Master of Science in Engineering

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

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by

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지도교수 안 창 범

이 논문을 공학석사 학위논문으로 제출함

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Abstract

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

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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.

Keyword : material delay; supply network management; supply network robustness; supplier ranking; social network analysis

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Chapter 1. Introduction

1.1. Motivation

Construction materials often contribute for 50-60% of the construction project's total cost, and they can affect up to 80% of a project's timeline[1]. Accordingly, material delays often lead to schedule delay at construction sites, resulting in increased costs [2,3]. Studies have found that late delivery of construction materials was responsible for approximately a quarter of total project delays in construction projects in Kuwait [4] and that late delivery of material ranked 1st among 25 factors contributing to main causes of schedule delays in the United Kingdom [5]. It is undeniable that effective materials management in construction projects has positive impacts on project cost, schedule and quality. The supply of materials in construction projects is exposed to different kinds of risks such as late delivery and natural hazards(e.g. tsunamis, earthquakes and economic crisis) [6]. In particular, in recent years, raw material shortages have occurred in the aftermath of the pandamic and war between countries, which has led to burdensome delays on construction projects. To effectively manage the possible risks in material supply, the concept of robustness has became a fundamental requirement in construction projects. Robustness of supply network is the network's ability to cope with external and inernal disruptions and disturbances. Previous studies have developed various models to assess and interpret the robustness of the supply network.

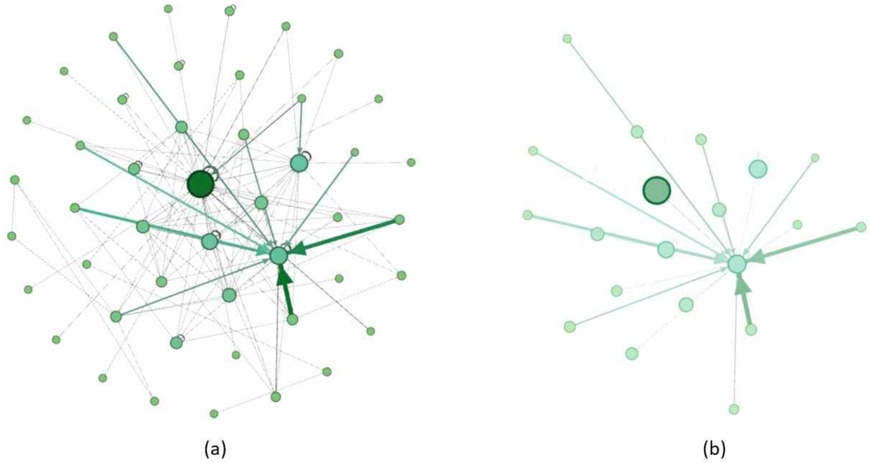


Figure 1-1. (a) A network representation of a recent real contruction project supply chain (b) A network representation of related suppliers of a supplier in the network

As construction projects get larger and more material suppliers engage from various countries, suppliers are connected in the form of a network and interact with one another. As a result, the interdependencies and complexity of the construction material supply network have been grown consistently [7]. As an exmaple, Figure 1-1. is a network representation of a recent real contruction project supply chain. Recent supply chain in construction projects includes multiple suppliers, related with high complexity and high connectivity. In accordance with Figure 1-1. (b), it is no wonder even disruptions on the smallest suppliers in the network could affect the entire system due to its complex relationships between material suppliers. Accordingly, there clearly exist a need of identifying the most influential suppliers and evaluating the robustness of the supply network based on its topology to effeciently ultilize the limited amount of managing capacity and to design a more robust supply network in advance.

Over the past decade, concepts and procedures to enhance the robustness of the supply network have evolved in response to the changing global environment. In traditional material supply networks, material suppliers, manufacturing facilities, distribution services, and customers were all linked and interpreted as a linear forward flow of materials and a feedback flow of information or materials [8,9].

However, recent studies have shown that supply network analysis based on such assumptions is no longer valid in today's complicated global supply network. To understand the complicated nature of recent supply network, social network analysis methodologies have been adopted instead of linear flow and feedback system [10,11].

Social network analysis, the technique of examining social structures using networks and graph theory, categorizes networked systems into nodes(individual actors or suppliers) and links(relationships or interactions between nodes) that connect them. The concept of social network analysis has been proven to be useful to study the patterns of complex interactions and material movement between suppliers in the network from a macro perspective [12]. Furthermore, social network analysis can be useful in material supply network analysis in that it allows us to quantitatively measure the topological characteristics of the material suppliers and the network itself. Along with these benefits of using social network analysis, recent studies have adopted the concept of social network analysis to anticipate the possible risks on the supply network and assess the network's robustness against the risks.

1.2. Problem Statement

Along with the growing complexity and diversity of the material supply network, there have been studies to capture the complex nature of supply networks and enhance its performance. By adopting social network analysis, Kim et al. [12] discovered that topological characteristics of the network impact its robustness, which symbolized the supply network's capacity to cope with external and internal shocks and disturbances. Recent studies [13,14] have also found that supply network interruptions(such as delays of materials caused by suppliers) even in the smallest suppliers result in enormous delays in the end owing to poor supply network topology design. In these studies, computational models and simulations with synthetic data were used to evaluate the network topology design and its impact on the supply network robustness. Computational decision model using synthetic or real dataset allows systemic exploration of possible risks of supply networks.

However, 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. As supply network data is often exclusive and resource intensive to collect, practitioners often rely on synthetic data or context-specific case studies which can easily be questioned about their validity for general application [11].

Moreover, in construction industry, each construction project necessitates the development of a single one-of-a-kind product that requires the collaboration of dozens, if not hundreds, of participants [15]. Since owners, contractors, subcontractors and suppliers work for a definite amount of time to deliver the project to the consumer and then move on to new projects, all activities in construction industry are often short-lived and therefore computational models with context-specific studies and datasets often loose their applicability for a construction project.

Accordingly, there needs a more generally adoptable managing method to proactively design the robust network topology to address possible disruptive events in construction material supply networks.

1.3. Research Objectives

This study aims (1) to identify topological indicators that best represents the influence of suppliers in today's complicated construction supply network and (2) to predict and evaluate the robustness of the supply network based only on its topological characteristics. To achieve this goal, we identify network indicators that can easily characterize topological features(e.g. the position of the suppliers in the network or relationships with adjacent suppliers of a supplier) of the supply network and evaluates their impact on its robustness. This study identifies 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 randomly generated supply networks with various structures under disruptive events such as material delay on raw material suppliers.

Chapter 2. Background

2.1. Computational Models for Robust Supply Network

Since the real-world supply network data is difficult to obtain, previous studies have relied on qualitative methodologies to acquire theoretical and practical insights on how to establish a robust network [16]. While qualitative interpretations have their own merits, their validity is compromised by a researcher's limited reasoning, which includes an inability to comprehend the supply network's complexity.

In this context, many previous studies have used computational simulation models to design a robust supply network. Decision makers can use computational models to analyze the influence of network structure on its robustness, detect risk diffusion patterns, and evaluate alternative scenarios [11]. For instance, Kamal Ahmadi et al. [17] found that procurement from a few dependable suppliers is more effective than procurement from a large number of susceptible suppliers, while Behzadi et al. [18] investigated the usefulness of dispersing supply demand in mitigating agriculture disruption. Basole et al. [11] developed a computational system model to assess and visualize the impact of network topology on risk diffusion.

2.2. Social Network Analysis for Robust Supply Network

Social network analysis(SNA) is the process of investigating social structures through the use of networks and graph theory. It classifies networked systems as nodes (individual actors, persons, or items in the network) and ties, edges, or links (relationships or interactions) that connect them. Scholars are beginning to see the potential of social network analysis to combine the operations and supply management discipline in that it allows us to capture structural characteristics of supply network with other branches of management science [19-21]. The ideas of social network analysis are particularly well suited to investigating how patterns of inter-firm(or inter-supplier) linkages in a supply network translate to advantages through material mobility and information dispersion management.

Recent studies have employed social network analysis to explore the impact of network topology on its robustness with context-specific case studies. Kim et al. [12] demonstrated how to use social network analysis to investigate the structural characteristics of supply networks via a case study in an automobile industry. In construction industry, previous studies have more focused on the information exchange and communication between suppliers in the network. For instance, Chinowsky et al. [22] has adopted social network analysis to focus on discovering effective social communication structure in construction project management. Akgul et al. [23] used SNA approach to investigate the partnership behavior of Turkish contractors in international construction projects. Shabani et al. [24] analyzed the effect of different procurement methods using SNA metrics.

SNA based strategic management in supply network in previous studies have embraced strategy analysis at two different level: Macro level(Network level) and Micro level(Node level) [12, 25].

- *Macro level Analysis(Network level Analysis)* uses metrics that compute how the overall network ties are organized form the perspective of an observer that has the bird's eye view of the network to explore behavioral mechanisms of entire supply networks.
- *Micro level Analysis(Node level Analysis)* uses metrics that measure how an individual node(or supplier) is embedded in a network from that individual node's perspective.

However, it is yet unclear how and to what extent the network topology impacts the robustness of the material delivery 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.

Chapter 3. Identifying Topological Characteristics of Suppliers and Supply Networks (SNA)

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 (Section 3.1), 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 (Section 3.2 and 3.3). Then the computational models to simulate these networks are developed (Section 3.4) and used to compute a delay of the material arrival at the network end (e.g., construction project) under random disruptive events (Section 3.5) on one node of the network (e.g., 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.

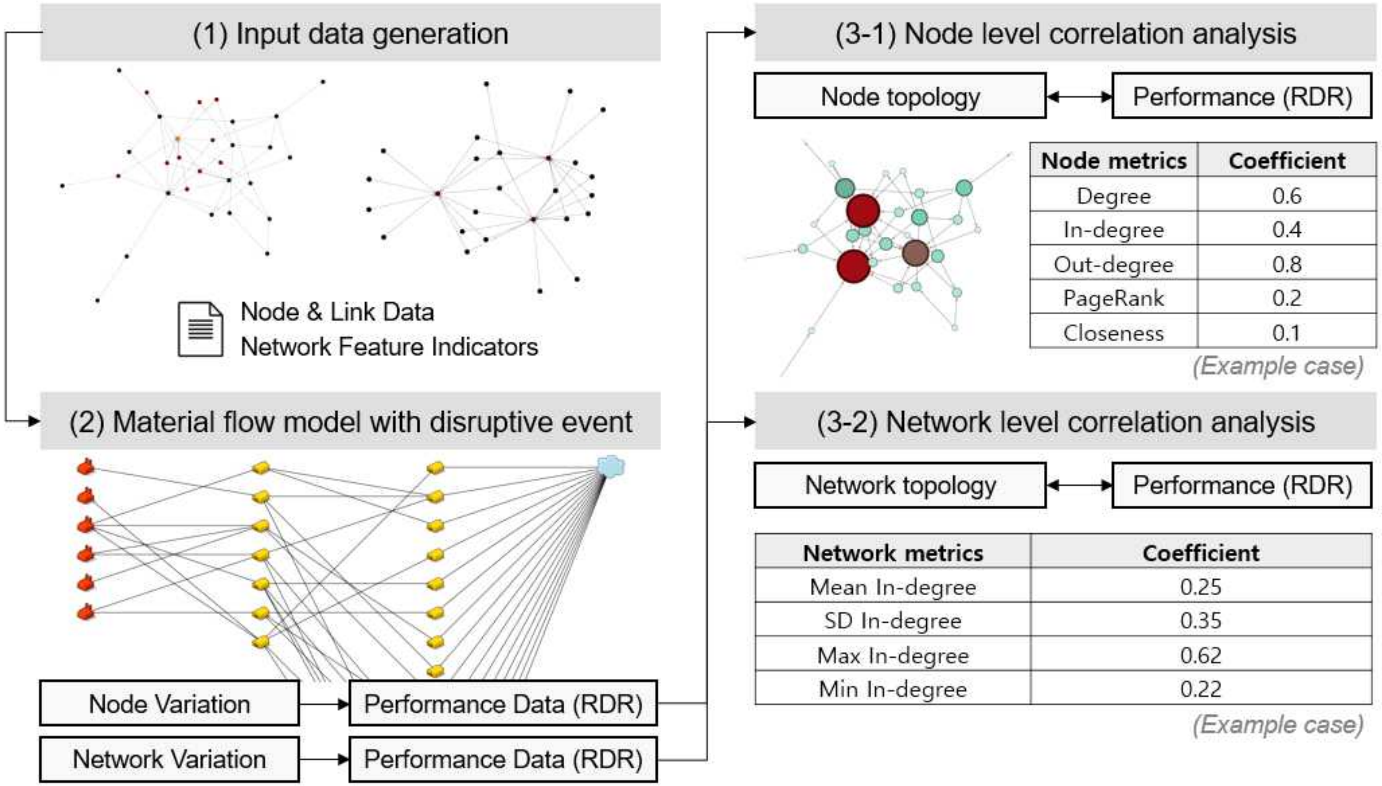


Figure 3-1. Process diagram of this study

3.1. Adoption of Common Network Centrality Measures

As mentioned in Section 2, this study uses various network measures to identify an important vertex in the network or distinctive characteristics of a network. One of the most common applications of SNA is to identify the major actors in a supply network [26]. The relative significance of individual nodes in a network is measured by centrality. The centrality of a node in a social network has a considerable influence on its behavior and well-being, as well as that of others [27]. There are several forms of centrality measures, each of which identifies significant nodes in different ways. Among various centrality metrics, this study identified several dominant centrality measures that have been used in various domains such as material procurement management, social network analysis and supply chain information flow management. Degree centrality, In-Degree centrality, Out-Degree centrality, Closeness centrality, Betweenness centrality and PageRank centrality were used in this study to capture the topological characteristics of each node in a material delivery network. Following descriptions for each centrality measures are based on the network with the set of nodes $V=\{v_1, v_2, v_3, \dots, v_N\}$(note that v_i represents each nodes in the network).

- *Degree Centrality (C_D)* is a measure that is based on the number of direct connections that a node(a supplier) has. C_D of the node v_i is the average number of adjacent links to v_i (1). Degree centrality is arguably the most common measure of centrality. This idea is based on the fact that the more direct linkages a node has, the more central it is. When a node is connected to a large number of other nodes, the node has high degree centrality.

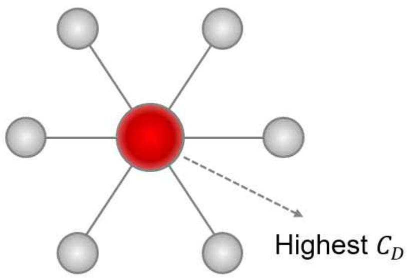


Figure 3-2. Illustration of degree centrality

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

In material supply networks, the connections are directed, and thus we can distinguish between backward(In-Degree Centrality) and forward(Out-Degree Centrality) supply network connections.

- *In-Degree Centrality* ($C_{D_{in}}$) is a measure that is based on the number of direct inbound adjacent connections that a node(a supplier) has. $C_{D_{in}}$ of the node v_i is the average number of adjacent inbound linkages to v_i (2). In terms of supply network, In-Degree Centrality is a measure with regard to the number of incoming materials or information.

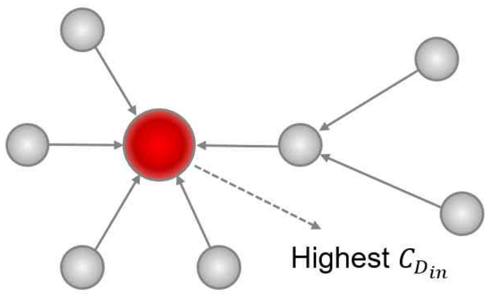


Figure 3-3. Illustration of in-degree centrality

$$C_{D_{in}}(v_i) = \frac{k_{i_{inbound}}}{N-1}, 0 \leq C_{D_{in}} \leq 1 \quad (2)$$

Nodes with higher In-Degree Centrality may be more prone to face supply challenges simply because of the greater amount of upstream materials required.

- *Out-Degree Centrality* ($C_{D_{out}}$) is a measure that is based on the number of direct outbound adjacent connections that a node(a supplier) has. $C_{D_{out}}$ of the node v_i is the average number of adjacent outbound linkages to v_i (3). In terms of supply network, Out-Degree Centrality is a measure with regard to the connectivity of a node with other material supplier, distribution center or the construction site.

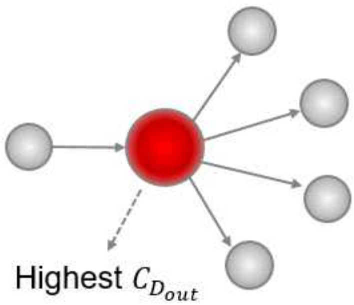


Figure 3-4. Illustration of out-degree centrality

$$C_{D_{out}}(v_i) = \frac{k_{i_{outbound}}}{N-1}, 0 \leq C_{D_{out}} \leq 1 \tag{3}$$

A greater Out-Degree Centrality of a node indicates that there are more suppliers or distribution centers engaged in the delivery of the product platform.

- *Closeness Centrality (C_{CL})* is the measure of closeness in a network and can be used to determine the length of the average shortest path between the node(supplier) and all other nodes(suppliers) in the network. C_{CL} of the node v_i is the inverse of its farness centrality(note that the farness centrality is the sum of a node's distances to all other nodes in the network) (4). In terms of supply network, Closeness Centrality measures how close a supplier is to all other suppliers in the supply network beyond ones that it is directly connected to. Closeness Centrality includes indirect linkages since a supplier is central if it can rapidly reach all the others.

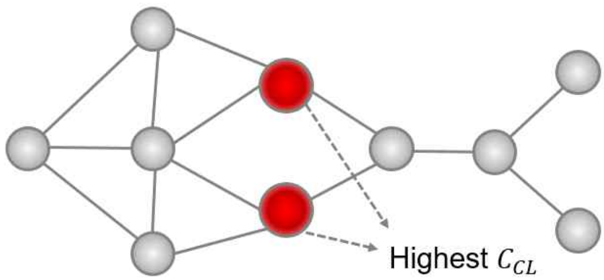


Figure 3-5. Illustration of closeness centrality

$$C_{CL}(v_i) = \frac{1}{\sum_{l=1, l \neq i}^{N} d(v_i, v_l)}, \frac{2}{(N-2)N} \leq C_{CL} \leq \frac{1}{N-1} \tag{4}$$

A node with a high Closeness Centrality is less influenced by others and has more ability for autonomous activity. These nodes grow less dependant on one other.

- *Betweenness Centrality (C_B)* measures how often a node lies on the shortest path between all combinations of pairs of other nodes. C_B of the node v_i counts the number of shortest path that pass through a specific node(supplier) from all nodes(suppliers) to all others (5). For suppliers with high Betweenness Centrality, because they are involved in the providing of many materials, either directly via manufacturing or indirectly through ownership by the same organization, these nodes can be considered major players in the supply chain (country or company).

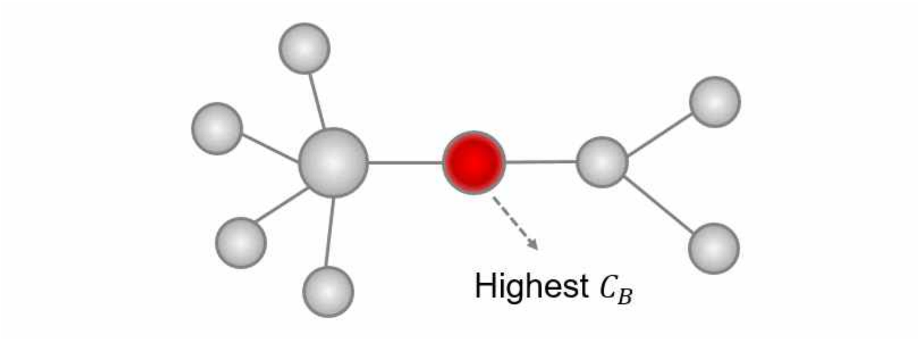


Figure 3-6. Illustration of betweenness centrality

$$C_B(v_i) = \sum_{r \neq s \neq i} \frac{l_{rs}(v_i)}{l_{rs}} \qquad (5)$$

Note that l_{rs} is total number of shortest paths from v_r to v_s; and $l_{rs}(v_i)$ is the number of shortest paths from v_r to v_s passing the node (supplier) v_i.

When a node with a high betweenness centrality is removed, material or information flows are more likely to be disrupted than if a random node is removed. The loss of any of these nodes is likely to have an impact on the entire supply chain network's performance, hence high-lighting these nodes is critical.

- *PageRank Centrality (C_{PR})* was invented by Google founders Larry Page and Sergei Brin and was designed for ranking web content, using hyperlinks between pages as a measure of importance [28]. 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) (6). Many prior research have discovered that Google page ranking is directly linked to search and search engine optimization (SEO) strategy, and that the ranking score reflects the efficacy of SEO strategy [29].

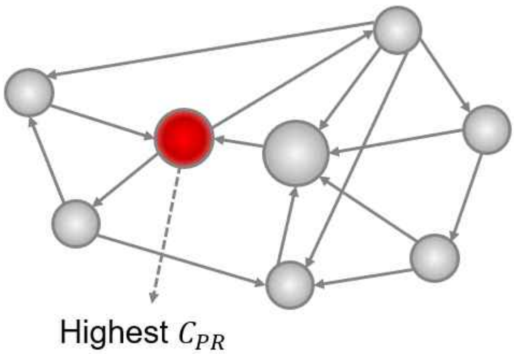


Figure 3-7. Illustration of PageRank centrality

$$C_{PR}(v_i) = \sum_{v \in V_{\in bound}} \frac{C_{PR}(v)}{L(v)} \tag{6}$$

In terms of supply network, PageRank Centrality measures a supplier's influence in the network by taking account the influence of its adjacent suppliers. It assumes that the centrality score of a supplier is proportional to the sum of the centrality scores of the neighbours (previous suppliers if the network is directed).

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.

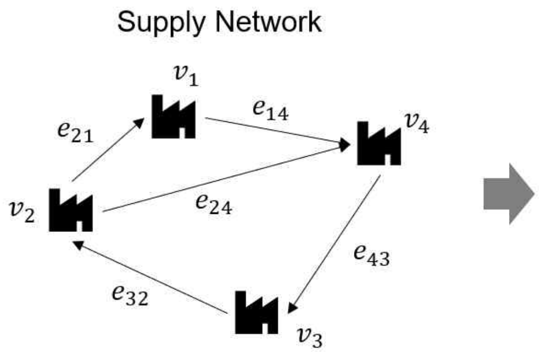
3.2. Representation of Supply Network in SNA

A supply network is a set of temporal and geographical operations carried out at facility nodes and via distribution connections that provide value to consumers by making and delivering items [30]. It refers to the broad condition of affairs in which all types of materials (both work-in-process and finished products) are changed and transferred between various value-added locations in order to maximize consumer value. It is often represented as a graph consist of nodes and links. In this study, the supply network was represented by a directed graph (since the link between suppliers represent the transportation of construction materials) $G=(V,E)$ where $V=\{v_1, v_2, v_3, \dots, v_N\}$ is the set of nodes (note that v_i represents material suppliers), and $E=\{e_{ij}=(v_i, v_j), v_i, v_j \in V\}$ 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 $N \times N$ symmetric matrix 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 in many previous studies in modeling the supply network [31].

In summary, construction material delivery supply network is represented as a graph (an illustrative example of network representation is provided in Figure 3-8.), and defined as follows :

- *Graph* $G = (V, E)$: Supply Network
- *Nodes* $V = \{v_1, v_2, v_3, \ldots, v_N\}$: Material Suppliers
- *Edges* $E = \{e_{ij} = (v_i, v_j), v_i, v_j \in V\}$: Material Transportations



$$
\begin{array}{c|cccc}
 & v_1 & v_2 & v_3 & v_4 \\
\hline
v_1 & 0 & 0 & 0 & 1 \\
v_2 & 1 & 0 & 0 & 1 \\
v_3 & 0 & 1 & 0 & 0 \\
v_4 & 0 & 0 & 1 & 0
\end{array}
$$

Figure 3-8. An illustrative example of supply network representation

Chapter 4. Supply Network Robustness Performance Simulation Under Disruption

4.1. Random Network Generation from Real Construction Project Dataset

Random supply networks were generated based on the supply network data from one mega plant construction project in Canada (Figure 3-9). This construction 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 [32]. Then the links between the suppliers were randomly created considering their tiers. Though the links between suppliers in the network were connected in a random way, there were several restrictions to reflect the material delivery process based on the real supply network for a construction project. (e.g., raw material suppliers are only connected to fabrication shops or module shops and cannot be directly connected to a construction site).

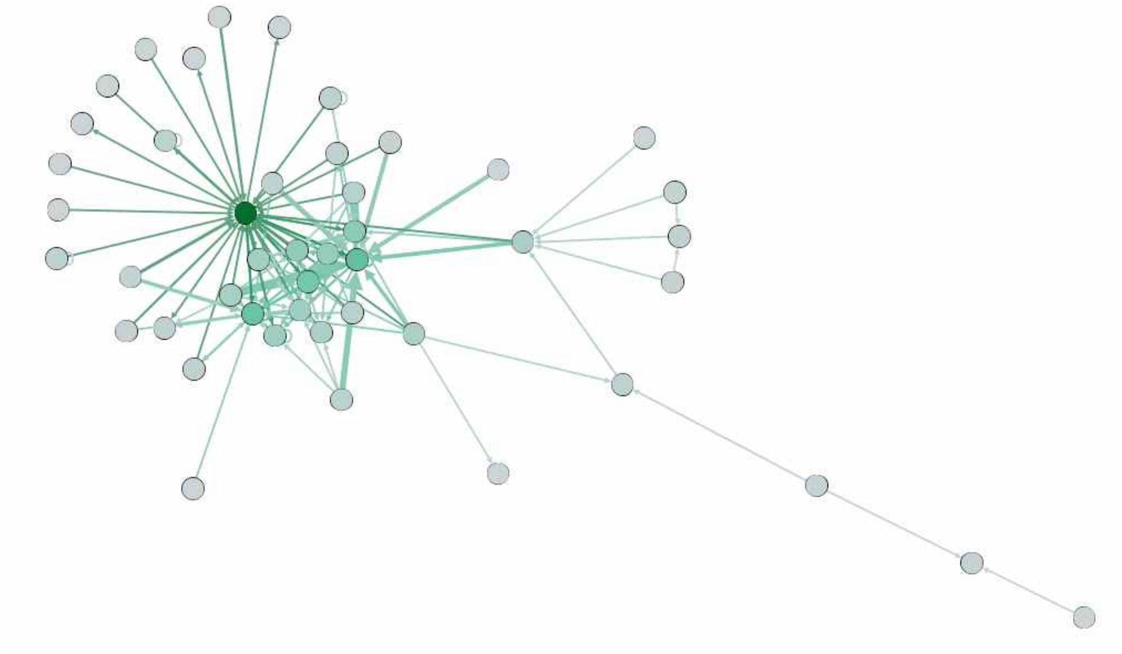


Figure 4-1. Network representation of a construction project in Canada

To generate random networks, the network topology of real material supply network in Figure 4-1 was modified. Randomly generated networks were represented in the form of node data and link data. 30 Nodes (note that each node represents the supplier) were created for each random network with identical index for each node. Node data file contained (1) the index of the node, (2) the tier of the node, (to identify whether the node is a raw material supplier, a fabrication shop, a module shop or a construction site) (3) the x and y location, (synthetic relative coordinates just for the visualization in the simulation tool) (4) and the capacity (material holding capacity for each node). Link data file contained the set of (1) source node index (the point at which construction materials depart for transportation) and target index (the point at which construction materials arrive by transportation).

Construction materials within the real construction project supply chain are produced by raw material suppliers and subjected to fabrication and assembly through the process of transportation of the supply chain. Therefore, the following regulations or assumptions are required when connecting links between suppliers :

- Raw material suppliers are only connected to fabrication shops or module shops and cannot be directly connected to a construction site.
- All suppliers delivering module-worked materials must be connected to the construction site.
- The supply network must be a direct network (where all links have a source and a target).

- There is no link where the higher level tier supplier becomes the source (there is no retrograde transportation).

The generated node, link information and adjacency matrix of the random networks are input values of the NetworkX (a Python package for the creation, manipulation, and study of the structure, dynamics, and functions of complex networks) and the material delivery simulation model. An illustrative example of generating random supply network is illustrated in Figure 4-2.

Node and Link data from real construction supply network

Source	Target	Weight
AGS Flexitallic (XX-1)	AGS Flexitallic (XX-1)	78
Fort Hills - Voyageur Site (XX-2)	CLEARWATER - FORT MCMURRAY	154
Fort Hills-SV (JS-4)	Daam Galvanizing (XX-1)	1
PCL Main Mod Yard (MB-3)	Fabricom (MD-3)	1
Advanced Insulation Korea (XX-1)	Fort Hills - Voyageur Site (XX-2)	260
CLEARWATER - FORT MCMURRAY	Fort Hills - Voyageur Site (XX-2)	2
Dubai - Advanced Insulation FZE (XX-1)	Fort Hills - Voyageur Site (XX-2)	19676
Fort Hills-SV (JS-4)	Fort Hills - Voyageur Site (XX-2)	2
Dubai - Advanced Insulation FZE (XX-1)	Fort Hills-SV (JS-4)	13149
KBR Mod Yard (MC-3)	Fort Hills-SV (JS-4)	4587
KNM Main Facility (XX-1)	Fort Hills-SV (JS-4)	37586
PARK DEROCHIE (XX-3)	Fort Hills-SV (JS-4)	25
PCL East 40 (MB-3)	Fort Hills-SV (JS-4)	59542
Fort Hills - Voyageur Site (XX-2)	KBR Fab Shop (MC-3)	2
Mokpo Newport - sungchang (M1-1)	KBR Fab Shop (MC-3)	109
Busan - OilTech (XX-1)	Kleysen (MA-2)	18281
Kleysen (MA-2)	Kleysen (MA-2)	52
Ulsan - Kukje (M3-1)	Kleysen (MA-2)	52617.1

⋮

Randomly modified network and adjacency matrix

$$
\begin{array}{c c}
 & \begin{array}{cccccc} v_1 & v_2 & v_3 & v_4 & & v_{30} \end{array} \\
\begin{array}{c} v_1 \\ v_2 \\ v_3 \\ v_4 \\ \vdots \\ v_{30} \end{array} &
\begin{bmatrix}
0 & 1 & 0 & 0 & \cdots & 1 \\
1 & 0 & 1 & 0 & & \\
0 & 1 & 0 & 1 & & \\
0 & 0 & 1 & 0 & & \\
\vdots & & & & \ddots & \\
1 & & & & & 0
\end{bmatrix}
\end{array}
$$

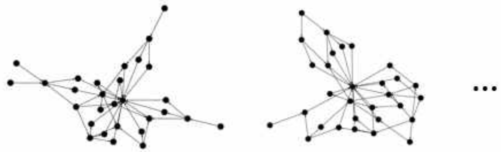


Figure 4-2. An illustrative example of the process of random network generation

4.2. Material Flow Simulation Modeling

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 $t=0$ 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.

Input parameters for initiating the material delivery simulation is provided in Table 4-1 and the schematic outline of simulation initiating is illustrated in Figure 4-3. The overall process models of raw material suppliers and fabrication/module shops are provided in Figure 4-4 and Figure 4-5.

Table 4-1. Input parameters for agents in material delivery simulation

Agent Category	Input
Network	Number of suppliers
	Tier of each suppliers
	Node information
	Link information (set of source and target)
Raw material supplier	Material production time interval t_p
	Material storage time t_s
	Material storage capacity
	Material production volume
Fab shop / Mod shop	Material storage time t_s
	Material storage capacity
Material	Material transportation time t_m
	Current node index N_c
	Available target node list

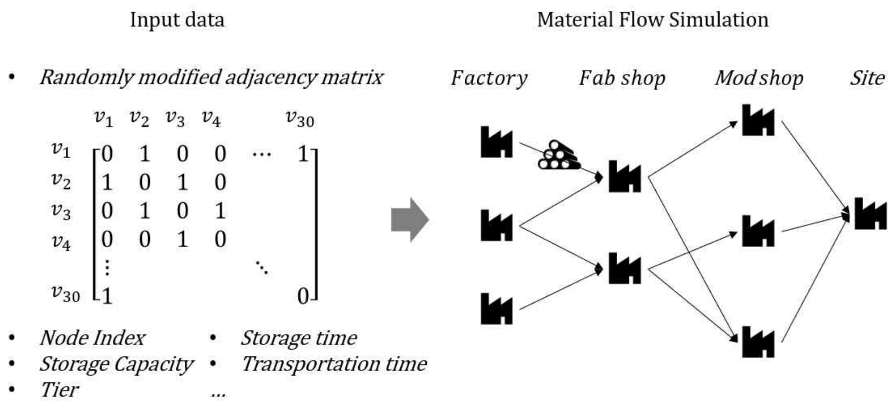


Figure 4-3. Schematic outline of material flow simulation initiating

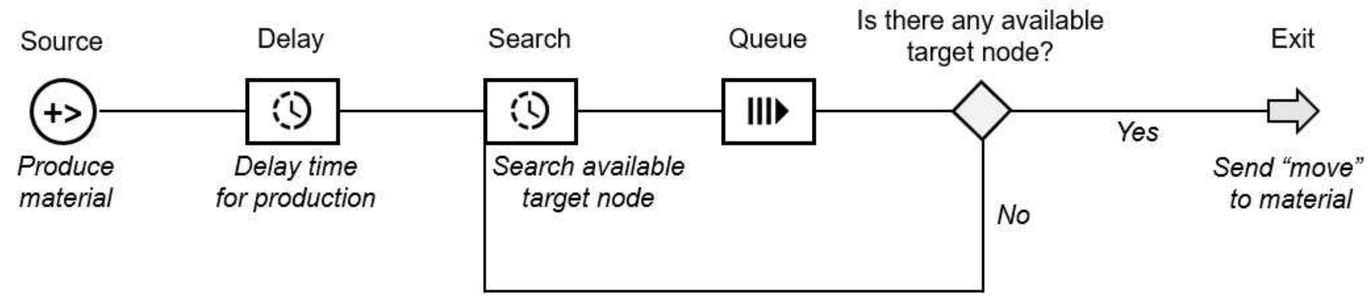


Figure 4-4. Process model of raw material supplier agents

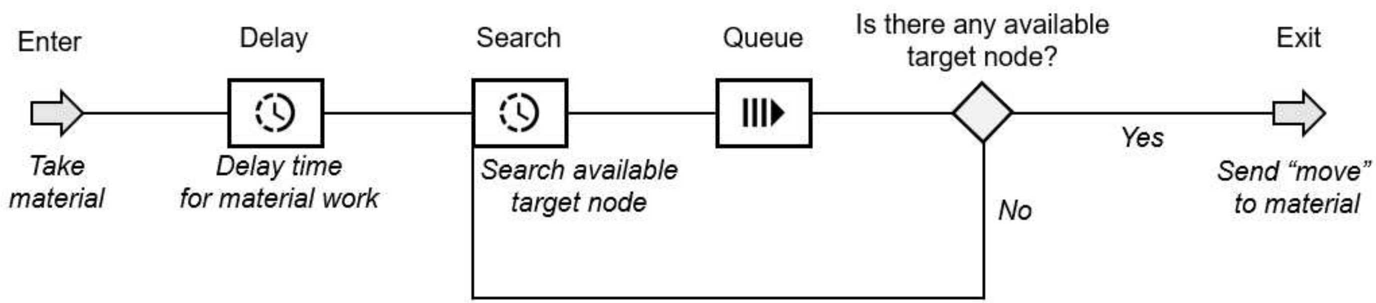


Figure 4-5. Process model of Fab/Mod shop agents

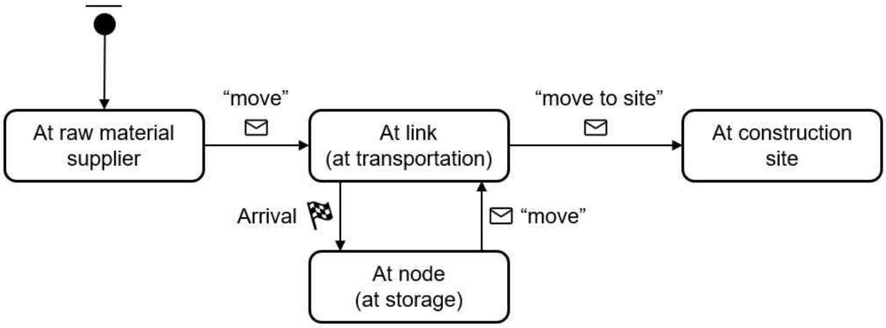


Figure 4-6. State chart of material agents

Materials are initially produced in the source block of raw material suppliers at each time step t_p and search for available target suppliers that are not full of storage capacity (note that the supplier that can be designated as a target must be linked to the provider that sends the material). If there is at least one supplier that can be targeted, supplier agent send a message “move” to the material. If there’s no target supplier available, the material waits in the queue block until there’s a supplier with spare storage capacity. Receiving the “move” message from the supplier agent, the material exits the supplier changing its state from ‘At raw material supplier’ to ‘At link (at transportation)’. By the arrival of material to a new supplier, the material change its state to ‘At node’ and is stored or processed in the process model of the supplier agent. The produced materials and suppliers will repeat this process until the available target nodes for the materials are set to the construction site. Material suppliers on the brink of the construction site send the message “move to site” at the exit block to the material which make the material change the state from ‘At link’ to the state ‘At construction site’. By entering the process model of the construction site agent, the delivered material records the total time taken t_t.

Material delivery simulation procedure was done by using AnyLogic, a simulation modeling software supporting agent-based, discrete event, and system dynamics simulation methodologies.

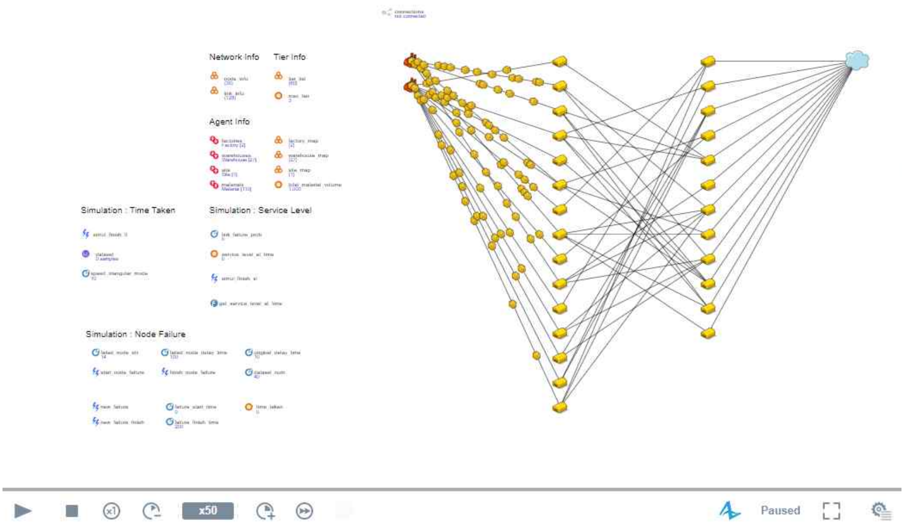


Figure 4-7. Screenshot of material delivery simulation in AnyLogic

4.3. Embodiment of Disruptive Event in the Simulation

The robustness of the network can be evaluated by its ability to cope with disruption in one of its nodes [33]. In this study, experiments were conducted by selecting an arbitrary supplier and caused a disruptive event on that supplier. The total material transportation time that varies by supplier was compared. 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. The values of storage time parameter were set referring to the real construction supply network data mentioned in Chapter 4.1.

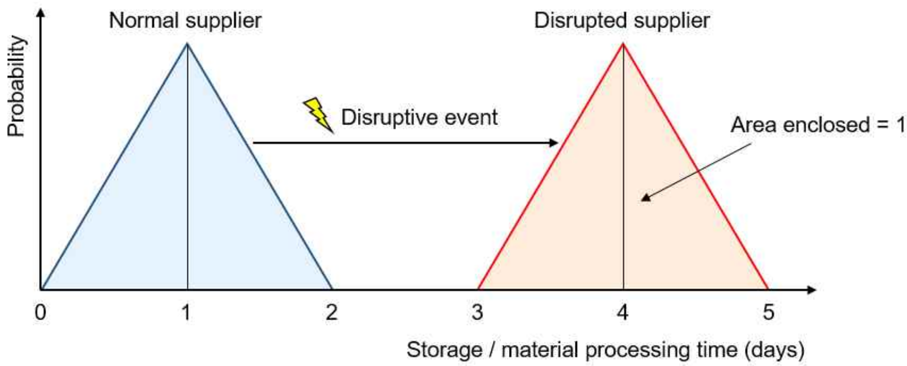


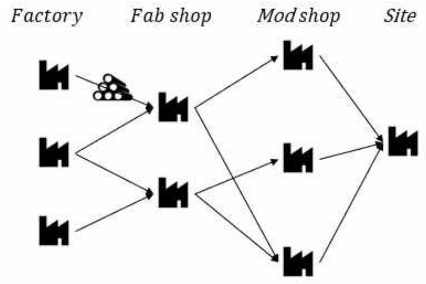
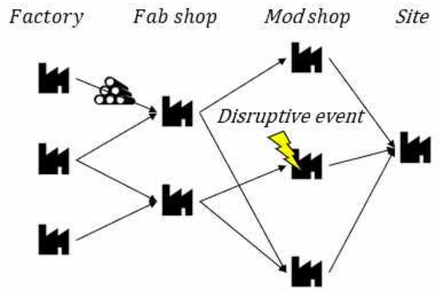
Figure 4-8. Variation of storage time as a disruptive event in the simulation model

Chapter 5. Correlation Analysis between Network Topology and Supply Network Performance

5.1. Experimental Setup for Correlation Analysis

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, resulting in total 9,000 iterations. The scenario for the simulation experiment was designed in two main directions. Scenario 1, the base case scenario was designed to be used as a control group, where storage time of all suppliers was set to be a triangular distribution of 0–1–2 days, without any disruption. Scenario i (note that i = disrupted node index, $2 \leq i \leq 30$), was designed to observe the impact of disruption of each supplier on the material delivery performance of the network. In scenario i, we caused a disruption on the supplier with index i by setting the material storage time to a triangular distribution of 3–4–5 days. In each iteration, the following relative delay rate was computed: Relative delay rate (RDR) $RDR = (t_{t\ \_disrupted}/t_{t\ \_normal}) - 1$ (total time taken for material delivery under disruptive event (under scenario i)/total time taken for material delivery under normal state (under the base case scenario)).

Table 5-1. Overview of the modelled scenarios

Scenario	Representation (example)	Features
Scenario 1 (Base Case)		Disrupted node index = *None* Storage time of all suppliers = *triangular distribution of 0–1–2 days*
Scenario i (i = disrupted node index, $2 \leq i \leq 30$)		Disrupted node index = i Storage time of supplier i = *triangular distribution of 3–4–5 days* Storage time of other suppliers = *triangular distribution of 0–1–2 days*

After all 30 experiments within one network are completed, the experiment is conducted again with another randomly generated network topology. We repeated experiments in which information from the newly generated random network is put as input to the material transport simulation model and regenerate the supply chain within the model to transport the materials from the raw material suppliers to the construction site agent. 300 randomly generated networks were simulated resulting in total 9,000 RDR records and topological metrics data. Material delivery simulation was conducted by implementing the following pseudo-code:

```
for j = 1 to 300:
    generate random node and link data
    initialize the simulation model
    for i = 1 to 30:
        set scenario i
        run material delivery simulation model
        if done:
            return recorded RDR data
```

5.2. Correlation Analysis to Identify Influential Suppliers

To analyze the impact of disruption on material supply delay on each supplier in the supply chain network, the correlation analysis between the RDR data obtained through simulation and the topological metrics of each supplier was conducted. For topological metrics of each supplier in node level correlation analysis, as mentioned in Chapter 3.1, Degree, In–degree, Out–degree, Closeness, Betweenness and PageRank Centralities were chosen. Total 9,000 topological metrics and RDR values from the material delivery simulation were used. Each set of values of topological indicators and RDR values were normalized before the analysis. Let $G=(V,E)$ be a network or graph with node set V and edge set E. Let $N=|V|$ be the number of vertices of G. Let $\mu(G)$ be the value of the metric μ evaluated on the graph G. Let s be the number of networks generated for the simulation. We normalized the measurements following the process of [34]. The measurements of the metric $(\mu(G_1),\mu(G_2),\ldots,\mu(G_s))$ are normalized by the expression $(\mu(G_1)/f_\mu(n_1),\mu(G_2)/f_\mu(n_2),\ldots,\mu(G_s)/f_\mu(n_s))$, where f_μ is a normalization function of the metric μ. Table 5-2. shows the topological metrics μ and corresponding normalization function f_μ used in this study. Pearson correlation coefficient was used in this study (for $|r|>0.5$, it is said to be a strong correlation).

Table 5-2. Metrics and normalization functions used in node level analysis

Metric μ	**Normalization function** f_{μ}	**Representation**
Degree Centrality	$(N-1)$	$C_D(v_i)=\frac{k_i}{N-1}, 0 \le C_D \le 1$
In-degree Centrality	$(N-1)$	$C_{D_{in}}(v_i)=\frac{k_{i_{inbound}}}{N-1}, 0 \le C_{D_{in}} \le 1$
Out-degree Centrality	$(N-1)$	$C_{D_{out}}(v_i)=\frac{k_{i_{outbound}}}{N-1}, 0 \le C_{D_{out}} \le 1$
Closeness Centrality	$(N-1)$	$C_{CL}(v_i)=\frac{N-1}{\sum_{l=1,l \neq i}^{N} d(v_i,v_l)}, \frac{2(N-1)}{(N-2)N} \le C_{CL} \le 1$
Betweenness Centrality	$(N-1)(N-2)$	$C_B(v_i)=\sum_{r \neq s \neq i} \frac{l_{rs}(v_i)}{l_{rs}}$
PageRank Centrality	–	$C_{PR}(v_i)=\sum_{v \in V_{\in bound}} \frac{C_{PR}(v)}{L(v)}$

5.3. Correlation Analysis to Assess the Robustness of Supply Network

To analyze the impact of disruption on material supply delay on each network topology, the correlation analysis between the RDR data obtained through simulation and the topological metrics of each random network was conducted. For topological metrics of each random network in network level correlation analysis, mean, standard deviation, and maximum and minimum centrality values of 300 networks and corresponding 300 mean and max RDR values were used. A total of 9000 node data were grouped between node data existing in the same random network, and for each network, the average, standard deviation, maximum, and minimum values of the centrality values of node data in the network were calculated. The calculated network level metrics were then analyzed and compared with the mean and maximum RDR values of corresponding random networks. Table 4-3. shows the topological metrics of j^{th} random network G_j, $(1 \leq j \leq s)$ used in correlation analysis (note that $C(G_j)$ is the set of centrality values of all nodes in the network G_j). As in the node level correlation analysis mentioned in Chapter 5.2, Pearson correlation coefficient was used in the network level analysis.

Table 5-3. Metrics used in network level analysis

Category	Metric (for j = 1 to 300)
Degree Centrality	mean $C_D(G_j)$
	SD $C_D(G_j)$
	max $C_D(G_j)$
	min $C_D(G_j)$
In-degree Centrality	mean $C_{D_{in}}(G_j)$
	SD $C_{D_{in}}(G_j)$
	max $C_{D_{in}}(G_j)$
	min $C_{D_{in}}(G_j)$
Out-degree Centrality	mean $C_{D_{out}}(G_j)$
	SD $C_{D_{out}}(G_j)$
	max $C_{D_{out}}(G_j)$
	min $C_{D_{out}}(G_j)$
Closeness Centrality	mean $C_{CL}(G_j)$
	SD $C_{CL}(G_j)$
	max $C_{CL}(G_j)$
	min $C_{CL}(G_j)$
Betweenness Centrality	mean $C_B(G_j)$
	SD $C_B(G_j)$
	max $C_B(G_j)$
	min $C_B(G_j)$
PageRank Centrality	mean $C_{PR}(G_j)$
	SD $C_{PR}(G_j)$
	max $C_{PR}(G_j)$
	min $C_{PR}(G_j)$
RDR	mean $RDR(G_j)$
	max $RDR(G_j)$

Chapter 6. Results of Correlation Analysis

6.1. Network Topology Indicators Associated with the Influence of Disruption on Suppliers

Node level topological metrics shown in Table 5-2 were compared to the material delivery performance (RDR) obtained from the simulation model. 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 6-1). The degree, in-degree, and closeness centrality measures were also found to have a strong correlation with the network robustness at the node level with the correlation coefficient value of 0.55, 0.53, 0.52 correspondingly. The result indicates that the topological characteristics of suppliers in the network impact the material delivery performance of the whole supply network. By looking at the natural characteristics of topological indicators with relatively higher correlation coefficient values (e.g., PageRank, Closeness and In-degree centralities), metrics that also consider relationships with remote providers, including directly connected suppliers, have been identified to have more significant impact on the material delivery performance than those that do not.

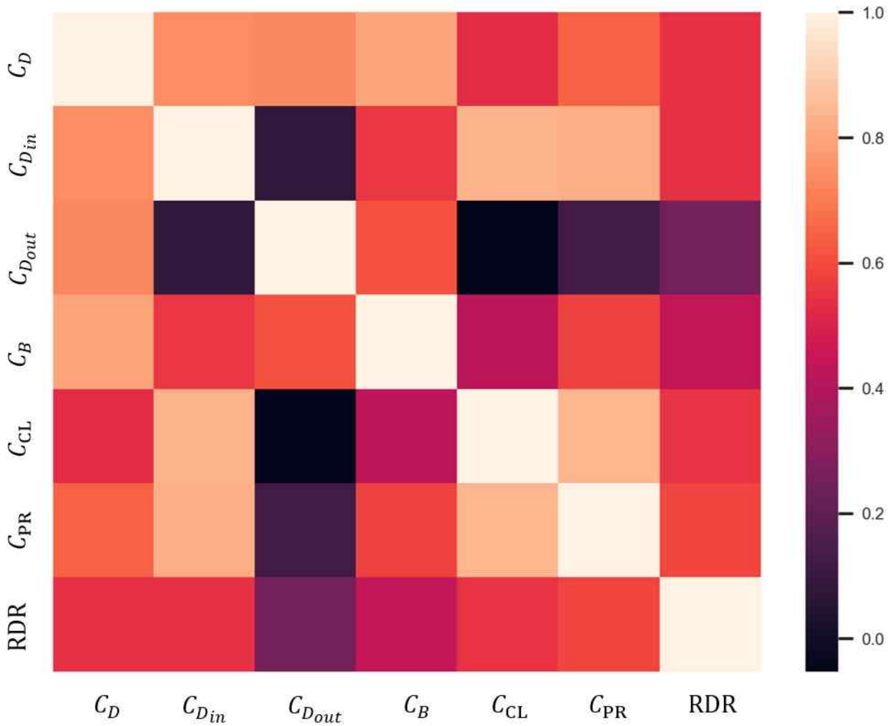


Figure 6-1. Heatmap of Correlation Coefficients in Node-Level Analysis

Table 6-1. Correlation Coefficients between Centrality Measures and RDR (Node-Level)

	RDR
Degree Centrality	0.55
In-degree Centrality	0.53
Out-degree Centrality	0.25
Betweenness Centrality	0.44
Closeness Centrality	0.52
PageRank Centrality	**0.60**

6.2. Network Topology Indicators Associated with the Robusteness of the Supply Network

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 6-2). 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. As in the results of node-level correlation analysis, the results in network-level analysis suggests that indicators that also count links with far-connected suppliers, including adjacent suppliers, are more influential than those that do not. Furthermore, it was found that the deviation of topological measures among the suppliers in the same network seem to have more impact on the material delivery performance than the maximum, minimum, or mean values of most centrality measures (e.g., Degree, In-degree, Out-degree, and PageRank centralities).

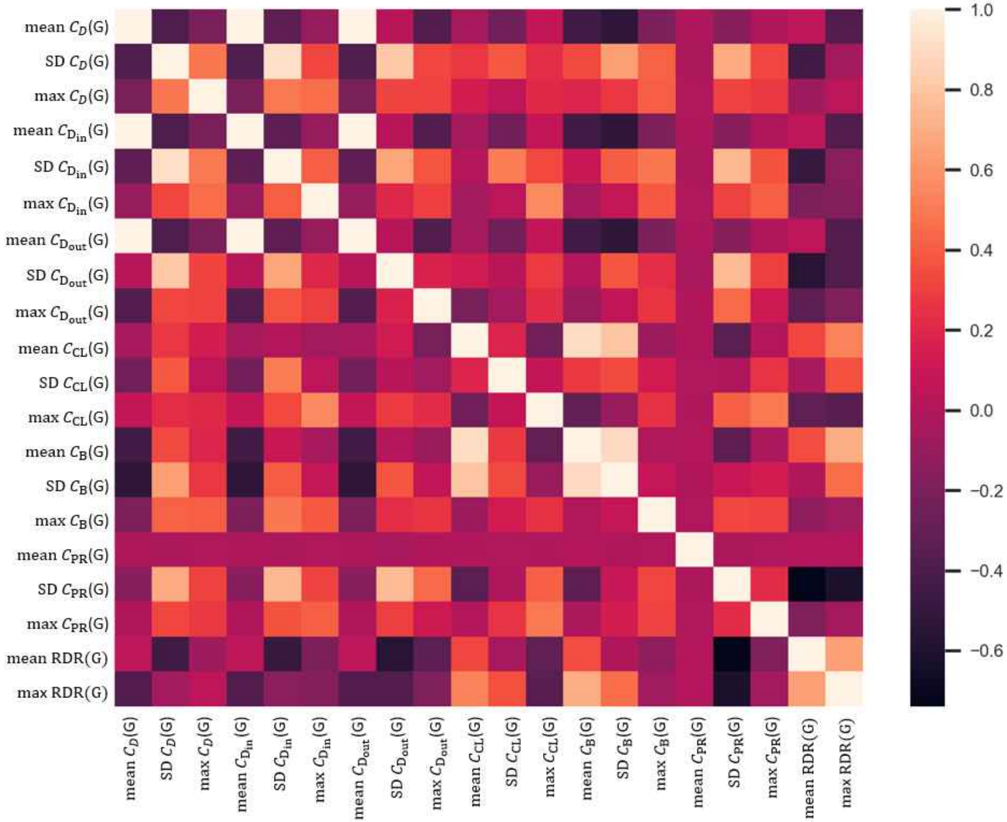


Figure 6-2. Heatmap of Correlation Coefficient in Network-Level Analysis

Table 6-2. Correlation Coefficients between Centrality Measures and RDR (Network-Level)

	Degree Centrality				**In-degree Centrality**				**Out-degree Centrality**			
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Mean $RDR(G)$	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 $RDR(G)$	-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 Centrality				**Betweenness Centrality**				**PageRank Centrality**			
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Mean $RDR(G)$	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 $RDR(G)$	0.53	0.36	0.20	-0.35	0.70	0.46	0.06	-0.07	0.01	**0.62**	0.08	-0.06

Chapter 7. Discussion

7.1. PageRank Centrality as a Measure of the Influence of Suppliers

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 6-1. 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. Unexpected delays on suppliers with higher PageRank centrality can thus consequently result in more impact(schedule delay in this case) on the construction site. Thus, the PageRank centrality of a node represents the relative impact of that node on the network.

Furthermore, in terms of material delivery management, the result indicates that the supplier managing strategy focusing on suppliers with relatively higher PageRank values might be more effective rather than treating the importance of all suppliers equally. With the limited amount of managing capacity, whether it be the cost, time or human resource, ranking suppliers with PageRank centrality and focusing on high rank suppliers would reduce the management cost during the construction project. Additionally, as previous management methods mainly focused on suppliers that are responsible for great amount of important materials, material delivery management strategy also considering topological characteristics of each supplier might bring the chance of discovering suppliers previously considered less important, but have significant impact due to unique topological characteristics of themselves.

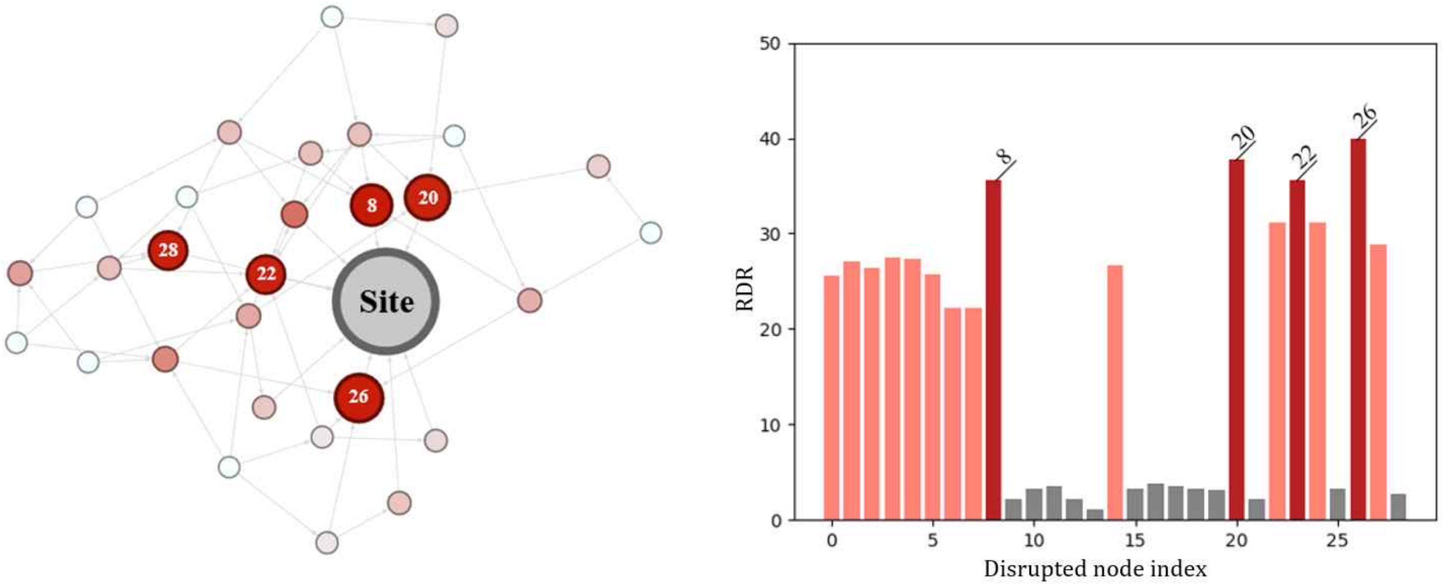


Figure 7-1. PageRank Centrality and RDR Comparison of an Example Network

7.2. Standard Deviation of PageRank Centrality as a Measure of Supply Network Robustness under Disruption

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. Figure 6-2 shows an illustrative example of two different supply networks with significant discrepancy of the network performance and the standard deviation values of PageRank among suppliers. The imbalanced centrality between adjacent nodes causes significant supply load on low-centrality nodes when adjacent high-degree nodes are under disruption. In terms of material delivery, supply networks with higher PageRank SD might suffer from exessive amount of concentrated supply load caused by material delays compared to networks with relatively lower PageRank SD. 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.

Moreover, in terms of material delivery management, the result indicates that the supply networks with lower value of standard deviation of PageRank values among suppliers are more robust to cascading impact of bottleneck phenomenon by dispersing the responsibility of material flow to adjacent suppliers. Therefore, practitioners might advantage from designing the supply network in a way that reduces the deviation of PageRank values (e.g. sourcing from multiple suppliers or having multiple distribution centers) or any other metrics that shown to have significant impact on material delivery performance in advance as a precautionary strategy even before the operation of the supply chain.

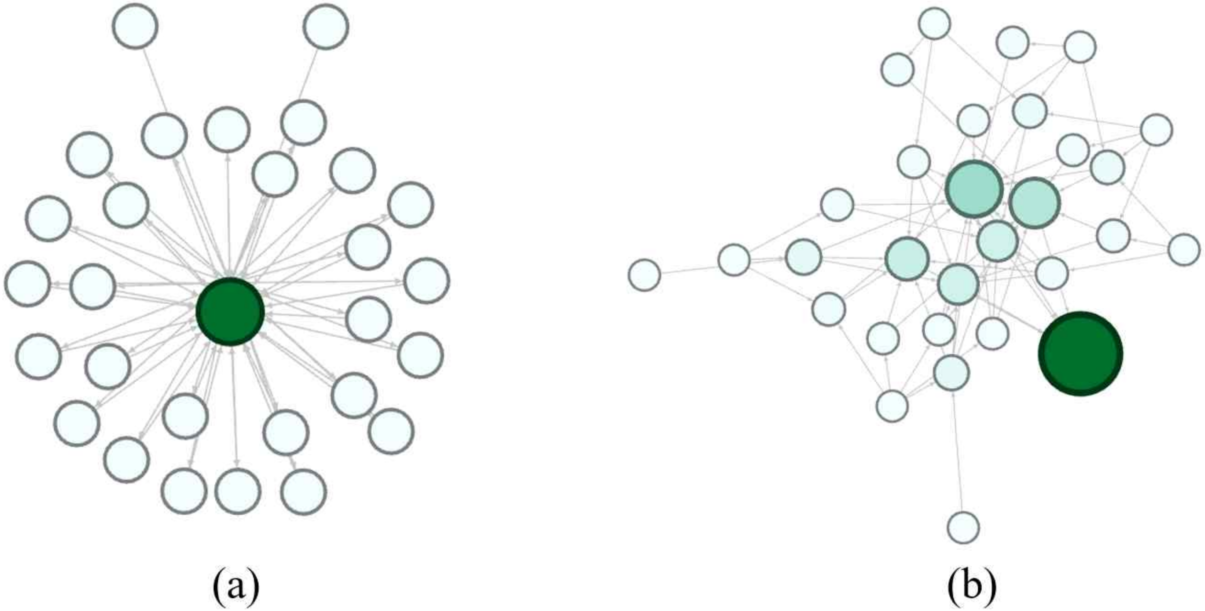


Figure 7-2. Illustrative Example of Supply Networks (Layout: Yifan Hu[35])
(a) $SD\ C_{PR}(G) = 0.050, Mean\ RDR(G) = 2.9\%$; and (b) $SD\ C_{PR}(G) = 0.074, Mean\ RDR(G) = 15.1\%$

Chapter 8. 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 among various topological metrics. Based on the results of the correlation analysis, it is suggested that suppliers with relatively higher PageRank values must be dealt with higher priority. The result also indicates that the managers might advantage from designing the supply network with lower standard deviation of PageRank values of suppliers in the whole network by preventing the cascading impact of bottleneck phenomenon among linked suppliers. 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.

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국 문 초 록

최근 건설 공급망은 COVID-19, 나라 간 전쟁 및 원자재 가격 상승 등으로 인한 자재 지연 및 프로젝트 스케쥴 지연으로 어려움을 겪고 있다. 이에, 공급망의 강건성(공급망 외부 및 내부에서 발생하는 예기치 못한 자재지연에 대처할 수 있는 능력)은 건설 프로젝트의 성공을 보장하는 데 있어 더욱 중요해지고 있다. 오늘날의 건설 프로젝트의 공급망에는 더 많고 다양한 공급업체가 포함되고, 그 관계 또한 복잡해지고 있기 때문에, 이전 선행연구들의 건설 공급망을 선형적인 모델로 분석하는 방법은 더 이상 최근 공급망에 유효하지 않다. 이에, 본 연구는 복잡화되고 있는 건설 공급망의 위상적 특징을 정량화하는 지표들과 공급망의 퍼포먼스 사이 상관관계를 분석하여 어떤 위상적 특성을 가지는 공급자들이 먼저 관리되어야 하고, 자재 지연에 강건한 공급망은 어떻게 설계되어야 하는지 확인하는 것을 목표로 한다. Social Network Analysis에서 위상적 특징을 수치화하는 데 일반적으로 사용되는 지표들이 활용되었고, 실제 건설 프로젝트 데이터에 기반하여 다양한 위상적 특성을 가지는 공급망을 무작위로 생성하여 자재 지연 발생시의 공급망의 퍼포먼스를 시뮬레이션을 통해 평가하였다. 공급망의 다양한 위상 지표들 중 PageRank Centrality가 공급망의 강건성과 가장 연관성이 큰 것으로 확인되었으며, 개별 공급자 수준 분석에서 0.6, 공급망 전체 수준 분석에서 0.74의 양의 상관계수를 가짐을 보였다. 본 연구의 결과는 실무자로 하여금 공급망의 위상적 특징을

기반으로 그 강건성을 평가하여 더 강건한 공급망을 설계할 수 있게 하며, 다른 공급자 대비 더 영향력 있는 공급자를 식별하여 집중 관리의 대상으로 선정할 수 있게 한다.

주요어: 자재 지연; 건설공급망 관리; 건설공급망 강건성; 소셜 네트워크 분석

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