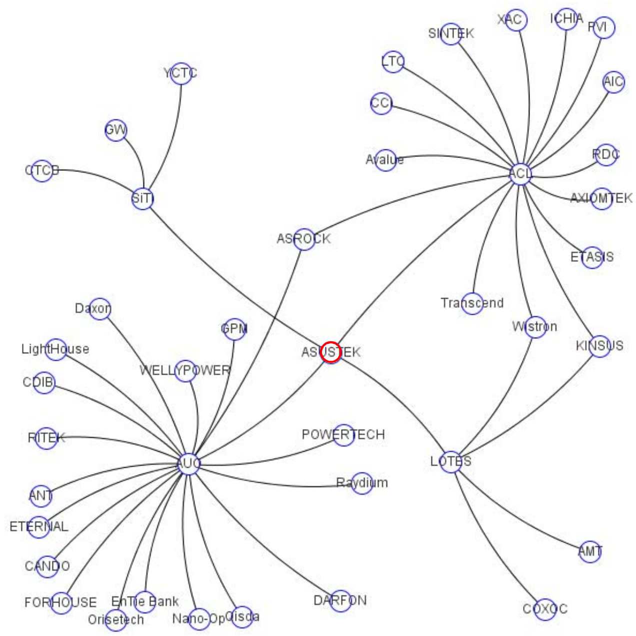

Figure 6. An ego-centric view of the StakeCompanyNet in Figure 5, showing two levels of ASUSTEK's neighbors.

We believe a search-based, ego-centric visualization tool is a useful way to visualize StakeNet, as users can easily identify the associations of a target company with its shareholders and other companies

Figure 7. A socio-centric view of the StakePersonNet constructed from the StakeNet in Figure 3. Only vertices of degree ≥ 10 are shown.

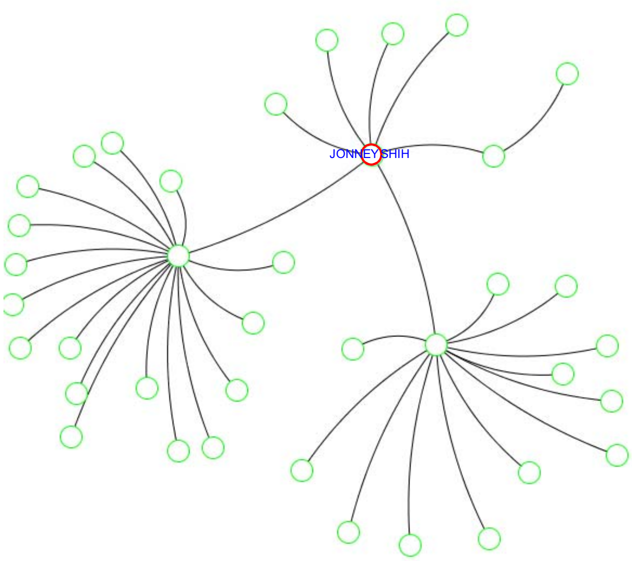

Figure 8. An ego-centric view of the StakePersonNet in Figure 7, showing two levels of neighbors of Jonney Shih (the chariman of ASUSTEK).

C. Social Network Analysis

(1) Static Analysis. Table 5 lists the results of static social network analysis using the StakeNet in Figure 3. The statistics provided in the table are: the number of verices (V), the number of edges (E), the average degree (Z), the average path length(APL), and the clustering coefficient (CC). For the clustering coefficient, we adopt the following definition [8]:

$$CC = \frac{3 \times number\_of\_triangles\_in\_the\_network}{number\_of\_connected\_triples\_of\_vertices}$$

In Table 5, we compare StakeNet to four social networks constructed in [9]: math coauthorship (MC), email messages (EM), email address books (EAB), and student relationships (SR). The CC value of StakeNet is similar to SR network, but smaller than MC, EM and EAB networks. In the other hand, the APL value of StakeNet is smaller than the SR network and similar to the MC network.

TABLE V. STATIC ANALYSIS, COMPARED TO OTHER SOCIAL NETWORKS.

Network	V	E	Z	APL	CC
StakeNet	36,688	43,538	2.37	7.31	0.003
Math Coauthorship (MC)	253,339	496,489	3.92	7.57	0.150
Email Messages (EM)	59,912	86,300	1.44	4.95	0.160
Email Address Books (EAB)	16,881	57,029	3.38	5.22	0.170
Student Relationships (SR)	573	477	1.66	16.01	0.005

The degree, in-degree, out-degree, and edge weight distribution of this StakeNet are shown in Figures 9, 10 11 and 12 respectively. Figures 9, 10 and 11 demonstrate that the total degree, in-degree, and out-degree distributions of person vertices follow a power law distribution. However, for company vertices, the out-degree distribution does follow a power law distribution, but the in-degree distribution does not (as shown in Table 6).We believe that this is because most stocks of publicly-traded companies in Taiwan are not held by a single shareholder and the average number of stakeholders in most companies is between 10 and 15.

It is also interesting to learn that the edge weight distribution (Figure 12) is closer to a log-normal distribution than a power law distribution. This is because that our public stakeholders' data does not contain retail (or individual) investors, which, if were included, should have been situated on the left-hand side of the distribution (and thus could form a Power-law).

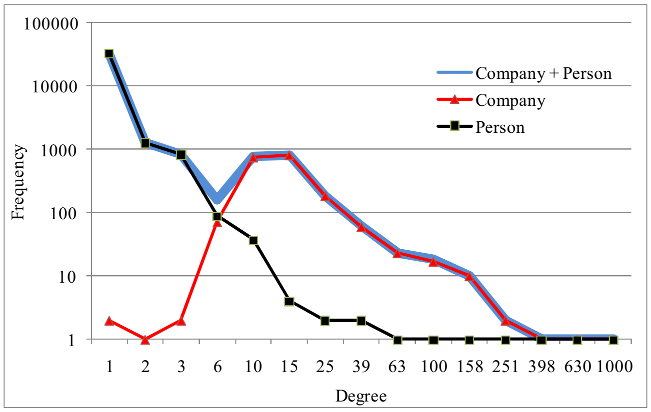

Figure 9. Degree distribution of the StakeNet shown in Figure 3.

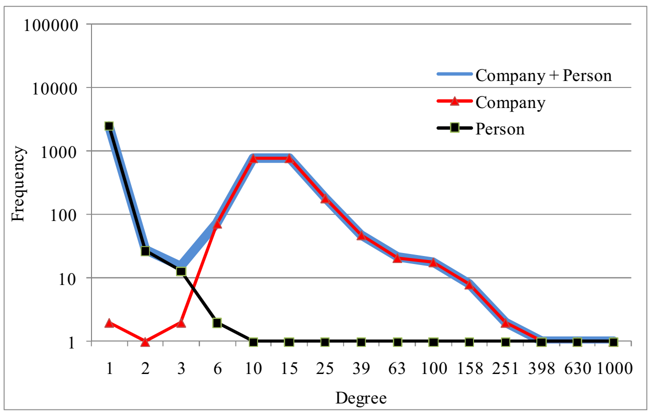

Figure 10. In-degree distribution of the StakeNet shown in Figure 3.

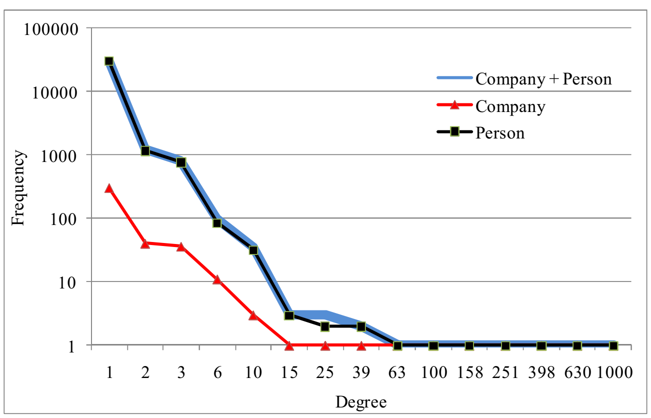

Figure 11. Out-degree distribution of the StakeNet shown in Figure 3.

TABLE VI. SUMMARY OF DEGREE DISTRIBUTIONS.

	In-Degree	Out-Degree
Person	Power Law	Power Law
Company	Distribution with peak frequency of degree from 10 to 15.	Power Law

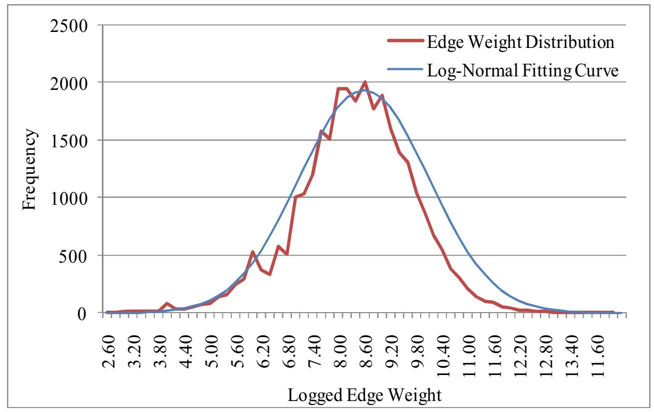

Figure 12. Edge weight distribution of the StakeNet shown in Figure 3.

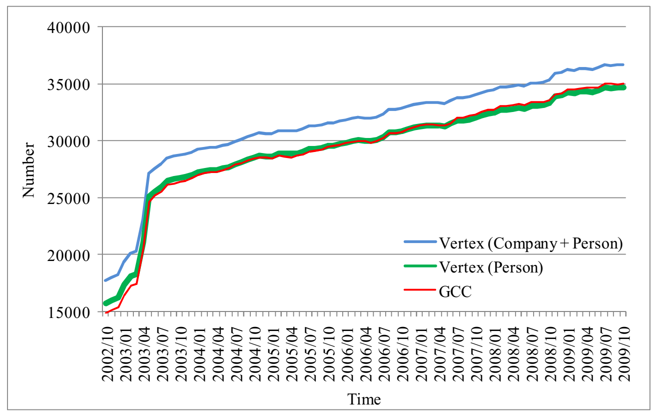

Figure 13. Changes in the total number of vertices, people type vertices, and the size of giant connected component during the study period.

(2) Dynamic Analysis. Figure 13 shows the changes in the total number of vertices, person type vertices, and the size of giant connected component (GCC) during the study period. The information about company vertices is not shown because the number of companies does not change over time. Changes in the number of edges, the average degree and CC during the study period are shown in Figures 14, 15 and 16 respectively; and the number of vertices versus the number of edges in StakeNet at different times is shown in Figure 17.

We identify three important phenomena from our results. First, the statistics of the first 7 months (from 2002/10 to 2003/04) were significantly different from those for the rest of the study period. We believe this is because the stakeholder information collected during that period was incomplete. Second, person vertices, the size of GCC, the average degree, and all types of edges grow linearly over time (except for the 7-month period mentioned above). This suggests that the growth pattern of the Taiwan stock market is stable. Finally, StakeNet follows the densification power law (Figure 17), which states that the number of edges grow super-linearly in terms of the number of vertices [5]. To summarize, our findings demonstrate that StakeNet has many of the general characteristics of dynamic social networks.

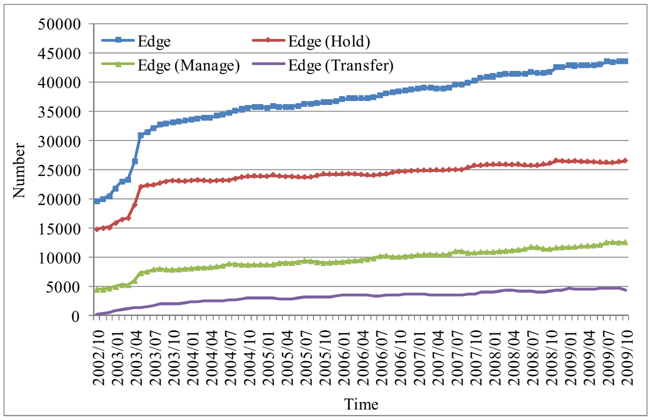

Figure 14. Changes in the number of edges during the study period.

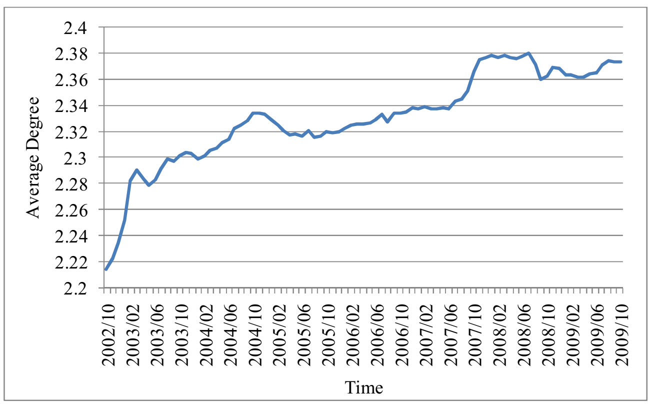

Figure 15. Changes in the number of average degree during the study period.

TABLE VII. THE TOP 10 RANKED COMPANIES IN STAKENET USING PAGERANK (WITH RESTART PROBABILITY = 0.15).

Company Name	PageRank Score	Found Year	Capital (USD)
Taiwan Business Bank	74.18	1950	1,210,499,375
Fui Industrial	73.52	1967	103,125,000
Chang Hwa Bank	72.67	1962	1,940,461,125
Taiwan Fire / Marine Insurance	72.54	1948	99,017,813
Chunghwa Telecom	72.52	1996	3,030,252,557
Central Reinsurance	72.47	1968	172,265,625
Formosa Plastics Corporation	72.28	1954	1,912,782,687
China Airlines	72.27	1959	1,428,827,810
Taiwan Life Insurance	72.25	1947	199,765,344
Kuo Yang Construction	72.24	1972	138,312,500

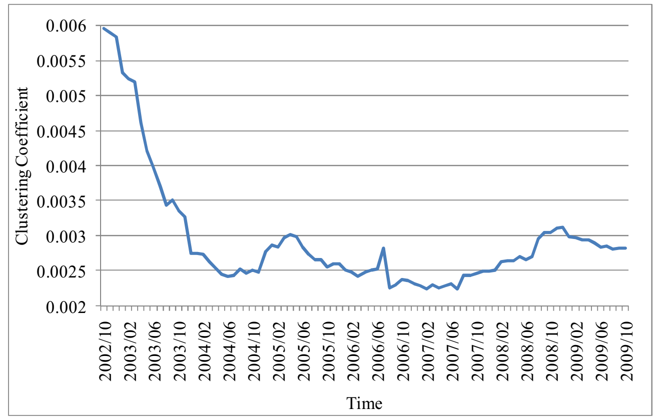

Figure 16. Changes in the Clustering coefficient during the study period.

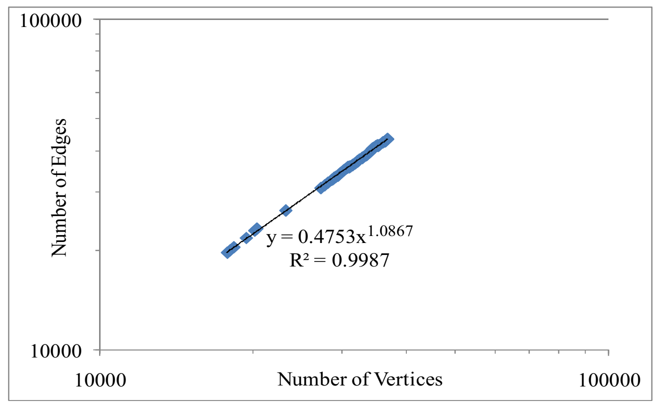

Figure 17. Densification power law of StakeNet.

D. *Corporate Ranking and Clustering*

We conducted the eigenvalue centrality analysis using the edge-weighted PageRank algorithm [10] in StakeNet. The top 10 ranked companies (with PageRank random restart probability = 0.15) are shown in Table 7. Most of the companies are banks, insurance companies, or industry leaders. For example, the Formosa Plastics Corporation is the largest plastics company in Taiwan.

We evaluate our corporate clustering result in terms of the Normalized Mutual Information (NMI) score [11]. The clusters generated from the StakeNet shown in Figure 3 are compared with the gold standard gathered from professional financial sources TCG [12]. Note that we only have ground truth of 496 companies, thus we compute NMI using these 496 companies only. We compare edge betweenness clustering algorithm [6] with a simple greedy heuristic method. In the heuristic baseline, we simply group companies which have at least one identical stakeholder together. The difference between our methods with the baseline is that edge-between algorithm utilizes the global topological information of StakeNet while the baseline results can be produced without using StakeNet. The result shows that the Edge Betweenness Clustering algorithm (0.97 in NMI) outperforms the baseline methods (0.70 in NMI) significantly. The results show that the StakeNet does provide useful information for corporation grouping.

IV. Related Work

Most machine learning and soft computing studies of stock markets focus on predicting stock prices or indexes in different environments. For example, some studies focus on forecasting the stock indexes of well-developed markets [13]; some exploit the indexes to track stock prices in emerging markets [14]; and some target specific independent stocks or portfolios of stocks [15]. To the best of our knowledge, the relationships between stakeholders and companies have not been modeled for prediction.

Sociologists, economists, and business administration researchers provide insights into stakeholder relationships. In one hand, the literature on stakeholder analysis focuses on the identification, manually-construction, and observation of stakeholders in various domains, such as national securities markets [16], natural resource management [3], or ocean environment protection [17]. In the other hand, studies related to stakeholder management address business management issues based on stakeholder relationships [4]. Although the works in the literature are comprehensive, most of them analyze stakeholder information manually. Our work provides a visualization platform for stakeholders as well as some intelligent analysis tools that facilitate advanced manual analysis of companies and markets.

Finally, researchers have studied different kinds of social networks such as kinship networks, movie networks, academic networks, and terrorist networks [18] [19]. However, we are not aware of any works that focus on constructing and studying social networks based on stakeholder information in stock markets. The study of stakeholder networks requires more advanced techniques because such networks are heterogeneous and dynamic.

V. Conclusion

This paper proposes a series of novel type of social networks: StakeNet, StakeCompanyNet, and StakePersonNet, constructed from stakeholder information. We also provide socio-centric and ego-centric visualization tools for the networks. Statically, we find that StakeNet yields similar statistical values to those derived by other social networks. The degree distributions generally follow the power law distribution, except for the in-degree distribution of company vertices (with an average degree between 10 and 15); and the market value of the stocks held by people follows a log-normal distribution rather than a power law distribution. Dynamically, we find that StakeNet's growth is stable in terms of person vertices, the size of GCC, the average degree, and all types of edges. It also obeys the densification power law. Finally, we propose using StakeNet to rank and group corporations and conduct experiments to show the usefulness of our proposal. We believe that StakeNet, StakeCompanyNet and StakePersonNet can provide in-depth and systematic insights for investors.

One possible application of StakeNet is link prediction. Since StakeNet is a dynamic social network, using old networks to predict new coming links might be plausible. Another possible research avenue is the use of StakeNet for anomaly detection to identify companies or individuals engaged in abnormal behavior, such as insider trading.

References

[1] R. E. Freeman, *Strategic management : a stakeholder approach*. Boston :: Pitman, 1984.

[2] G. S. Atsalakis and K. P. Valavanis, "Surveying stock market forecasting techniques - Part II: Soft computing methods," *Expert Syst. Appl.,* vol. 36, pp. 5932-5941, 2009.

[3] C. Prell, K. Hubacek, and M. Reed, "Stakeholder Analysis and Social Network Analysis in Natural Resource Management," *Society and Natural Resources,* 2009.

[4] A. J. Hillman and G. D. Keim, "Shareholder Value, Stakeholder Management, and Social Issues: What's the Bottom Line?," *Strategic Management Journal,* vol. 22, pp. 125-139, 2001.

[5] J. Leskovec, J. Kleinberg, and C. Faloutsos, "Graph evolution: Densification and shrinking diameters," *ACM Trans. Knowl. Discov. Data,* vol. 1, p. 2, 2007.

[6] M. Girvan and M. E. Newman, "Community structure in social and biological networks," *Proceedings of the National Academy of Sciences of the United States of America,* vol. 99, pp. 7821-7826, 2002.

[7] TWSE, "Taiwan Stock Exchange (http:/www.twse.com.tw)."

[8] ASUSTEK, "ASUSTek Computer Inc. (http://www.asus.com/)."

[9] M. E. J. Newman, "The structure and function of complex networks," *SIAM Review,* vol. 45, pp. 167-256, 2003.

[10] S. Brin and L. Page, "The anatomy of a large-scale hypertextual Web search engine," *Computer Networks and ISDN Systems,* vol. 30, pp. 107-117, 1998.

[11] I. H. Witten and E. Frank, *Data Mining: Practical machine learning tools and techniques*, 2nd ed. San Francisco: Morgan Kaufmann, 2005.

[12] TCG, "The Captal Group (http://www.capital.com.tw)."

[13] A.-S. Chen, M. T. Leung, and H. Daouk, "Application of neural networks to an emerging financial market: forecasting and trading the Taiwan stock index," *Comput. Oper. Res.,* vol. 30, pp. 901-923, 2003.

[14] K. Georgios, C. Eleni, G. Robert, and K. Avo, "Regime Switching and Artificial Neural Network Forecasting of the Cyprus Stock Exchange Daily Returns," *International Journal of Finance and Economics,* Sep 2006.

[15] G. S. Atsalakis and K. P. Valavanis, "Forecasting stock market short-term trends using a neuro-fuzzy based methodology," *Expert Syst. Appl.,* vol. 36, pp. 10696-10707, 2009.

[16] W. E. Baker, "The social structure of a national securities market," *American Journal of Sociology,* vol. 89, p. 775, 1984.

[17] K. E. Sovacool, "A Stakeholder Analysis of the Creation of High Seas Marine Protected Areas within the Antarctic Treaty System," in *Department of Geography*. vol. Master Blacksburg, VA: Virginia Tech College of Natural Resources, 2008.

[18] J. Scott, *Social Network Analysis: A Handbook*: SAGE Publications, 2000.

[19] M. E. J. Newman, A.-L. Barabasi, and D. J. Watts, *The structure and dynamics of networks*. Princeton, N.J.: Princeton University Press, 2006.