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Multi-Objective Optimization of Tactical Rescue Strategies Using QHBM and IoT in Urban Conflict Zones

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Abstract

This study addresses the challenge of balancing personnel safety, operational costs, and travel efficiency in complex decision-making environments. This study evaluates the Queen Honey Bee Migration (QHBM) algorithm in comparison to Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Firefly Algorithm (FA) under various risk conditions. The objective of this research is to determine the most effective optimization technique for improving personnel safety, cost efficiency, and convergence rate. This study uses experimental implementation of QHBM, GA, FA, and PSO within specified risk constraints and assesses their performance with optimization metrics. The results show that QHBM outperforms other algorithms in terms of cost efficiency, convergence speed, and personnel safety. QHBM can improve PSO performance by 20% over GA and FA in terms of personnel safety. QHBM is 15% more cost efficient than GA, FA, and PSO methods with the fastest QHBM convergence rate of only 30 to 50 iterations. This study also found the potential of QHBM as a robust and adaptive optimization technique compared to other algorithms. Further research is recommended to implement QHBM in the real world, especially in complex, high-risk work operations.

Keywords: Cost Efficiency, Hostage Rescue, Internet of Things, Optimization.

1 Introduction

Hostage rescue operations represent one of urban security's most critical and complex challenges, with extreme risks involved at every step (Greipl, 2023; Irmanto et al., 2024; Moghaddam, 2018). Global statistics show how important the effectiveness of these operations is, where between 2000 and 2019, there were more than 3,200 hostage-taking incidents worldwide, with an average survival rate of only 64.3% in urban environments (Global Terrorism Database) (Riberto et al., 2018; Wu & Lin, 2022;

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Ranjan et al., 2021; Meng et al., 2021; Sabar et al., 2023). The complex landscape of modern urban environments - multi-story buildings, dense infrastructure, and unpredictable spatial configurations - creates significant obstacles for rescue teams trying to navigate high-risk scenarios with minimal risk to hostages and operational personnel (Wang et al., 2023; Emem, Ogidan, & Salami, 2022; Rajora, 2024). Research by the International Association of Chiefs of Police shows that approximately 73% of urban hostage rescue efforts rely heavily on real-time spatial intelligence and rapid route optimization (Pawlisiak & Maslii, 2024).

Technological development has accelerated significantly in recent years. In recent years, the Internet of Things (IoT) has become one of the most promising technological breakthroughs, enabling electronic devices to communicate with each other and share data through the internet (Abhishek, Sri, & Kavya, 2024). The advantage of this technology lies in its ability to connect various sensors and smart devices in real time, providing accurate and fast data to users. In hostage liberation operations, implementing an IoT-based personnel monitoring system can provide vital information to the TNI operations command that monitors and controls the operations, helping leadership elements accelerate making timely decisions amid critical situations (Lott, Raglin & Metu, 2020; Aripriharta et al., 2023).

Among various optimization strategies, the Queen Honey Bee Migration (QHBM) method offers a biologically inspired approach tailored to dynamic rescue scenarios (Gao, 2025). This method puts forward a natural behaviour-based solution search, which has the potential to provide the best path and location in highly dynamic military operations.

In the case of hostage rescue, comparing the effectiveness of optimization algorithms is very important to get maximum results. Other optimization algorithms such as Genetic Algorithm (GA) (Velliangiri et al., (2021), Firefly Algorithm (FA), and Particle Swarm Optimization (PSO) Yuan et al., (2024) have been proven to be applicable where the approach used has its uniqueness in certain environments, but its performance in emergencies that require high mobility still needs further exploration. This study will compare optimization algorithms, namely FA, GA, PSO and QHBM, in hostage rescue operations as well as IoT integration in real-time adaptation (Aqlan et al., 2023). This study will assess how IoT integration improves the capabilities of each algorithm so that it can be an accurate solution to changing conditions in the field with high mobility. This study is expected to find a more efficient hostage rescue strategy in a high mobility environment.

2 Related Works

There are seven aspects related to this research, which we have summarized as follows:

- **Urban Warfare in Hostage Rescue Mission**

This work will focus on reducing the time required for execution, thus optimizing hostage rescue strategies (Boopathy et al., 2024). Achieving this concept requires knowledge of the team tactics used, coordination between personnel, and proper personnel placement (Xu, Li & Liu, 2023). Field considerations include several important aspects such as the attack used, precision shooting, sieges, and covert infiltration. Several variables need to be considered, such as the duration of the situation assessment, response time, strategy formulation time, and execution time. As well as possible factors such as potential risks, operational resources, and coordination efficiency, considerations of the operational environment can also influence mission success.

- **Internet of Things (IoT) Optimization**

The use of IoT technology in hostage rescue strategies aims to increase operational effectiveness and minimize risks in urban warfare (Adji et al., 2024). QHBM, a swarm intelligence algorithm inspired by queen bee migration, is used to optimize infiltration/exfiltration paths, resource management, and team coordination. Previous studies have explored various approaches focusing on IoT sensors for situational awareness (without swarm intelligence) Pang, Li & Han (2023), combining QHBM with IoT monitoring (limited to basic sensors), using AI for enemy movement prediction (lacking unit coordination and real-time sensor integration) and leveraging IoT sensor networks for interoperability (without QHBM optimization) (Aripriharta et al., 2024). This study proposes a holistic framework that integrates IoT-based situational awareness with QHBM optimization for adaptive strategy formulation (Eiriemiokhale & James, 2023). This approach is more effective in adjusting tactics to changing situations, minimizing risks, reducing response time, and increasing security compared to previous partial research (Perera, & Wickramasinghe, 2024).

- **Queen Honey Bee Migration (QHBM)**

The QHBM algorithm is a swarm intelligence adaptation of honeybee colonies (Adji et al., 2024). The model uses the hierarchical structure of bees to solve complex multi-objective tactical optimization problems (Aripriharta et al., 2023) (Sethupathi et al., 2024). QHBM integrates important factors such as hostage safety, operation time, hostage control, and perational risk, with adjustable weights. The strategy is represented as a multi-dimensional vector that includes team formation, entry route, execution time, and resource allocation (Wibowo et al., 2019). In the queen bee simulation, the worker bee swarm represents the implementation of position and speed, and the queen is the most optimal performer. In the simulation, premature convergence can be prevented by the swarm exploring new areas. The QHBM will learn updates to the Q value from previous operations, which will be useful for strategy adaptation. Integrated IoT will change the sensor time, which will be used as optimization input. Strategy evaluation is based on hostage survival rate, time efficiency, resource utilization, and victim minimization (Karimov & Bobur, 2024).

- **Particle Swarm Optimization (PSO)**

The population-based PSO algorithm is an implementation inspired by the behavior of animal groups. PSO also offers good performance for real-time parameter optimization in high-mobility environments. PSO particles are influenced by individual and collective (pbest) or (gbest), which will create optimal solutions (Garudkar et al., 2011). Collective decision-making by the PSO is crucial for operational optimization when the situation is no longer the same as at the start of operations, making adjustments crucial. The PSO can simultaneously optimize unit points and movements, and easily adapt to sudden changes, resulting in a more efficient optimization strategy in a high-mobility work environment (De la Fontaine et al., 2024). PSO can increase the ability and speed of adaptation to hostage rescue strategies that allow for immediate use with consideration of many tactical parameters (Kapoor et al., 2017).

- **Genetic Algorithms (GA)**

GA is an optimization algorithm inspired by natural selection, where it finds solutions under complex conditions and spaces (Swathi, 2022). GA has the advantage of being able to maintain a large number of solutions, adapt to dynamic, high-mobility conditions, and avoid premature convergence (Caruso, 2023; Luckshika et al., 2023).

- **Firefly Algorithm (FA)**

The Firefly Algorithm (FA) is inspired by the behavior of fireflies that use light to attract mates. This algorithm models light intensity as a quality of solution, making it an effective tool for multi-modal and multi-objective problems in hostage rescue strategy optimization. Each firefly represents a candidate solution, and brighter (better) fireflies will attract others, allowing exploration of many solutions and convergence to the optimum (Prasanna et al., 2022). Research Prasanna et al. (2022) used FA to optimize evacuation routes and resource allocation in hostage rescue, considering risk and enemy density. Although FA can find safe and effective routes, it did not integrate inter-unit coordination or dynamic changes in field situations. In contrast, our study proposes FA with dynamic adjustment that considers external factors (e.g. weather or enemy positions) and ensures better inter-unit coordination. Research Shu (2025) applied FA to optimize broader military mission planning, including troop deployment and resource allocation. However, this study lacks real-time adaptation to rapidly changing situations, which is crucial in hostage rescue. Our research adapts FA principles with real-time integration, ensuring the solution can adapt quickly to changing information during operations.

- **High-Frequency Adaptive Particle Swarm Optimization Algorithm (HFAPSO)**

HFAPSO is an extension of the classical PSO algorithm that improves its capabilities by automatically and frequently (high frequency) adjusting its internal parameters during the optimization process (Seyyedabbasi et al., 2023). Unlike PSO, which uses fixed parameters, HFAPSO is designed to balance exploration (finding new solution areas) and exploitation (improving existing solutions) dynamically, making it more effective in avoiding local optima traps and finding optimal global solutions. Although it offers the potential for increasing convergence speed, this high-frequency adaptive characteristic can sometimes cause larger performance fluctuations compared to other, more stable algorithms. Research Seyyedabbasi et al. (2023). Uses HFAPSO to determine the optimal scale of a hybrid renewable energy system that has fast time performance and convergence (Seyyedabbasi et al., 2023). Although HFAPSO can excel in convergence and time fluctuations, the results can provide uncertainty in each test.

3 Experimental Process

This research proposes an IoT-based approach optimized using the QHBM algorithm to improve the effectiveness of hostage rescue operations in urban environments.

- **System Description**

The distributed security system consists of five tactical nodes (Nodes 1-5) optimally positioned based on the QHBM algorithm to maximize visibility, minimize detection risk, and ensure communication redundancy. The mesh network shown with the red line enables real-time data transmission and comprehensive situational monitoring.

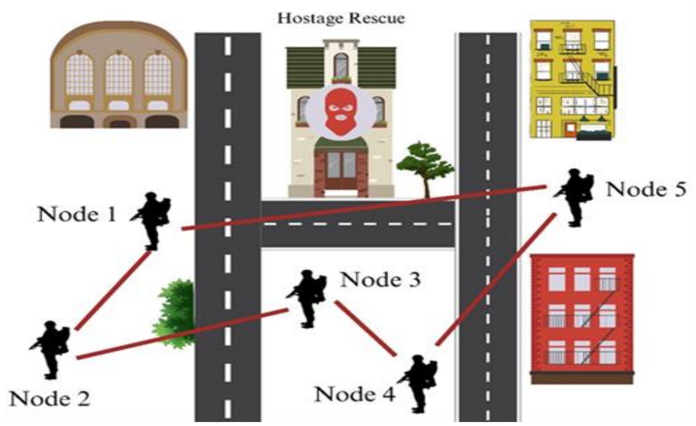


Figure 1: Scenario of Hostage Rescue Operation in an Urban Environment

Figure 1 shows the implementation of an optimized IoT sensor network to support hostage rescue operations in an urban area. The main building in the center, with the red-masked hostage taker, serves as the command center of the tactical operation, surrounded by urban infrastructure.

- **Problem Formulation**

The objective function is a multi-objective optimization model that balances three competing goals in a hostage rescue operation. The first term, weighted by w1, minimizes the total travel distance j of the rescue team moving between locations i and j at time t, ensuring a rapid response. The second term, weighted by w2, maximizes safety by selecting routes with higher safety scores $S_{i,j,t}$ which are derived from real-time IoT sensor data assessing environmental risks such as enemy presence, visibility, and structural hazards. The third and fourth terms, weighted by w3 and w4 respectively, Harbi et al. (2019) minimize the operational costs of deploying drones and assigning rescue personnel by considering the cost of each drone C_k and the personnel cost per hostage P_m as shown in equation (1).

$$\min = (W_1 \sum_{i,j,t} d_{i,j} \times X_{i,j,t} - W_2 \sum_{i,j,t} S_{i,j,t} \times X_{i,j,t} + W_3 \sum_{k,t} C_k \times y_{k,t} + W_4 \sum_{m,t} P_m \times Z_{m,t}) \qquad (1)$$

$$\sum_j X_{i,j,t} \leq 1, \forall_{i,t} \qquad (2)$$

$$\sum_j X_{i,j,t} - \sum_j X_{i,j,t+1} = 0, \forall_{i,t} \qquad (3)$$

$$\sum_m z_{m,t} \leq N, \forall_t \qquad (4)$$

The constraints ensure feasibility within the operation. The first constraint enforces that the rescue team can only take one route at a given time (Schiller et al., 2022). The second constraint ensures continuity in movement, meaning that if a team enters a location, they must either exit or stay in place. The third constraint limits the number of hostages that can be assisted simultaneously to N, preventing resource overload (Li et al., 2021). The fourth constraint restricts the number of deployed drones to M, ensuring operational feasibility given limited aerial surveillance resources. Finally, the binary constraints enforce those decisions regarding movement $x_{i,j,t}$ drone (6) deployment $y_{k,t}$ (7), and hostage assignment $z_{m,t}$ (8) must be either 0 (not taken) or 1 (taken) Decision Variables:

$$x_{i,j,t} \in \{0, 1\} \rightarrow 1 \qquad (5)$$

If the rescue team moves from location i to j at time t, 0 otherwise.

$$y_{k,t} \in \{0, 1\} \rightarrow 1 \qquad (6)$$

If node k is deployed at time t, 0 otherwise.

$$z_{m,t} \in \{0, 1\} \rightarrow 1 \qquad (7)$$

If hostage m is assigned to a rescue team at time t, 0 otherwise. In this model, the parameters include $d_{i,j}$ which represents the distance between locations i and j, and $S_{i,j,t}$ which describes the security score for movement from location t to j at time t determined through IoT sensors (Zarzoor, 2022). The parameter C_k defines the operational cost of deploying node k, P_m while representing the personnel assignment cost for hostage m. To balance the various objectives in the optimisation model, weighting factors W1, W2, W3, and W4 are used. The model also considers capacity constraints, where N represents the maximum number of hostages that can be assisted at one time, and M represents the maximum number of nodes that can be deployed simultaneously (Nguyen et al., 2021; Senthil, Raaza & Kumar, 2021). This formula connects sensor data with IoT monitoring to optimize operations while still taking into account movement, costs, and risks.

- **Simulation Setup**

The QHBM effectiveness assessment began with real-time testing of movement optimization, including drone movements and personnel assignments. This testing utilized IoT sensor data for real-time decision-making and resource allocation. The testing was conducted in a virtual environment in a multi-room building, with experiments under various levels of hazard and threat in operational scenarios. The variables used included social, operational, and environmental factors.

Table 1: System Parameters

Symbol	Description	Value	Unit
$d_{i,j}$	Distance between locations i and j	5—20	Meters
$S_{i,j,t}$	Safety score based on sensor data	0.1—1.0	Probability
C_k	Operational cost of drone k	50	USD per hour
P_m	Cost of assigning personnel to hostage m	100	USD
N	Maximum number of hostages handled	3	Hostages
M	Maximum number of drones deployed	2	Drones
W_1	Weight for response time	0.4	-
W_2	Weight for safety	0.4	-
W_3	Weight for drone cost	0.1	-
W_4	Weight for personnel cost	0.1	-

Table 1 presents the main parameters used in hostage rescue trials in an operational environment. Sensor data will provide potential survival values under various threat conditions.

- **Scenarios**

This study used three different model testing schemes under different conditions. Scheme 1, with a low risk level, was used in a small building containing 5 rooms and 1 hostage, with the enemy being present at a minimal level with a high security score. This was done to obtain results in a simple environment. Scheme 2 used a medium-risk building with 10 rooms and 2 hostages, with the enemy moving between rooms and varying security scores. Scheme 3 was tested with a high risk level in a large building containing 20 rooms and 3 hostages.

Experiments will be conducted over a predetermined period by simultaneously evaluating model performance calculated from the rescue time while also accounting for the number of hostages and the costs involved. The formula for finding the best solution requires various inputs when using QHBM-based optimization with more than one objective. The required inputs include weights W1, W2, W3, W4, the distance matrix $d_{i,j}$, the room capacity $S_{i,j,t}$, the operational cost C_k, the personnel assignment cost Pm, and the number of scouts N_{scout}. The minimum step size ϵ, the initial radius r_0, and the maximum iteration N_{max} are the inputs required to obtain the best solution x, y, and z as well as the best fitness value F.

The experiment was conducted by placing the queen at X_m, Y_m, Z_m, and each scout, then determining the search sector with an iteration initialization of it←0. During the Iteration period, the algorithm will evaluate by calculating the fitness value using the input data to find the best solution, which will then place the queen in the best position, e.g., X_m (it+1) = X_m (it) + $r_m \times \cos(\theta)$. The iteration will stop if the radius r_m is below the specified threshold ϵ.

The QHBM algorithm, which optimizes multiple positions, is essentially inspired by the behavior of bees, where swarm migration is initiated by the migration of the queen bee. Initially, the queen's position (x_m,y_m,z_m) is randomly assigned within the search space, while a predefined number of scout bees, N_{scout} are distributed across the domain to explore potential solutions. The search area is partitioned into multiple sectors, each representing a possible migration direction. The initial search radius, r_0 defines the scanning region for queen movement, and the maximum iteration count, $N_{max,}$ is set to constrain the optimization process. The following is the code for finding the best solution and best fitness. During each iteration, scout bees evaluate candidate solutions using a predefined objective function 8.

$$F = W_1 \sum d[i,j]\times x[i,j,t] - W_2 \sum S[i,j,t]\times x[i,j,t] + W_3 \sum C[k]\times y[k,t] + W_4 \sum P[m]\times z[m,t] \qquad (8)$$

Where W_1, W_2, W_3, W_4 denote weighting coefficients, d[i,j] represents distance-related costs, S[i,j,t] accounts for resource constraints, C[k] represents penalty costs, and P[m] signifies prioritization factors. The variables x[i,j,t], y[k,t] and z[m,t] correspond to decision variables within the optimization framework. Based on the fitness evaluation, the queen selects an optimal migration sector using a probabilistic function 9.

$$P_j = \frac{c_j}{\sum_{j=1}^{8} c_j} \qquad (9)$$

Where c_j represents the cumulative evaluation score of scouts within sector S_j. The queen's migration follows an adaptive update strategy (10).

$$X_m\,(it+1) = X_m(it) + r_m \cos(\theta) \qquad (10)$$

In the optimisation iteration, the queen bee's position is dynamically updated using equations of motion that combine the current position $X_{m(it+1)}$ and $Y_{m(it+1)}$ with a displacement factor Rm that is affected by the cosine angle $\cos\theta$.

$$X_{m(it+1)} = X_{m(it)} + r_m \cos(\theta) \qquad (11)$$

Where r_m represents the migration distance, dynamically adjusted by (12).

$$r_{m(it+1)} = 1 - (g_{m(it)}) \times r_0 \qquad (12)$$

With $r_{(m(it)}$ serving as a convergence control factor. Scout bees subsequently realign their positions based on the queen's updated coordinates (13).

$$x_{k(it+1)} = x_{k(it)} + \Delta\, x_m(it+1) \qquad (13)$$

$$y_{k(it+1)} = y_{k(it)} + \Delta\, y_m(it+1) \qquad (14)$$

Ensuring continuous refinement of the search space. The algorithm terminates when the migration distance falls below a predefined threshold, i.e.

$$r_m < \epsilon \qquad (15)$$

Where ϵ represents the minimum allowable step size. Alternatively, termination occurs upon reaching N_{max} iterations or satisfying the desired fitness threshold.

Table 2: System Parameters

Parameter	Symbol	Description	Typical Range
Number of scout bees	N_{Scout}	Total scout bees exploring the search space	10 - 50
Initial search radius	r_0	Initial scanning region for queen movement	0.1 - 1.0
Maximum iterations	N_{max}	Maximum number of algorithm iterations	100 - 1000
Migration distance	r_m	The distance the queen moves in each iteration	Adaptive
Convergence control factor	$g_m(it)$	The factor controlling the reduction in migration distance	0 - 1
Minimum step size	ϵ	Threshold for stopping the search	10-6 - 10-3
Fitness function weights	W_1,W_2,W_3,W_4	Weighting factors in the objective function	Problem-dependent
Probability function	P_j	Probability of selecting sector S_j	0 - 1

Table 2 shows the QHBM parameters that influence its convergence behavior. QHBM efficiently integrates exploration and exploitation functions, allowing the best solution to problems with multiple objectives to easily adapt to various solution spaces and conditions.

4 Results and Discussions

The value fluctuations illustrate the ability of QHBM to overcome dynamic and high-risk uncertainty.

Figure 2: Comparison Chart of Security Scores on Various Scenarios Over Time

Figure 2 shows the results of the safety scores at each different time of the 3 test scenarios carried out, which were optimized with the QHBM algorithm. Scheme 1 had a high safety value ranging from 0.75 to 0.8. This scheme experienced a drastic drop in safety value early in the trial before reaching a steady state, surpassing the other two schemes, reaching a value above 0.8. Scheme 2 shows a safety value that moves in the range of 0.5 to 0.6, creating a relatively stable pattern, in contrast to the pattern shown in Scheme 1, where there was a significant decrease at the beginning of the experiment. Scheme 3 has the lowest safety score at the beginning of the experiment, its value ranges from 0.35 to 4.0, but increases over time, precisely at time 10, until it exceeds the value of scheme 2 at time 20 to 30. Overall, these 3 QHBM schemes create good adaptation.

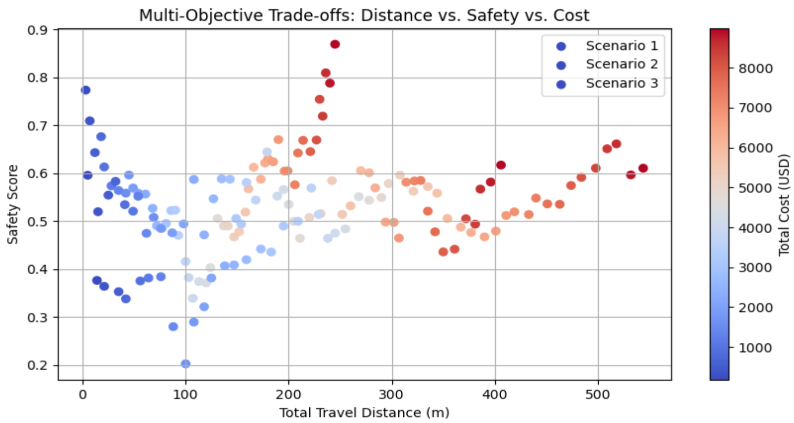


Figure 3: Distance, Safety, and Cost Multi-Objective Comparison Chart

Figure 3 illustrates the values of distance, cost, and safety when the experiment was conducted with QHBM. The safety value obtained ranged from >0.3 to <0.8 with a short distance of less than <100 m, which cost <3000 USD. Increasing the experimental distance obtained increasingly stable results, ranging from a safety value of 0.5 to 0.6, with costs also increasing, ranging from 3000 USD to 6000 USD at distances of more than 100 meters to 300 meters. The safety value continues to increase at distances of more than 300 meters until it reaches a safety value of >0.7 with an increasing cost of >6000 USD. QHBM shows that low-cost solutions must be followed by short distances, and vice versa, with high costs for high-security solutions required high costs.

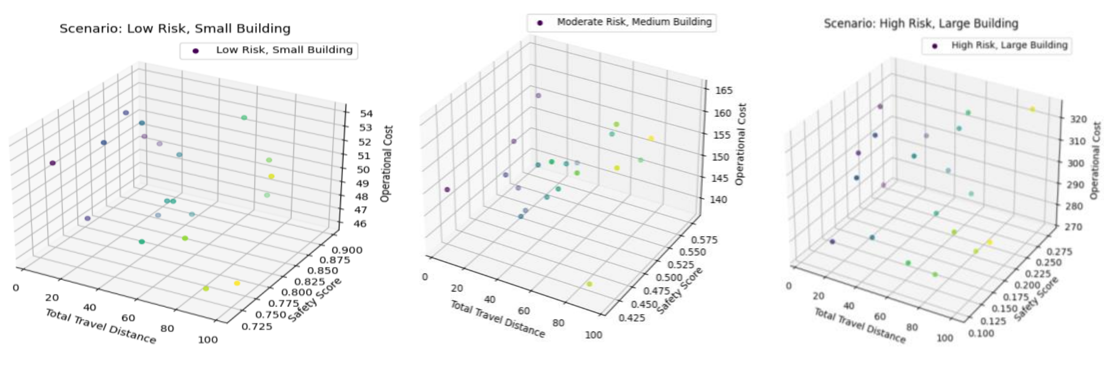


Figure 4: Effectiveness of QHBM Algorithm in Three Risk Scenarios, (A) Low-Risk Small Buildings, (B) Moderate-Risk Medium Buildings, (C) High-Risk Large Buildings

Figure 4 illustrates the effectiveness of QHBM in different scenarios, with low-risk scenarios showing consistent safety scores of >85% with minimal costs of <5%. Moderate-risk scenarios also show varying scores, ranging from 80% to 90%, with mileage increasing by 0.5% for a 15% cost variation. In high-risk scenarios, safety scores reach 95%, but costs also increase by >25%, with mileage also increasing by 30% to 50%.

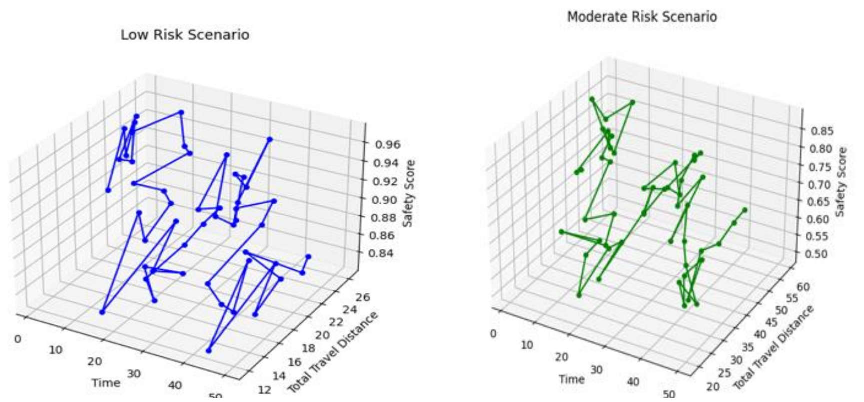
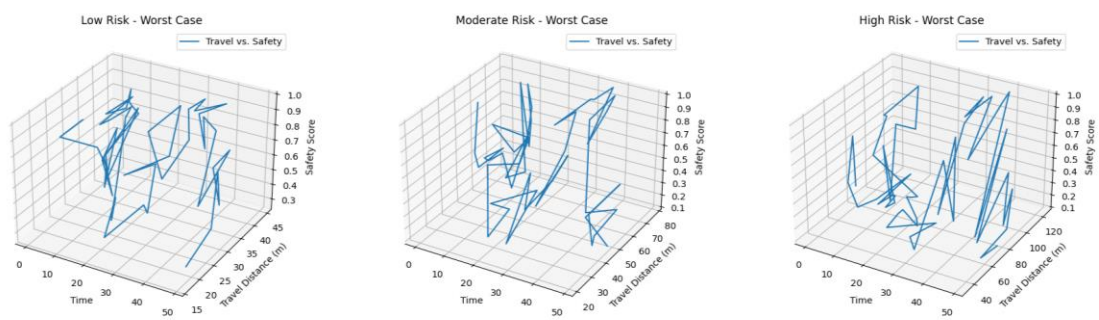


Figure 5: QHBM Results with Different Optimization Challenges, (A) Low-Risk Scenario, (B) Moderate-Risk Scenario, (C) High-Risk Scenario

Figure 5 illustrates the ability of the QHBM algorithm in handling various levels of risk. At low risk, the resulting solution appears more stable and efficient in terms of cost and safety, the mileage remains relatively the same and within the normal range, although there are slight variations, which implement good convergence. In scheme 2 with a medium risk level, the search complexity increases, and the range of resulting solutions also becomes wider. QGBM successfully maintains optimal cost and safety in a medium-risk situation, and the required mileage also increases according to the required cost. In scheme 3 with high risk, the required solution path is more dynamic than the previous two schemes. QHBM explores many possible best solutions that are adjusted to cost and safety. Overall, QHBM can adapt efficiently to different safety, cost and mileage at various risk levels.



(A) (B) (C)

Figure 6: The QHBM Results in Under Challenging Conditions, (A) Low-Risk Worst-Case Scenario, (B) Moderate-Risk Worst-Case Scenario, (C) High-Risk Worst-Case Scenario.

Figure 6 illustrates the results of QHBM performance even in the worst-case scenario. Performance in the worst-case scenario is divided into three risk levels: low, medium, and high. At low risk, fluctuations still exist but are within normal control with safety values ranging from 0.4 to 1.0 at distances of 10 to 50 meters. These results indicate that the existing deviation can still maintain a good level of efficiency. At medium risk, variations increasingly affect safety values at distances > 70 meters. The resulting navigation trade-offs are also more complex; this may be due to increased safety that may require longer distances. At high risk, more complex fluctuations occur with distances > 120 meters, resulting in highly dynamic optimization paths and varying safety values. This indicates that QHBM always adjusts its strategy in conjunction with optimizing other objectives to find a feasible solution. QHBM has proven capable of handling various levels of risk in the simulations conducted, thus achieving adaptability even in multi-objective challenges.

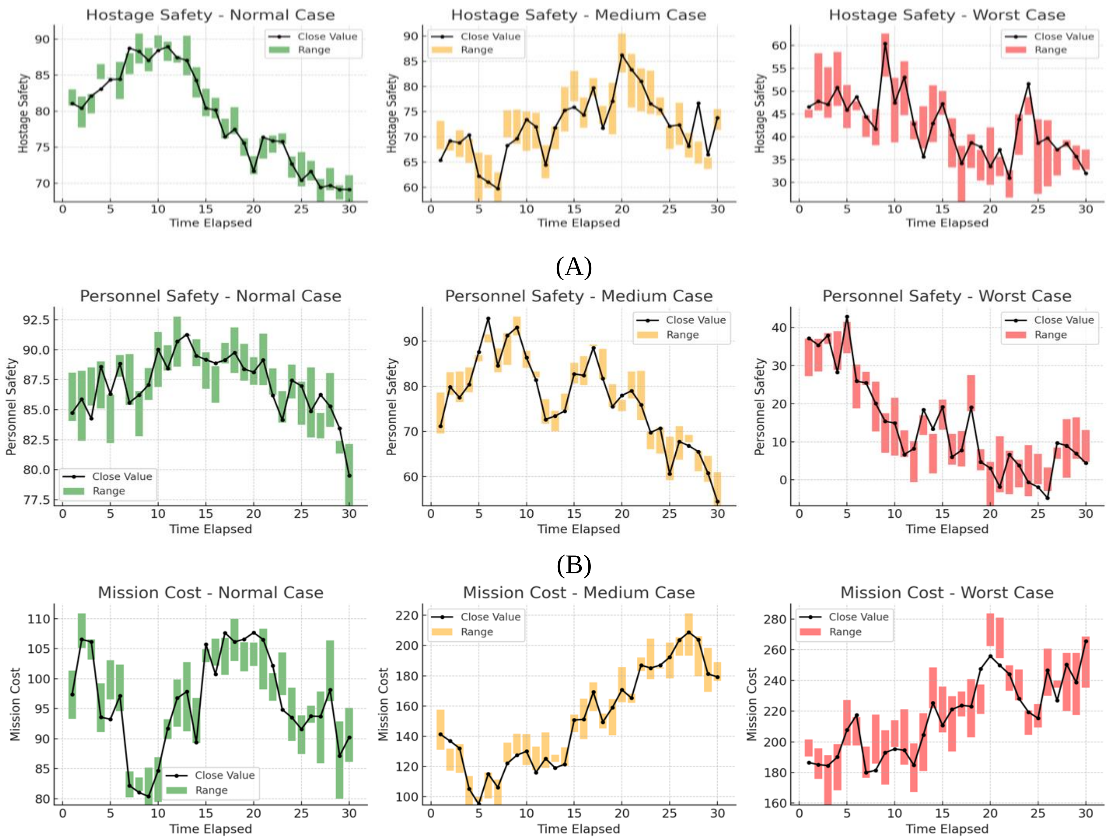


Figure 7: Stochastic Safety and Cost Scenario with Fluctuations, (A) Hostage Safety, (B) Personnel Safety, (C) Mission Cost.

Figure 7 displays a stochastic analysis of various risk conditions, including hostage safety, personnel safety, and operational costs. The graph shows fluctuations in each parameter over time, which illustrates the risk management and costs incurred for each operation at each risk level.

In normal cases, hostage safety experiences significant fluctuations initially, ranging from a value of 80 to 90 until it drops drastically to a value of 70. In moderate cases, hostage safety has various fluctuations in value from an initial value of 60 to 70, rising to 70 to > 85, which illustrates high uncertainty. While in the worst case, the fluctuation of hostage safety uncertainty experiences a downward trend along with the amount of time required, which tends to have a hostage safety value continuing to decline between 70 <35, indicating a significant risk in a high-level threat situation. In the stochastic of personnel safety, the trends formed in normal and high cases tend to be the same but with different movements, in contrast to the fluctuations created in moderate cases, which have a value tendency where initially > 90 continues to decrease to <60 this indicating an unfriendly impact on the risk of the operation. The stochastic of operating costs trends created for normal and moderate cases is the same as the stochastic of hostage safety, where in normal conditions the cost trend ranges from 150 to 220, even though at the beginning of the time, there is a very sharp decrease in costs. In the medium case, the required costs continue to increase, ranging between 160 and 260, while in the worst case, the required costs range between 170 and 300, with increasing deviations reflecting operational uncertainty.

Overall, risk escalation evidence has a significant impact on safety and cost parameters. Worst-case scenarios with the highest levels of uncertainty require more resource optimization and hands-on decision-making. Moderate scenarios, both stable and unstable, require sound risk management. In normal scenarios, even with relatively stable trends, continuous monitoring is still required. These results can aid decision-making in optimizing mission planning to be more precise and find the best solution.

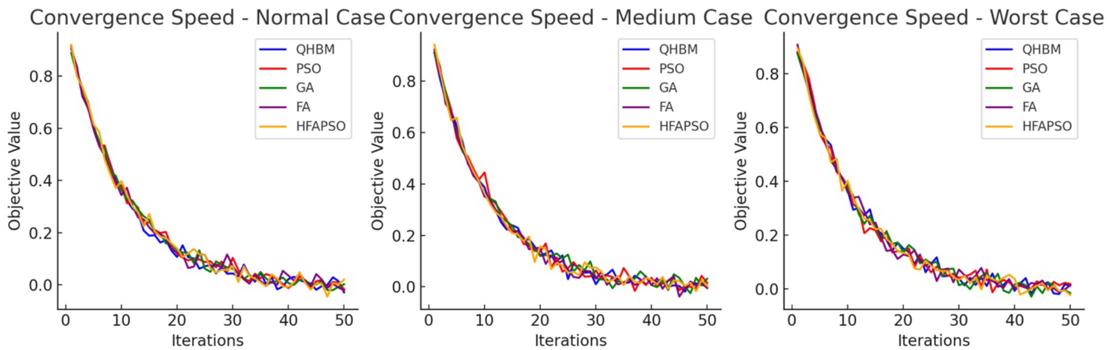


Figure 8: The QHBM Results in Under Challenging Conditions, (A) Low-Risk Worst-Case Scenario, (B) Moderate-Risk Worst-Case Scenario, (C) High-Risk Worst-Case Scenario

Figure 8 illustrates the convergence speed of the five optimization algorithms used in each normal, medium, and worst-case scenario. In the normal case, the QHBM and PSO algorithms are slightly faster than the other algorithms, and in the first 20 iterations, all algorithms experience a significant decrease. In the medium case, there is a deviation in the FA and GA algorithms that increases the sensitivity of the work, along with increasing uncertainty. At iteration 30, PSO and QHBM provide performance close to optimal, while HFAPSO maintains the same performance as in the normal condition. In the worst-case scenario, the convergence speed decreases, indicating the objective value at the beginning of fluctuations in higher performance, including in FA and GA. QHBM and PSO show superior performance until reaching an objective value below 0.2 at iteration 50. The worst-case scenario shows that QHBM is able to maintain better exploration while maintaining convergence efficiency, making it a better algorithm in optimization environments with high mobility and uncertainty. Robustness under uncertainty makes QHBM suitable for use in real-world operations that prioritize adaptive and robust optimization.

Figure 9: Solution Quality Comparison

Figure 9 illustrates the quality of solutions generated by various algorithms in the normal, medium, and worst-case scenarios. Lower values indicate better optimization results. In the normal scenario, PSO and QHBM performed best, with objective values approaching optimal between 0.8 and 0.9. In the medium scenario, FA, QHBM, and HFAPSO performed best, and in the worst-case scenario, QHBM maintained relatively strong results, reflecting its resilience in the face of high levels of uncertainty. QHBM proved stable in all scenarios and was able to provide good objective values, followed by PSO and HFAPSO, which became competitors, while FA and GA showed high sensitivity to increasing uncertainty.

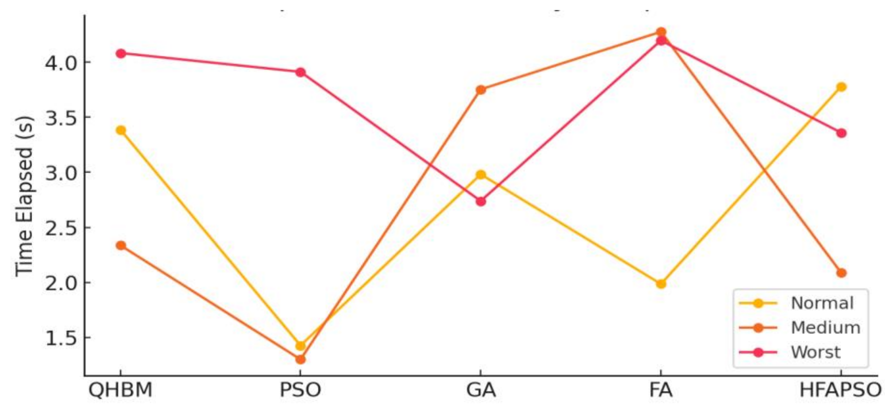


Figure 10: Computational Efficiency Comparison

Figure 10 illustrates how a comparative analysis was performed on each algorithm, showing clearer performance differences. QHBM has the fastest performance compared to other algorithms, where QHBM only requires 10-25 iterations, followed by PSO, which requires 30-50 iterations, while HFAPSO, GA, and FA require 100-150 iterations. These results indicate that QHBM is more optimal and requires less computational power.

In terms of solution quality, QHBM also achieved the best objective value compared to other algorithms, with the lowest cost and highest security, followed by PSO, but its optimization was still lacking compared to QHBM. HFAPSO performed quite well, but not as well as QHBM and PSO. FA and GA performed poorly, while FA required the highest cost and the lowest efficiency.

Computational efficiency was also a key factor in QHBM's outperformance. HFAPSO also offered fairly good computational time, but not superior to QHBM. PSO required 30% more computational time than QHBM. GA and FA required more computational time than QHBM, with the difference in computational time being nearly double. These results indicate that QHBM is suitable for use in real-world, high-risk environments requiring rapid decision-making.

QHBM has stable robustness compared to other algorithms, and the resulting convergence also has minimal fluctuations, thus preventing high uncertainty. Therefore, QHBM is more reliable to use compared to GA and FA, which have high variability in stability and robustness. In stochastic factors, QHBM has the main advantage over other algorithms in consistent performance even under complex conditions. Meanwhile, GA and FA are difficult to adapt to conditions and often fail to maintain their efficiency. QHBM allows for efficient use on large-scale problems. In contrast, GA and FA slow down as the problem size increases, but it is not better than PSO and QHBM.

Overall, QHBM is the best algorithm across all key metrics, including computational speed, solution quality, stability, and robustness. PSO is next, nearly surpassing QHBM in computational efficiency and scalability. HFAPSO outperforms GA and FA but falls short of the efficiency levels of PSO and QHBM.

Table 3: Performance Comparison for Each Algorithm

Algorithm	Personnel Safety Score	Total Cost (USD)	Distance traveled (m)
QHBM	0.72 – 0.91	4500 – 8200	50 – 120
PSO	0.65 – 0.85	5000 – 8700	55 – 130
GA	0.60 – 0.80	5200 – 8900	60 – 140
FA	0.58 – 0.78	5300 – 9100	65 – 145
HFAPSO	0.67 – 0.86	4700 – 8500	52 – 125

Table 3 shows the performance of each algorithm, indicating that QHBM obtained the best results with a safety value of 0.72 to 0.91, far exceeding other algorithms. In terms of cost efficiency, QHBM requires the lowest cost in the range of 4500-8200 USD, making it more economical than other methods such as FA and GA, which require costs of 5200 to 9100 USD. It is even superior to PSO, which costs between 5100 and 8700 USD, and HFAPSO, which costs 4700 to 8500 USD. The distance traveled by QHBM ranges from 55 to 115 after optimization. PSO achieves shorter distances on some solutions but sacrifices lower safety. GA and FA travel longer distances due to weak optimization strategies, resulting in unnecessary distance wastage. QHBM has a convergence time of only 37-48 iterations, outperforming FA and GA, which require more iterations to reach optimal conditions. While PSO requires fewer iterations but sacrifices security, in high-risk scenarios, QHBM is more stable in maintaining performance than FA and GA, which are highly volatile. While PSO has better stability than GA and FA, its robustness in maintaining balance across multiple objectives and conditions is still not inferior to QHBM.

5 Conclusion

In the personnel safety measurement matrix, QHBM is superior to PSO by 120% of PSO performance, while GA and FA performance are lower than PSO performance. QHBM can achieve optimal and more stable performance and is superior to PSO, FA, GA and HFAPSO algorithms in various risk conditions, which makes it more efficient to use to improve safety for both personnel and hostages. QHBM's cost efficiency is 115% higher than GA and FA, which require higher costs due to inefficient resource allocation. PSO achieves moderate operating costs but neglects safety, so QHBM is superior in its ability to balance costs and safety. QHBM can achieve optimal results with 130% faster computing resources than GA and FA while still maintaining high accuracy. QHBM can maintain fast and reliable output when algorithms such as FA take longer to reach stable conditions, and GA, PSO and HFAPSO have difficulty dealing with fluctuations in uncertainty. QHBM can maintain stability, ensuring more efficient multi-objective optimization in various conditions and risks. QHBM results in better and more reliable multi-objective decision-making effectiveness in safety-critical implementations.

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