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Abstract

This paper introduces a novel technique to design the level of service (LOS) for facilities or sub spaces of buildings for the purpose of evacuation planning. LOS is a standard qualitative indicator used to describe flow characteristics in a pedestrian environment. Some evacuation planners use LOS to help determine the network parameters when solving evacuation planning problems by the network flow approach. However, there is currently limited research into the optimization of the LOS parameters themselves to construct more efficient evacuation networks. In this paper the authors used a genetic algorithm optimization approach to determine LOS for facilities to improve the evacuation performance of building networks. Each individual chromosome containing a LOS design represents a fully defined evacuation network that can be solved. The fitness of each network is measured by minimum clearance time, which is calculated by the Capacity Constrained Route Planner (CCRP) approach. A comparative computational test in a hypothetical three-story building shows that the evacuation network under the optimized LOS design has a roughly 11% less minimum clearance time compared to the network under the original LOS design. Sensitivity analysis is also included, focusing on how the population size and the building layout influence the LOS design. In addition, an additional computational test for a twelve-deck cruise ship shows that the approach is scalable to solve more complex evacuation networks. The proposed approach has the potential to provide better LOS assignments for facilities for the government officials to develop effective emergency management strategies.

Keywords: level of service; evacuation planning; network flow model; network parameters; genetic algorithm

1 Introduction

Natural and man-made disasters such as earthquakes, hurricanes, fires, nuclear leakage, and terrorist attacks continue to be a problem and cause mass casualties worldwide. To prepare for these disasters, government officials must develop effective emergency management strategies to evacuate people from hazardous regions to safe places. One way the policy makers can obtain valuable information of evacuation routes and schedules for evacuees is by the use of evacuation planning procedures. However, as buildings and facilities are built more complex, it is becoming more difficult to establish rapid evacuation plans. In order to address the challenges, evacuation planning approaches need to be strengthened and improved from every possible aspect.

Current approaches to solving evacuation planning problems can be divided into two main categories: simulation-based approaches and optimization-based approaches. Simulation-based approaches use simulation models such as cellular automata models (Wolfram, 1983; Wang et al., 2011), social force models (Helbing, 1995; Zheng et al., 2009) and agent-based models (Chen et al., 2008; Shi et al., 2009) to simulate interactions among evacuees with individual characteristics. These approaches allow for the evaluation of the dynamic evacuation process and the test of predefined evacuation plans with the consideration of human behavior, which is an important aspect of pedestrian movement (Fang et al., 2010). However, simulation models often need a long time to run, especially for those problems with a large population and/or a complex environment, rendering it almost impossible to optimize an overall evacuation process with this approach (Kang et al., 2015).

Optimization-based approaches, on the other hand, have the ability of optimizing the evacuation process because they simply treat evacuees as homogenous groups flowing through a topological network, which is the physical aspect of pedestrian movement (Zhang et al., 2011; Porzycki et al., 2017). Although objective functions may vary according to specific evacuation problems (Saadatseresht et al., 2009; Fang et al., 2011), a basic goal is to minimize the clearance time, i.e., to transport all the evacuees from their initial position(s) to the destination position(s) as fast as possible. Most optimization algorithms have been proposed to solve the evacuation problem in the context of network flow theory (Chalmet et al., 1982; Hamacher et al., 2001; García-Ojeda et al., 2013). These algorithms fall into two categories: Linear Programming (LP) approaches and heuristic approaches. LP approaches are able to produce optimal solutions for evacuation planning, but they suffer from high computational cost when dealing with large building networks. Compared to LP approaches, heuristic approaches have the advantage of significantly lower computational cost; however, they do not guarantee exact solutions (Lu et al., 2005).

As a heuristic optimization approach, the Genetic Algorithm (GA) approach is widely used in evacuation planning fields. Goerigk et al. (2014) proposed a comprehensive evacuation planning model that considers the location of shelters, bus routing for public transport, and routing for individual traffic simultaneously. To handle large-scale evacuation problems with acceptable computation times, they developed a genetic algorithm to solve the model heuristically. In order to deal with the uncertainty in evacuation demand in an evacuation vehicle routing problem, Pourrahmani et al. (2015) designed a genetic algorithm based on fuzzy credibility theory to optimize with the objective of minimizing the total travel time. Saadatseresht et al. (2009) adopted NSGA-II (Deb et al., 2002), an extended method of GA, to solve the distribution of evacuees to the safe areas, which is a spatial multi-objective optimization problem. This method keeps the best individuals through sequential generations and avoids the problem of the early uniformity in population during generations. Kongsomsaksakul et al. (2005) developed a GA-based approach to solve a shelter location-allocation model with capacity constraints for a flood evacuation planning problem. However, the approach is only suitable for solving small or medium size networks because larger networks make the total calculation time of the GA longer.

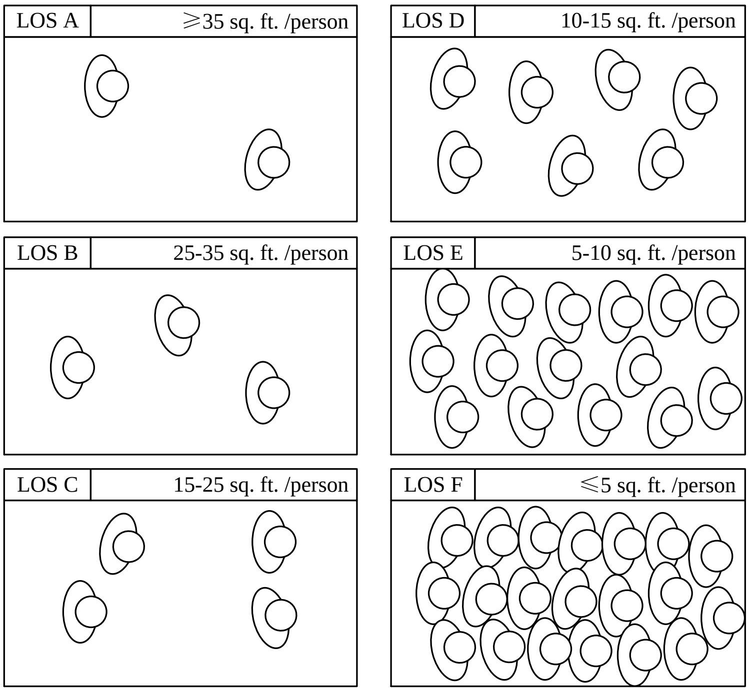


Figure 1 Level of service for walkways

In order to construct the evacuation network used in optimization-based approaches, the Level of Service (LOS) approach has been adopted to determine network parameters including node capacity, arc capacity and arc transit time (Kisko et al., 1985; Choi et al., 1988). The concept LOS was first developed by Fruin (1970) to represent crowd conditions of transportation facilities and interior building space. There are 6 levels of service from A to F that range from free circulation to severe congestion, for queueing, walkways, and stairways (see Figure 1 and Appendix Tables A1-A3). With the consideration of the properties of network parameters such as the limit of node capacity and the relationship between arc capacity and arc transit time, the LOS approach has shown more reasonability in constructing an evacuation network in contrast to traditional methods that calculate the maximum or average values of network parameters (Lu et al., 2003; Hamacher et al., 2001). For the advantage of the LOS approach, evacuation planning tools such as EVACNET (Kisko et al., 1998) have adopted the approach to model building evacuation problems. Ashraf et al. (2013) and Haworth et al. (2015) have also acknowledged LOS as a critical factor affecting evacuation performance of facilities. However, there is currently not enough empirical evidence showing that LOS is suitable across crowd types, evacuation scenarios, and environment configurations (Haworth et al., 2015).

Although the LOS concept has been applied in evacuation planning, little work has been done to optimize the design of LOS on facilities to model more efficient evacuation networks in order to make better evacuation plans. For example, EVACNET does not give an approach to choosing the proper LOS for a facility and the choice relies heavily on the users' expertise. This paper extends the approach of using LOS in evacuation planning problems. As shown in Figure 2, instead of choosing LOS by human, this paper uses an optimization algorithm to obtain better

LOS design(s). The optimization algorithm is a two-stage standard Genetic Algorithm (GA), in which minimum clearance time and total absolute deviation are selected as the fitness function subsequently. In order to calculate the minimum clearance time of an evacuation network under a LOS design, the authors adopt the Capacity Constrained Router Planner (CCRP) algorithm, which is shown to be an effective heuristic algorithm capable of producing a nearly optimal solution (Lu et al., 2005; Shekhar et al., 2012). For the validation test, the authors will discuss the feasibility of this approach in a building evacuation problem. The proposed approach has the potential to design optimized LOS for facilities and reduce evacuation time, thus providing valuable information for the government officials to develop effective emergency management strategies.

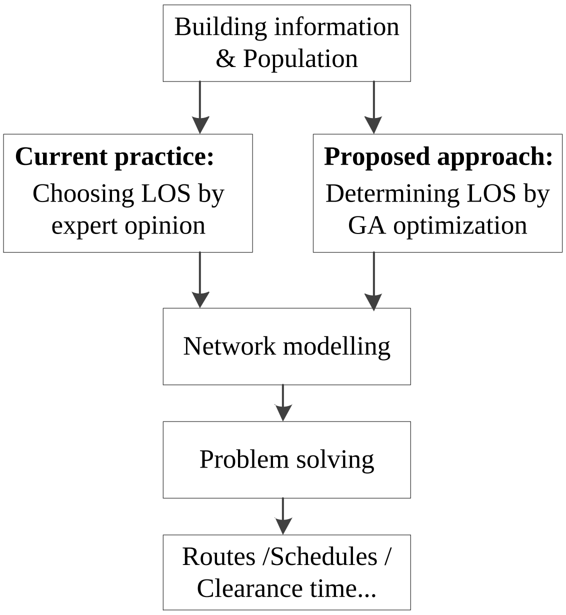


Figure 2 Problem flow diagram for using the LOS approach in evacuation planning showing current practice and the proposed approach

This paper is organized as follows. Section 2 introduces the network model and defines the LOS optimization problem. Section 3 puts forward a two-stage standard genetic algorithm to solve the optimization problem of LOS. Section 4 demonstrates the results of computational experiments on a hypothetical three-story building and conducts sensitivity analyses on how the evacuation population size and the building layout influence the optimized LOS design. Section 5 discusses some critical points of the proposed approach. Section 6 gives some concluding remarks. Finally, further research directions are discussed in Section 7.

2 Problem Definition

2.1 Network Modelling of Building Evacuation

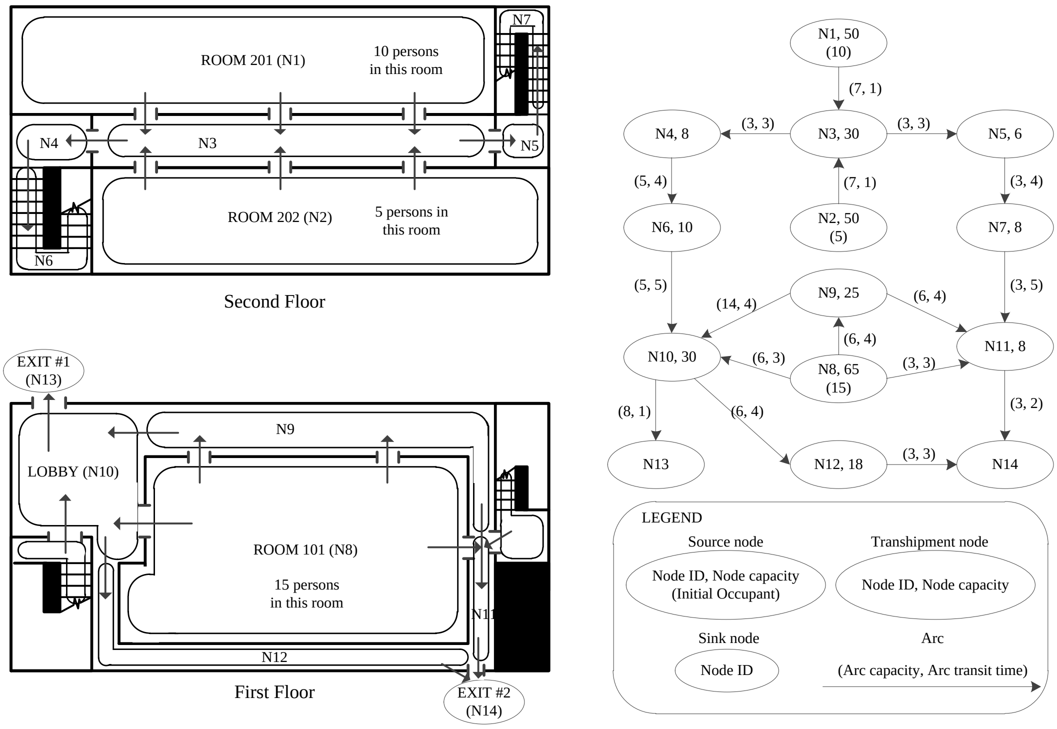
As the LOS concept is used here to help decide the occupant-related parameters of an evacuation network, it is necessary to introduce the process of converting a building layout into an evacuation network (see also, Chalmet et al., 1982) before the definition of the LOS optimization problem. A building consists of different kinds of components such as lobbies, halls, rooms and stairwells. Here the authors do not consider the elevators as they are usually not used when an emergency happens. Building components are represented by nodes, and the connections between paired nodes are represented by directed arcs, and then a topological network is obtained. For example, as shown in Figure 3, a two-story building is transformed into a network with 14 nodes and 17 arcs (Lu et al., 2003). In order to fully define the network to prepare for evacuation planning, first source nodes with initial occupants and sink nodes representing safe areas should be given. Then other occupant-related parameters are introduced, including node capacity, arc capacity and arc transit time. The three parameters are defined and calculated by the LOS approach (Kisko et al., 1998) as follows. See Table 1 for a simplified version of the calculation process.

(1) Node capacity

The capacity of a node is the maximum number of people simultaneously allowed to stay in the physical space allocated to the node. This capacity can be determined by

$$Node\ Capacity\ =\frac{Floor\ Space\ Area}{Area\ Occupancy\ at\ Queueing\ LOS\ X} \tag{1}$$

where the floor space area represents the usable standing area of the building sub-space the node represents, and the area occupancy is obtained from the data of the assigned queuing LOS (see Appendix Table A1). For example, in Figure 3, the floor space area of the node N8 (ROOM 101) is 51.52 m^2. If LOS C is chosen for the room, the average pedestrian area occupancy will be 0.79 m^2 / person. Then the node capacity of N8 equals to 51.52/0.79 = 65.22, or 65 persons.



(a) A building layout (b) A fully defined network

Figure 3 Modelling a building evacuation problem by a fully defined network

(2) Arc capacity

The capacity of an arc, also called dynamic capacity or flow capacity, refers to the number of people allowed to pass the connection the arc represents per second. This capacity can be calculated by

$$Arc\ Capacity\ =\ Walkway\ Width\ \cdot Flow\ Volume\ at\ Walkway\ LOS\ X \qquad (2)$$

where the walkway width represents the minimum width of the walkway, and the flow volume is obtained from the data of the assigned walkway/stairway LOS (see Appendix Tables A2-A3). For example, in Figure 3, the arc from N8 to N10 represents the walkway from ROOM 101 to LOBBY. The width of the walkway connecting them is 1.75 m. If LOS C is chosen for the walkway, the average flow volume will be 0.68 person /m /s. The arc capacity of N8-N10 equals to 1.75× 0.68=1.19 person/s, or 6 persons /5s, where 5s is chosen as the length of a time period, which is also the basic unit of arc transit time. For more discussion on the length of a time period, see the work of Chalmet et al. (1982).

Here it should be noted there are other connection types such as down stairway, up stairway and doorway, where doorway can be treated as walkway for their similarity (Fruin, 1971). Equation (2) and the following Equation (3) can be applied to other connection types by updating terminology "Walkway".

(3) Arc transit time

The transit time of an arc is the time that people take to travel from the midpoint of one component/node to the midpoint of another component/node. The time can be calculated by

$$Arc\ Transit\ Time\ =\ \frac{Walkway\ Length}{Flow\ Speed\ at\ Walkway\ LOS\ X} \qquad (3)$$

where the speed is obtained from the data of the assigned walkway/stairway LOS (see Appendix Tables A2-A3). For example, in Figure 3, the length of the walkway connecting ROOM 101 and LOBBY (arc N8-N10) is 18.25 m. If LOS C is chosen for the walkway, the average flow speed will be 1.22 m /s. The arc transit time of N8-N10 equals to 18.25/1.22=14.96s, or 3 time periods.

Table 1 Calculation of the three network parameters

<table>
<tr><th>Node/Arc ID</th><th colspan="2">Layout data</th><th colspan="2">LOS design</th><th colspan="2">Network parameter</th></tr>
<tr><td rowspan="3">Node N8
(ROOM 101)</td><td colspan="2" rowspan="2">Space area①
(m^2)</td><td colspan="2">LOS C</td><td colspan="2" rowspan="2">Node Capacity
=①/②
(person)</td></tr>
<tr><td colspan="2">Area occupancy②
(m^2 / person)</td></tr>
<tr><td colspan="2">51.52</td><td colspan="2">0.79</td><td colspan="2">65</td></tr>
<tr><td rowspan="3">Arc N8-N10
(ROOM
101-LOBBY)</td><td rowspan="2">Walkway
width③
(m)</td><td rowspan="2">Walkway
length④
(m)</td><td colspan="2">LOS C</td><td rowspan="2">Arc
Capacity
=③ ×⑤
(persons/5s)</td><td rowspan="2">Arc
Transit
time
=④/⑥
(5s)</td></tr>
<tr><td>Flow
volume⑤
(person /m /s)</td><td>Flow
speed⑥
(m/s)</td></tr>
<tr><td>1.75</td><td>18.25</td><td>0.68</td><td>1.22</td><td>6</td><td>3</td></tr>
</table>

With the determination of all the parameters, an evacuation network is fully defined. It should be noted that the above three network parameters must be positive integers. Then it can be solved by linear programming approaches or heuristic approaches. Here the authors use a known heuristic algorithm CCRP, which is put forward and validated by Lu et al. (2005), to solve the evacuation network. As this paper focuses on the optimization method, the CCRP is not further introduced. See Lu et al. (2005) for more details on the algorithm.

2.2 Problem Description

Given a topological network $G = (N, A)$ with layout and population information from a building that needs to be evacuated, the authors are to design the LOS x_i for nodes and the LOS y_i for arcs of the network, i.e., the facilities of the building, to construct a fully defined evacuation network that is able to evacuate occupants with minimized clearance time. The information includes the floor space area a_i of each node, the walkway /stairway width d_i and length l_i of each arc. Source nodes and destination nodes (safety areas) need to be pointed out. Initial occupants p_i are located in each source node. Let $o_i(x_i)$ be the area occupancy of ith node at queueing LOS x_i, $f_i(y_i)$ be the flow volume of ith arc at walkway/stairway LOS y_i, and $v_i(y_i)$ be the flow speed of ith arc at walkway/stairway LOS y_i. The problem can be formulated as follows.

Assumptions:

(1) Network parameters are determined by the building information and the LOS data.

(2) No individual behavior is considered because the movement of occupants is to be planned and optimized in the calculation of minimum clearance time.

(3) No hazard influence is considered for the evacuation process.

Minimize:

$$T = F(G) \tag{4}$$

Subject to:

$$n_i = \frac{a_i}{o_i(x_i)} \tag{5}$$

$$c_i = d_i \times f_i(y_i) \tag{6}$$

$$t_i = \frac{l_i}{v_i(y_i)} \tag{7}$$

where T is the minimum time period from the beginning of the evacuation to the end of the evacuation, namely, the clearance time of $G = (N, A)$. For a fully defined network, T can be solved by the CCRP approach. Expressions (5) (6) (7), where n_i is the node capacity of ith node, c_i is the dynamic capacity of ith arc, and t_i is the arc transit time of ith arc, are identical to expressions (1) (2) (3). As the building layout gives the information of a_i, d_i, and l_i, the remaining unknown variables are x_i and y_i, i.e., LOS for nodes and arcs, which will be solved by the following proposed approach.

3 Proposed Approach

For a network with m nodes and n arcs, an evacuation planner has to decide $(m + n)$ LOS for $(m + n)$ facilities. Because there are 6 possible LOS for each facility, the planner needs to search the optimal design(s) from 6^{m+n} designs, which can be an extremely large number even when the scale of the network is not large. For example, for the network with 14 nodes and 17 arcs in Figure 3, the search space is $6^{14+17} = 1.33 \times 10^{24}$ designs. This paper adopts a standard Genetic Algorithm (GA) to do the optimization work, as genetic algorithms have been applied to solve optimization problems (Chu et al., 1997; Gonçalves et al., 2005) that include large search spaces, which exactly describes the above LOS design problem. Although the GA does not necessarily give an optimal or close to optimal solution, it is possible to find improved solutions quickly with the help of the GA.

In order to apply the GA to optimize LOS, the first step is to define an individual and its genes. A design of LOS for all the nodes and arcs in a building network is an individual here. Naturally each LOS for a node or an arc is a gene. As LOS is used to determine network parameters, each individual with a LOS design also represents a fully defined evacuation network, and each gene is a node or an arc of the network. The fitness of each individual is measured by the minimum clearance time, which is a basic performance indicator of an evacuation network. The time is calculated by the CCRP approach with the input of a defined network each individual represents. The following steps outline the GA setup as used in this paper.

(1) Input: Obtain the information of the building layout and the population, such as the areas of sub-spaces, the widths and the lengths of walkways and stairways, the locations of exits, and the initial occupants and their locations.

(2) Initialization: Create a group of fully defined networks with random LOS designs or one same original LOS design (the latter is adopted in this paper).

(3) Evaluation: Calculate the minimum clearance time of each defined network.

(4) Selection: Pick the good networks with shorter minimum clearance time and replace the bad ones in the network group by the roulette wheel selection method.

(5) Crossover: Exchange the nodes and arcs of paired networks with a certain possibility (usually high, 0.80 is used in this paper) to create a new network group.

(6) Mutation: Assign a new LOS for each node and each arc of each network with a certain possibility (usually low, 0.05 is used in this paper) to generate a new network group.

(7) Evaluation: Calculate the minimum clearance time of each network obtained from (6).

(8) Elitist: Preserve the best network in each generation to avoid the degradation of the network group.

(9) Terminal condition: Decide whether the process satisfies a termination rule such as "the shortest minimum clearance time does not change for 100 generations" (the termination rule "generations does not exceed 300" is adopted for the three-story building case study in this paper as the best fitness value stays stable after 300 generations). If it is true, go to (10); if it is false, go to (4).

(10) Output: Show the LOS design for the network with the shortest minimum clearance time.

When the authors tested the above approach by computational experiments, it was easy to get an optimized LOS design. In fact, numerous optimized LOS designs with the same shortest minimum clearance time were output when the iteration continued without terminal condition. This phenomenon makes sense as the networks under different LOS designs may have the same evacuation performance. However, it will make an evacuation planner confused when he applies this approach to solve a practical problem.

In order to avoid confusion caused by multiple solutions, this paper gives a second stage of the GA optimization to generate a single optimized LOS design. In the second stage the authors put forward the concept of the Base LOS Design (BLD), which is the design to which the optimized LOS designs with the shortest minimum clearance time should be kept close as much as possible. The BLD can be set by the preference of the planner, or it can be the original LOS design if there is one. The distance between the BLD and an optimized LOS is measured by the total absolute deviation, which is calculated as follows:

$$D = \sum |x_i - x_{0_i}| + \sum |y_i - y_{0_i}| \tag{8}$$

where x_{0_i} is queueing level of service of ith node in the BLD, and y_{0_i} is walkway/stairway level of service of ith arc in the BLD. Here it should be noted the LOS A-F are represented by numbers 1-6 in equation (8). The optimized LOS design closest to the BLD will be the final solution, which requires the least amount of changes to LOS design to maximize the evacuation performance.

With the BLD concept, the second stage optimization work is able to be done with the similar GA process by changing the fitness value from the minimum clearance time to the minimum total absolute deviation and adjusting corresponding operations in the iteration process.

4 Computational Experiments

This paper conducted two computational experiments based on a hypothetical three-story building and a twelve-deck cruise ship. The former is used as the main example to show the applicability of the approach in optimizing LOS design, to reveal the possible reasons why it works, and to analyze the sensitivity of the optimized LOS design when evacuation configurations change. The second case study presented is to test the scalability of the approach.

4.1 Experiment Design

The hypothetical three-story building, provided by Kisko et al. (1998), has 6 rooms, 2 stairs, 2 exits, and several open spaces (see Figure 4a). With the layout information, the building is transformed manually into a network with 22 nodes and 28 arcs (see Figure 4b). Each node, representing a certain space, has the property of area. Each arc, representing a connection, has the properties of width and length. The length of a time period is set to be 5 seconds in the measurement of arc capacity and arc transit time. In the building, 212 people are distributed among 6 rooms. Accordingly, source nodes N18, N19, N20, N11, N12, and N5 in Figure 4b are assigned 36, 16, 18, 36, 34, and 72 initial occupants respectively. Two exits are represented by two sink nodes N21 and N22.

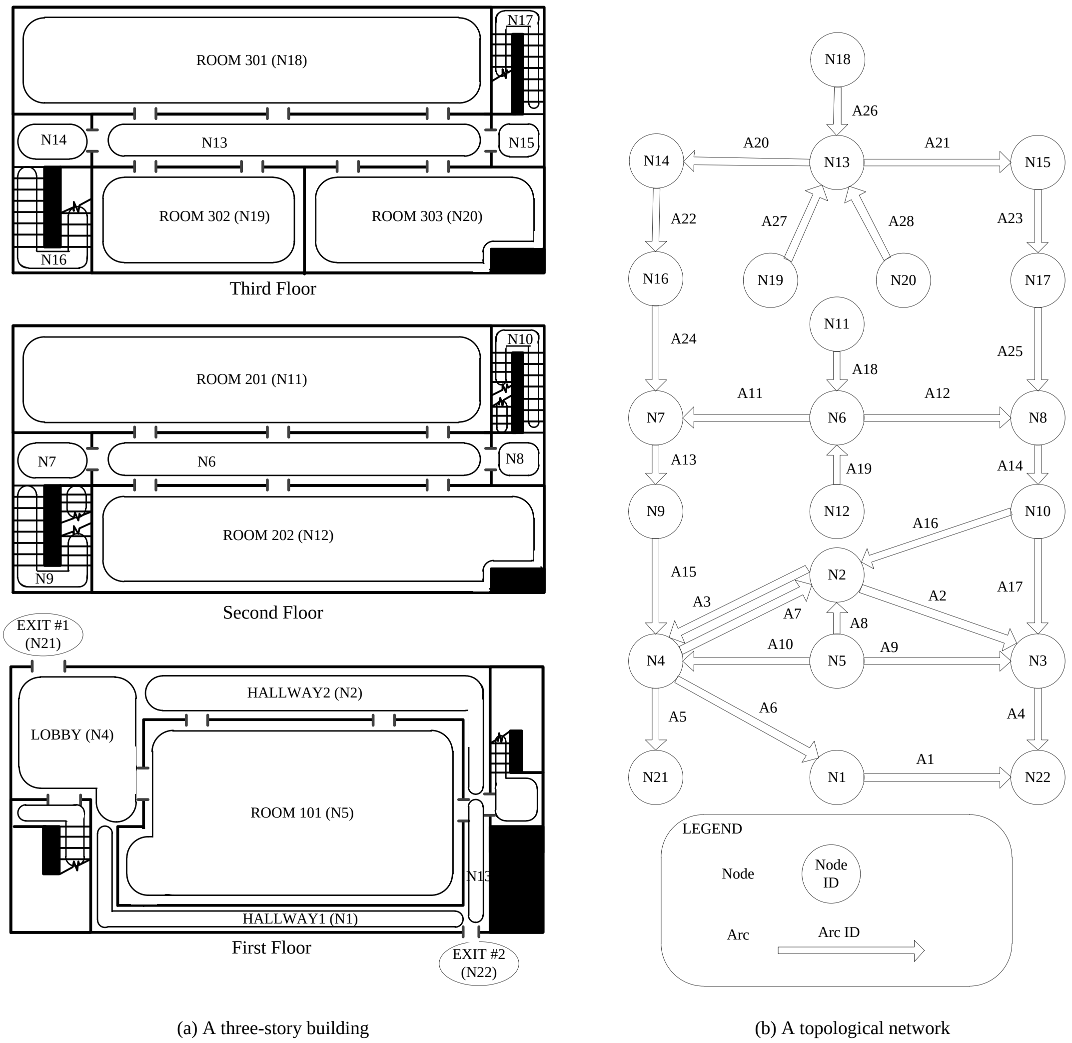


Figure 4 A hypothetical three-story building and its network

There is an original LOS design for nodes and arcs of the network from Kisko et al. (1998), as shown in Figure 6a, which is used as the BLD. By using the GA approach, an optimized LOS design was obtained. Two fully defined evacuation networks under two LOS designs were compared and analyzed by evacuation planning results including evacuation curves, total arc movements, and remaining capacity of arcs. The proposed two-stage GA approach was implemented in the Visual C++ environment and run on a personal computer with Intel Core i5 CPU 2.50GHz and RAM 4.00GB. It took about several seconds to finish the optimization process.

4.2 Result Analysis

Figure 5 shows the optimization process of two fitness values, namely the minimum clearance time and the total absolute deviation, for GA individuals (building networks) through the GA approach. The minimum clearance time for the building network under the original LOS design is 37 time periods. After about 110 generations, the minimum clearance time reached its minimum value, 33 time periods, which means that the shortest minimum clearance time appeared and one of the optimized LOS designs for the building network was obtained. It also means that the final optimized network is able to evacuate occupants faster than the original network by 4 time periods, which is an 11% improvement of evacuation performance. When the first stage of optimization ended at 300 generations, the second stage of optimization for the deviation started. The initial deviation is about 58, after nearly 270 iterations (at 570 generations) it reaches its minimum value 3, which is a small deviation as there are totally 50 arcs and nodes with their own LOS.

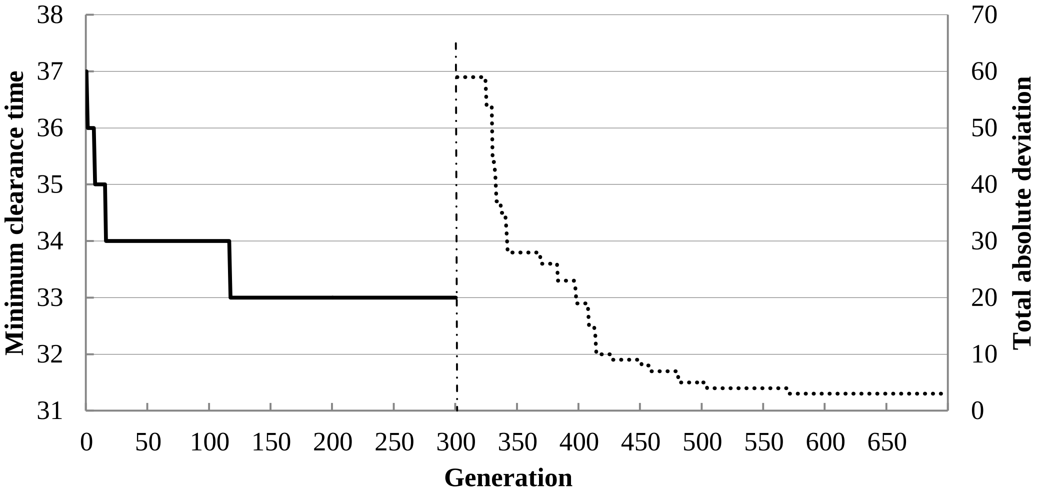


Figure 5 The GA optimization process for the clearance time and the deviation

The original network and the optimized network are demonstrated in Figure 6, with the different colours of nodes and arcs representing different LOS of building facilities. In the original network, there are two queueing LOS, LOS C and LOS D, for the nodes, and two walkway/stairway LOS, LOS C and LOS D, for the arcs. The assignment is probably based on the rule of making occupants evacuate fast and feel comfortable with not too low or too high LOS. Compared to the original LOS design, the optimized one shows differences in three arcs A11, A17, and A20. The arcs all elevate their LOS from D to E, which means they allow more people pass through at one time period but delay the travel time as the arcs are getting more crowded.

Based on the original network and the optimized network shown in Figure 6, further results are shown and analysed to answer two questions. First is whether the optimized network is better than the original network in the measurement of the minimum clearance time. As the CCRP approach is heuristic, it is not completely certain that the network is optimized without the validation of an accurate approach. So the two evacuation networks are also solved by the LP approach, as shown in Figure 7. The second question is how the optimized LOS design brings positive changes to the evacuation network by only small deviation compared to the original LOS design. This question will be answered by giving more details on the two evacuation plans solved by the CCRP approach, as shown in Table 2 and Figure 8.

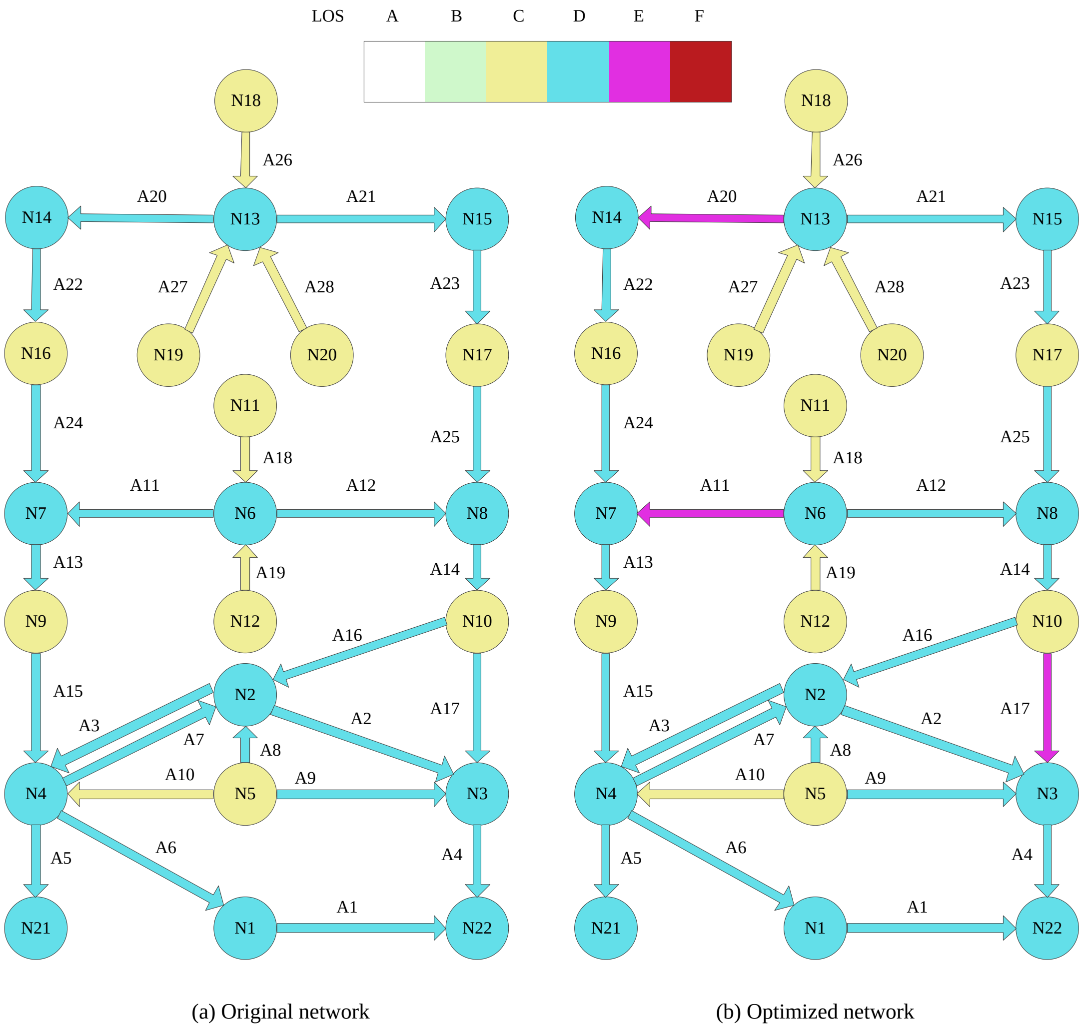


Figure 6 Networks before and after the optimization of LOS

Figure 7 depicts the evacuation curves for the original network (OriNet) and the optimized network (OptNet). Under the calculation of the CCRP approach, the remaining occupants for both networks decreases and then stays stable before 13 time periods, but after that the curve for the original network goes down slowly until the clearance time of 37 time periods while the curve for the optimized network first continues to stay the stable for a short time, and then descends quickly, and finally stops at 33 time periods. On the other hand, under the calculation of the LP approach, the two curves keep the same trend as the curves solved by the CCRP. However, the original network becomes clear at 34 time periods, faster than the result by the CCRP. As a result, the difference between the minimum clearance times for two networks is smaller. Figure 7 shows that the optimized network indeed has better evacuation performance than the original one, although not by much, with 33 time periods versus 34 time periods (3% improvement).

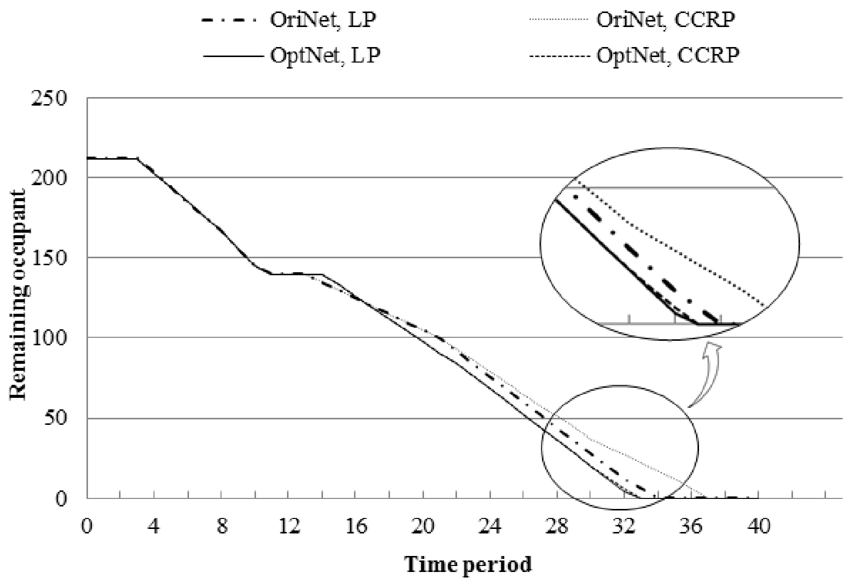


Figure 7 Evacuation curves for two networks by two approaches

Table 2 shows the total occupants moving through a few selected arcs in the evacuation plans of two networks. These arcs include arcs (A11, A17, and A20) showing the different LOS and arcs (A1, A4, and A5) linking directly to sink nodes. According to the table, it's clear that the numbers of occupants passing through the two arcs leading to exits, A5 for EXIT #1 and A4 for EXIT #2, are different. For the optimized network, 8 more occupants are choosing EXIT #2 as the exit instead of EXIT #1. The differences of movements for arcs A11, A17, and A20 are consistent with the above change. In conclusion, Table 2 shows that the optimized LOS design improves the network by changing the distribution of occupants among destinations.

Table 2 Total movement through arcs

Arc ID	**Original network**		**Optimized network**	
	#▲	**%■**	**#**	**%**
A1	0	0.0%	0	0.0%
A4	69	32.5%	77	36.3%
A5	143	67.5%	135	63.7%
A11	42	19.8%	40	18.9%
A17	48	22.6%	56	26.4%
A20	48	22.6%	44	20.8%

▲The total number of occupants passing through an arc.

■The percentage in the total initial occupants.

Figure 8 demonstrates the change of the remaining capacity for selected arcs in two networks as time goes by. The difference of LOS designs makes the remaining arc capacity between the corresponding arcs different in the evacuation plans. Each arc in the optimized network is used for more time periods compared to the corresponding arc in the original network. For example, the arc A11 is used from 4 to 27 time periods in the optimized network while occupants enter the arc from 1 to 10 time periods in the original network. In conclusion, the Figure 8 shows that the optimized

LOS design leads to shorter minimum clearance time by increasing the utilization of arcs in the evacuation plan.

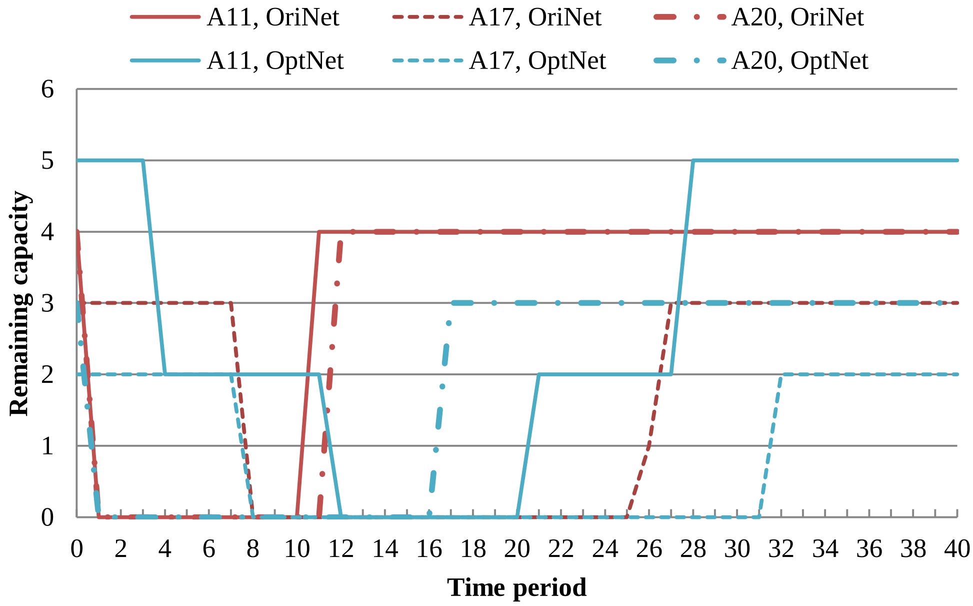


Figure 8 The remaining capacity for arcs A11, A17, and A20 in two networks

4.3 Sensitivity Analysis

As shown above, the proposed approach is able to obtain a LOS design with shorter clearance time for a building network. In this section, the evacuation configurations, including initial population and building layout, are changed to test how they influence the LOS design. The initial population gives the information of the number and the position of occupants in the building, which is supposed to change the evacuation result as more occupants locating farther from the safe areas will take more time to evacuate. On the other hand, the building layout relating to the geometric properties of sub-spaces is also supposed to affect the evacuation performance as a wider and a closer exit always lead to shorter clearance time.

The same three-story building above is used to do the following sensitivity analysis. This sensitivity analysis focuses on a few critical points. For the population aspect, the authors change the number of initial occupants (36) in the node N18 (ROOM 301), as shown in Figure 9. For the layout aspect, the width (1.52 m) of the arc A5 (EXIT #1), is changed, as shown in Figure 10. The optimized LOS design above is selected as the BLD. The minimum total absolute deviation is regarded as the main index to reflect the change of the optimized LOS design. The shortest minimum clearance time is also demonstrated to give references.

Figure 9 shows how the number of initial occupants in node N18 influences the optimized LOS design. The result shows that the BLD is adaptable to various initial occupants in N18 as there are only 3 configurations, 52, 60, and 68, showing the deviation of 2. With the selected BLD for the networks with different populations, the networks can be solved with their shortest minimum clearance times in most conditions.

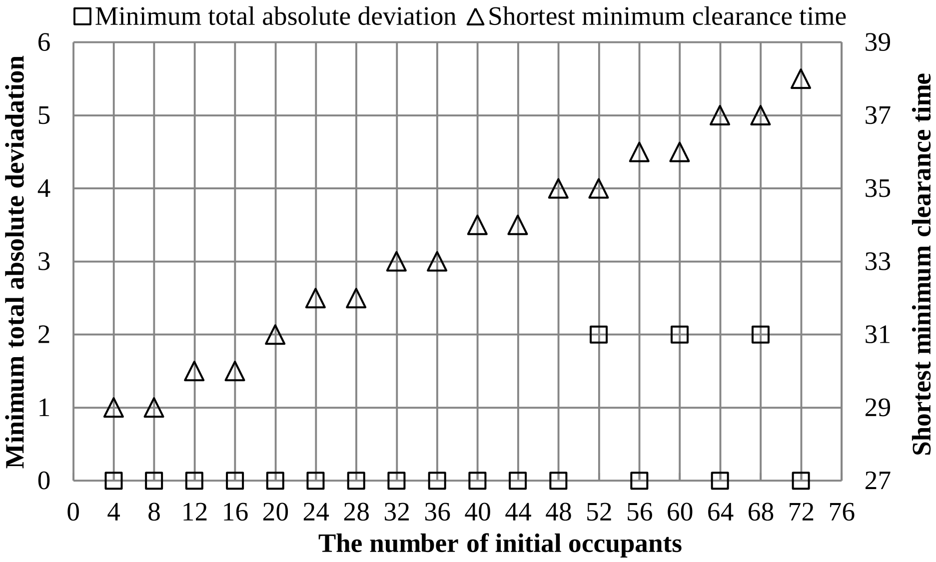


Figure 9 The LOS sensitivity to the change of initial occupants in N18

Figure 10 shows how the width of the arc A5 influences the optimized LOS design. When the arc width increases from 0.6m to 2.3m, the optimized LOS design should be adjusted to get the shortest minimum clearance time only for the 0.6m configuration. It can be concluded that the LOS design is not sensitive to the change of the width of arc A5. The selected BLD is suitable for the different layout configurations to get best evacuation performance.

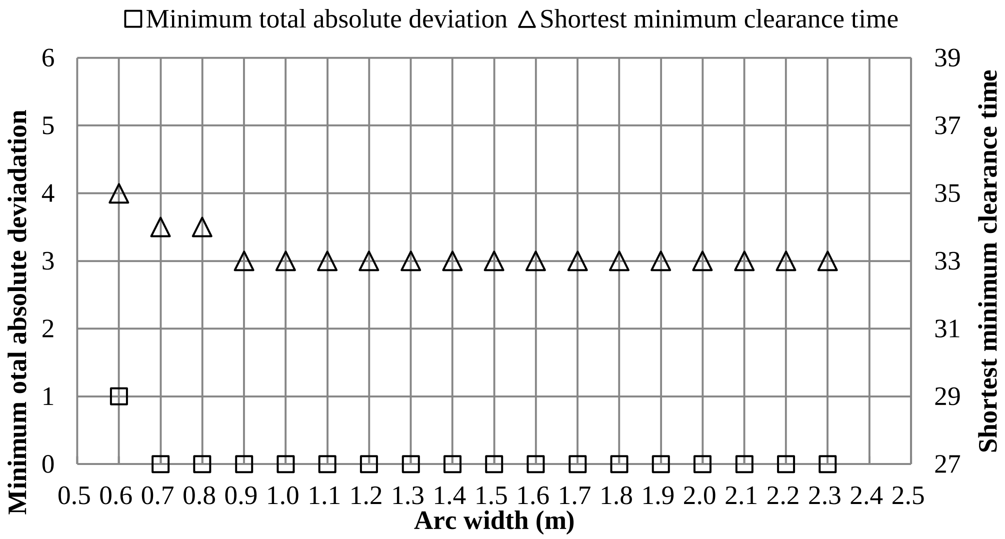


Figure 10 The LOS sensitivity to the change of the width of A5

4.4 Case Study on a Cruise Ship

Here a second computational experiment on a twelve-deck cruise ship was conducted to study the applicability of the proposed approach for more complex environments. The ship layout and evacuation configuration are from the SAFEGUARD project (2011). The ship is about 254 meters long and 32 meters wide and 33 meters high from the lowest deck to the highest deck. There are 1717 people located on various areas of the ship. They should be assigned to 4 assembly stations, 3 on the fourth deck and 1 on the fifth deck (see the green nodes in Figure 11). The layout is transformed manually into a network with 389 nodes and 940 arcs (see Figure 11). The original LOS design for nodes and arcs of the network is obtained according to the following rule: for nodes/arcs representing or connecting possible bottleneck areas such as stairways or crossways, LOS D is assigned; for other nodes/arcs which may allow less crowded pedestrian flow, LOS C is assigned. The length of a time period is set to be 1 second in the measurement of arc capacity and arc transit time.

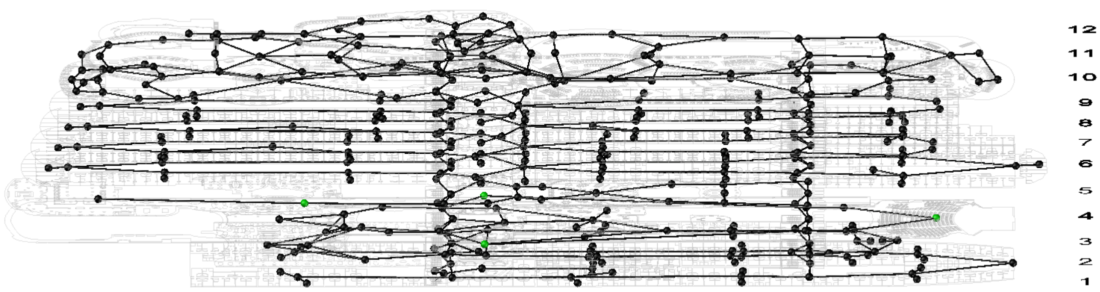


Figure 11 The layout of a cruise ship and its network

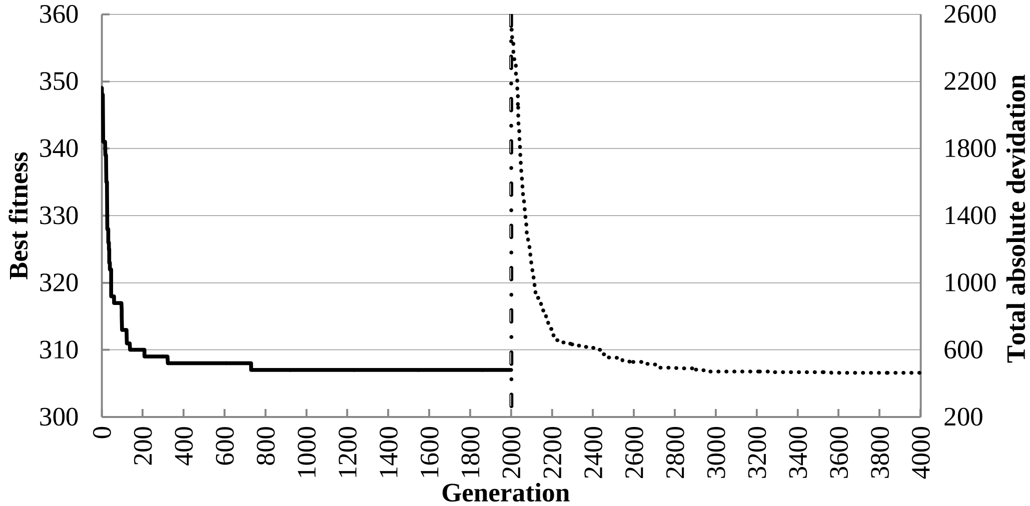


Figure 12 The GA optimization process for the clearance time and the deviation

With the layout information as the input and the original LOS design as the BLD, the proposed two-stage GA optimization approach was implemented and run on a personal computer with Intel Core i5 CPU 2.50GHz and RAM 4.00GB. It took about 24 hours to get the result of the GA optimization with the setup of 20 individuals and 4000 generations, as shown in Figure 12. The minimum clearance time for the network under the original LOS design is 349 time periods. After about 720 generations, the minimum clearance time reaches its minimum value, 307 time periods, which is 42 time periods less than the value under original LOS design (12% improvement of evacuation performance). In the second stage of optimization, the initial deviation is about 2500, and after nearly 1300 iterations (at 3300 generations) the deviation reaches its minimum value 462, part of which is shown in Figure 13.

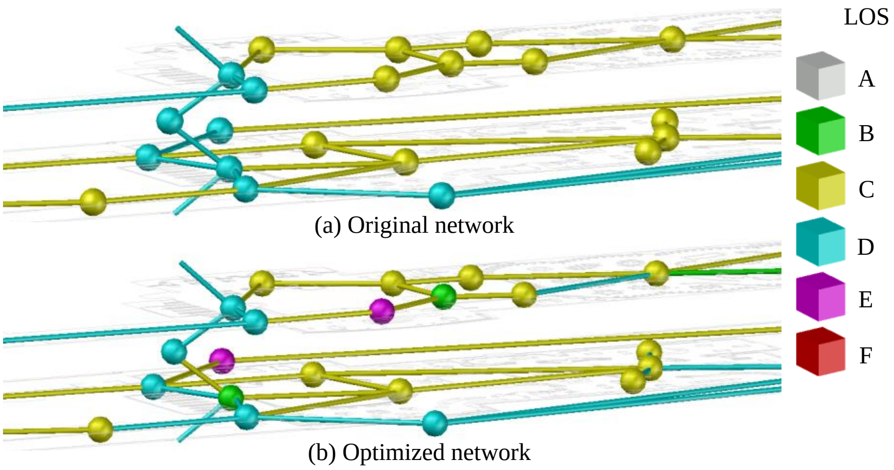


Figure 13 Partial networks (the middle of Deck 4 and Deck 5) before and after the optimization of LOS

The evacuation curves for the original network (OriNet) and the optimized network (OptNet) under the CCRP and the LP are shown in Figure 14. Here the authors focus on the curves generated by the LP approach as it gives exact solutions. Under the calculation of the LP approach, the optimized network indeed has better evacuation performance than the original one, with 303 time periods versus 347 time periods (13% improvement).

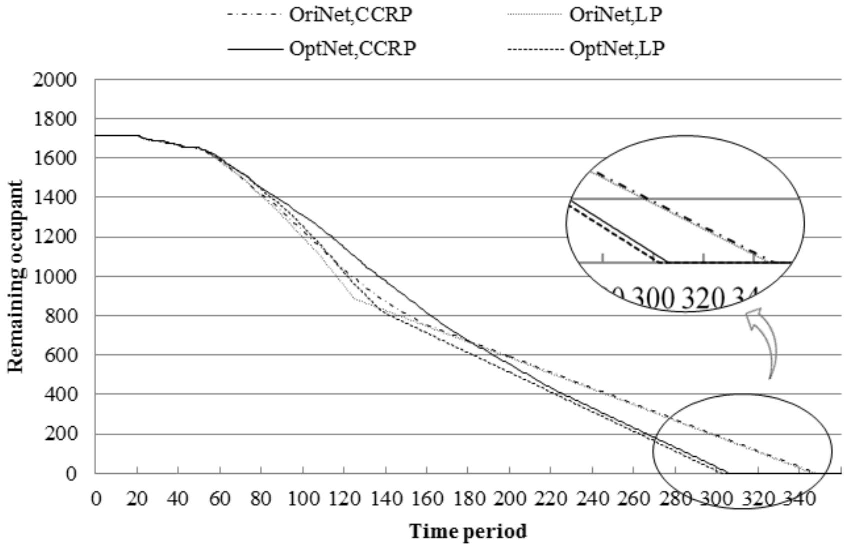


Figure 14 Evacuation curves for two networks by two approaches

5 Discussion

The authors believe that the approach of using LOS concept to construct the network used in evacuation planning (Kisko et al., 1998) is reasonable and practical for its consideration of the relationship between crowd density and network parameters. As previous work does not provide a clear way to choose LOS for arcs and nodes in a network, this paper uses a GA optimization approach to design LOS with the purpose of constructing efficient evacuation networks with shorter clearance time. The computational test on a three-story building showed that the approach was able to improve the evacuation performance of a building network by modifying the LOS of a few facilities. Furthermore, sensitivity analysis showed that after obtaining the optimized LOS design of a building network, the design could keep the network of high efficiency when there was a small change in the building layout or population size. An additional computational test demonstrated that the approach could be applied in practical problems with larger networks.

While the focus of this paper is on evacuation planning, it is recognized that pedestrian behavior aspects were not included in the analysis. The authors, however, are concurrently working on evacuation simulation models that do account for these aspects. On the other hand, the LOS data used in this paper (Fruin, 1970) reflect the physical aspect of crowd evacuation, but they may be not accurate today as they have not been updated for over 40 years. LOS data should be collected and updated for specific applications. Finally, as this study only optimizes the LOS for a three-story building and a twelve-deck cruise ship, more tests should be done before applying it to larger buildings or even city areas. However, the heuristics of the GA and the CCRP make the proposed approach show great potential to design LOS efficiently for larger networks.

Notwithstanding its limitation, this study does suggest a practical way of combining layout design and evacuation planning. It is possible that by using the proposed approach building designers are able to design safer buildings with efficient evacuation network, and policy makers can develop better evacuation plans quickly when an emergency occurs.

6 Conclusion

This paper provides an optimization approach to design level of service (LOS) on facilities of a building for crowd evacuation, which is based on a standard genetic algorithm and a heuristic evacuation planning approach CCRP (Lu et al., 2005). The proposed approach gives the optimized LOS design with shortest minimum clearance time and minimum total absolute deviation with the input of building layout, population and base LOS design. The computational experiment on a three-story building demonstrates that the approach has the ability of improving the evacuation performance of a building by assigning optimized LOS for facilities. Furthermore, the sensitivity analysis shows that the optimized LOS is adaptable when the population size and the building layout vary.

7 Future Work

The followings are areas of future work. First, this paper designs the LOS on the macroscopic evacuation planning method, without the consideration of crowd behaviour. It is a challenging task to do the optimization work and the microscopic simulation at the same time for the sake of high computational cost. However, the improvement of algorithms and multi-process techniques may make the combination possible. Second, hazardous scenarios are not included on this research, which makes the real world situation more complex. The integration of this approach with hazard handling approaches may eliminate the assumption. Finally, this paper assumes that the LOS is only determined by the building layout information, but in fact some factors like floor loading must be considered. Future work will further study the approach under more scenarios and expand the application on large buildings or city areas to make it more practical and capable.

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Appendix

The data of levels of service for queueing, walkways, and stairways (Fruin, 1970) are listed here respectively in Tables A1-A3, in which the median value is the average of the upper limit and the lower limit of the range. The median value is used in this paper.

Table A1 Level of service for queueing

LOS	Average Pedestrian Area Occupancy	
	Range (ft^2/person)	Median (m^2/person)
A	⩾13	1.208▲
B	10-13	1.068
C	7-10	0.790
D	3-7	0.465
E	2-3	0.232
F	⩽2	0.186*

▲This median value is solved only from the lower limit, 13 ft^2/person, as there is no certain upper limit. This rule is also used in Tables A2-A3.

*This median value is solved only from the upper limit, 2 ft^2/person, as there is no certain lower limit.

Table A2 Level of service for walkways

LOS	Average Flow Volume		Average Speed	
	Range (person/min/ft)	Median (person/m/s)	Range (ft/min)	Median (m/s)
A	0-7	0.191	⩾260	1.321
B	7-10	0.465	250-260	1.295
C	10-15	0.684	230-250	1.219
D	15-20	0.957	200-230	1.092
E	20-25	1.230	110-200	0.787
F	⩾25	1.367	0-110	0.279

Table A3 Level of service for stairways (down stair)

LOS	Average Flow Volume		Average Speed	
	Range (person/min/ft)	Median (person/m/s)	Range (ft/min)	Median (m/s)
A	0-5	0.137	⩾125	0.635
B	5-7	0.328	120-125	0.622
C	7-10	0.465	115-120	0.597
D	10-13	0.629	105-115	0.559
E	13-17	0.820	85-105	0.483
F	⩾17	0.930	0-85	0.216

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