Integration of BIM, Bayesian Belief Network, and Ant Colony Algorithm for Assessing Fall Risk and Route Planning

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Abstract

The majority of routing decision approaches in emergency response operations aim at fire emergency in buildings and normally focus on building operation and maintenance phase. However, in the construction industry, falls are the most frequently occurring types of accidents resulting in fatalities, and there exists limited research considering potential fall risk on working routes where construction workers perform tasks such as material handling at the construction stage. This research contributes to providing an approach to consider potential fall risk on working routes and suggest one route with relatively lower risk by integrating BIM, Bayesian belief network and ant colony algorithm**.** Building information modeling can retrieve building geometry, integrate information from surrounding environment and thus help identify and evaluate potential risk at the construction stage. Based on the geometry information retrieved from the BIM model, Bayesian belief network is applied to assess potential fall risk of different identified fall scenarios. The obtained data after Bayesian belief network analysis is input into ant colony algorithm to plan safe working routes on a typical construction site. An example is presented to demonstrate the simulation result.

Introduction

The construction industry is one of the most dangerous industries in most of the countries in the world. Construction safety is a worldwide issue and statistics have shown that 40% of construction fatalities involved incidents related to falls from height (Hinze et al., 2011; U.S. Bureau of Labor, 2010). The risk of falling for building workers is increasing with the rapid development of high-rise buildings. For example, one study in China reported that in 2011, there were a total of 589 accidents and 738 deaths from housing municipal engineering safety production, with 314 falls from elevation accidents, occupying half of the total number (Ministry of Housing and Urban-rural Development of the People's Republic of China, 2012).

Route planning is important for fall prevention and building emergency, but the majority of research considers fire risk, especially in operation and maintenance phase. Although researchers have applied BIM approach for evacuation regulation checking (Choi et al., 2014), indoor localization for fire hazards (Li et al., 2014), rescue and evacuation for in-building response operations (Chen et al., 2015), and identified different cases of fall protection scenarios (Zhang et al., 2013), there exists limited research for the potential fall risk assessment in various paths such as moving personnel, material handling at the construction stage. Considering risk assessment while planning routes in construction stage is an important measure for the construction workers for their own safety.

This paper is aiming at assessing construction fall risk and planning safe working routes at the construction stage. BIM model is used to provide the corresponding spatial and geometric information of each object. In order to assess the risk, Bayesian Belief Network (BBN)(Cheng et al., 2001) is applied to calculate the occurrence and severity of different fall scenarios. Fall risk can then be identified and determined during the construction stage, and ant colony algorithm (ACA) (Duan et al., 2004) is used to plan the safe working route to reduce fall risk in construction.

Literature Review

Due to the influence of various risk factors existing at construction sites, a risk assessment tool has been proposed for construction sites, and various risk parameters have been evaluated (Forteza et al., 2016). As for the fall risk, factors such as falling height, the degree of risk control, occurrence frequency and the possibility of risk and the number of workers are all taken into consideration (Forteza et al., 2016). In addition, a qualitative risk assessment model for fall from height has also been proposed. The model is divided into two parts: how to protect workers before the accident and how to reduce the impact after the fall (Aneziris et al., 2008). It is important to note that the quality of obtained pieces of evidence strongly depends on the accuracy of applied assessment methods. General safety risk assessment methods are not specific for construction (Pinto et al., 2011), and some instruments for assessing specific construction risks have been developed. One example is the Qualitative Occupational Safety Risk Assessment Model (QRAM) that incorporates uncertainty using fuzzy set (Pinto, 2014). QRAM analyses up to nine types of accidents, taking into account the effectiveness of the protections and the possibility and severity of risks. Risk assessment includes the dimension of organizational safety climate and the workplace safety level.

BIM has advanced in recent years in the domain of civil engineering (Liu et al., 2013). Building information modeling (BIM) applications can facilitate various rule checking and simulations for evaluating building designs in the earlier phases of a project (Eastman et al., 2008). Researchers have applied automated safety rule checking to BIM models, which detect safety hazards such as fall-related accidents in different project conditions (Zhang et al., 2013). There have been researching efforts on the integration of BIM with traditional building evacuation issues. For example, an add-in toolbox has been developed to estimates the capacity and time for building evacuation (Wang et al., 2012), prevention of bottlenecks and congestion during construction (Wang et al., 2012) and evacuation regulation checking for high-rise and complex buildings (Choi et al., 2014).

Recently there has been researching on route planning. Combination of network analysis and BIM model to make emergency response decision can put forward a graphical construction algorithm that combine Visibility Graph and Medial Axis Transform, automatically calculating the optimal escape route in BIM model, so as to improve the efficiency and accuracy on decision making on indoor rescue and evacuation (Chen et al., 2016). A multi-purpose geometric network model (MGNM) based on BIM is also proposed (Teo et al., 2016), combined with geographic information system (GIS) of the outdoor information network, to explore the association between indoor and outdoor and achieve the purpose of multi-purpose escape route planning. There are a variety of route planning algorithms, such as the shortest path algorithm (Dijkstra, 1959), the hierarchical shortest path algorithm (computational time as the minimization criterion) (Fu et al., 2006) and the least risk path algorithm which considers both path length and risk value on the path (Grum, 2005). The least risk path algorithm calculates the path between two points where a way-finder has the least risk of getting lost by selecting all edges and intersections with a minimal risk value, but not for the particular risk source such as fall risk that exists on construction sites. On the other hand, ant colony algorithm, a novel category of bionic algorithm for optimization problems (Duan et al., 2004), is also used in route planning, as a part of construction site layout planning, to ensure the safety of the working environment (Ka－Chi Lam et al., 2007).

The Proposed Approach

The proposed approach includes fall risk assessment and route planning. At the risk assessment stage, BIM model is used to illustrate different cases of fall scenarios and provide required geometry and spatial information. Bayesian Belief Network (BBN) is selected to calculate the occurrence and severity of different fall scenarios in order to assess the potential risk of different cases of fall scenarios. This particular instrument has been chosen because occurrence and severity are uncertain things (Scott, 2005) and because the empirical data in this research is lacking. This lack of data is something that is reasonable because in reality, empirical data are almost lacking in real-world risk analysis. It may, therefore, be impractical, unethical, or even impossible to collect relevant empirical data.

In order to overcome this problem, the authors choose four variables as impact factors which may influence the occurrence of the risk accident in a construction project, namely distance workers from opening, channel width near an opening, opening type, and stability of opening edge (Aneziris et al., 2008).

At the route planning stage, ant colony algorithm is used to select the route that has the minimum fall risk because it is a search algorithm based on the probability of selection which makes a good combination with the fall risk, and it can adapt to the randomness on construction sites. Through fall risk assessment and route planning stages, safety awareness of workers can be improved and the fall risk during construction can be reduced. Fig. 1 shows the whole flowchart of the proposed approach.

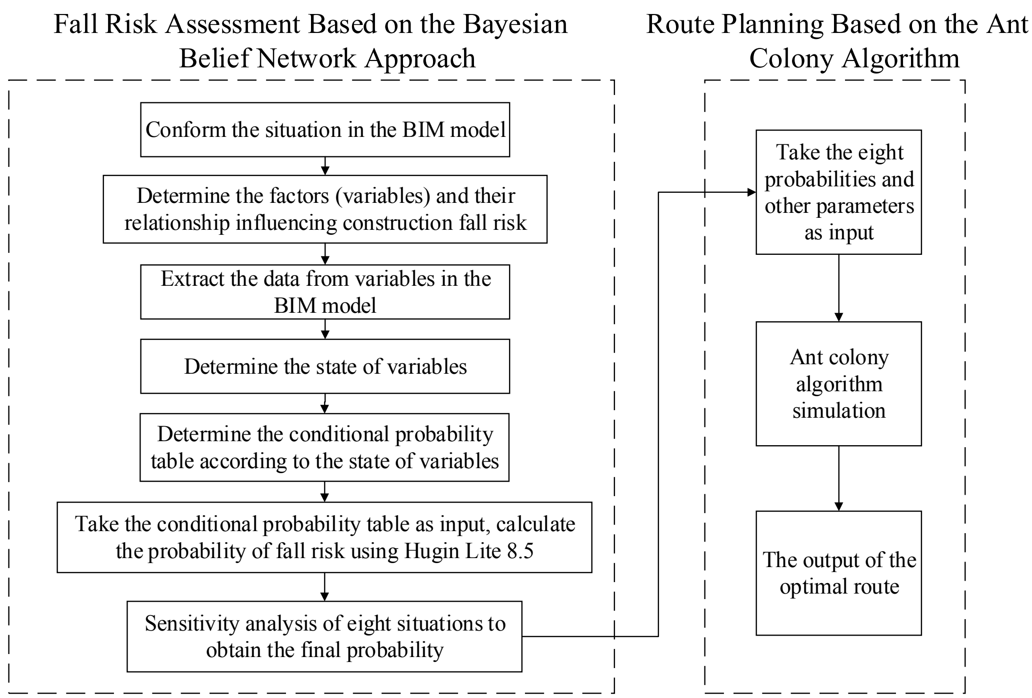


Figure 1. Flowchart of the Proposed Approach

Fall Risk Assessment Based on the Bayesian Belief Network Approach

Fall Risk Situation Analysis Based on the BIM Model

On the construction site, there mainly have three kinds of openings that may cause fall risk, namely: (1) openings left after the building is accomplished; (2) temporary openings when permanent structures have not yet completed; (3) temporary openings during the construction process in order to meet the needs of construction. These three kinds of openings can be identified as six different fall scenarios (Zhang et al., 2013), which listed in Fig. 2(a). The fall scenarios can be illustrated in a BIM model as eight real cases labeled 1-8 in Fig. 2(b) and detailed in Table 1.

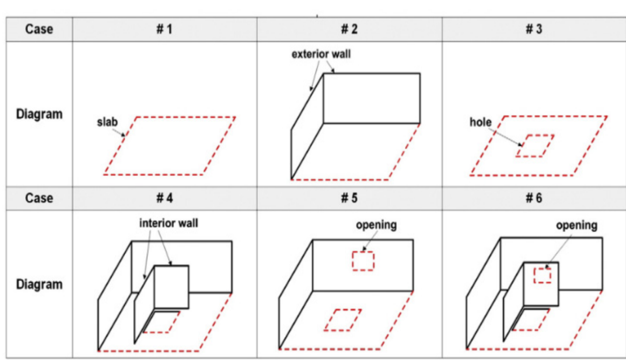


Figure 2(a). Cases for fall risk situation

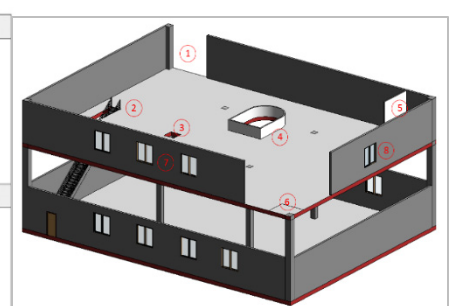
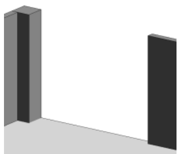
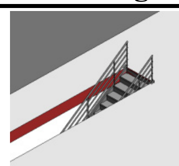
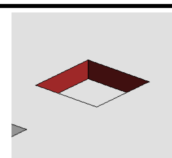
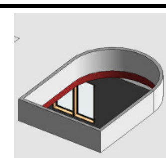
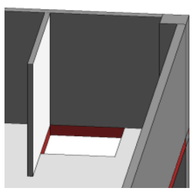
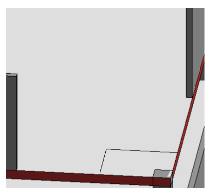
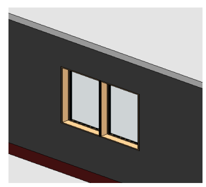
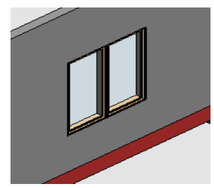


Figure 2(b). Fall risk situations in the BIM Model

To be specific, case 1 in Table 1 represents #2 in Figure 2(a), namely slabs with exterior wall (horizontal opening); case 2 and 3 in Table 1 represent #3 in Figure 2(a), namely holes without interior wall (horizontal opening); case 4 in Table 1 represents #6 in Figure 2(a), namely openings in interior wall (vertical opening); case 5 in Table 1 represents #4 in Figure 2(a), namely slabs with interior wall (horizontal opening); case 6 in Table 1 represents #1 in Figure 2(a), namely slabs without exterior wall (horizontal opening); case 7 and 8 in Table 1 represent #5 in Figure 2(a), namely openings in exterior wall (vertical opening).

Table 1. Eight Situations in the Model

Situation				
Case	1	2	3	4
Situation				
Case	5	6	7	8

Risk Assessment Based on Bayesian Belief Network

The interaction among variables (distance workers from opening, channel width near an opening, opening type, and stability of opening edge) may affect the possibility of the fall risk. The relationship between the variables (Chien et al., 2014) can be described in Fig. 3.

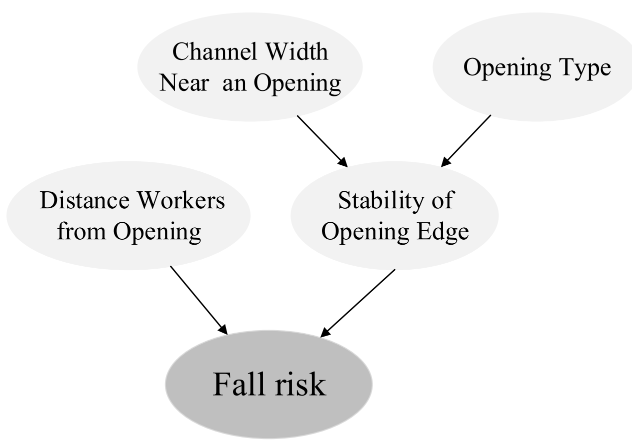


Figure 3. Relationship among four variables

BIM model is then used to provide distance and channel width near the opening and show opening type in terms of eight cases. According to the retrieved data from BIM model (listed in Table 2.) and two values of each variable (take the middle value from the maximum to the minimum as the boundary), the value of each variable in each case in BIM model can be determined, as showed in Table 3. (Opening type refers to horizontal/vertical; stability of opening edge use qualitative analysis here, poor stability refers to the situation that material stacking or incomplete structure leads to the poor stability during the construction process.)

Table 2. Variable Data in BIM Model

Case	channel width near the opening (mm)	distance workers from opening (mm)	opening type	stability of opening edge
1	2200	0-4150	#2	good
2	700/1000	0-13000	#3	good
3	2250/2400	0-1700	#3	poor
4	1500/1700	0-7000	#6	poor
5	1050	0-3100	#4	poor
6	3050	0-3100	#1	good
7	650/950	0-2700	#5	good
8	700/800	0-13000	#5	good

Table 3. Value of Each Variable in Each Case in BIM Model

Case	channel width near the opening	distance workers from opening	opening type	stability of opening edge
1	wide	close	horizontal	good
2	narrow	far	horizontal	good
3	wide	close	horizontal	poor
4	narrow	close	vertical	poor
5	narrow	close	horizontal	poor
6	wide	close	horizontal	good
7	narrow	close	vertical	good
8	narrow	far	vertical	good

The total percentage of two values for each variable is 100%. So the probabilities in the conditional probability table can be calculated according to the percentage of number of case values in Table 3 (showed in Table 4). Because of the influence of other variables (Fig 3), the conditional probability table of stability of opening edge contains the two preconditions (opening type and channel width near opening), that leads to the difference of the percentage of the conditional probability table (Table 5). In order to build the modeling process, the results of Table 4 and Table 5 are put into the conditional probability table provided by Hugin Lite 8.5 and then the probability result can be shown. Figure 4(a) shows the probability result 65.91% (in the red circle), and all the probabilities in eight cases need to do the sensitivity analysis because the value of each variable is fixed. Figure 4(b) shows the example result of case 1 (in the red circle), and the result of other cases are listed in Table 6.

Table 4. Conditional Probability Table 1

channel width near the opening		distance workers from opening		opening type	
wide	0.375	close	0.75	horizontal	0.625
narrow	0.625	far	0.25	vertical	0.375

Table 5. Conditional Probability Table 2 (Stability of Opening Edge)

opening type	horizontal		vertical	
channel width near the opening	wide	narrow	wide	narrow
good	0.67	0.5	0.5	0.67
poor	0.33	0.5	0.5	0.33
Total	100%	100%	100%	100%

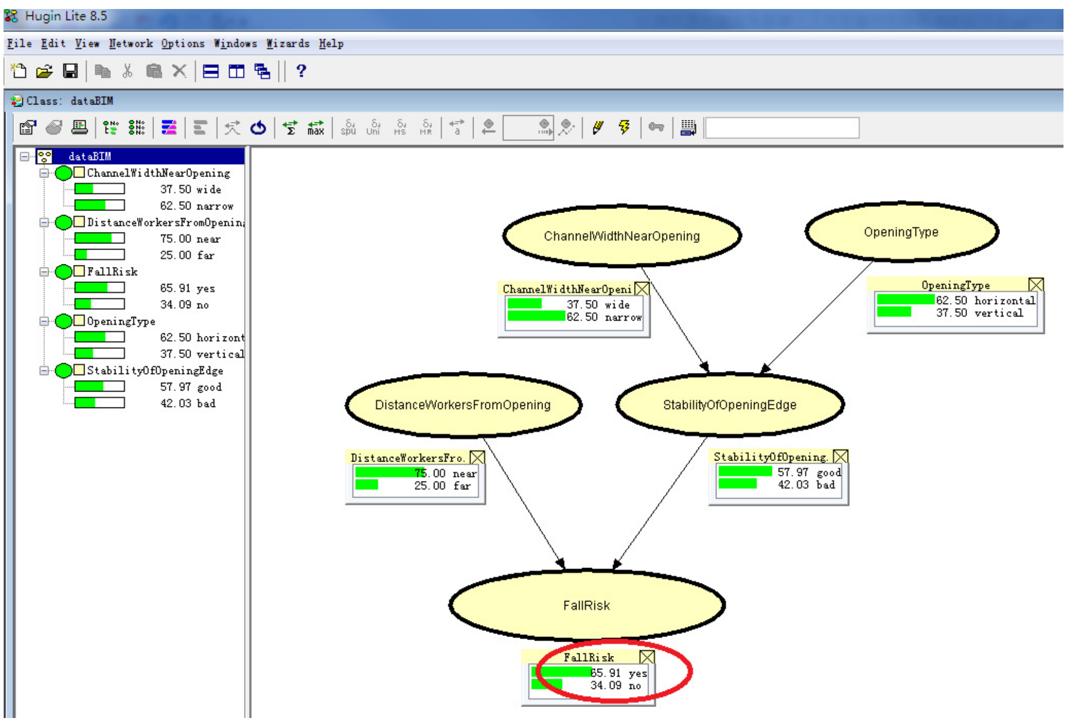


Figure 4(a). Probability of falls risk in BIM model

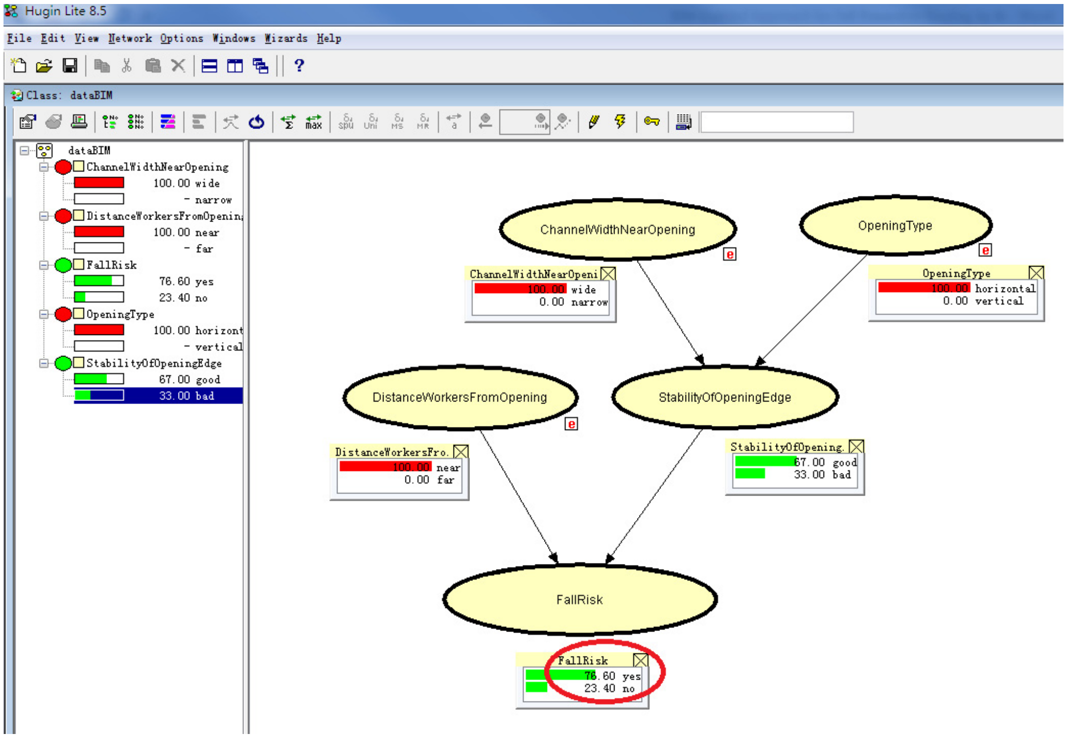


Figure 4(b). Probability of case 1 in BIM model

Table 6. Probability of Falls Risk in Eight Cases

Case	1	2	3	4	5	6	7	8
Probability	76.6%	30%	76.6%	76.6%	80%	76.6%	76.6%	26.6%

Route Planning Based on the Ant Colony Algorithm (ACA)

Solution steps for the ACA

The fall risk probabilities are used as the parameter, to plan the working route used by ant colony algorithm. The model is constructed assuming that a worker needs to pass all eight cases respectively according to a certain order, and the fall risk from low to high. In the model, workers spend the least time and pass the lowest risk case first to accomplish a task. The flow chat is showed in Fig. 5.

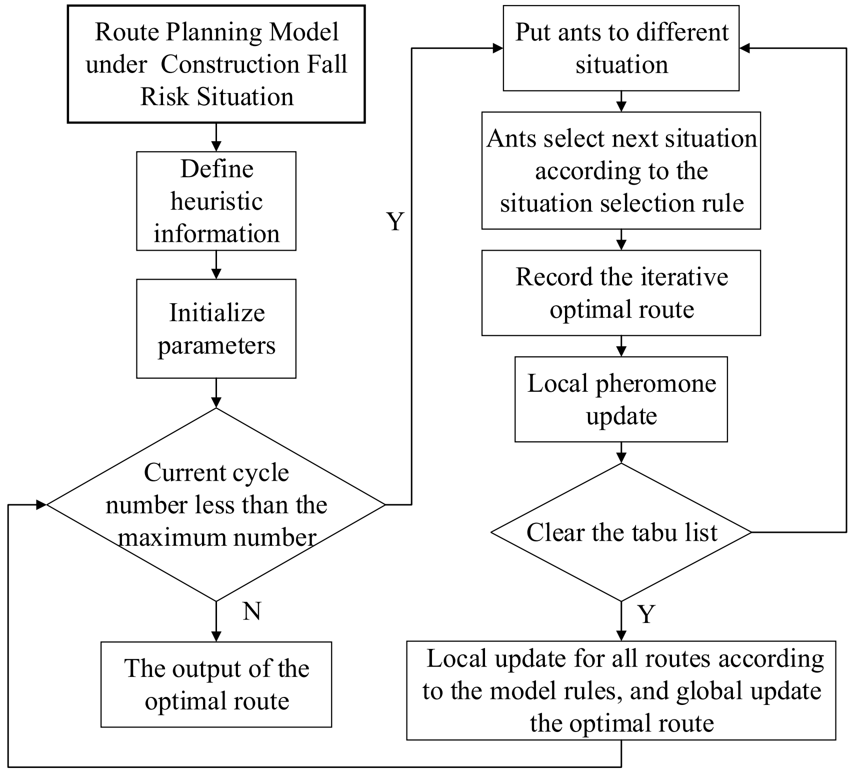


Figure 5. Ant Colony Algorithm Flow Chat

Steps established for the proposed model are as follows.

Step 1. Heuristic information: Heuristic information is defined in accordance with the problem characteristics, which enable the algorithm to be more applicable in solving any combinatorial problem.

The heuristic information is given by Equation (1)

$$J_{ij} = jT_{ij} + k\frac{Pf_j}{Pf_i} \tag{1}$$

The vector T_{ij} represents the time from location *i* to location *j*, here we use the distance to replace time because it is precise to measure. The vector $P_f$presents the probability of the risk situation, and vector J_{ij} represents the performance move directly from location *i* to location *j,* called selection cost. The final result using ACA is to minimize the selection cost J_{ij}. *j* and *k* are the constant value.

Step 2. Solution construction: At each selection step, an ant *k* move from location *i* to an available location (*j*) with a probability of

$$P_k(i,j) = \begin{cases} \frac{\tau^{\alpha}(i,j)\eta^{\beta}(i,j)}{\sum \tau^{\alpha}\eta^{\beta}}, j \in allowed_k \\ 0, otherwise \end{cases} \tag{2}$$

where $\tau(i,j)$ is the pheromone trail at iteration $L(i,j)$ (L represents any available path), $\eta(i,j)$ is the heuristic desirability, where $\eta(i,j) = 1/J_{ij}$. It should be noted that α and β are the parameters that determine the relative influence of the pheromone and heuristic information, respectively. $Allowed_k = \{0,1, \ldots, n-1\}$is the set of locations that are still available in the neighborhood of node i.

Step 3. Pheromone updating: The pheromone trail update is applied after a complete solution is constructed. Pheromone trails of all couplings *(i, j)* are updated in accordance with Equation (3)(4)

$$\tau^{new}(i,j) = (1-\rho)\tau^{old}(i,j) + \rho[\Delta\tau(i,j) + e\Delta\tau^{e}(i,j)] \tag{3}$$

$$\Delta\tau(\mathrm{i},\mathrm{j}) = \textstyle\sum_{k=1}^{m} \Delta\tau^{k}(i,j) \tag{4}$$

where ρ presents pheromone trail evaporation rate, $\Delta\tau$ represents the pheromone increment in one iteration. And the amount of pheromone added by ant k is given by Equation (5)(6)

$$\Delta\tau^{k}(i,j) = \begin{cases} \frac{Q}{J_k}, & \text{if the ant } k \text{ go through path } L(i,j) \\ & 0, \text{otherwise} \end{cases} \tag{5}$$

$$\Delta\tau^{e}(i,j) = \begin{cases} \frac{Q}{J_e}, & \text{if the path } L\ (i,j) \text{ belongs to the global optimal path} \\ & 0, \text{otherwise} \end{cases} \tag{6}$$

where Q is a constant value, representing the increasing intensity of pheromone, e is also a constant value.

Step 4. Local search and global search: Local search procedure is added to the algorithm to avoid finding a local optimum solution. Compare the local solution with the previous global solution, if the local solution is better than the former, then the former is replaced by the current solution and the search continues until no better solution is found.

Route planning simulation result

The construction site area is simplified as a coordinate plane (showed in Fig. 6), and eight cases including coordinate value (X and Y) and risk probability (Pf) are listed in Table 7.

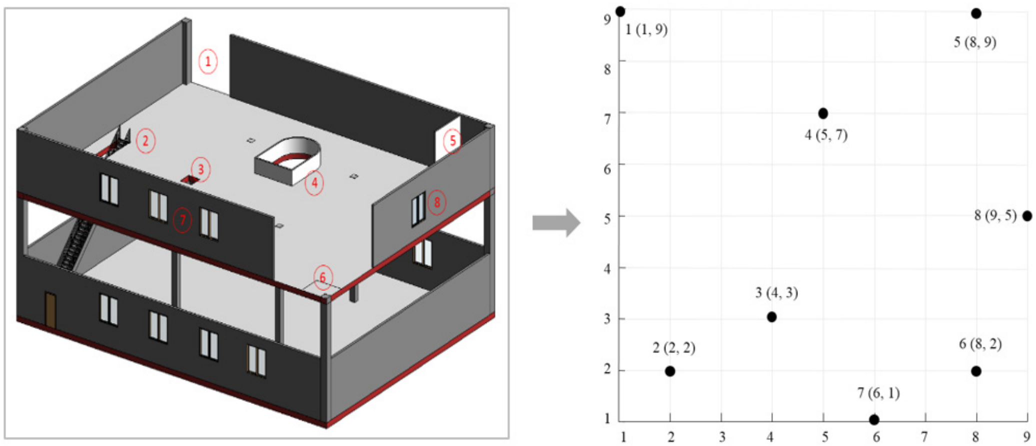


Figure 6. Eight cases in the coordinate plane

Table 7. Case Data

Case	1	2	3	4	5	6	7	8
X	1	2	4	5	8	8	6	9
Y	9	2	3	7	9	2	1	5
Pf	0.77	0.30	0.77	0.77	0.80	0.77	0.77	0.27

According to the experience in repeated tests (Yu et al., 2001), parameters are set as follows: α=3, β=4, j=1.2, k=20, e=2, Q=20, ρ=0.5. The number of ants m=20, and the maximum number of cycles sets to 50. The initial information at each path is 1. The simulation result of the construction operation route planning is:

Route: 8→6→7→3→2→1→4→5

$$\sum J_{ij} = 29.73$$

where the order and the probability of each situation are listed in Table 8.

Table 8. Result of the Construction Working Route Planning

Order	8	6	7	3	2	1	4	5
Pf	0.27	0.77	0.77	0.77	0.30	0.77	0.77	0.80

As showed in Table 8, it is generally accomplished that the situation passes first has the lower risk probability. Fig. 7 shows the convergence rate of the ACA. The X-axis is the number of cycles from 1 to 50, and the Y-axis represents the value of $\sum J_{ij}$. Simulation results demonstrate that the algorithm increases convergence rate. Fig. 8 is the route diagram, each node represents a fall risk case, and the coordinate is the distance among each situation.

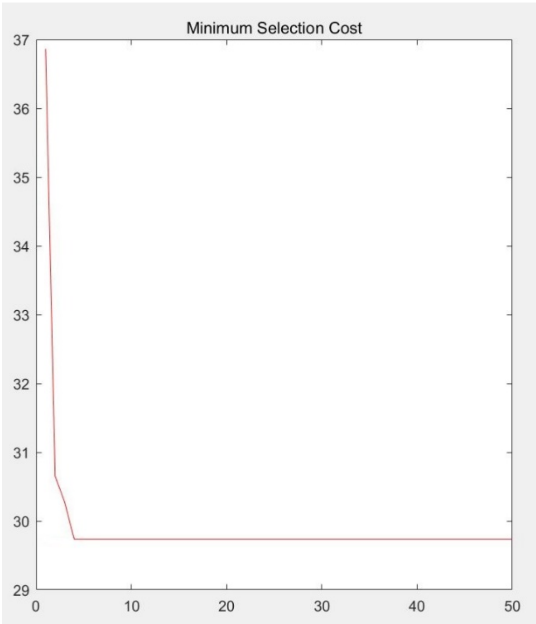


Figure 7. Minimum selection cost

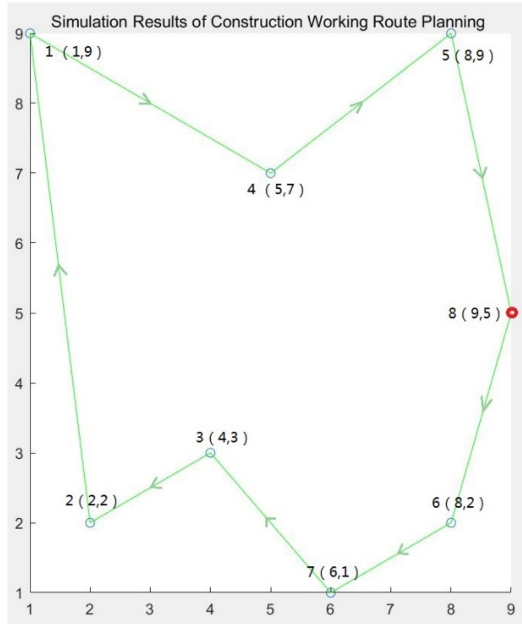


Figure 8. Result of route planning

Conclusion

This study aims to propose an approach for working route planning while considering potential fall risk. Building geometry and spatial information are retrieved from the BIM model and Bayesian Belief Network method is applied to calculate the occurrence and severity of different fall scenarios. Through the identified impact factors (also called variables), distance workers from opening, channel width near an opening, opening type and stability of opening edge (Aneziris et al., 2008) in different fall scenarios in the BIM model, the probabilities of fall risk can be determined through Bayesian Belief Network. The analysis data from Bayesian Belief Network is input into ant colony algorithm to plan the construction operation route while considering fall risk situation.

The Bayesian Belief Network (BBN) as a proposed method can rely upon an intermediary between subjective and objective views on risk when it is provided by appropriate and complete data. It is more objective than the traditional approach that only relies on experience or intuition of the project's safety engineers. In addition, the ant colony algorithm is that the ants choose the solution in accordance with the level of pheromone and the heuristic information about the locations. The controllable parameters of the ant colony algorithm mean that less time is required to reach an optimal solution, which is more effective compared to other algorithms. This paper combines the advantages of the two methods. Compared with the traditional risk assessment and route planning research, this study is fundamentally different for the following reasons: 1) measuring the objective and uncertain fall risk in construction quantitatively; 2) providing operational route plan considering the fall risk and the distance from different cases at the same time; 3) providing a more scientific planning scheme for the construction organization design under the premise of taking full account of the construction risk.The simulation result shows that the suggested route can make an effect when workers choose the fall scenario with lower risk first.

The results of this paper can be summarized as the following two points:

1) Combining the geometric and spatial information from BIM model, the Bayesian Belief Network is used to quantitatively assess the fall risk in construction, and the probability of construction fall risk in different cases is proved. This method proves that it is feasible and effective in assessing the fall risk in construction.

2) In this study, the ant colony algorithm is used to plan the optimal operational route considering the probability of fall risk and the distance from different cases. The optimal route considering both risk and distance factors is obtained, and the result provides ideas for safer and more efficient operations in construction projects.

The proposed approach needs validation via a case study in the future.

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