International Journal of Applied Mathematics, Sciences, and Technology for National Defense
Volume 4, Issue 2, 199-216
e_ISSN: 2985-9352, p_ISSN: 2986-0776
https://www.journal.foundae.com/index.php/JAS-ND
DOI : https://doi.org/10.58524/app.sci.def.v4i2.1096

Weighted graph-based tsunami evacuation route optimization for enhancing disaster resilience in Yogyakarta International Airport

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Article Info

Article history:

Received: December 21, 2025
Revised: April 19, 2026
Accepted: June 2, 2026

Keywords:

Artificial Bee Colony
Evacuation
Route Optimization
Tsunami
Weighted Graph

Abstract

Background: Yogyakarta International Airport (YIA) is located on the southern coast of Java Island, which is prone to tsunamis due to tectonic plate subduction. The high passenger density in the terminal requires a fast, safe, and efficient evacuation system. However, evacuation route planning is generally still based on the shortest distance without considering passenger density, which has the potential to cause congestion during emergencies.
Aims: This study aims to develop a tsunami evacuation route optimization model on the ground floor of YIA by simultaneously considering distance and passenger density factors through a weighted graph approach and the artificial bee colony metaheuristic algorithm.
Method: Spatial data of the terminal layout is processed into a graph consisting of nodes and edges using QGIS. Edge weights are calculated from a combination of physical distance and passenger density. The optimization process is carried out using the ABC algorithm through the stages of population initialization, fitness evaluation, solution exploration, and selection of the best route to determine the minimum evacuation route from several starting points to the exit point.
Result: The optimization results show that all ten initial evacuation points were efficiently allocated to six exit points with a minimum total weight. The resulting routes are not only shorter in terms of distance, but also avoid high-density areas, resulting in a more even distribution of passenger flow and reduced potential for congestion. Point EG was identified as the most optimal route based on a combination of distance and low density.
Conclusion: The weighted graph approach based on artificial bee colony is effective in determining fast and adaptive tsunami evacuation routes in large-scale public facilities. This model has the potential to support more realistic disaster mitigation planning and can be applied to airports and other public infrastructure.

To cite this article: Purnomo, D. H., Christi, D. E. N., Shukla, A., & Anggraini, D. (2026). Weighted graph-based tsunami evacuation route optimization for enhancing disaster resilience in Yogyakarta International Airport. *International Journal of Applied Mathematics, Sciences, and Technology for National Defense,* 4(2), 199-216.

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INTRODUCTION

Tsunamis are large ocean waves generated by the sudden displacement of massive water bodies due to seismic activities, submarine landslides, volcanic eruptions, or explosions. These events can cause catastrophic coastal inundation, resulting in extensive damage to infrastructure, disruption of social systems, and threats to national security, thereby requiring effective and well-planned disaster mitigation strategies (Röbke & Vött, 2017; Evers et al., 2019; Syarifah et al., 2020). From the perspective of disaster resilience, tsunamis represent not only a natural hazard but also a complex risk that emerges from the interaction between physical threats, population exposure, and the limited capacity of communities to respond and recover. Indonesia is one of the countries most vulnerable to tsunami hazards due to its geographical location along the Pacific Ring of Fire, where several major tectonic plates converge. This tectonic setting generates frequent seismic activities capable of triggering tsunamis. In addition, Indonesia possesses an extensive coastline exceeding 99,000 kilometers, which significantly increases the exposure of coastal populations, settlements, and strategic infrastructure to tsunami impacts. Data from the National Disaster Management Agency (BNPB) indicate that more than 80% of Indonesia's coastal regions face a high level of tsunami risk, particularly areas located near active subduction zones such as the southern coast of Java (Röbke & Vött, 2017). High population density, tourism activities, and economic centers concentrated in coastal areas further amplify potential disaster impacts.

Beyond the physical hazard itself, a major challenge in strengthening disaster resilience lies in the limited preparedness and response capacity of vulnerable communities. Previous studies have shown that inadequate early warning dissemination, insufficient evacuation infrastructure, and poorly planned evacuation routes can significantly increase casualties during tsunami events, especially in areas with high public activity and limited access to safe zones (Evers et al., 2019). In many coastal settlements, evacuation planning is often not supported by detailed spatial analysis or real-time data integration, which reduces the effectiveness of emergency responses during critical situations. Therefore, enhancing tsunami disaster resilience requires the development of integrated, data-driven, and spatially based evacuation systems that can support rapid decision-making during emergencies. Such systems can improve evacuation planning, optimize route accessibility, and identify safe assembly points more effectively. By incorporating spatial analysis and disaster risk data, these approaches play a crucial role in strengthening disaster preparedness, minimizing casualties, and supporting broader national defense strategies against large-scale natural hazards.

Yogyakarta International Airport (YIA) is located in the southern coastal area of Java Island, which is included in the tsunami red zone due to the subduction activity of the Indo-Australian and Eurasian plates (Syahidah et al., 2023). As an international airport that serves thousands of passengers per day, the existence of a planned and adaptive evacuation system is an urgent need. However, until now, YIA has not had a tsunami evacuation route that is openly and clearly available to the public, increasing the potential for safety risks in emergency situations (Nirwana & Putrie, 2023). Determining an effective evacuation route does not only depend on the shortest distance but must also consider dynamic conditions such as passenger density on each route. Several previous studies have emphasized the importance of evacuation route planning in various contexts, including buildings, transportation hubs, and disaster-prone areas. For example, Cheff et al. (2018) analyzed pedestrian evacuation behavior in high-rise buildings, highlighting the need for alternative routing based on crowd density. In the airport context, Jasztal et al. (2022) modeled evacuation flow in terminals under fire scenarios and concluded that combining spatial data with crowd flow estimation enhances route planning. These studies, although conducted in different domains, share the same objective which is ensuring safe and efficient evacuation by accounting for both spatial structure and dynamic human movement. Recent approaches in disaster management have explored hybrid swarm intelligence for evacuation, showing that multi-objective optimization can produce more robust solutions in coastal scenarios (Barus et al., 2022). Therefore, weighted graph-based route modeling is the right approach. In this model, nodes represent evacuation points, and edges represent paths between points with weights determined based on a combination of distance and density parameters (Sholikhan et al., 2019). To address uncertainties in evacuation planning, Davoodi (2021) proposed efficient shortest path algorithms under uncertain networks, which provide important insights for modeling evacuation graphs and support the integration of fuzzy arc weights in this study.

This study uses the Artificial Bee Colony (ABC) algorithm, a nature-inspired metaheuristic based on the aging behavior of honeybees. ABC is known for its ability to explore solution spaces efficiently and avoid local optima, making it suitable for complex optimization problems such as evacuation route planning. ABC was chosen because it can perform efficient global searches, is easy to implement, and is effective in handling complex problems with many variables (Ebrahimnejada et al., 2021). With three main mechanisms employed bees, onlooker bees, and scout bees ABC can explore various route alternatives and avoid local solution traps. Compared to conventional algorithms such as Dijkstra, ABC is more flexible in non-deterministic and multi-criteria scenarios such as dynamic evacuation (Zong et al., 2022; Jovanović et al., 2024). Novel swarm-based methods such as chaotic and neighborhood-enhanced Artificial Bee Colony (Xiao et al., 2023) continue to demonstrate improvements in exploration and convergence, supporting the use of ABC in real-time disaster contexts. The purpose of this study is to apply the ABC algorithm to a weighted graph to determine the optimal evacuation route at YIA in a tsunami scenario. The model considers two main parameters, namely distance and density, with the results visualized using QGIS software. It is hoped that the results of this study can be a recommendation for a responsive, efficient evacuation system that is ready to be implemented in vital infrastructure such as airports. GIS-based tsunami risk mapping in Indonesia further confirms the vulnerability of coastal airports and urban areas, such as Yogyakarta International Airport, emphasizing the urgency of evacuation route planning (Jihad et al., 2023; Jumadi et al., 2025).

The main contributions of this research can be summarized as follows: (1) development of a two-parameter weighted graph model that integrates physical distance and passenger density to produce more realistic evacuation routes than conventional shortest path approaches, (2) implementation of the ABC algorithm for multi-point evacuation route optimization in airport terminal networks, capable of handling spatial complexity and producing computationally efficient solutions, (3) a real world case study at Yogyakarta International Airport, which provides data-based tsunami evacuation route maps and recommendations as a practical solution for high-risk public facilities that previously did not have official evacuation maps.

METHOD

Experimental Data

This study was initiated by identifying the absence of a comprehensive tsunami evacuation route map at Yogyakarta International Airport (YIA), which is considered a high-risk location due to its proximity to the active subduction zone along the southern coast of Java. Airports located in coastal regions with high seismic activity face significant challenges in disaster preparedness, particularly in ensuring the rapid and safe evacuation of large numbers of passengers during emergency situations. Despite the strategic importance of YIA as a major transportation hub with high daily passenger traffic, a spatially optimized evacuation route system specifically designed for tsunami hazards has not yet been systematically developed.

To address this gap, spatial data collection and preparation were carried out using the ground floor plan of YIA in shapefile (SHP) format. The use of geospatial data enables detailed spatial analysis and facilitates the identification of critical infrastructure elements that play an important role during evacuation processes. The floor plan was analyzed to determine several strategic points that may influence evacuation efficiency, including main entrances, public circulation areas, emergency staircases, corridors, and building exits. These elements represent potential nodes and pathways that could be utilized by passengers and airport personnel during an emergency evacuation scenario.

Furthermore, the ground floor layout of YIA was systematically divided into several functional zones to better understand the spatial distribution of passenger activities and movement patterns within the terminal. These zones include the arrival curbside area, the arrival lobby, the domestic baggage claim area, and the international baggage claim area. Each of these zones has distinct spatial characteristics and levels of passenger density, which significantly influence evacuation dynamics, crowd movement, and potential bottlenecks during emergency situations. Understanding these variations is crucial for designing evacuation routes that are not only efficient but also capable of accommodating high passenger volumes under time-critical conditions. The zoning configuration used in this study is illustrated in Figure 1.

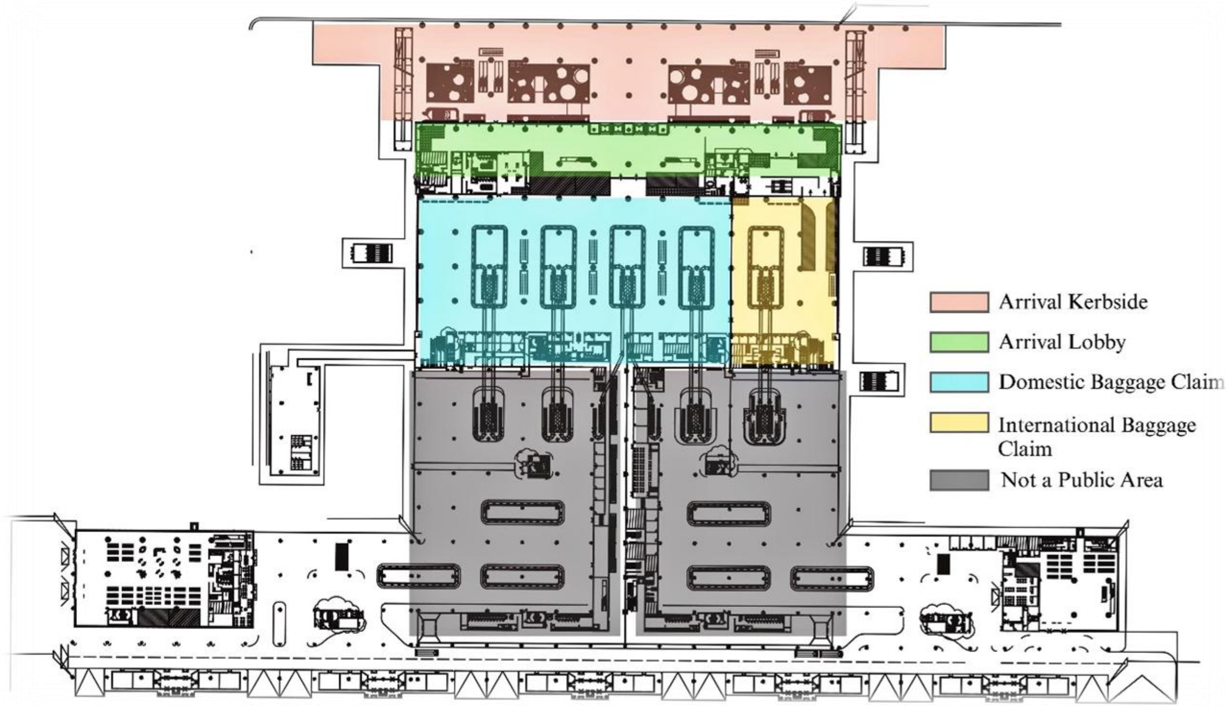

Figure 1. YIA ground floor zone layout.

This study began by identifying the problem related to the absence of a tsunami evacuation route map at Yogyakarta International Airport (YIA), then spatial data collection was carried out in the form of airport plans, potential evacuation points, and passenger density estimates through passenger distribution simulations during peak hours. The collected data was used to build a weighted graph model, where nodes represent evacuation points and edges represent paths between points. The weight on each side is determined based on two main parameters, namely the physical distance between points and the density level of the area passed through.

In weighing each edge of the evacuation graph, both physical distance and dynamic density conditions are integrated, reflecting practices seen in intelligent evacuation routing models. For example, Zhang et al. (2023) propose dynamic weighting of road segments based on proximity to evacuation centers to reduce crowding. Similarly, real-time sensor data, including crowd density, is added to the graph weights for emergency routes. Our approach applies to this dual-parameter weighting in a structured scoring and weighting framework, ensuring that each edge reflects both spatial and human-flow characteristics. Recent studies show that fuzzy-based shortest path models are highly effective for such problems (Raut et al., 2023; Raut et al., 2025). These two parameters are standardized in the form of scores and combined using equation (1).

$$W_{Total} = \sum_{n=1}^{\infty} (W_i * X_i) \tag{1}$$

where:
W_{Total} = final value of path weight
W_i = weight for the i-th parameter
X_i = class score on the i-th parameter

The score classification and weighting used in this study are presented in Table 1.

Table 1. Scoring and weighting table

Parameter	Class	Score	Weight
Distance (between points)	0-10	1	0.5
	11-20	2	
	21-30	3	
	31-40	4	
	41-50	5	
	51-60	6	
	61-70	7	
	71-80	8	
	81-90	9	
	91-100	10	
	>100	11	
Density (between points)	Tall	5	0.5
	Currently	3	
	Low	1	

Before weighting, each parameter is calculated separately. The distance parameter is obtained directly from spatial data in shapefile format (SHP) through QGIS software, which reflects the real distance between points on the YIA ground floor layout. Meanwhile, density is calculated based on the number of passengers crossing a certain area in a certain time unit, using the pedestrian flow approach. The calculation of flow (Q) is done with equation (2).

$$Q = \frac{\text{Number of Pedestrian}}{\text{Duration} \times \text{ Path Length}} \tag{2}$$

and density values using equation (3).

$$D = \frac{\mathrm{Q}}{V_s} \tag{3}$$

with D is the number of people crossing the area, Q is the duration of observation (in minutes), and V_s is the average human walking speed assumed to be based on human evacuation literature (Yosritzal et al., 2020). Based on the D value, the density of the path can be classified into three categories. If the D value < 0.2 then it is categorized as low density, if it is between 0.2 to less than 0.5 it is included in the medium density category, and if $D \geq 0.5$ then it is included in high density. (Vanumu et al., 2017).

These calculated scores are then assigned to each edge in the graph based on the route's associated zone characteristics and length. This process ensures that each path segment reflects both spatial constraints and real-world passenger flow conditions. The resulting weighted adjacency matrix serves as the main input for the Artificial Bee Colony (ABC) algorithm in determining the optimal evacuation routes.

Artificial Bee Colony Algorithm

The Artificial Bee Colony (ABC) algorithm is a metaheuristic algorithm inspired by the behavior of honeybee colonies in searching for food sources (nectar) and has been proven effective in solving various optimization problems (Niyomubyeyi et al., 2019; Karaboga & Ozturk, 2005). ABC works by forming a random initial solution population, where each solution is represented as a food source position and its quality is assessed through a fitness function. ABC consists of three main phases. In the employee bee phase, each bee explores new solutions by modifying the previous solution, then comparing its fitness value. Information about the best solution is forwarded to the onlooker bee through a waggle dance mechanism. In the onlooker bee phase, the bee chooses a solution based on the probability calculated from the fitness value, then explores new solutions from the candidates (Ebrahimnejada et al., 2016; Alsamia et al., 2024). If there is no increase in the fitness value in several iterations, the scout bee will replace the stagnant solution with a new solution generated randomly to avoid convergence on a local solution. This iterative process continues until the maximum iteration limit is reached. In the context of route modeling, the position of the food source is represented as a candidate route, and the nectar value as the level of optimality of the path based on the total weight (distance and density). To further clarify the ABC algorithm process, here is a more detailed description of the algorithm

1. Initialization Phase

   Initialization phase is run to generate initial routes from 10 initial evacuation points (SA, SB, SC, …, SJ) to each of its safe points (EA, EB, EC, …, EM) available on the ground floor of Yogyakarta International Airport (YIA). At this stage, each route is randomly generated based on the previously constructed weighted graph structure. The initial route consists of a series of nodes connecting the origin to one of the exit points through connecting paths between nodes. The initial population based on the weighted graph is 68 paths in total. All connecting nodes (middle nodes) can change depending on the randomization results, while the origin and exit points are fixed according to the evacuation scenario. After all initial routes are generated, the fitness value is calculated for each route using the path weight-based evaluation function as follows.

$$fit_i = \begin{cases} \dfrac{1}{1 + X_{ij}} & ; \ f \geq 0 \\ 1 + |X| & ; \ f < 0 \end{cases} \tag{4}$$

   where:
   fit_i = fitness value of the solution is proportional to the nectar amount of food source at the position i.
   X_{ij} = the sum of the weights of each initial solution.

2. Employee Bee Phase

   To improve the quality of the solution, Neighborhood Operators are used in the form of Swap Operators and Swap Sequences, which work by selecting two different positions (for example, the nth and mth indices, with $n \neq m$) in a solution, then swapping those positions to explore alternative configurations that are potentially more optimal (Kaveh et al., 2020). For example, if the selected indices are 1 and 5, then the elements at those positions will be swapped (see Figure 2).

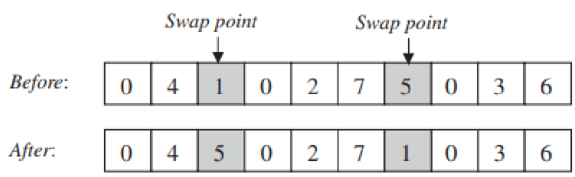

Figure 2. Swap operator

3. Onlooker Bee Phase

   In the onlooker bee phase, the fitness value obtained from the employee bee phase will be used to calculate the probability value of each solution. This calculation aims to determine which solution has the greatest chance of being selected and developed further, based on the selective probability formula as follows.

$$P_i = \frac{fit_i}{\sum_{n=1}^{SN} fit_n} \tag{5}$$

   where:
   P_i = probability value
   fit_i = fitness value of the i-th solution

$\sum_{n=1}^{SN} fit_n$ = sum of the i-th fitness values to SN (number of population paths that are the same as employed bees)

Optimization is continued with insert operator based on roulette wheel selection, where solutions with higher fitness values have a greater chance of being selected (see Figure 3). This operator moves elements from one index to another randomly, then rearranges the rest. This process is carried out as many times as the population and is called Insert Sequence (Kaveh et al., 2020).

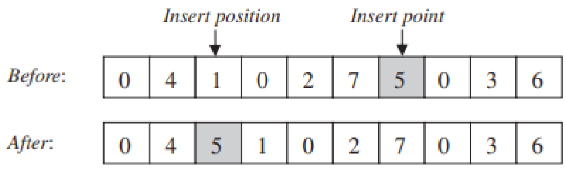

Figure 3. Insert operator

4. Scout Bee Phase

   After going through two phases of solution improvement employee bee and onlooker bee the process continues to the scout bee phase. The number of scout bees is dynamic, depending on the number of solutions that do not improve after passing the trial iteration limit. If a solution has a trial value exceeding the specified limit (limit = 3), then the solution is considered stagnant and will be replaced by a new solution generated randomly using the random value [0,1]. This new solution is used to update the total distance on the route, and the trial value will be reset to zero. The goal is to prevent the search process from getting stuck in a local solution. In this study, scout bees were inactive because all solutions were still within the allowed trial limit.

5. Choosing the best food source

   After the scout bee phase is completed, the algorithm returns to the employee bee phase and continues the iteration process until it reaches the stopping criterion, which is the maximum number of iterations. The best evacuation route with the highest fitness value will be selected and saved as the final solution.

For a better understanding, the ABC algorithm flowchart can be seen in Figure 4.

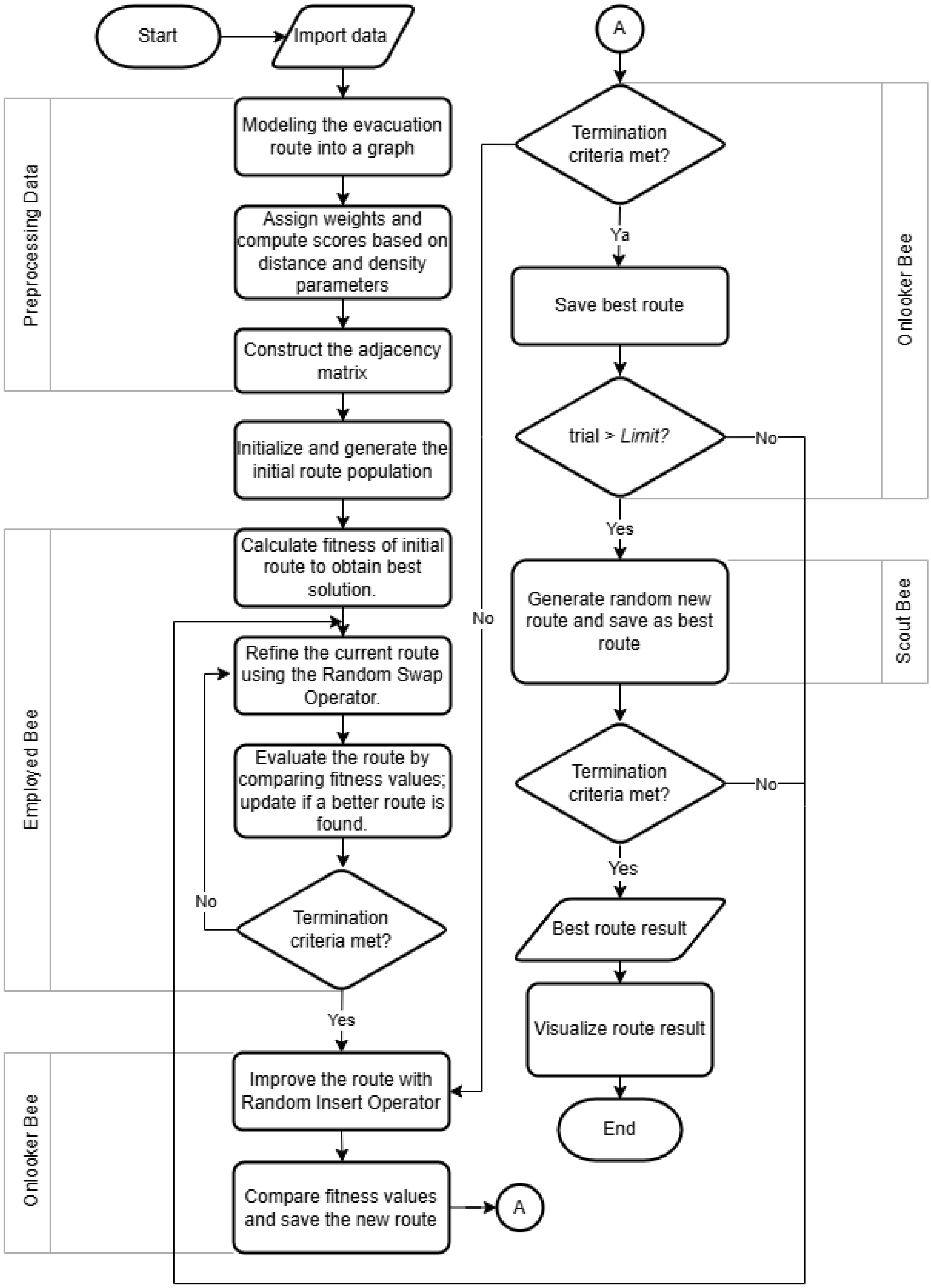

Figure 4. Artificial Bee Colony flowchart.

RESULTS AND DISCUSSION

Data Analysis

The data analysis phase in this study was carried out to support the optimization of the shortest evacuation routes under a tsunami disaster scenario at YIA, using the ABC. This process involves transforming spatial and passenger movement data into a weighted graph that reflects both distance and pedestrian density factors. The following steps summarize the analysis process:

1. Compiling data on initial evacuation points (assembly zones) and safety points (exits) based on the YIA ground floor layout in SHP format.
2. Calculate the distance between points and estimate the density level based on passenger movement data using QGIS, while density levels for each route segment were estimated based on pedestrian movement simulations during different time conditions (working days, short working days, holidays)
3. Each edge in the graph was assigned a weight based on two parameters: physical distance and pedestrian density. These parameters were first converted into numeric scores, which were then combined using a weighted sum with equal weight (0.5 for each parameter), following equation (1).
4. The final weighted graph was transformed into a proximity matrix, which served as the input for the ABC to determine the optimal evacuation paths.
5. The shortest paths from each starting point to the nearest exit points were visualized spatially using QGIS to ensure interpretability and validation.

In this study, multiple evacuation starting points and six designated safe points were distributed throughout the airport area. The topological and functional structure of the ground floor was translated into a graph model, as illustrated in Figure 5.

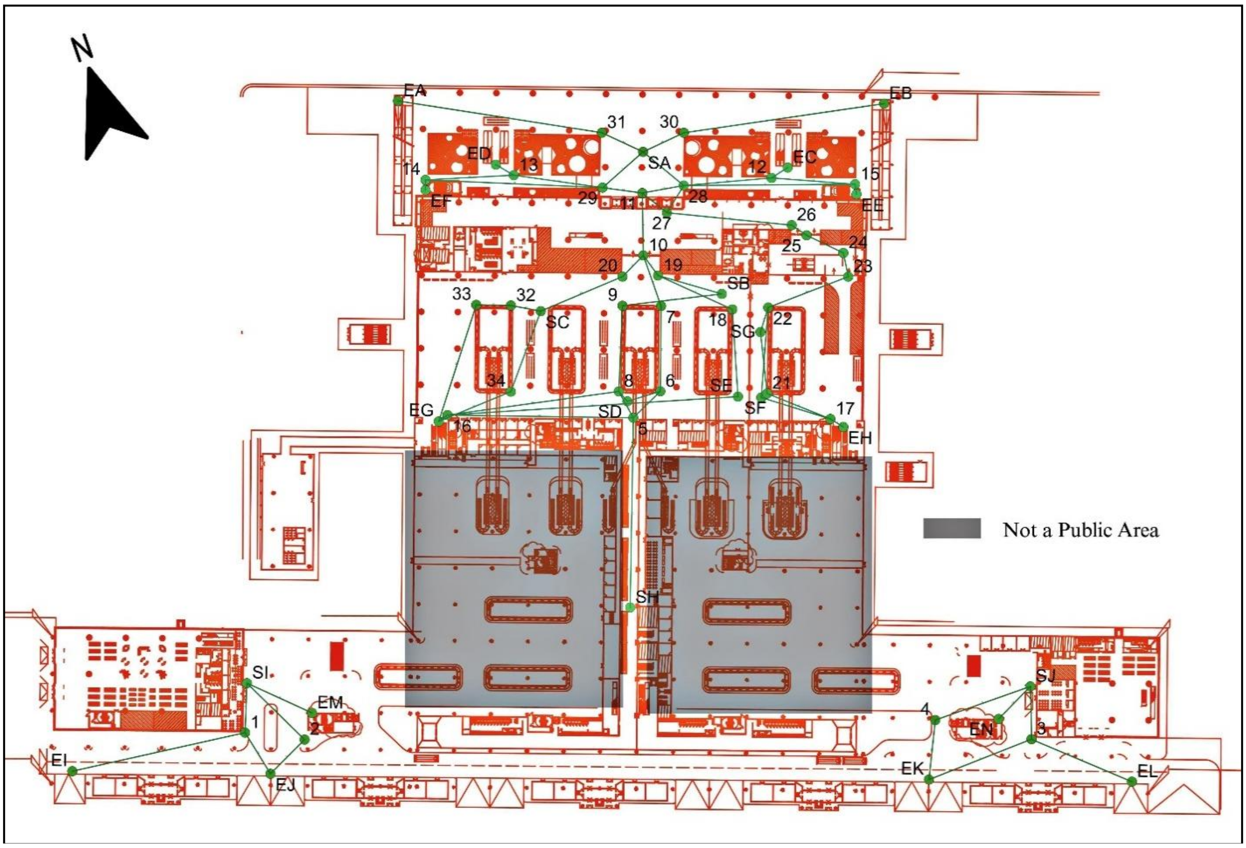

Figure 5.YIA ground floor graphics

To support the density component of the model, pedestrian flow was simulated under various day conditions. The calculation involved parameters such as line length, number of pedestrians, pedestrian speed, and resulting density. The results are summarized in Table 2 below.

Table 2. Density data and analysis

Indicator		Line Length (m)	Number of Pedestrians	Pedestrian Speed $\left(m/_{\min}\right)$	Pedestrian Flow (Q)	Lane Density (D) $\left(\text{people}/_{m^2}\right)$	Category
luggage Domestic	Working days	137	2582	0.095139	0.013088	0.137567	Low
	Short Working Day		1629		0.008257	0.086792	Low
	Holiday		2535		0.01285	0.135063	Low
International Baggage	Working days	45	442	0.03125	0.006821	0.218272	Currently
	Short Working Day		234		0.003611	0.115556	Low
	Holiday		390		0.006019	0.192593	Low
Arrival Lobby	Working days	170	14455	0.118056	0.059048	0.500173	Tall
	Short Working Day		9511		0.038852	0.3291	Currently
	Holiday		14684		0.059984	0.508097	Tall
Arrival Curbside	Working days	188	17940	0.130556	0.066268	0.507583	Tall
	Short Working Day		10048		0.037116	0.284292	Currently
	Holiday		25117		0.092779	0.710644	Tall

These density classifications were converted into numeric scores ($1 = \text{low}, 3 = \text{medium}$, and $5 = \text{high}$) and used alongside distance-based scores in the final edge weighting. After applying the scoring system and normalization, all edges were encoded into a proximity matrix. This matrix served as the primary input for the ABC algorithm in the next phase. Graph modelling and parameter weighting were conducted in QGIS, enabling both numerical computation and spatial visualization of evacuation routes. The shortest route from each starting point to the designated safe point was then extracted based on the lowest cumulative weight, which accounts for both distance and dynamic human flow.

Experimental Results

Based on the existing data, a weight proximity matrix is obtained which is represented by the following proximity matrix as shown in Table 3 partition.

Table 3. Graph Adjacency Matrix

Weight	12	13	14	15	*EC*	*EF*	21	22
1	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0
12	0	0	0	4.5	3	0	0	0
13	0	0	4.5	0	0	0	0	0
14	0	4.5	0	0	0	3	0	0
15	4.5	0	0	0	0	0	0	0
EC	3	0	0	0	0	0	0	0
ED	0	3	0	0	0	0	0	0
SG	0	0	0	0	0	0	2	1
SH	0	0	0	0	0	0	0	0

The nodes on the graph represent the location points on the ground floor of YIA, while the edges represent evacuation routes with weights based on distance and density. These weights are optimized by ABC to determine the fastest and most efficient path to the safe point shown in the Figure 6.

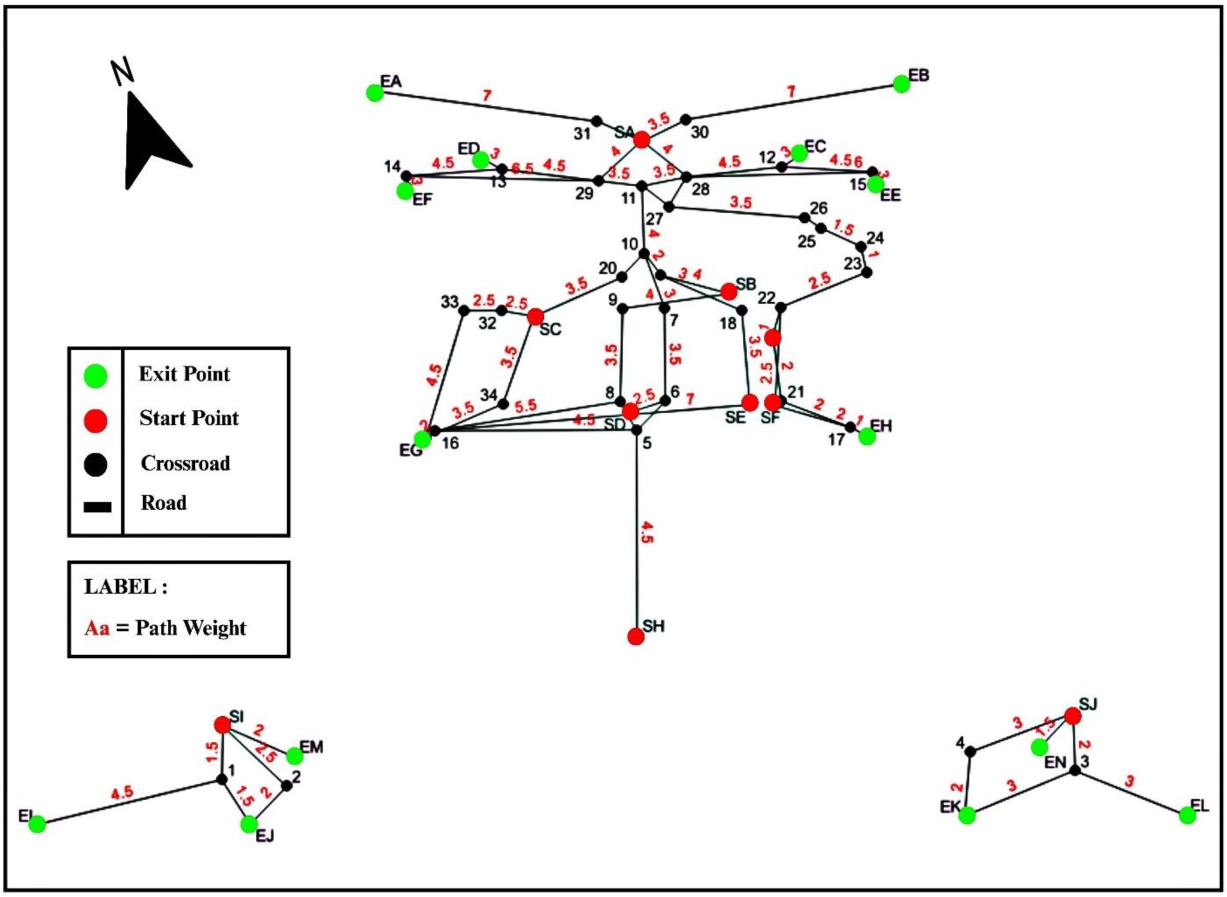

Figure 6. Weighted graph model of the YIA ground floor evacuation network

The steps for solving with ABC on the SA starting point sample data are as follows.

1. Defining Parameters
   In ABC calculations, the parameters that will be used are:
   a. Number of Iterations = 5
   b. Population Number = 6
   c. Number of Employee Bees = Onlooker Bees = Population = 6
   d. Limit = 2
2. Initialization Phase
   In the initialization phase, the SA point has six initial routes (populations) to various safe points. These six populations represent the initial solutions that will be further evaluated in the ABC iteration process. After the route is formed, each population is calculated for its fitness value based on the total route weight and the fitness results are described in Table 4 below.

Table 4. Fitness initialization phase

Index	Population	Fitness
1	SA-31-EA	0.086957
2	SA-30-EB	0.086957
3	SA-29-13-ED	0.08
4	SA-29-14-EF	0.068966
5	SA-28-12-EC	0.08
6	SA-28-15-EE	0.068966

3. Employee Bee Phase
   In this phase, Swap Operator is used as a mutation method to explore solutions. This operator randomly swaps two nodes in one route, except the start and end points. The process is carried out as many times as the population (6 times), with exchanges only at the middle index so that the path structure remains valid (see Table 5).

Table 5. Employee bee phase fitness

Index	Population	Fitness
1	SA-31-EA	0.086957
2	SA-30-EB	0.086957
3	SA-13-29-ED	0.046512
4	SA-14-29-EF	0.036364
5	SA-12-28-EC	0.046512
6	SA-15-28-EE	0.038462

The fitness value of the mutation result in the Employee Bee phase is compared with the initial value. If the fitness increases, the solution is accepted and the trial value is reset to 0. Otherwise, the old solution is retained, and the trial is increased by 1 (see Table 6). This mechanism helps detect stagnant solutions to be replaced in the Scout Bee phase.

Table 6. Fitness comparison of initialization phase and employee bee

Index	Fitness Initialization	Fitness Employee Bee	Comparison Results	Trial
1	0.086957	0.086957	0.086957	
2	0.086957	0.086957	0.086957	
3	0.08	0.046512	0.046512	1
4	0.068966	0.036364	0.036364	
5	0.08	0.046512	0.046512	
6	0.068966	0.038462	0.038462	

4. Onlooker Bee Phase
   In this phase, the best solution is selected based on the probability value calculated from the previous fitness value. Probability reflects how well a solution performs compared to the rest of the population and is calculated using Equation (5) and the following results are obtained as shown in Table 7.

Table 7. Population probability

Index	Population	Probability
1	SA-31-EA	0.254436
2	SA-30-EB	0.254436
3	SA-13-29-ED	0.136094
4	SA-14-29-EF	0.106401
5	SA-12-28-EC	0.136094
6	SA-15-28-EE	0.112539

After obtaining the probability value of each population, the selection process is carried out using the roulette wheel method to determine which solution will be modified. This method is random but proportional, where solutions with better fitness values have a greater chance of being selected. The random values generated are in the range [0,1], and if the value matches the probability interval of a solution, then the solution is selected for updating.

The selected solution is then modified using the neighbourhood operator in the form of an insert operator. This operator works by selecting two random indices in the route, moving the element from the second index to the first index position, and reordering the rest. This process is carried out for the entire population, and the sequence is called the insert sequence. After the changes are made, the fitness value is recalculated to evaluate the quality of the modified solution, and the fitness value is obtained can be seen in Table 8.

Table 8. Fitness Phase Onlooker Bee

Index	Population	Fitness
1	SA-31-EA	0.086957
2	SA-30-EB	0.086957
3	SA-29-13-ED	0.08
4	SA-29-14-EF	0.068966
5	SA-28-12-EC	0.08
6	SA-28-15-EE	0.068966

The fitness value in the Onlooker Bee phase is compared with the previous phase. If it increases, the solution is considered improved and the trial value is reset to zero; otherwise, the trial is increased by one. This mechanism maintains the balance between exploration and exploitation and determines which individuals will be replaced in the Scout Bee phase if they exceed the trial limit. Table 9 shows the comparison of the Onlooker Bee phase with the previous phase.

Table 9. Employee bee and onlooker bee phase fitness comparison

Index	*Fitness Employee Bee*	*Fitness Onlooker Bee*	Comparison Results	*Trial*
1	0.086957	0.086957	0.086957	1
2	0.086957	0.086957	0.086957	
3	0.046512	0.08	0.046512	0
4	0.036364	0.068966	0.036364	
5	0.046512	0.08	0.046512	
6	0.038462	0.068966	0.038462	

5. Scout Bee Phase
   The Scout Bee phase is a continuation of the solution improvement process in the Employee and Onlooker phases. At this stage, the algorithm identifies solutions that do not experience an increase in fitness until they exceed the trial limit (set at 2). Stagnant solutions will be replaced with new solutions generated randomly using the generate_random_path() function between the starting point and the ending point. This new solution is then calculated for its fitness value and replaces the old solution, while the trial value is reset to zero. This phase serves to prevent the algorithm from getting stuck in a local solution and expands solution exploration.
6. Choosing the best food source
   After all iterations are completed, the best solution is selected based on the highest fitness value, which represents the route with the lowest total weight.

Table 10. Final fitness value

Index	*Population*	*Fitness*
1	SA-31-EA	0.086957
2	SA-30-EB	0.086957
3	SA-29-13-ED	0.08
4	SA-29-14-EF	0.068966
5	SA-28-12-EC	0.08
6	SA-28-15-EE	0.068966
Best Solution: SA-31-EA and SA-30-EB		

After ABC is implemented using the Python programming language, the simulation process is carried out for 5 iterations for each predetermined evacuation starting point. The results of the simulation produce the best evacuation route from each starting point to the exit point based on the highest fitness value and the smallest total cost. The best route obtained reflects the optimal combination of the path with the lightest weight, both in terms of distance and node density factor. Table 11 presents the summary of the results of the iteration, including the starting point, the best route from the simulation, the fitness value obtained, and the total path weight (total cost) that must be passed.

Table 11. YIA ground floor best evacuation route iteration results

Starting Point	Best Route	Fitness 5th Iteration	Total Cost
SA	SA - 31 - EA	0.087000	10.5
	SA - 30 - EB	0.087000	
SB	SB - 9 - 8 - 16 - EG	0.062500	15
SC	SC - 34 - EG	0.125000	7
Elementary School	SD - 8 - 16 - EG	0.095200	9.5
SE	SE - 16 - EG	0.100000	9
SF	SF - 17 - EH	0.250000	3
SG	SG - 21 - 17 - EH	0.166700	5
SH	SH - 5 - 16 - EG	0.083333	11
SI	SI - EM	0.333333	2
SJ	SJ - EN	0.400000	1.5

Evacuation Route Visualization and Result Analysis

Visualization of ABC implementation results is carried out to display the best evacuation route from each starting point on the YIA ground floor. The simulation process using Python programming is run for five iterations for all evacuation starting points (SA–SJ). Each route is evaluated based on the highest fitness value and the smallest total cost, which represents the path with the most efficient combination of distance and density weights. The simulation results show that all starting points are successfully allocated to six of the fourteen available exit points, namely EA, EB, EG, EH, EM, and EN. Point EG is the most dominant exit point used (by five starting points), followed by EH (two starting points), while the rest is only used by one starting point. The final evacuation route map is visualized in Figure 7, which shows the evacuation direction from each point based on the optimization results.

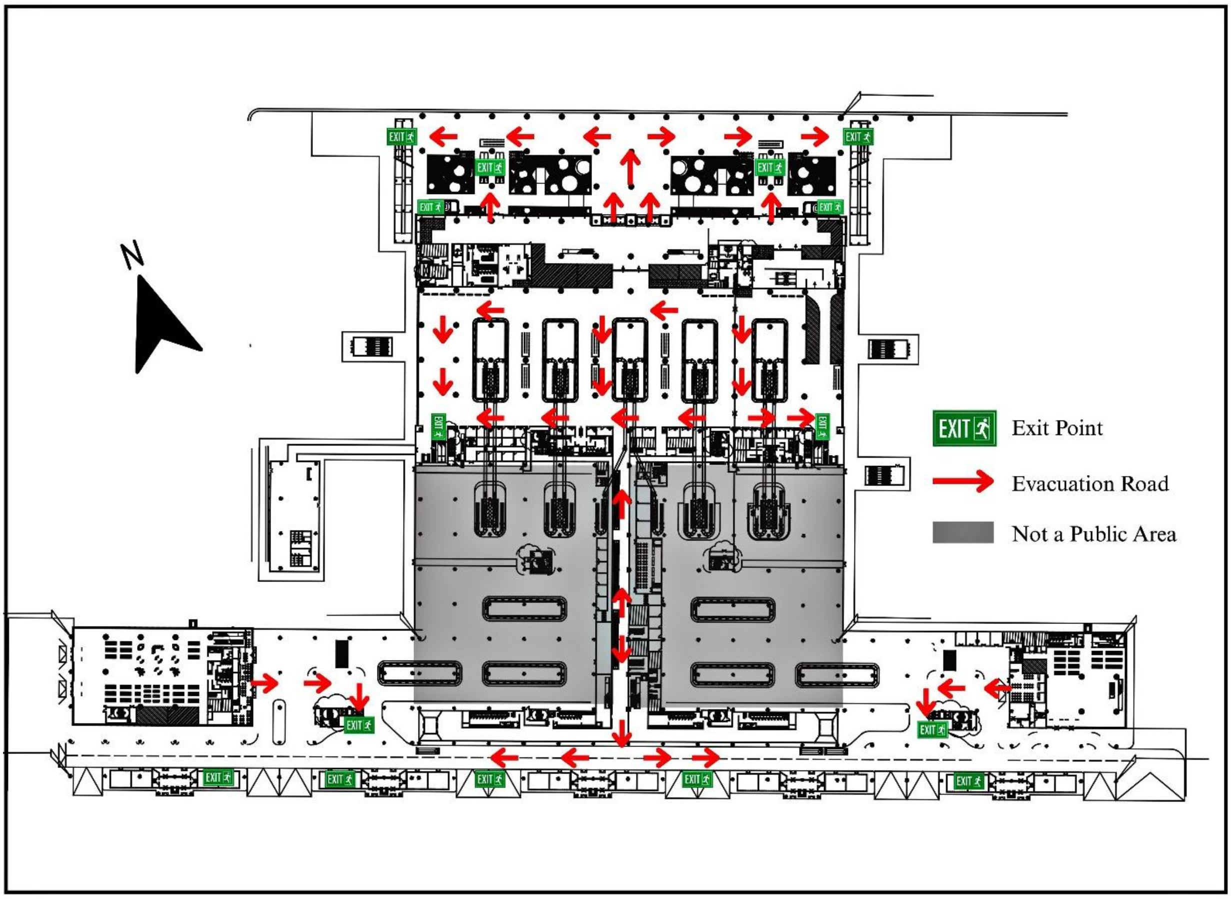

Figure 7. YIA Ground Floor Tsunami Evacuation Map

The resulting movement pattern indicates that evacuation behavior differs across functional zones within the terminal. Individuals located in the kerbside area tend to move toward the nearest ramp, as it provides the most direct and accessible route to higher and safer areas during a tsunami evacuation scenario. In contrast, passengers located inside the terminal, particularly in the arrival lobby and baggage claim areas, are directed toward vertical circulation facilities such as emergency staircases and escalators leading to the mezzanine floor. These facilities play a critical role in facilitating rapid vertical evacuation from potentially inundated ground-level areas. The spatial visualization of these flows also reveals potential congestion points in high-density areas, highlighting the importance of considering crowd distribution and infrastructure accessibility when designing evacuation strategies in complex public facilities such as airport terminals. From a methodological perspective, the results demonstrate that weighted graph modeling provides a more realistic representation of evacuation dynamics compared to conventional shortest-path approaches. By incorporating both distance and crowd density as weighting parameters within the network model, the analysis is able to capture variations in movement speed and potential bottlenecks caused by passenger accumulation. This network-based optimization approach enables the identification of evacuation routes that balance path efficiency and crowd safety, rather than relying solely on geometric proximity. Consequently, integrating spatial network analysis with crowd density parameters offers a more robust framework for designing data-driven and spatially optimized public evacuation systems in high-density transportation infrastructures.

Compared to previous studies such as Furqan et al. (2022) which used ABC to optimize the distribution of clean water pipes with one starting point and one destination, and the study by Yousuf et al. (2025) in the context of logistics based on the Traveling Salesman Problem (TSP), this study offers higher complexity. The model in this study integrates multi-starting points and multi-destination points, and combines two important parameters in graph weighting, namely distance and density. This combination allows the identification of evacuation routes that are not only spatially short but also consider aspects of safety and smooth mass movement. The results obtained in this study are consistent with findings in the literature, where advanced metaheuristics such as reinforcement learning and hybrid swarm intelligence methods have also demonstrated strong performance in evacuation route optimization (Mas et al., 2024; Barus et al., 2022). Case studies in Indonesia further highlight the practicality of graph-based evacuation modeling. For instance, Costrada et al.(2023) as well as Putra and Ariastina (2023) successfully applied Dijkstra's algorithm with pedestrian density, proving the applicability of weighted graph approaches for tsunami evacuation routes. These comparisons indicate that while classical algorithms like Dijkstra remain useful for small-scale or less complex scenarios, swarm intelligence methods such as ABC and its recent variants offer greater scalability and adaptability, making them more suitable for modeling evacuation in large and dynamic environments such as airports (Xiao et al., 2023; Cui et al., 2023; Zhou et al., 2025).

This study presents a novel application of spatially optimized tsunami evacuation modeling within the operational context of Yogyakarta International Airport (YIA), a critical transportation hub located in a tsunami-prone coastal region. Unlike conventional evacuation guidance currently available at the airport, which is limited to basic signage indicating emergency exits, this research introduces a spatially informed evacuation framework that integrates network analysis and optimization techniques. The absence of a publicly accessible evacuation map that incorporates route efficiency, spatial configuration, and passenger density represents a critical gap in the existing disaster preparedness system at YIA. By addressing this gap, the study provides a new perspective on how spatial data and computational modeling can support more effective evacuation planning in large-scale public infrastructures.

From a theoretical standpoint, this research contributes to the advancement of evacuation modeling by integrating weighted graph-based optimization with spatial infrastructure analysis. Traditional evacuation planning often relies on shortest-path algorithms that prioritize geometric distance without considering dynamic factors such as crowd density and infrastructure capacity. In contrast, the proposed approach incorporates both distance and density parameters within the network model, enabling a more realistic representation of evacuation dynamics in complex indoor environments. This integration expands the application of graph theory within disaster management studies and demonstrates how network-based optimization can be used to evaluate and improve evacuation efficiency in high-density facilities.

In terms of practical implications, the results of this study provide a data-driven foundation for developing official evacuation maps that are more informative and responsive to real emergency conditions. The optimized routes identified through spatial network analysis offer clearer guidance for passengers and airport personnel by considering accessibility to vertical evacuation facilities, potential congestion points, and the spatial distribution of passenger activities within the terminal. Implementing such an evacuation framework could significantly enhance emergency preparedness at YIA by improving route clarity, minimizing evacuation bottlenecks, and supporting faster and more organized movement toward safe zones during tsunami emergencies.

More broadly, the findings of this research contribute to strengthening disaster resilience in coastal transportation infrastructure. Airports located in hazard-prone areas must not only function as transportation hubs but also as critical nodes in emergency response and evacuation systems. By integrating spatial analysis, crowd dynamics considerations, and network optimization, this study supports a more resilient approach to infrastructure planning and disaster risk reduction. The methodology developed in this research also provides a transferable framework that can be adapted for other large public facilities such as seaports, railway stations, or coastal urban infrastructures exposed to tsunami hazards.

CONCLUSION

This study demonstrates that the Artificial Bee Colony (ABC) algorithm can be effectively applied to determine optimal tsunami evacuation routes on the ground floor of Yogyakarta International Airport by integrating distance and pedestrian density within a weighted graph model. The proposed approach successfully allocates all evacuation starting points to six designated exits, with EG identified as the most frequently selected and efficient destination. By simultaneously considering spatial proximity and crowd dynamics, the model produces routes that are not only shorter but also more realistic and safer under emergency conditions. Beyond its methodological contribution, this study provides the first spatially optimized evacuation map for YIA, offering practical decision-support for disaster mitigation planning in high-risk public infrastructures.

Future research could further enhance this framework by incorporating real-time data, dynamic crowd simulation, and behavioral modeling to capture more complex evacuation scenarios. In addition, integrating multi-floor evacuation modeling and real-time decision-support systems could improve the adaptability of evacuation strategies under rapidly changing emergency conditions. Such developments would contribute to more comprehensive disaster resilience strategies for critical infrastructures located in high-risk coastal environments.

AUTHOR CONTRIBUTIONS

D.H.P.: Conceptualization, formal analysis, investigation, methodology, writing – original draft. D.E.N.C.: Data curation, formal analysis, software, writing – original draft. A.S.: Validation, supervision, and writing - review & editing. D.A.: Validation, formal analysis, and writing - review & editing.

CONFLICT OF INTEREST

The authors declare that have no conflict of interest.

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