Equipment Logistics Performance Measurement Using Data-Driven Social Network Analysis

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ABSTRACT

The construction industry relies heavily on the use of equipment. Equipment management for a single project is, in itself, challenging, and large contractors who want to achieve long-term success must also manage equipment at an intra-organizational level. While vast amounts of data are collected and updated dynamically to track equipment status within an organization, current practices do not consider these data during the decision-making process. Rather, companies often rely on a single metric, equipment utilization, for evaluating management performance. Inspired by the ability of social network analysis (SNA) to examine the interactions and relationships between people or objects, a SNA-based method for investigating equipment movements between project sites and equipment shops is proposed. This study proposes a novel performance metric, the direct dispatch index (DDI), which adds a distance weight to the clustering coefficient of SNA, to measure equipment dispatching performance from equipment logistics data. Historical equipment logistics data from the equipment and project management systems of a company in Alberta, Canada, were used to demonstrate the functionality and feasibility of the proposed approach. The methodology was found capable of evaluating the logistical effort associated with equipment dispatch and planning, thereby enhancing equipment management through improved decision-making.

Keyword: Resource Planning; Equipment Management; Social Network Analysis

INTRODUCTION

Equipment represents a large expense for heavy civil construction projects and corporations. While equipment management is essential for ensuring that projects are completed on time and on budget (Vorster, 2009), optimization of this process can have a considerable impact on project efficiency and, in turn, overall cost. Accordingly, many construction organizations are interested in evaluating equipment management performance. In current practice, however, evaluation of equipment management is solely based on rates of equipment utilization, with increased utilization suggestive of improved management performance.

Equipment utilization represents slightly different concepts depending on the management level to which it is applied. Utilization at a project level (El-Rayes and Moselhi, 2001; Wang et al., 2004) is based on equipment downtime, which is affected by a variety of factors such as site conditions, operator skills, equipment conditions, and force majeure (Prasad and Park, 2004). Utilization at the corporate level, also known as deployment, assesses the utilization of equipment over its lifetime (Vorster, 2009). This level of management, also known as centralized equipment management, is performed to allocate self-owned mobile equipment across various projects at a corporate level (Mitchell, 1998; Fan et al., 2006). Factors influencing corporate-level equipment utilization include the length of the construction season, economic situation, and ongoing project numbers.

Although an important metric for evaluating equipment management performance, utilization rates do not consider the logistical effort associated with equipment management at a corporate level. Inefficient deployment of equipment between worksites and equipment shops can increase logistics-associated effort, expenditures, and reduce the amount of time equipment is available to work. Methods capable of reliably quantifying logistical effort of equipment management practices, however, remain relatively unexplored. Social network analysis (SNA) is an analysis or investigation method used for examining the interaction or relationship between studied objects. It is a powerful tool to study intra-organizational interactions that is well-suited to study the movement of equipment from project to project or equipment shop using existing company data—a process that is relatively unexplored in equipment management literature. Although useful for determining the number of equipment movements, SNA does not consider the distance of each movement, which is an important factor when assessing logistical performance. To address this limitation, this research has developed a novel decision metric—the direct dispatch index (DDI)—that adds a distance weight to the clustering coefficient of SNA to more comprehensively evaluate the logistical effort associated with equipment management practices. Use of the DDI can enhance the ability of construction companies to more comprehensively and, in turn, more reliably assess equipment management practices and to compare them between various equipment managers or groups within the organization.

The content of this paper is organized as follows: First, previous research on equipment management and applications of SNA in construction are reviewed. Then, the DDI performance metric is formulated, data sources are detailed, data cleaning and fusion are described, and social network theory and characteristics of SNA are introduced. To demonstrate the functionalities of the decision-support metric, a case study is conducted using historical data collected by a large contractor in Alberta, Canada. Potential applications of the DDI and strategies to improve performance are suggested. Research contributions, limitations, and future work are discussed.

LITERATURE REVIEW

Construction Equipment Management

Equipment management is an essential component of a construction business that can affect both project and corporate performance (Samee and Pongpeng, 2016). Over the past decades, construction equipment management has been studied from various perspectives that can be classified into three major topics: (1) equipment costs associated with acquisition, operations, maintenance, and disposal of equipment (Mitchell, 1998; Fan et al., 2008; Bayzid et al., 2016); (2) equipment and fleet management using modern tracking technology (Azar and Kamat 2017); and (3) equipment selection and operation to improve equipment utilization at the project level (Chae and Yoshida, 2010; Alshibani and Moselhi, 2016).

Equipment cost is the most frequently studied amongst all equipment management factors. With the development of data mining technology, recent regression models capable of using historical equipment data to predict equipment maintenance cost at any point in time for any maintenance interval have been developed (Yip et al., 2014; Bayzid et al., 2016). Rather than using internal historical data, equipment residual value analysis is now primarily being performed using auction and re-sale records collected in online databases—a practice that is widely accepted in literature (Lucko, 2003). Recently, advanced heuristic algorithms and spatial cost analysis based on regression models have been further developed (Lucko 2003; Fan et al., 2008; Ponnaluru et al. 2012). In short, these models are used to estimate life-cycle or maintenance costs of equipment, to provide analytical support for determining when equipment should be acquired, and to determine if a make or model is worth being acquired.

Due to the rapid development of tracking technology, recent equipment operation studies have focused on tracking and analyzing equipment data. While systems based on global positioning systems (GPS) developed by equipment manufacturers have been designed to locate individual pieces of heavy equipment and to diagnose their mechanical health (e.g., equipment engine hours, fuel consumption, and geo-location of equipment) in real time, these systems lack in-depth analytical capabilities and are limited by poor accuracy (Azar and Kamat, 2017). Other researchers have focused on coupling tracking technology with other types of technological advances. Taking advantage of pattern recognition technology and algorithms, recent research has investigated the incorporation of non-location data, such as the weight, payload, and pose of the machine, with tracking technology to improve model accuracy (Ibrahim and Moselhi, 2014; Pradhananga and Teizer, 2015).

At the project level, real-time tracking has been used to record the cycle time of equipment and to reduce idle time on large worksites by facilitating fleet management and equipment dispatch for material handling problems, such as concrete delivery (Lu et al. 2007) and earthmoving projects (Song and Eldin, 2012; Alshibani and Moselhi, 2016). Taking advantage of shortest path algorithms in logistics, real-time optimization of transportation routes have been developed to improve earthmoving operations based on GPS on mining worksites (Choi and Nieto, 2011). However, the overwhelming costs associated with achieving real-time data together with the rigidity of simulation and optimization methods have limited the practical application of these methods. Indeed, it remains common practice in construction to examine tracking data weekly or monthly, with analyses being conducted quarterly or annually.

While equipment logistics have been seldom studied or considered in equipment management research, several researchers have contended that consideration of equipment dispatch and transport may enhance decision-making (Fan et al., 2006; Hendi, 2007). Furthermore, in contrast to real-time tracking data, equipment logistics data, which involves recording equipment movements from project to project, can be tracked economically and updated dynamically. In spite of these advantages, methods capable of transforming logistics data into useful information have not yet been reported.

Social Network Analysis

SNA was first introduced into sociology, anthropology, and political science based on knowledge from networks and graph theory. Nodes (i.e., vertices) and edges (i.e., ties) comprise the network structure of SNA, where nodes can represent individuals, groups, or companies and edges can represent relationships, communications, or movements between nodes. Taking advantage of its visualization power, an increasing number of studies are adopting SNA to analytically evaluate social relationships and network characteristics (Zheng et al., 2016). SNA has been applied in construction engineering and project management, and has proven to be a powerful tool for illustrating business relationships and behaviors between construction projects (Borgatti and Foster, 2003; Tortoriello et al., 2012; Hansen et al., 2005). Recently, human mobility using civil infrastructure was studied using geo-social network analysis using mobility data collected from Twitter (Wang and Taylor, 2015).

SNA can be used to investigate network issues in the field of engineering project organization (Chinowsky and Taylor, 2012). Among 63 recent SNA-based papers in construction engineering and management, 15 papers examined intra-organizational relationships and 47 papers examined inter-organizational relationships. Only one paper did not examine intra- or inter-organization relationships, instead using nodes to represent defects rather than individuals or organizations (Zheng et al., 2016). At the inter-organizational level, which comprises the scope of most studies, SNA is often used to evaluate business activities, such as supply chain management and strategic alliances. Many believe that the ability of SNA to conduct multiple-level analysis and integrate quantitative, qualitative, and graphical data represents a unique approach for solving certain project management problems (Pryke, 2012). SNA has been used to study (1) historical data for construction project coalitions, which revealed close relationships between some consultants and contractors (Pryke, 2004), and (2) resource management to investigate business relationships at the inter-organizational level (Sandhu and Helo, 2006).

At the intra-organizational level, SNA can be applied to study the communication problems between key individuals in a complex network that are difficult to investigate using other methods. With the development of virtual design technologies in civil engineering, SNA has been conducted using digital logs generated by Building Information Modeling (BIM) software to visualize collaborations and rank importance of designers (Zhang and Ashuri, 2018). In addition, intra-organizational SNA can demonstrate positive relations between relationships and performance, allowing the efficiency and performance of corporate operations to be evaluated using SNA (Lin and Tan, 2013; Priven and Sacks, 2015).

By failing to provide sufficient detail to improve overall performance intra-organizationally, previous studies have not fully addressed the practical needs of equipment management personnel. The present research is proposing an analytical method designed to generate interpretable information for practitioners to improve intra-organizational equipment management performance *in terms of equipment movement*. Data obtained from a large general contractor has been used to validate and to demonstrate the functionality of the proposed approach, rendering the method ready for implementation.

METHODOLOGY

A data-driven performance measurement method capable of quantitatively and reliably assessing logistical effort associated with equipment deployment is proposed. Workflow of the developed methodology is summarized in Figure 1. Briefly, data collected from equipment tracking and project management systems are first fused and cleaned. Based on the mapped equipment logistics data, a social network model is established using social network theory. To map the management scope of each equipment shop, community structures are detected in the network using the Louvain method (Blondel et al., 2008). Centrality measurements are calculated to identify the importance of shops. The novel DDI performance metric is then used to evaluate the logistical performance of each shop.

Data Input

Equipment logistics, involving equipment dispatch and transport, can be extracted from equipment movement data, especially for heavy mobile equipment such as large excavators. Equipment manufacturers offer subscriptions that allow companies to record the real-time geo-locations of their equipment. Alternatively, self-developed systems, commercial tracking systems, or manual recording practices can be used to obtain real-time equipment location data. An example of equipment tracking data is shown in Table 1.

To connect the geo-locations with internal identifications of projects and shops, project details from the project management system are extracted. Details, such as project internal identifications, project location, and project descriptions, are used to geographically associate each piece of equipment with the equipment tracking data. Data adapters are then used to combine data from these various sources into one centralized dataset, providing richer information for data mining (Ji and AbouRizk 2018).

In this study, the data adapter was designed to extract only the portion of the information contained in the equipment tracking and project management systems that are required for input into the social network model. The data adapter was developed in *R* (R Core Team, 2017), an open-source statistics software program capable of handling large-scale data, which performs several functions including data connection, wrangling, cleaning, and mapping. In this study, the *dplyr* and *tidyr* packages in R, which can process large-sized datasets in relatively little time, were used to perform data wrangling tasks. Output of the data adapter are mapped logistics data, exemplified in Table 2, which detail the location and assigned project for each piece of equipment at any point in time.

Social Network Modeling

The social network model, presented as a weighted network diagram, consists of nodes and edges. In social network studies, nodes are, typically, the individual or group being studied, while edges represent relationships, communications, or behaviors between nodes. In this study, project and equipment shops, where equipment is used, maintained, and stored, are the individuals being studied. Similarly, the movement of equipment can be represented as a communication between a shop and a project, or between two project sites.

As such, nodes represent locations of project jobsites or equipment shops (i.e., storage sites), and edges represent the movement of equipment between sites. In the example outlined in Table 3, equipment shops (e.g., S600016 and S600019) and projects (e.g., PE09190, PE09194, and PE09196) are identified as nodes. The edge (e.g., ID 1), represents the movement of construction equipment between nodes S600016 and PE09190. Weights of edges are often used to denote the strength of the relationship between nodes. Here, the weight, w_{ij}, is defined as the total count of the equipment movements between node i and j, which can be obtained through accumulating each movement associated with individual equipment from historical logistics data. In this example, there are 7 movements along edge 1 between nodes S600016 and PE09190.

Social Network Analysis

A social network model can be used to (1) recognize patterns of relationships, (2) identify the importance of each node through centrality measurements, and (3) detect the community structure in a network as subgroups or subsets (Zhang and Ashuri, 2018). Since shops and projects are usually divided into geographically-distinct groups in practice, the community structure can be detected by modularity to identify the management area of an equipment shop. The centrality of nodes representing the equipment shops can also be measured by either a social network model or a community structure of the social network.

Centrality measurements are used to rank the importance of nodes. Characteristics including degree (i.e., number of edges connected to the node in the network), closeness (i.e., average length of the shortest path between the node and all other nodes), betweenness (i.e., number of times that a node is on the shortest path between two other nodes in the network), and clustering coefficients (i.e., degree to which nodes in a social network tend to cluster together) are well-defined in SNA to quantitatively evaluate the centrality of a node. In an undirected graph, the local clustering coefficient can be calculated using Eq. 1, which ranges from 0 to 1.

$$C_i = \frac{2e_i}{k_i(k_i-1)} \quad (1)$$

Where k_i is the number of neighbours of the ith node, and e_i is the number of connections between these neighbours.

Long-distance transport of equipment across states or provinces is a costly endeavor. Consequently, equipment management is usually divided geographically and assigned to equipment shops instead of managing the equipment at a corporate level. Each equipment shop manages the equipment in a certain region, with management scope including planning, dispatch, maintenance, and repair. Accordingly, equipment movements within management regions often account for a substantial portion of the data, with a few equipment movements occurring from region to region to fulfill the urgent needs of projects. To investigate the performance of each shop, regions managed by each shop must be identified.

Modularity, which aims to divide networks into smaller groups and detect community structures within a network, can be used to identify the management region of each shop. Following the application of modularity techniques, the nodes in a community are more densely connected with each other that the rest of the network. Among the proposed modularity algorithms, the Louvain method, essentially a greedy optimization method, is the most popular due to its ability to outperform similar methods in terms of modularity and speed (Blondel et al. 2008). In each iteration of the Louvain method, the nodes are first grouped into small communities based on the value ΔQ as shown in Eq. 2.

$$\Delta Q = \left[\frac{\Sigma_{in}+k_{i,in}}{2m} - \left(\frac{\Sigma_{tot}+k_i}{2m}\right)^2\right] - \left[\frac{\Sigma_{in}}{2m} - \left(\frac{\Sigma_{tot}}{2m}\right)^2 - \left(\frac{\Sigma_{tot}}{2m}\right)^2\right] \quad (2)$$

Where $\sum_{in}$ is the sum of the weights of the links inside C, $\sum_{tot}$ is the sum of the weights of the links incident to nodes in C, k_i is the sum of the weights of the links incident to node i, $k_{i,in}$ is the sum of the weights of the links from i to nodes in C, and m is the sum of the weights of all of the links in the network.

Nodes in the communities then become the nodes, and the optimization method is again applied to the new network. Through iterations, modularity results are achieved, and tight relationships between projects and shops within the community structures of the network emerge. From this, the management scopes of shops are easily identified.

Direct Distance Index Performance Metric

Equipment dispatch in real practice must be investigated and divided into two strategies: (1) equipment that can be dispatched from the equipment shop or (2) equipment that can be dispatched from another project when the locations of two projects are close. Other than when equipment must be sent back to equipment shops for repairs or rebuilds, equipment should be dispatched from one project to another. Direct dispatch of equipment from project to project can not only reduce the logistical effort but may also reduce equipment travel time and, in turn, increase long-term equipment utilization.

Notably, clustering coefficients can be used to evaluate dispatch strategies by quantifying the number of times that equipment is dispatched from projects as a ratio of the number of dispatches from shops. For nodes representing shops, the numerator of the clustering coefficient (i.e., e_i) refers to the number of equipment movements from project to project. Clustering coefficients are currently limited by their inability to consider the impact of distance on project performance (i.e., cost and time). While the number of movements (as calculated by clustering coefficients) is significant, it is also important to consider distances associated with each movement. As such, to overcome the limitation of clustering coefficient, a second weight, distance, is introduced to achieve the DDI. The DDI is, therefore, designed to quantify the reduction in the distance that equipment must travel to reach its destination. Here, the distances between nodes in kilometers, d_{ij}, are the distances that must be driven to transport equipment from one location to another given the geo-locations of the nodes for both shops and projects. In this study, driving distances are determined using navigation tools from transportation routes; algorithms to determine distances are not applied. *DDI*, which considers both the number of equipment movements, w_{ij}, and the logistical distances, d_{ij}, can be calculated using Eq. 3 and 4.

$$d_{ij}^{*} = d_{is} + d_{sj} \tag{3}$$

$$DDI = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}(d_{ij}^{*} - d_{ij}) \times w_{ij}}{\sum_{i=1}^{n}\sum_{j=1}^{n} d_{ij}^{*} \times w_{ij}} \tag{4}$$

Where d_{ij} is the distance from node i to node j, d_{ij}^{*} is the distance from node i to node j through shop S, and w_{ij} is the total count of equipment movements between node i to node j.

The index ranges from 0 to 1, with a greater value indicating improved dispatch efficiency. When the index is 0, equipment is inefficiently dispatched from equipment shops to projects, and when the index is 1, all equipment is efficiently dispatched from project to project.

ILLUSTRATIVE EXAMPLE

This example compares two dispatch plans, which are illustrated as social network models in Figures 2 and 3. Both social network models include a shop, four projects that are represented by five nodes, with five pieces of equipment travelling from location to location. Shop and project locations, and, consequently, the distance between nodes (i.e., d_{ij}), are the same in both models. However, because equipment dispatch plans vary between the models, the number of equipment movements (i.e., w_{ij}) differs. Data are summarized in Tables 4 and 5.

As per Eq. 2, clustering coefficients are calculated for Models A and B as 0 (=0/6) and 0.5 (=3/6), respectively. While there are a maximum of 6 edges between nodes 1, 2, 3, and 4, there are 0 edges in Model A and 3 edges in Model B. Using Eq. 3 and Eq. 4, *DDI* are calculated as 0 (=0/400) and 0.7125 (=19×5/400+19×5/400+19×5/400=285/400) for Models A and B, respectively. Note that denominators of both *DDI* ($\sum_{i=1}^{n} d_{ij}^{*} \times w_{ij}$) are the same (i.e., 400). For Model A, both the clustering coefficient and *DDI* of node *S* are 0. For Model B, the clustering coefficient of node *S* is 0.5, and the direct dispatch index is 0.7125. A greater *DDI* indicates that fewer detours comprise the dispatch plan outlined in Model B compared to that in Model A, consistent with illustrations in Figures 2 and 3.

As the number of projects managed by the shop increases, the difference between the clustering coefficient and DDI will increase. An extreme case, demonstrated in Figure 4, is illustrated. Here, the same dispatch plan in Model B is used to sequentially complete *N* projects in the same location that are managed by one shop. In this case, the clustering coefficient is 2/*N*, which approaches 0 when *N* is large. In contrast, however, the *DDI* remains close to 1. Altogether, these results demonstrate that dispatch efficiency can be reliably evaluated regardless of project number when using the DDI metric.

CASE STUDY

The proposed methodology was applied to a case study. Historical data were collected from a construction contractor in Alberta, Canada, between 2013 and 2016. Equipment data were extracted from the internal equipment management system, *SAP ERP* (SAP SE, 2018), and project data were collected from a self-developed project management system. Data from both systems were combined, and missing data were omitted using *R* (R Core Team, 2017).

Following the application of the proposed methodology, the social network model, based on the historical data, is demonstrated in Figure 5. Note that all edges are bidirectional. Here, nodes denote project sites or equipment shops, the sizes of the nodes their degree, and the thicknesses of the edges are determined by the number of equipment movements (i.e., w_{ij}).

The social network model is comprised of 297 nodes including 7 equipment shops and 290 projects. Based on the Louvain method, four communities (i.e., management areas) are detected and marked as orange (Shop 1), green (Shop 6/3), blue (Shop 5), and purple (Shop 7, 4, and 2) in Figure 5. In two communities, orange and blue, only one equipment shop was determined to be managing projects in that region. In the other two communities, green and purple, multiple shops were found to be responsible for the projects. One possible explanation is that small shops did not have sufficient equipment to supply projects, thereby requiring assistance from larger shops. In this case study, the resolution value of the Louvain method applied was 1; adjusting this value will affect the number of communities that are detected with the numbers of communities detected increasing as the resolution value increases.

The five nodes representing five major shops are listed in Table 6 in order of degree (i.e., number of projects connected with the shop in the network). After dividing the network into communities, closeness, betweeness, the clustering coefficient, and DDI were calculated for each node (Table 6). The DDI was calculated based on four years' worth of data, which were used to evaluate the overall dispatch performance during this time.

The proposed methodology was then applied to each of the four years. Results of the five shops are illustrated in Figure 6, with the dashed line indicating the average value for each year.

Given the DDI, equipment management performance of the shops were evaluated and ranked, with a greater DDI indicative of a greater dispatch efficiency. Annual DDI of each shop were compared with the average four-year value. For example, the DDI for Shop 1 in 2016 was 0.212, which is above average for the five shops that year. However, its performance in 2016 was lower than that in 2015, which may require additional investigation. Performances of various equipment shops were also compared with each other.

Equipment Utilization Rate

As mentioned previously, equipment utilization is the primary metric by which equipment management performance is evaluated. It is generally accepted that high equipment utilization rates indicate efficient use of equipment. At a corporate level, equipment utilization, also known as deployment (Vorster, 2009), can be defined by Eq. 5.

$$Equipment\ Utilization = \frac{Used\ Time}{Total\ Ownership\ Time} \tag{5}$$

Where *Total Ownership Time* is the time (in days or hours) that equipment has been owned by the corporation and *Used Time* is the time (in days or hours) that equipment is allocated to a project, regardless of its operation on the jobsite.

For comparative purposes, annual equipment utilizations for the five major shops are illustrated in Figure 7, with the dashed line indicating the average value for each year.

Investigation of both metrics simultaneously can reveal further insight into the equipment management practices of each shop. While Shop 1 would have been considered average in terms of equipment utilization in 2016, its logistical performance was above average. Conversely, while Shop 2 is close to average with respect to its utilization rate in 2016, it is considerably below average with respect to logistical performance. Consideration of both factors reveals that, although these two shops share a similar utilization rate, Shop 1's equipment management performance exceeds that of Shop 2.

To ensure the proposed performance metric is capable of reliably evaluating practical logistical performance, expert validation was conducted. Three equipment managers, each with more than ten years of working experience, were invited to evaluate the functionalities of the proposed metric and calculation methodology based on their own professional experience and knowledge. All three subject matter experts indicated that the metrics was aligned with the needs of the industry in Western Canada, which is interested in the development of more comprehensive quantitative methods for assessing logistical performance to reduce wasteful practices and improve overall project outcomes.

POTENTIAL APPLICATIONS

Lack of reliable, comprehensive performance measurements renders the improvement of equipment management challenging in practice. The proposed DDI performance metric is designed to quantitatively evaluate the logistical performance of equipment shops and to provide analytical decision-support to equipment managers and executives of construction companies. Potential applications of the proposed performance metrics include: (1) benchmarking equipment management, (2) logistics-oriented equipment management, and (3) resource management.

Benchmarking Equipment Management

Following the implementation of the proposed methodology, executives will be able to determine which equipment shops are most proficient in equipment logistics. Managers of these equipment shops should be invited to share their professional knowledge for employee training purposes, particularly in the area of equipment dispatch. Companies may also standardize the equipment management process as per the high-performance equipment shops' dispatching strategies. Sharing best practices company-wide is essential for improving overall equipment management.

Logistics-oriented Equipment Management

The DDI emphasizes the importance of considering equipment logistics in equipment management. Currently, logistical costs are not deliberately considered in equipment dispatch and transport. Examination of current practices using the proposed analytical method (or the development of an optimization method) can be used to design equipment dispatch plans that minimize logistical costs while maximizing utilization rates. Logistics-oriented equipment management offers companies the potential to improve long-term equipment management efficiency.

Resource Management

As a major resource in construction, it is anticipated that the proposed methodology can be generalized to other resource-based logistical problems. Social network theory and analysis can be easily generalized and embedded into the current material or labour management systems to visualize dynamic data and facilitate performance evaluation. Poor resource logistics can be identified and mitigated in a timely manner.

CONCLUSION AND FUTURE WORK

Previous research has not yet addressed how to make use of equipment logistics data collected from equipment and project management systems to enhance decision-making. This research proposes the use of a social network analysis-based approach, commonly applied in sociology, to facilitate the visualization of equipment logistics and investigation of logistical performance. A dispatch distance-based performance metric, which can be used in conjunction with other metrics such as the equipment utilization to evaluate the performance of intra-organizational equipment management, is also proposed. The ability of the DDI metric to quantify the distance savings of various dispatch plans was demonstrated in the illustrated example provided, and the functionality of the proposed approach was confirmed following its application to a practical case study. When examined in conjunction with equipment utilization rates, the social network analysis-based method together with the DDI index can be used to more comprehensively examine equipment management practices.

Efficiency of equipment dispatch plans varies considerably between shops and organizations. It is possible to improve equipment management through benchmarking of the new performance metric. In addition, best practices identified using the proposed method can be shared within the company or even between companies to improve the time and cost-effectiveness of equipment dispatch. Research deliverables are anticipated to be of immediate use in practice and to satisfy the needs of large contractors that are eager to more comprehensively evaluate equipment management performance. Furthermore, the SNA-based approach described here can be generalized to identify and solve problems of other logistics-associated resources, such as labor and material.

To further support decision-making for equipment management and to facilitate the implementation of the quantitative, integrative methodology into real practice, further improvements of this research will be required:

1) The relationship between equipment utilization and the DDI may be further studied. Equipment utilization is primarily affected by the length of the construction season, ongoing

project numbers, and economic conditions, which may not impact the DDI. In short, after collecting sufficient time series of both performance metrics, a serial correlation analysis can, and should, be conducted.

2) In this study, it is assumed that logistical costs are primarily determined by distance. However, the logistical costs may also be affected by the size of equipment, the remoteness of project locations, and the permit fee of certain routes. The replacement of the second weight in the DDI with these logistical costs may serve as a method for rapidly estimating cost savings associated with various equipment dispatch plans in contrast to the very time-consuming process of obtaining multiple quotations from equipment transportation companies.
3) Other than optimizing equipment logistics, equipment dispatch may also be improved by adjusting the management region of equipment shops and the quantity of self-owned equipment. Notably, the proposed performance metric can quantitatively evaluate the dispatch efficiency after these improvements. However, the impact of such improvement strategies on the performance metric should be studied and an appropriate sensitivity analysis should be conducted in future research work.

DATA AVAILABILITY STATEMENT

Data analyzed during the study were provided by a third party. Requests for data should be directed to the provider indicated in the Acknowledgements.

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LIST OF FIGURES

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TABLES

Table 1. Sample of Equipment Tracking Data

Equipment ID	Description	Location	Start Date	End Date	Utilization
10005217	Excavator	S600016	5/1/2013	5/31/2013	0.00
10005218	Excavator	PE12110	5/1/2013	5/31/2013	0.82
10005231	Excavator	PE11077	5/1/2013	5/31/2013	0.76

Table 2. Sample of Mapped Equipment Logistics Data

Date	Equipment ID	Departure	Departure Location	Arrival	Arrival Location
5/13/2013	10005237	S600016	City A	PE13008	City B
5/15/2013	10013234	S600002	City C	S600016	City A
5/18/2013	10016007	PE11077	City D	PE11079	City E

Table 3. Example of Logistics Data for Modeling the Social Network

Edge ID	Node *i*	Node *j*	Weight
1	S600016	PE09190	7
2	PE09196	PE09190	3
3	S600019	PE09190	1
4	S600016	PE09194	3
5	PE09190	PE09194	1
6	PE09196	PE09194	3

Table 4. Edge Data in Social Network Model A

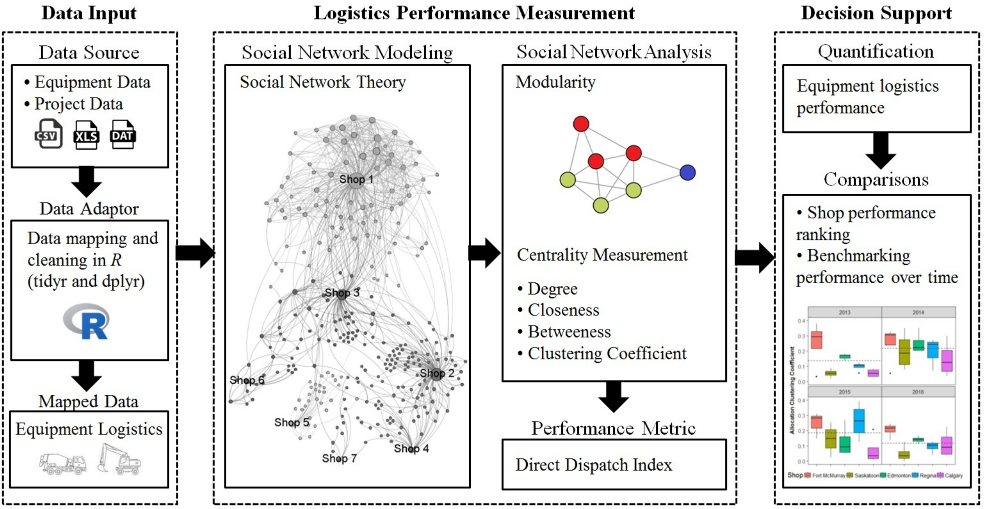
Edge ID	Node *i*	Node *j*	w_{ij}	d_{ij}
1	S	1	10	10
2	S	2	10	10
3	S	3	10	10
4	S	4	10	10
5	1	2	0	1
6	2	3	0	1
7	3	4	0	1

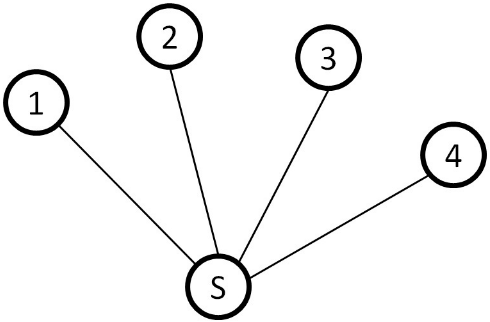
Table 5. Edge Data in Social Network Model B

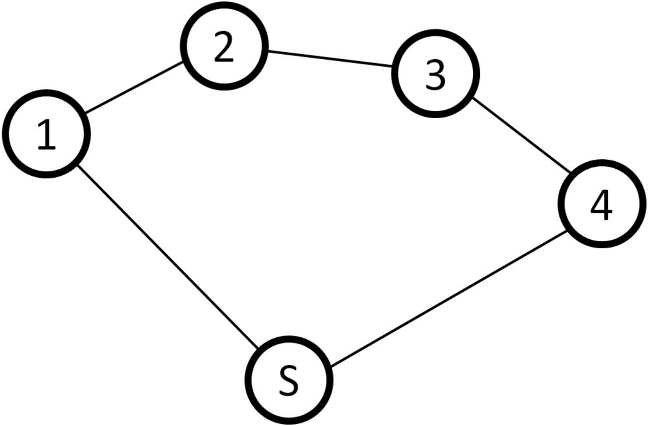
Edge ID	Node *i*	Node *j*	w_{ij}	d_{ij}
1	S	1	5	10
2	S	2	0	10
3	S	3	0	10
4	S	4	5	10
5	1	2	5	1
6	2	3	5	1
7	3	4	5	1

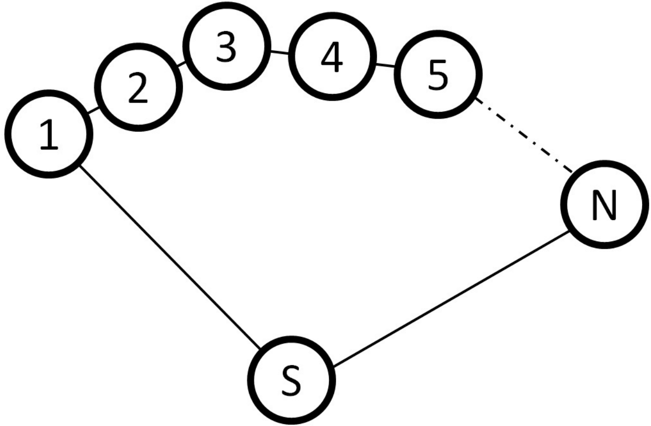
Table 6. Logistical Data of Each Shop for Four Years

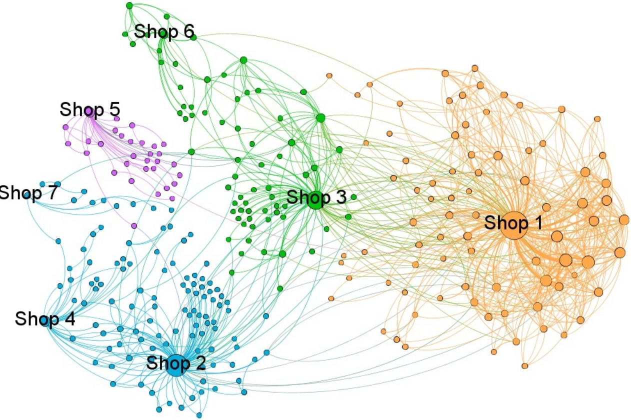
Node ID	Description	Degree	Closeness	Betweenness	Clustering Coefficient	DDI
S001	Shop 1	130	0.482	12193	0.118	0.254
S002	Shop 2	96	0.492	20678	0.016	0.066
S003	Shop 3	76	0.485	15222	0.038	0.155
S004	Shop 4	31	0.375	5305	0.035	0.107
S005	Shop 5	25	0.339	8152	0.012	0.038


Data Input
Logistics Performance Measurement
Decision Support
Data Source
• Equipment Data
• Project Data
CSV
XLS
DAT
Data Adaptor
Data mapping and cleaning in R (tidyr and dplyr)
R
Mapped Data
Equipment Logistics
Social Network Modeling
Social Network Theory
Shop 1
Shop 3
Shop 2
Shop 6
Shop 5
Shop 7
Shop 4
Social Network Analysis
Modularity
Centrality Measurement
• Degree
• Closeness
• Betweeness
• Clustering Coefficient
Performance Metric
Direct Dispatch Index
Quantification
Equipment logistics performance
Comparisons
• Shop performance ranking
• Benchmarking performance over time
2013
2014
2015
2016
Allocation Clustering Coefficient
Shop
Fort McMurray
Saskatoon
Edmonton
Regina
Calgary

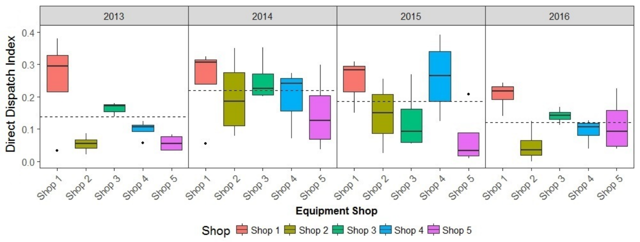

1
2
3
4
S


2
3
1
4
S

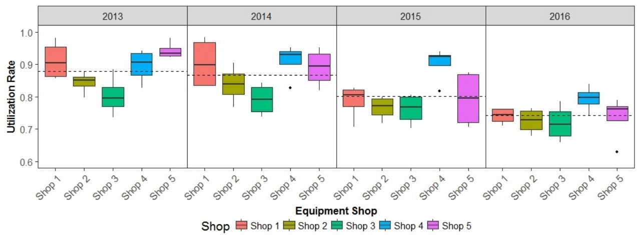

1
2
3
4
5
N
S



Shop 6
Shop 5
Shop 7
Shop 3
Shop 1
Shop 4
Shop 2



2013
2014
2015
2016
Direct Dispatch Index
0.0
0.1
0.2
0.3
0.4
Shop 1
Shop 2
Shop 3
Shop 4
Shop 5
Equipment Shop
Shop
Shop 1
Shop 2
Shop 3
Shop 4
Shop 5


2013
2014
2015
2016
Utilization Rate
1.0
0.9
0.8
0.7
0.6
Shop 1
Shop 2
Shop 3
Shop 4
Shop 5
Equipment Shop
Shop
Shop 1
Shop 2
Shop 3
Shop 4
Shop 5