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STUDY ON THE DYNAMIC SAFETY RISK OF STRUCK-BY-EQUIPMENT HAZARD: RISK ANALYSIS, PREDICTION AND SAFETY PERFORMANCE EVALUATION

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Abstract: Having a system that can proactively identify risks on sites is the key to the success of hazard identification and prevention in the dynamic and hazardous construction environment. Safety performance evaluation also is a primary means to enhance construction safety. Leading indicators are aspects reflecting safe practices or observations that can be used to strengthen safety performance prior to the occurrence of an undesirable consequence. Thus this paper employs a network-based model and a probabilistic method with two safety leading indicators to investigate the dynamic struck-by-equipment risk. In the network-based model, entities' dynamics and the interactions among them are monitored, quantified, and analyzed to identify risk and their risk-related behaviors. Degree centrality and algebraic connectivity are employed as the leading indicators to measure the struck-by-equipment risk at the entity and network levels. Meanwhile, a probabilistic method with Monte Carlo simulation is applied to predict the risk at the two levels. Thus, real-time, posterior, and prospective safety performance evaluation can be conducted. The implementation and assessment of the network-based model and the probabilistic method for risk analysis, prediction and safety performance evaluation were conducted by using two simulated examples. The safety performance of entities (i.e., workers-on-foot and equipment) and job sites pertinent to struck-by-equipment hazard was evaluated. Accordingly, safety managers can gain a full understanding of workforce behaviors and job sites in terms of safety, to proactively eliminate unsafe actions and practices. The results also provide insight into the development of safety training strategies and programs.

1 Introduction

Construction remains a high-risk industry for occupational health and safety. A leading cause of construction injuries and fatalities is the struck-by-equipment hazard (workers-on-foot struck by equipment or equipment struck by equipment). The occurrence of a hazard is the consequence of mutual interactions of multiple risk factors. The vulnerability of workforce can be described as a combination of individual and workplace factors, such as lack of situational awareness, that increase the risk of struck-by-equipment hazards. Thus having a system that can proactively identify risks on sites is the key to the success of hazard identification and prevention in the dynamic and hazardous construction environment. Extensive attention has been paid on developing methods or systems for the detection and identification of struck-by-equipment hazards in construction, such as the proximity detection systems using RFID, Bluetooth, Radar and other technologies (Choe et al. 2014, Wang and Razavi 2015). However, most of the existing studies investigated the interactions (e.g., proximity) between each paired entities and placed a major emphasis on detecting hazards for such paired entities, while the overall dynamic interrelationships and interactions in the system were not considered and the risk level of the job site (i.e., the network level) was not investigated. This paper aims to investigate the struck-by-equipment risk for each entity (i.e., the entity level) by considering all the interactions undertaken by the entity with others around it, as well as the risk for the entire job site (i.e., the network level). Thus this paper takes a step forward by integrating all of the entities on the job site into a connected network as a system in which the dynamic interrelationships and interactions among all entities are not overlooked. Furthermore, the current studies on struck-by-equipment risk are more focused on real-time hazard detection, while or shortly before the occurrence of hazards (Andolfo and Sadeghpour 2015). Therefore, the prediction of struck-by-equipment risk needs to be studied further for timely and proactive responses to the upcoming hazards.

Safety performance evaluation also is a primary means to enhance construction safety. Workplace safety performance is measured using two major categories of indicators, i.e., lagging and leading indicators. The safety performance of a complex and dynamic construction environment cannot be represented accordingly with lagging indicators which fail to provide enough insight or information for proactive hazard prevention (Salas and Hallowell 2016). In addition, the potential severity of an outcome cannot be revealed by lagging indicators. On the other hand, leading indicators are aspects reflecting safe practices or observations that can be used to strengthen safety performance prior to the occurrence of an undesirable consequence. The insight and information gained from leading indicators have significant potentials to impact safety performance. As thus, exploration and development of safety leading indicators are a promising approach to proactively perceive and represent safety risks in the continuously changing site circumstances.

As the needs identified in the literature, this paper studies the dynamic struck-by-equipment risk using a network-based model with two safety leading indicators (i.e., algebraic connectivity and degree centrality). The risk at both network and entity levels are evaluated. Entities' predicted kinematics are also taken into consideration in the network-based model for risk analysis. On the basis of the network-based model, a probabilistic method with Monte Carlo simulation is adopted to predict the risk at the two levels. Furthermore, the safety performance of entities as well as job sites pertinent to the struck-by-equipment hazard is evaluated. As such, safety managers can gain a full understanding of unsafe workforce behaviors and job sites' safety, to proactively eliminate unsafe actions and practices. The evaluation also provides valuable insight into the development of safety training strategies and programs. In this paper, two simulated examples are used to elaborate the network-based model and the probabilistic method for struck-by-equipment risk analysis, prediction, and the safety performance evaluation. Finally, discussion and concluding remarks are summarized.

2 Methodology

The network-based model and the probabilistic method are illustrated in Figure 1 and explained in detail in the following sections. The network-based model, including four major steps, is capable of analyzing the struck-by-equipment risk at both entity and network levels. The entity-level analysis using the degree centrality evaluates the risk level of individual entities with respect to the struck-by-equipment hazard on the site. The network-level analysis using the algebraic connectivity investigates the overall risk level of the entire job site regarding the struck-by-equipment hazard. Consequently, the safety performance of both entities (i.e., workers-on-foot and equipment) and job sites can be evaluated.

Using the state information (position, velocity, and orientation) monitored at the current moment (i.e., time *t*), the probabilistic method adopts normal distributions and applies Monte Carlo simulation to estimate entities' state information at time *t+1* and in this way, the risk at the network and entity levels can be predicted.

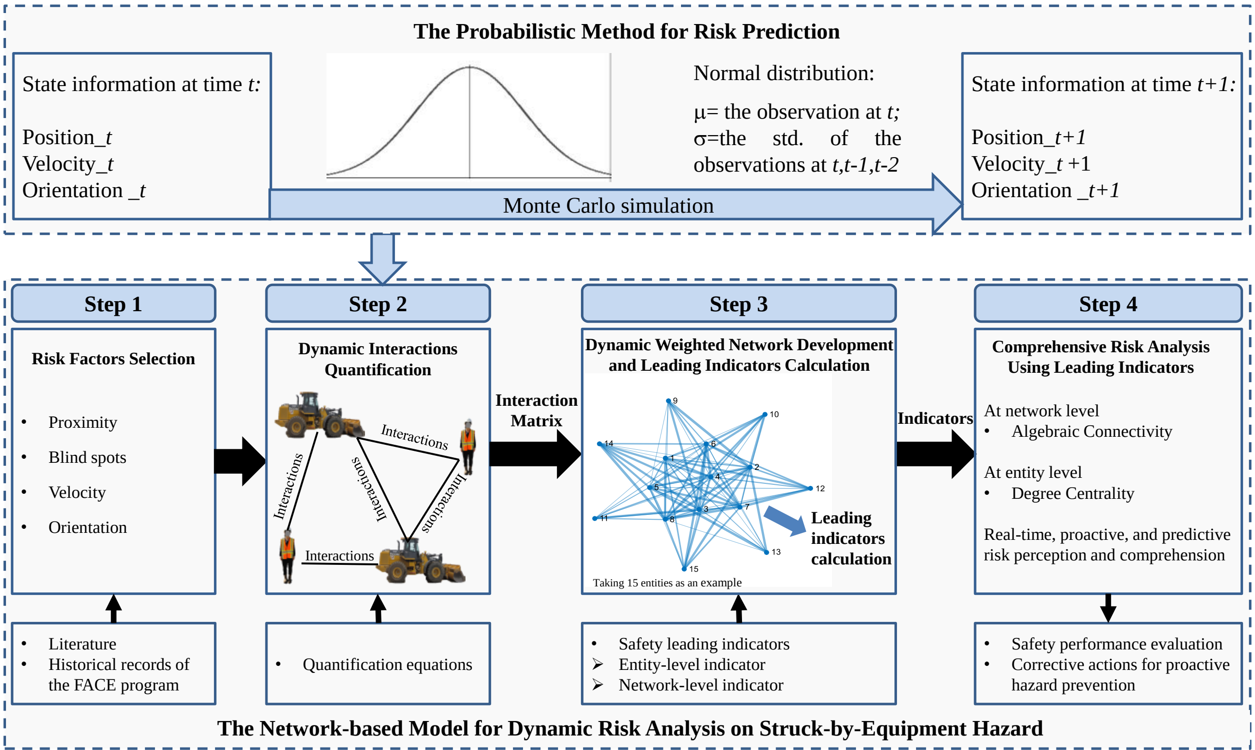


Figure 1: Illustration of the network-based model and the probabilistic method

2.1 A Network-based Model for Dynamic Safety Risk Analysis on Struck-by-Equipment Hazard

The occurrence of a hazard is the result of the mutual interactions of multiple risk factors. Thus the network-based model evaluates the struck-by-equipment risk by quantifying and analyzing the dynamic interactions among site entities. Site entities and the quantified interactions among them are conceptualized and modeled as a weighted network. In this way, the problem of safety risk analysis is converted into the analysis of weighted network. Based on the generated network, the safety leading indicators (i.e. degree centrality and algebraic connectivity) can be computed and used for comprehensive safety risk analysis. The degree centrality, an entity-level indicator, signifies node centrality and strength in the network and is denoted by degree score for the corresponding node (Opsahl et al. 2010). In the context of safety risk analysis, degree centrality is adopted to indicate the risk level of individual entities. The nodes with relative higher degree centrality imply that the corresponding entities have a higher probability of causing a hazard. The algebraic connectivity is a network-level indicator to represent the overall risk level of a construction site, by investigating how well the generated network is connected and interacted (Wei et al. 2014). The more intensive and extensive connections in the network are, the higher the overall risk (i.e., the algebraic connectivity) of a job site is. The included four steps are explained below.

2.1.1 Step 1: Risk Factors Selection

Four major risk factors causing struck-by-equipment hazards, including proximity, velocity, blind spots, and orientation, were selected from the historical reports of the FACE program and the literature (Golovina et al. 2016, NIOSH 2016, Teizer et al. 2010). The four risk factors were selected to quantify the interactions between entities from different aspects.

2.1.2 Step 2: Dynamic Interactions Quantification

The dynamic interactions between each paired entities associated with the selected risk factors are quantified over time by monitoring entities' real-time states, including position, velocity, and orientation. The interaction of each risk factor is quantified by considering two parameters, i.e., weight of the factor and severity (Golovina et al. 2016). The weight of each factor represents the significance of the factor compared with other risk factors in causing a collision (Wang and Razavi 2017). At the current stage of this study, the weight of each selected factor was quantified and determined by using the 118 historical struck-by-equipment accident reports extracted from the FACE program (NIOSH 2016).

Entities' states are assumed being monitored in real time, thus the severity of a factor is quantified based on the real-time detected state of that factor. In addition, entities' future motion characteristics are also considered in the interactions quantification. The severity of proximity factor is quantified by measuring two distances: (i) the actual distance between entities, and (ii) the required distance that the involved entities need to come to a complete stop upon realizing a hazard. The severity of velocity is quantified by measuring the magnitude of the relative velocity between two entities and comparing the measured magnitude with its allowance, if the two entities have already been identified as getting closer to each other at the moment (Wang and Razavi 2015). The severity of blind spots is quantified by using the severity of the region relative to equipment that the entity is located in, only if the entity has been identified within the equipment blind spots. The severity of each region around equipment was determined from the 118 historical accident reports. The severity of orientation is quantified based on the severity of the identified region around equipment that the entity will be located in, if the entities have been identified as getting closer to each other at the moment. For each selected factor, the production of the weight and the real-time quantified severity is adopted as the interaction of the factor. The sum of the interactions of all factors is considered as the final interactions between entities (Wang and Razavi 2017).

2.1.3 Step 3: Dynamic Weighted Network Development and Leading Indicators Calculation

Site entities and the quantified interactions among them are modeled as an undirected weighted network. In the generated network, each entity is represented as a node and the interactions between each pair of entities are presented as a link between those two. The intensity of the quantified interactions between two entities is the weight of the corresponding link. Afterward, entities' degree centrality scores and the job site's algebraic connectivity are calculated based on the generated network (Wang and Razavi 2017). In this paper, to more accurately symbolize the weights distribution in a weighted network, an improved method of calculating the degree centrality is adopted which considers both the number of links that a node has to other nodes and their weights (Opsahl et al. 2010).

2.1.4 Step 4: Comprehensive Risk Analysis Using Leading Indicators

The risk levels of entities and job sites can be assessed in real time. A threshold can be set for degree centrality and algebraic connectivity respectively. The entities with degree centrality higher than the threshold which indicates they have a high risk of causing hazards can be identified. An obtained algebraic connectivity score higher than the threshold indicates that the situation presented on the job site has a high possibility to have struck-by-equipment hazards. Thus attention can be paid and corrective actions can be applied to the entities with high degree centrality.

The risk levels of entities and job sites over time can be recorded and in this way, their safety performance can be evaluated. The entities that exhibited more risk-prone actions during a given period can be identified. Specialized and proactive safety training can be provided for the identified entities. Job sites also can be ranked with respect to the struck-by-equipment risk and the ones with lower algebraic connectivity scores can be identified and rewarded. The job site planning and practices in maintaining a safer environment that implemented on the identified job sites are worth being promoted.

2.2 A Probabilistic Method for Risk Prediction

On the basis of the network-based model, this paper develops and uses a probabilistic method to predict the risk at the entity and network levels. As explained earlier, entities' state information including position, velocity, and orientation is collected and used in the network-based model for safety risk analysis. Therefore, the risk is predicted through estimating the state information in a probabilistic manner.

The primary idea of the probabilistic method is computing and predicting each piece of state information (i.e., position, velocity, and orientation) at the next moment (i.e., time *t+1*) using a normal distribution which is created based on the corresponding state information observed at time *t, t-1, t-2.* The mean of the normal distribution is the real observation at the current moment (i.e., time *t*) (Zhang et al. 2017) and its standard deviation is the standard deviation of the observations at time *t, t-1, t-2.* For example, the orientation at the next moment *t+1* is obtained from a normal distribution in which the mean is the orientation observed at the current moment *t* and the standard deviation is the standard deviation of the observed orientations at *t, t-1, t-2* (Andolfo and Sadeghpour 2015). The Monte Carlo simulation is applied to generate the state information which is input to the network-based model. Compared with the existing state estimation methods, e.g., Kalman Filter, this paper adopts the probabilistic method as this method (i) only relies on the real observations and does not involve the assessment of noises (Zhu et al. 2016); and (ii) outputs the risk at the two levels with uncertainty.

3 Risk Analysis, Prediction and Safety Performance Evaluation

Using two examples of simulated job sites with moving entities, this section describes the implementation and evaluation of the network-based model and the probabilistic method for struck-by-equipment risk analysis, prediction, and safety performance evaluation.

3.1 Two Simulated Examples

Two examples were simulated using the Autodesk Softimage. Each example included 1400 frames and had six dump trucks and six workers-on-foot with multiple types of motion characteristics, such as line and curve trajectories, dynamic velocity, backing up equipment and others, as summarized in Table 1. The total numbers of collisions and near misses over the 1400 frames are used to preliminarily represent the risk level for each job site. Entities' motions were designed to make the two job sites' collisions and near misses greatly differed from each other (Table 1).

Table 1: A summary of the two simulated examples

Characteristics	Example 1	Example 2
Backing up equipment	One piece of equipment	No backing up equipment
Trajectories	Lines and curves	Lines and curves
Entities' moving area on the job site	Constrained area	The entire site
The number of near misses*	769	0
The number of collisions*	3734	0

* A near miss is defined when the distance between entities is between 0.5 and 1.5 meters;
* A collision is defined when the distance between entities is smaller than 0.5 meters.

3.2 Results Analysis

3.2.1 Safety Performance Evaluation

The safety performance of entities as well as the entire job sites over the first 1350 frames is evaluated with respect to the struck-by-equipment hazard. Using the network-based model, the degree centrality of each entity at each frame was calculated. As such, the identified entity with the highest degree centrality at each frame represented the entity at the highest risk. For instance, the Figure 2(a) presents the identified entities that had the highest degree centrality at each frame in the simulated example 1. It can be found that the entity 3 had the most frames with relatively higher probability of causing hazards, followed by the entity 6.

Furthermore, the evolution of an entity's degree centrality ranking among all entities can be tracked and recorded. For example, the degree centrality ranking of the entity 6 over the 1350 frames is shown in Figure 2(b). The 12 in the y axis means the entity has the highest degree centrality compared with other entities at that frame. In this way, the time periods that an entity undertook relatively higher degree centrality scores can be identified. Based on the evaluation of entities' safety performance, specialized and proactive safety training can be provided for specific entities.

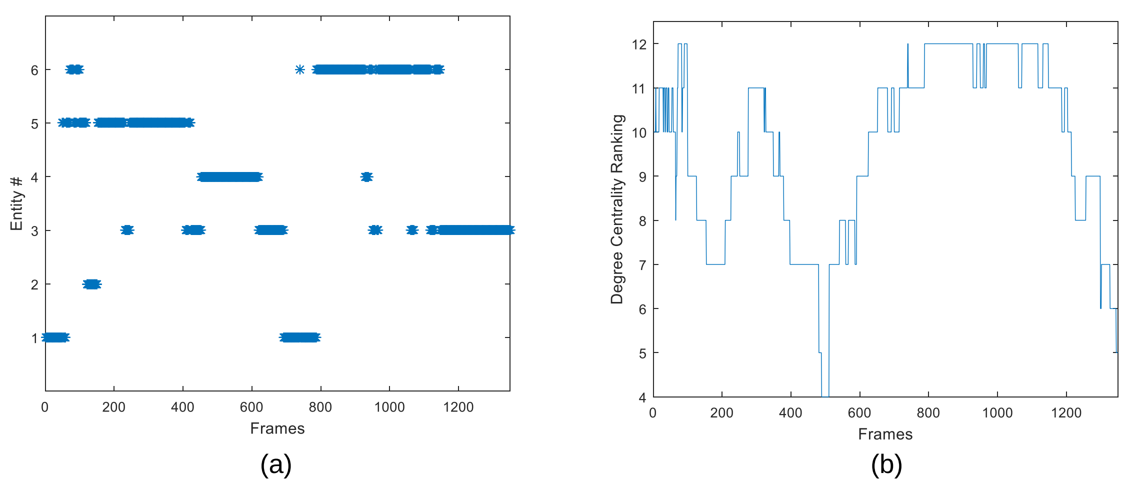
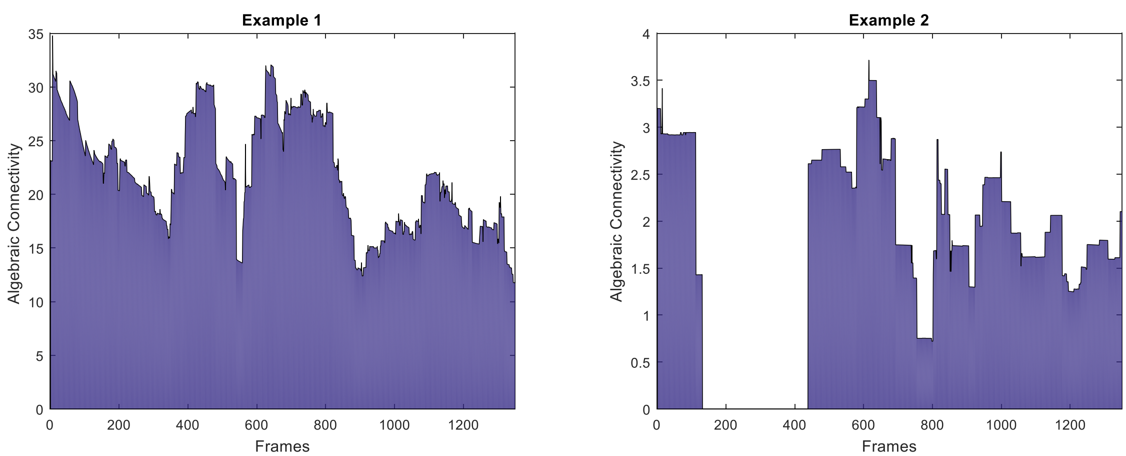


Figure 2: (a) The identified entity at each frame and (b) the degree centrality ranking of the entity 6

Also, the algebraic connectivity of each frame over the first 1350 frames for the two examples was calculated to identify the network level risk, as shown in Figure 3. In overall, job sites can be evaluated with respect to the struck-by-equipment risk and the ones with a better performance can be identified and rewarded. The obtained results indicate that the simulated example 2 had the much lower algebraic connectivity scores which also is consistent with the truth or the numbers of collisions and near misses simulated in the two examples. The site planning and practices in maintaining a safer environment on job site 2 are worth being promoted.

In addition, through evaluating the safety performance at the entity and network levels, the thresholds for the degree centrality and algebraic connectivity can be preliminarily determined. For the degree centrality, a threshold of 15 and 9 is preliminarily determined and adopted for equipment and workers-on-foot, respectively. For the algebraic connectivity, its threshold is set as 18. The determined thresholds will support and be used in the subsequent risk analysis at the two levels. The 15 and 9 were preliminarily used as the thresholds of degree centrality in this paper as the entities presented the high potential of having collisions in the simulated frames if their degree centrality scores became higher than the determined values. The 18 was adopted for the algebraic connectivity as when the algebraic connectivity of the situation presented on the job site turned out to be larger than 18, the situation showed the high potential of occurrence of collisions, with entities gathering and locating close to each other on the site. More statistical analysis will be conducted in the future to explore and determine more robust thresholds for the leading indicators.



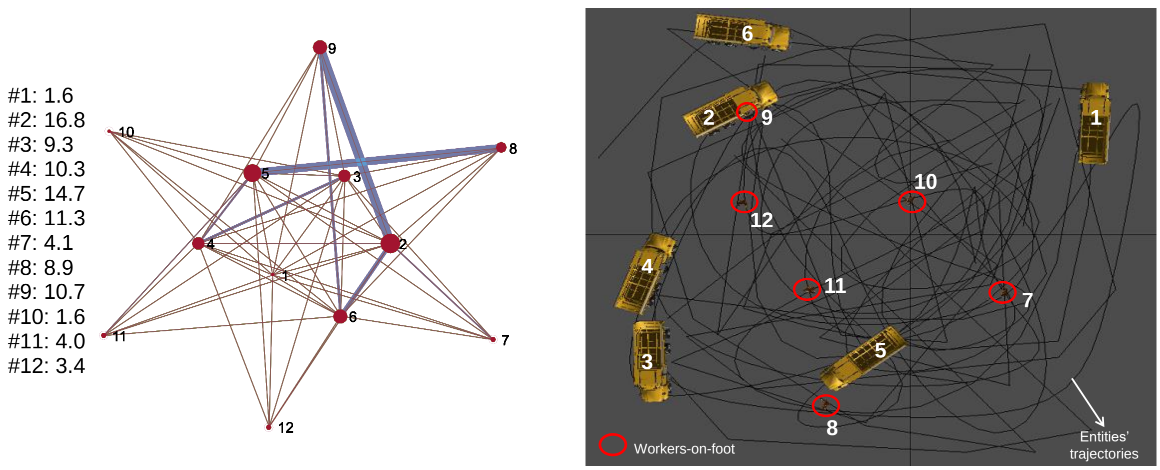
(a) (b)

Figure 3: The risk at the network level: (a) the example 1 and (b) the example 2

3.2.2 Risk Analysis at Entity and Network Levels

The struck-by-equipment risk at the entity and network levels can be analyzed at each frame. Taking the frame 1369 of job site 1 as an example, the calculated degree centrality of each entity is shown in Figure 4(a). In Figure 4(a), each node represents an entity. A bigger node in size indicates a higher degree centrality of the node. The width of the link represents the intensity of the interactions between entities. The simulated situation at the frame 1369 is presented in Figure 4(b). The nodes' numbers in Figure 4(a) correspond to the entities' numbers in Figure 4(b). Using the thresholds determined from the first 1350 frames, the entities #2 and #9 are identified as risky entities as their degree centrality scores are higher than the thresholds (i.e., 15 and 9 for equipment and workers-on-foot, respectively). As shown in Figure 4(b), the identified entities collide with each other. The degree centrality scores of the entities #5 and #8 are extremely close to their thresholds and in Figure 4(b) the two entities show the potential of colliding with each other.

As mentioned earlier, different from the entity-level analysis, the network level analysis focuses on investigating the entire job site's struck-by-equipment risk. In addition to the safety performance evaluation for job sites, the algebraic connectivity also can support the risk identification and hazard prevention. For example, if the measured algebraic connectivity is higher than the previously set threshold, attention can be paid and corrective actions can be applied to the entities that have relatively higher degree centrality scores at the current moment (even the scores might be smaller than the degree centrality thresholds).



(a) (b)

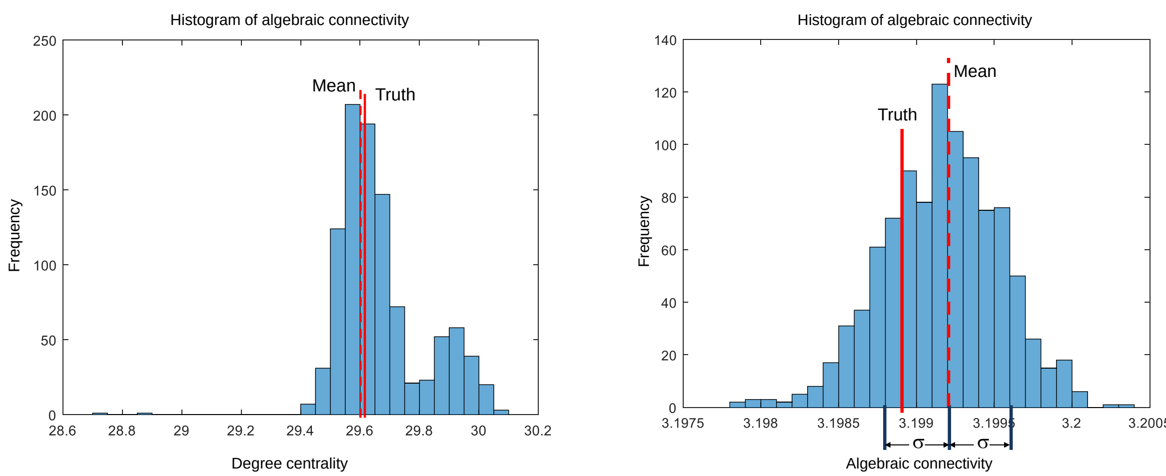
Figure 4: (a) Degree centrality scores and interactions in the network and (b) the simulated situation

3.2.3 Risk Prediction

In this paper, the accuracy of the probabilistic method is evaluated by comparing the predicted risk with the safety leading indicators calculated from the corresponding simulated frame. The further evaluation of the prediction method's performance needs the implementation of the work of this paper on the real-world job sites. Using the frame 7 in the job site #2 as an example, the probabilistic method with Monte Carlo simulation was applied to predict the degree centrality and algebraic connectivity for the frame 8. The obtained results are shown in Figure 5. Furthermore, the leading indicators of another 1000 frames were predicted and compared with their corresponding truth.

The prediction of degree centrality was conducted to the entity #1 as the entity #1 had been identified with the highest degree centrality at the frame 7 [Figure 2(a)]. The output of the probabilistic method for the degree centrality is summarized in the histogram in Figure 5(a). The degree centrality of entity #1 at the frame 8 is represented using the solid line (i.e., the truth) and the mean of the output is indicated using the dash line. The output's percent error and relative uncertainty is 0.19% and 0.49%, respectively. The magnitudes of the two measures (i.e., percent error and relative uncertainty) are smaller than 1%. One main reason leading to obtain such accuracy and precision is that entities' motions changed slightly between the continuous frames. To be more specific, the accuracy and precision of the probabilistic method will be improved with the increasing of the frequency of prediction. Running the method to predict the degree centrality of entity #1 for another 1000 frames, the true degree centrality of the 64% of the 1000 frames fell in the range [mean-standard deviation, mean+ standard deviation] and 82% of the 1000 frames fell in the range [mean-2*standard deviation, mean+ 2*standard deviation]. Herein, for the real-world applications, it is suggested to perform the degree centrality prediction only for the entities that their degree centrality scores are close to their thresholds [e.g., the equipment with centrality within (13.5, 15) and workers-on-foot with centrality within (8.5, 9)].

The results of the algebraic connectivity for the frame 8 are summarized in Figure 5(b). The algebraic connectivity at the frame 8 (i.e., the truth) is represented using the solid line. The output of the probabilistic method is presented in the histogram with its mean and standard deviation. It can be found that the truth fell in the range [mean-standard deviation, mean+ standard deviation]. Similarly, running the method to predict the algebraic connectivity for another 1000 frames, the true algebraic connectivity of the 84% of the 1000 frames fell in the range [mean-standard deviation, mean+ standard deviation] and 94% of the 1000 frames fell in the range [mean-2*standard deviation, mean+ 2*standard deviation].



(a) (b)

Figure 5: The risk of frame 8: (a) degree centrality of entity #5 and (b) algebraic connectivity

4 Discussion

The implementation of the network-based model and the probabilistic method relies on real-time data collection and communication. The dynamics of the site can be monitored by mounting sensors on individual entities or using cameras and computer vision-based methods to acquire their real-time state information (Park and Brilakis 2016). In the recent decade, the real-time data collection and communication have been studied extensively which greatly enhances the applicability of the work of this paper (George et al. 2014, Liu et al. 2015). The proposed probabilistic prediction method is fairly straightforward to use. A balance between the performance of the prediction method and the prediction frequency needs to be maintained. Validating the network-based model and the probabilistic method for risk analysis, prediction, and safety performance evaluation on the real-world job sites is the next step of this study.

5 Conclusion

Struck-by-equipment hazard remains one of the leading causes of construction injuries and fatalities. Exploration and development of safety leading indicators are a promising approach to proactively perceive and represent safety risks in the continuously changing site circumstances. This paper uses a network-based model and a probabilistic method with two safety leading indicators to investigate the risk of struck-by-equipment hazard. The network-based model quantifies the dynamic interactions among entities and is capable of analyzing the risk at both entity and network levels. On the basis of the network-based model, the probabilistic method with Monte Carlo simulation is adopted to predict the risk at the two levels. Meanwhile, the safety performance of entities and job sites, particularly, pertinent to the struck-by-equipment hazard can be evaluated. Two simulated examples were used to explain the implementation and assessment of the network-based model and the probabilistic method for risk analysis, prediction, and safety performance evaluation. Based on the outputs, real-time risk analysis and prediction can be conducted. Safety managers can gain a full understanding of workforce behaviors and job sites in terms of safety, to proactively eliminate unsafe actions and practices. The work presented in this paper can also be extended to be applied to analyze the safety risk for other types of hazards on construction sites.

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