ICCEPM 2022
The 9th International Conference on Construction Engineering and Project Management
Jun. 20-23, 2022, Las Vegas, NV, USA

Measuring the Impact of Supply Network Topology on the Material Delivery Robustness in Construction Projects

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Abstract: The robustness of a supply chain (i.e., the ability to cope with external and internal disruptions and disturbances) becomes more critical in ensuring the success of a construction project because the supply chain of today's construction project includes more and diverse suppliers. Previous studies indicate that topological features of the supply chain critically affect its robustness, but there is still a great challenge in characterizing and quantifying the impact of network topological features on its robustness. In this context, this study aims to identify network measures that characterize topological features of the supply chain and evaluate their impact on the robustness of the supply chain. Network centrality measures that are commonly used in assessing topological features in social network analysis are identified. Their validity in capturing the impact on the robustness of the supply chain was evaluated through an experiment using randomly generated networks and their simulations. Among those network centrality measures, the PageRank centrality and its standard deviation are found to have the strongest association with the robustness of the network, with a positive correlation coefficient of 0.6 at the node level and 0.74 at the network level. The findings in this study allows for the evaluation of the supply chain network's robustness based only on its topological design, thereby enabling practitioners to better design a robust supply chain and easily identify vulnerable links in their supply chains.

Key words: material delay, supply network management, supply network robustness, supplier ranking, social network analysis

1. INTRODUCTION

Materials typically account for 50%–60% of the total construction project cost and can influence up to 80% of the schedule of a project [1]. The material delivery in construction projects often causes schedule delay and cost overrun [2,3]. Studies have found that nearly one-fourth of the total project delays were due to the late delivery of materials in Kuwait [4] and that late delivery of materials ranked 1st among 25 factors contributing to causes of nonexcusable project schedule delays in the United Kingdom [5].

As construction projects become larger and more material suppliers participate, multiple suppliers are connected in the form of a network and interact with one another. Accordingly, interdependencies and complexity between construction supply network entities are growing [6].Supply networks were traditionally viewed as systems made up of material suppliers, manufacturing facilities, distribution services, and customers, all linked by a linear feed forward flow of materials and a feedback flow of information [7,8]. However, recent studies have indicated that the supply chain analysis based on such assumption is not valid in today's complex supply chain. Alternatively, social network analysis methods have been adopted to understand the complex nature of supply networks [9,10]. Social network analysis is the process of investigating social structures using networks and graph theory, and characterizes networked structures in terms of nodes (individual actors, suppliers) and the links (relationships or interactions) that connect them. By adopting social network analysis, Kim et al. [11] found that topological characteristics of the network affect its robustness, which represents the network's ability to cope with external and internal disruptions and disturbances. Recent studies [12,13] also found that disruptions even in the smallest suppliers caused massive delays at the end due to the poor design of the network topology. These studies relied on the computational models/simulations in evaluating the network topology design and its impact on the network robustness, but the complexity of these computational models raises a great challenge in using them to design the network topology in practice at the early stage of a project. This study aims to identify network indicators that can easily characterize topological features of the supply chain and evaluates their impact on its robustness. We identify various network centrality measures that are commonly used to evaluate an importance of a vertex in social network analysis, and evaluate their effectiveness in predicting the robustness by simulating supply networks with various structures under random disruptive events. The findings of this study are expected to provide a relatively easy to use indicator to assess the impact of network topology on its robustness, thereby helping practitioners design more robust supply networks and identify and manage vulnerable links in their networks.

2. BACKGROUND

Due to the difficulties in obtaining real-life supply chain data, previous studies have relied on qualitative methods to acquire theoretical and practical insights to build a robust network [14]. While qualitative interpretations have virtues, their validity is jeopardized by a researcher's constrained rationality, including the inability to understand the complicated nature of the supply network. In this context, many previous studies have used computational simulation models to design a robust supply network. Computational models enable decision makers to understand the impact of network structure on its robustness, identify patterns of risk diffusion, and assess alternative scenarios [10]. For instance, Kamal Ahmadi et al. [15] observed that it is more effective to source from a few reliable suppliers than from many vulnerable suppliers, while Behzadi et al. [16] analyzed the effectiveness of distributing supply demand in mitigating disruption in the agribusiness industry. Basole et al. [10] developed a computational system model to assess and visualize the impact of network topology on risk diffusion. Recent studies have used social network analysis to understand the impact of network topology on its robustness with context-specific case studies. Kim et al. [11] demonstrated how to use social network analysis to investigate the structural characteristics of supply networks via a case study in an automobile industry. However, it is yet unclear how and to what extent the network topology impacts the robustness of the network in the construction industry, and thereby, a gap exists in how to characterize and assess the topology of supply networks. In this context, this study focuses on identifying and validating the network indicators that can reliably characterize the network topology and help predict the robustness of the supply network.

3. METHODOLOGY

In social network analysis, various centrality measures have been proposed and used to characterize an important vertex in the network. These centrality measures assign numbers or rankings to nodes corresponding to their position in the network, thereby allowing the observer to estimate how important a node or an edge is for the connectivity or information flow of the network. Thus, this study focuses on whether and which centrality measures can predict the robustness of the supply networks in construction. We identify several centrality measures from the social network analysis literature, and compute their values for randomly generated supply networks. A number of supply networks with different topology are created based on the data from a real-world project. Then the computational models to simulate these networks are developed and used to compute a delay of the material arrival at the network end (i.e., construction project) under random disruptive events on one node of the network (i.e., material delay of one supplier). Finally, the correlation between centrality measure values and simulated delay time at the network end is conducted to identify the most relevant measure.

3.1. Network Centrality Measures

The following network centrality measures are commonly used in the social network analysis [17] and are included in this study.

The *degree centrality* C_D of v_i is the average number of adjacent edges to v_i. The degree centrality measures how many direct, *one hop* connections each supplier has to other suppliers in the network. Degree centrality can be modified in directed networks as *in-degree centrality*, where k_i is the number of inbound adjacent links and *out-degree centrality*, where k_i is the number of outbound adjacent links

$$C_D(v_i) = \frac{k_i}{N-1}, 0 \leq C_D \leq 1 \tag{1}$$

The *closeness centrality* C_{CL} of v_i is the inverse of its farness centrality (the sum of a node's distances to all other nodes in the network: $C_F(v_i) = \sum_{l=1,l\neq i}^{N} d(v_i, v_l)$

$$C_{CL}(v_i) = \frac{1}{C_F(v_i)}, \frac{2}{(N-2)N} \leq C_{CL}(v_i) \leq \frac{1}{N-1} \tag{2}$$

The *betweenness centrality* C_B of v_i measures the number of times a node lies on the shortest path between other nodes in the network and is defined as follows:

$$C_B(v_i) = \sum_{r\neq s\neq i} \frac{l_{rs}(v_i)}{l_{rs}}, \tag{3}$$

where l_{rs} = total number of shortest paths from v_r to v_s; and $l_{rs}(v_i)$ = number of shortest paths from v_r to v_s passing the node v_i.

The *PageRank centrality* C_{PR} of v_i is calculated by the sum of inbound nodes' C_{PR} over the number of links connected to previous nodes $L(v)$ (the number of outbound links of v) [18]

$$C_{PR}(v_i) = \sum_{v\in V_{inbound}} \frac{C_{PR}(v)}{L(v)} \tag{4}$$

More detailed descriptions for the metric are provided in [19].

These centrality measures are computed for each node of a network for the node level analysis, which gives us insights on how important the node is in the network. To assess how the network topology affects the nodes and robustness of the whole network, measures for network level analysis were identified. The set of centrality values of all nodes in each network are collected separately, then mean, standard deviation, and maximum and minimum centrality are calculated for each network to capture the topological characteristics of the network.

3.2. Supply Network Simulation

1) *Representation of Supply Network*: The supply network was represented by a directed graph $\mathrm{G} = (\mathrm{V}, \mathrm{E})$ where $\mathrm{V} = \{v_1, v_2, v_3, \dots, v_N\}$ is the set of nodes (note that v_i represents material suppliers), and $\mathrm{E} = \{e_{ij} = (v_i, v_j), v_i, v_j \in \mathrm{V}\}$ is the set of edges (note that e_{ij} represents material transportation from supplier v_i to supplier v_j). The adjacency matrix $A_G = (a_{ij})_{1 \le i,j \le N}$, is a $\mathrm{N} \times \mathrm{N}$ symmetric matrix in which the element a_{ij} takes 1 or 0 depending on whether v_i and v_j are connected or not. This is a common method used in many previous studies in modeling the supply network [20].

2) *Random Network Generation*: Random supply networks were generated based on the supply network data from one mega plant construction project in Canada. This project's supply network included suppliers for around 800,000 types of construction materials, and a lag time in each supplier (e.g., processing time) of this project was also used as the baseline data of randomly created supply networks in this project. While the total number of suppliers remains the same, the topological designs of supply networks were modified in a way to assign a random role (i.e., raw material supplier, fabrication shop, and module shop) to each supplier. The networks only included four different levels (i.e., tiers) of the nodes (raw material supplier, fabrication shop, module shop, and construction site) as they are commonly used as tier setting in supply network modeling [9]. Then the links between the suppliers were randomly created considering their tiers (e.g., raw material suppliers are only connected to fabrication shops or module shops and cannot be directly connected to a construction site).

3) *Material Flow Simulation*: The material flow under a supply network was simulated using an agent-based model. The simulation model takes a set of supply network data consisting of node data (node index, capacity, tier, etc.) and link data (source node index and target node index) as an input. Nodes representing suppliers are generated based on the input node data. At $\mathrm{t} = 0$ nodes are connected based on the input link data. Nodes assigned as raw material suppliers produce materials at each time step t_p and search for the next possible target nodes to send the material. Target node for each material is selected randomly from the linked nodes (a set of nodes connected to the current node). Material is sent from the current node N_c to the assigned target node N_t with material transportation time t_m. Once the material is delivered to the target node, N_c and N_t are updated. The node assigned as a fabrication shop or module shop takes materials delivered from the former nodes and holds it for storage time t_s for the storage and material fabrication. After the delay, material is sent to the target node N_t sequentially. The node assigned as a site takes materials from former nodes and records the material arrival time and current storage volume. When all the materials arrive at the node assigned as construction site, the iteration is terminated and records the total time taken t_t.

The storage capacity of each node is set in propotion to the number of inbound links of the node, considering the amount of materials the nodes have to process. During the material transportation, if the storage of the node is full, that node is temporarily eliminated from the linked node list and the material searches for another available target. If there's no available target at the moment, materials stay in the queue until at least one target node is available.

4) *Disruptive Event Simulation*: The robustness of the network can be evaluated by its ability to cope with disruption in one of its nodes. As disruption in the network, a delay in a random supplier, was created and simulated with the increased storage time. While the storage time of a supplier was assumed to have a triangular distribution of 0–1–2 days, the storage time of a –disrupted supplier was assumed to have a triangular distribution of 3–4–5 days.

3.3. Experimental Design

To evaluate the relevance of the selected centrality measures, we conducted an experiment using supply network simulation. A total of 300 supply networks were created, and each supply network was simulated for 30 iterations. In each iteration, the following relative delay rate was computed: Relative delay rate (RDR) RDR $= t_{t\_disrupted}/t_{t\_normal}$ (total time taken for material delivery under disruptive event/total time taken for material delivery under nomal state).

Then the mean and max relative delay rate were determined for each supply network. These representative values of the network robustness were compared with the centrality measures for supply networks. Specifically, correlation analysis was conducted between the centrality measures and the representative values for relative delay rates of networks. Analysis was done with two different levels (network level and node level). Centrality values of 9,000 nodes (30 nodes per network, total 300 networks) and 9,000 RDR values were used in node level correlation analysis. For the network level analysis, mean, standard deviation, and maximum and minimum centrality values of 300 networks and corresponding 300 mean and max RDR values were used. Pearson correlation coefficient was used in this study (for $|r| > 0.5$, it is said to be a strong correlation).

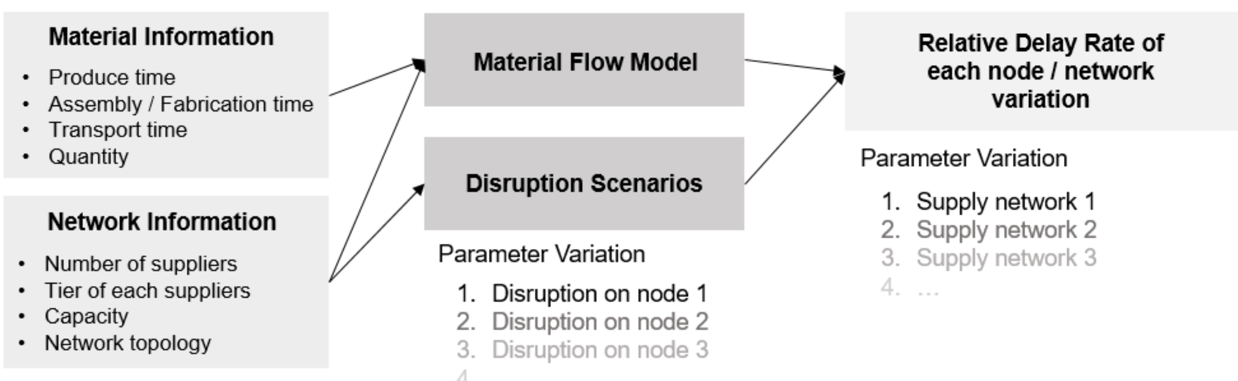

Figure 24. Illustration of the overall simulation process

4. RESULTS AND DISCUSSION

4.1. Network Level Results and Discussion

Standard deviation (SD) of PageRank centrality of the network was found to have the greatest correlation with the robustness of the supply network (see Table 1). In addition, standard deviation of out-degree, mean of closeness, and mean of betweenness measures were found to have a strong correlation with mean, max, and max RDR, respectively, but the standard deviation of PageRank centrality was the only measure that shows a strong correlation with both the mean and max RDRs. This indicates that the variance of PageRank centrality is highly relevant to the robustness of the network.

Table 1. Correlation coefficients between centrality indicators and delay rate (network level)

	Degree				In-degree				Out-degree			
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Mean RDR	0.05	-0.44	0.05	-0.07	0.05	-0.49	0.19	-0.20	0.05	-0.56	0.40	-0.33
Max RDR	-0.38	-0.06	-0.03	0.04	-0.38	-0.15	0.20	-0.18	-0.38	-0.38	0.22	-0.19
	Closeness				**Betweenness**				**PageRank**			
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Mean RDR	0.33	-0.03	0.15	-0.32	0.34	0.01	0.14	-0.13	0.01	**0.74**	0.22	-0.19
Max RDR	0.53	0.36	0.20	-0.35	0.70	0.46	0.06	-0.07	0.01	**0.62**	0.08	-0.06

Networks with higher standard deviation of PageRank centrality tend to have more high-centrality nodes connected to comparably low-centrality nodes, resulting in higher delay rates in the simulation (see Figure 2). The imbalanced centrality between adjacent nodes causes significant supply load on low-centrality nodes when adjacent high-degree nodes are under disruption. Thus, it was observed that networks with lower standard deviation of PageRank centrality (where nodes with equal or similar centrality are often linked) are more robust, reducing the impact of material delay of suppliers on the construction site.

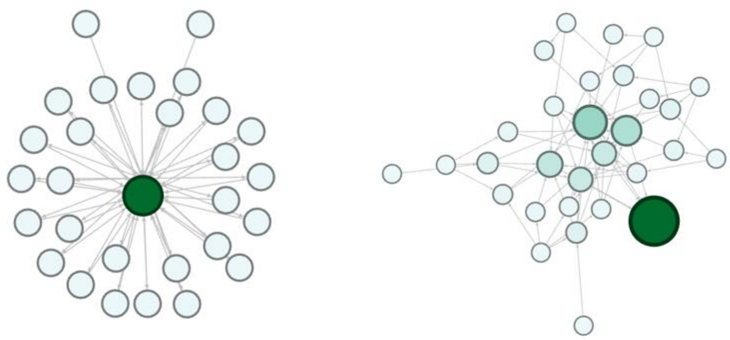

Figure 2. Illustrative example of supply networks (Layout: Yifan Hu [20])
(a) $C_{PR}\ SD = 0.050,\ Mean\ RDR = 2.9\%$; and (b) $C_{PR}\ SD = 0.074,\ Mean\ RDR = 15.1\%$.

4.2. Node Level Results and Discussion

It was found that the PageRank centrality has the greatest correlation with the network robustness with the positive correlation coefficient of 0.6 (see Table 2). The degree, in-degree, and closeness centrality measures were also found to have a strong correlation with the network robustness at the node level.

Table 2. Correlation coefficients between centrality indicators and delay rate (node level)

	Degree	In-degree	Out-degree	Betweenness	Closeness	PageRank
RDR	0.55	0.55	0.25	0.44	0.55	**0.60**

This result indicates that a disruption on the node with a higher PageRank centrality would produce a higher delay rate of the entire network in the simulation. An example is visualized in Figure 3. The size of each node represents its PageRank value. Each node's impact on material delay rate was compared to its PageRank. Nodes with a higher PageRank centrality value tend to receive more materials from front-end suppliers with high centrality. In other words, suppliers with higher PageRank centrality have to deal with more supply load, not only affecting the adjacent material receivers but also the construction site at the end. Thus, the PageRank centrality of a node represents the relative impact of that node on the network.

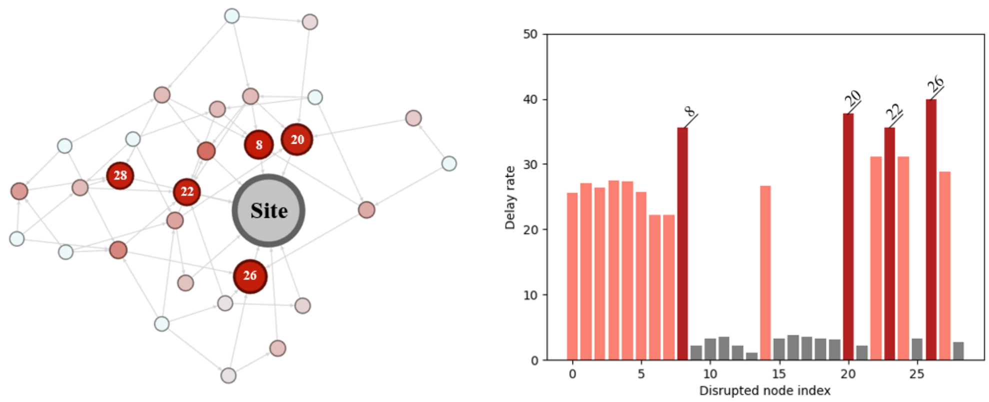

Figure 3. PageRank centrality and RDR comparison of an example network

5. CONCLUSION

This study analyzed the association of topological features of suppliers with the robustness of the material delivery network. Through simulations and correlation analysis, it was found that PageRank centrality has the greatest association with the robustness of the network in both node and network levels. Findings in this study will enable practitioners in construction projects to evaluate the robustness of supply networks in advance, based only on the network topology. Thus, managers will be able to adopt precautionary strategies to uncertain disturbances in material delivery with minimum information in the early stage of a project. However, this work considered materials to be homogeneous. Future study will include analysis on different characteristics of construction materials in terms of shipping manners and lead time.

ACKNOWLEGEMENTS

This work was supported by the New Faculty Startup Fund from Seoul National University.

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