

Stochastic Optimization for Hostage Rescue Using Internet of Things and Queen Honey Bee Algorithm

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ABSTRACT

This study proposes a stochastic optimization model to enhance the efficiency of hostage rescue operations using Internet of Things technology and the Queen Honey Bee Migration algorithm. The model aims to reduce response time and energy consumption by leveraging real-time data from IoT sensors to adapt dynamically to field conditions. Simulation tests conducted in a multi-story building environment demonstrated a 40% improvement in response time and a 35% reduction in energy consumption compared to conventional methods. The system also achieved up to 94.8% positioning accuracy using RSSI analysis and demonstrated consistent performance across floors. The results indicate that integrating QHBM and IoT provides a scalable and adaptive solution for mission-critical operations, with potential applications in real-world tactical planning.

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1. INTRODUCTION

Hostage rescue operations are among the most complex and high-risk activities in modern military and tactical missions. These operations require fast and precise decision-making, real-time adaptability, and efficient use of resources to ensure mission success while minimizing risks to hostages and personnel [1]. Traditionally, such operations rely on heuristic and reactive approaches, which often fail to optimize critical factors such as time and energy efficiency [2]. In high-risk scenarios, these inefficiencies can lead to mission delays or increased risk. In recent years, the advent of the Internet of Things (IoT) technology has opened up new avenues for improving decision-making and operational efficiency in dynamic environments [3]. IoT facilitates real-time data acquisition through interconnected sensors and devices, thus enabling rapid response to evolving conditions in the field. While there is considerable research on IoT applications in various sectors, the potential of IoT to enhance the performance of military operations, particularly in hostage rescue scenarios, remains largely unexplored. Furthermore, few studies have addressed the integration of IoT data with optimization algorithms to balance time and energy efficiency in complex and time-sensitive missions [4].

This research proposes a new stochastic model to optimize the efficiency of hostage rescue operations by integrating IoT technology with the Queen Honey Bee Migration (QHBM) algorithm [5]. The Queen Honey Bee Migration (QHBM) algorithm is an evolutionary optimization method inspired by the natural behavior of honey bee colonies in locating and exploiting optimal food sources. The algorithm simulates a balance between exploration (through scout bees) and exploitation (via worker bees), allowing it to solve complex optimization problems with high adaptability. Unlike conventional algorithms, QHBM integrates stochastic movement and adaptive search intensity, making it suitable for dynamic and uncertain environments such as hostage rescue operations. By embedding this algorithm into IoT-based systems, this research introduces a flexible and energy-aware solution capable of real-time decision-making and multi-objective optimization. QHBM is an evolutionary algorithm inspired by the foraging behavior of honeybees, known for its effectiveness in solving complex optimization problems with various constraints and uncertainties. By utilizing IoT-generated data in real-time, the proposed model aims to enhance the decision-making process and optimize resource allocation, thereby minimizing mission time and energy consumption [6].

The main objective of this research is to develop and validate a stochastic optimization model that improves the time and energy efficiency of hostage rescue missions [7]. The integration of IoT and QHBM is hypothesized to offer significant advantages over traditional methods, reducing operational delays and energy expenditure while increasing mission success rates [8–10]. Through simulation and analysis, this research demonstrates the effectiveness of the proposed model in real-world scenarios and discusses its broader implications for military operations [11]. The novelty of this research lies in several key aspects. First, this research is the first to combine IoT technology with the QHBM evolutionary optimization method in the context of hostage release operations, an area that has not been widely explored so far. Secondly, the stochastic model developed in this research is specifically designed to address the challenges of simultaneous time and energy efficiency, utilizing real-time data from IoT devices to provide more adaptive and responsive decisions to changing situations in the field. Third, this research extends the application of the QHBM algorithm to the complex and uncertain military domain, offering a new approach to managing missions that require multi-criteria optimization under dynamic conditions. Simulation results demonstrate that this approach is significantly superior to traditional methods in reducing response time and energy consumption, offering a more efficient and effective solution for modern military operations.

This research makes several important contributions, namely introducing a new stochastic model that utilizes real-time data from IoT devices to optimize time and energy efficiency in hostage release operations, integrating IoT technology with the QHBM algorithm that creates a hybrid approach in operational planning, and demonstrating significant improvements in response time reduction and energy consumption through applying the QHBM algorithm to IoT data. In addition, this research extends the application of QHBM to the military context, proves its validity through simulations that show performance advantages over conventional methods, and contributes to the growing literature on the utilization of IoT in military operations, particularly in hostage release scenarios. Previous research on hostage rescue operations has primarily focused on static planning models or heuristic approaches that do not adapt in real time [2, 3, 5]. Studies such as [6, 11, 12], explored robotic support or mathematical formulations but lacked integration with real-time IoT data. In addition, most of these works optimized only one objective—either time or energy—without considering the trade-off between them in dynamic scenarios. Although some methods, such as fuzzy logic and PSO, have been applied [4, 10], to our knowledge, none have utilized the Queen Honey Bee Migration (QHBM) algorithm for real-time optimization in hostage rescue operations.

This study fills that gap by introducing a stochastic model that leverages real-time data from IoT sensors and applies the QHBM algorithm to optimize time and energy efficiency simultaneously. The model is designed to adapt dynamically to changing field conditions and supports multi-floor rescue planning. This integration of QHBM with IoT in a tactical context presents a novel, scalable, and adaptive approach that has not been explored in previous studies.

2. RESEARCH METHOD

This study follows a quantitative-experimental approach that integrates stochastic modeling with real-time IoT data acquisition and swarm-based optimization. The research method is divided into several stages, as follows in Figure 1.

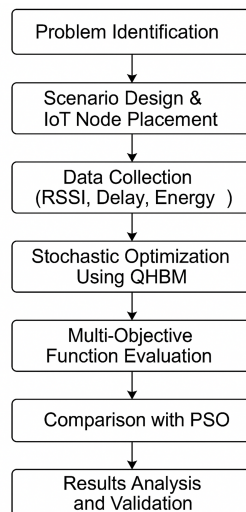


Figure 1. Research Methodology Flowchart

2.1. Experimental Framework and Scenario Design

The experiment simulates a multi-floor hostage rescue scenario within a controlled lab environment, representing a 3–5 story building structure. Each floor is equipped with IoT nodes ($n1$ – $n5$) acting as sensors/actuators to monitor and transmit real-time data. The testbed scenario includes variable distances, obstacles, and transmission conditions. The scenario also varies energy and delay parameters to reflect realistic operational conditions, as shown in Figure 2.

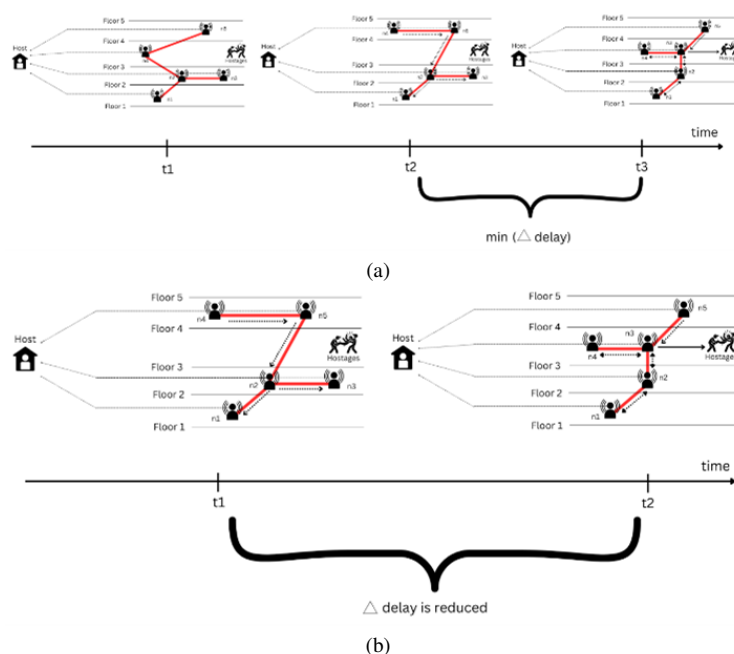


Figure 2. Problem definition for Hostage liberation (a) not yet solution (b) after using the algorithm

The implementation of an IoT-based communication network in hostage operations is illustrated through a five-story building scenario, where multiple IoT nodes (n1-n5) are strategically positioned to establish an optimal communication path [13]. Figure 2 shows the temporal evolution of the communication pattern across three time periods (t1, t2, and t3), demonstrating how the system adapts to minimize delays in information transmission. The solid red lines represent the main communication paths, while the dashed lines indicate alternative routes [14]. In the traditional approach shown in t1, the communication path follows a linear sequence through the nodes, potentially creating congestion and increasing response time. However, with the implementation of our proposed QHBM optimization algorithm shown at t2 and t3, the system dynamically adjusts the communication route to reduce the transmission delay or Δ delay [15]. Figure 3 further illustrates how the optimization process significantly reduces the overall delay between t1 and t2 by enabling parallel communication channels and selecting more efficient paths based on real-time network conditions.

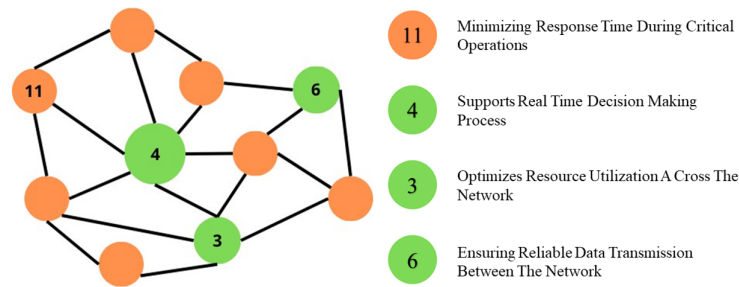


Figure 3. Adaptive communication strategy

Minimizing response time during critical operations is essential to ensure efficient performance. It also involves ensuring reliable data transmission across the network, which optimizes resource utilization. By doing so, the network facilitates real-time decision-making processes, enabling swift and effective responses. In Figure 3, this adaptive communication strategy is critically essential in modern technological systems. Its primary objective is to minimize response time during critical operations, enabling rapid and precise system reactions. The strategy ensures reliable data transmission between network nodes, guaranteeing the consistency and integrity of shared information. Moreover, it optimizes resource utilization across the entire network, allowing for efficient and economical use of system capabilities. Ultimately, this adaptive communication approach enables real-time decision-making processes, empowering systems to respond promptly to changes and make informed decisions with unprecedented speed and accuracy.

2.2. Scenario Generation

A comprehensive evaluation of our proposed model necessitates a series of extensive tests that cover various operational scenarios. This evaluation process not only focuses on the system's basic performance, but also assesses its adaptability to various levels of complexity and operational challenges that may arise in real-world situations. This extensive testing is crucial given the high-risk nature of hostage release operations and the serious consequences of failure. To ensure thorough validation of the system's performance and adaptability, we have developed a sophisticated scenario generation framework. This framework is designed by considering various operational aspects, including:

1. Variations in the complexity of the operating environment
2. The changing dynamics of the tactical situation
3. Various levels of information uncertainty
4. Diverse configurations of targets and obstacles
5. System failure scenarios and contingency planning

2.3. Algorithm Design and Parameters

The implementation of the QHBM algorithm represents a groundbreaking approach in the development of advanced optimization frameworks, particularly for high-stakes hostage release operations [16]. This sophisticated algorithmic strategy draws profound inspiration from the remarkable collective intelligence and intricate foraging mechanisms observed in honey bee colonies, translating natural biological behaviors into a powerful computational problem-solving methodology [17]. By meticulously mimicking the complex decision-making processes and collaborative strategies of honeybees, the algorithm demonstrates an extraordinary capacity to navigate multidimensional optimization challenges with unprecedented precision and adaptability [18].

The development of this biologically-inspired algorithm involves an intricate and comprehensive process of parameter tuning and systematic optimization, carefully designed to address the most challenging and dynamic operational environments. Researchers have invested significant effort in analyzing and replicating the nuanced communication and navigation strategies employed by honey bee swarms, transforming these natural mechanisms into a robust computational framework [19]. The algorithm's core strength lies in its ability to efficiently explore vast solution spaces, balance exploration and exploitation, and rapidly converge on optimal solutions in mission-critical scenarios that demand both energy efficiency and strategic precision. In practical applications, particularly within high-risk hostage release operations, the QHBM algorithm provides a transformative approach to planning and decision-making, dynamically responding to complex and rapidly changing operational conditions and offering strategic insights that can be crucial in time-sensitive and high-risk missions.

2.4. Optimization Process

The algorithm operates through an iterative process of solution exploration and refinement. During each iteration, scout bees explore new potential solutions while employed bees focus on exploiting promising areas identified in previous iterations [20]. The process begins with an initial random exploration, followed by an increasingly focused search pattern as promising solutions are identified. This adaptive search strategy allows the algorithm to efficiently navigate the complex solution space that characterizes hostage release operations.

The implementation includes sophisticated mechanisms to handle multiple objectives simultaneously. The algorithm must strike a balance between the competing requirements of time efficiency and energy conservation while maintaining operational effectiveness. This is achieved through a weighted objective function that combines these various factors into a single optimization metric, with weights adjusted based on mission-specific priorities. The QHBM algorithm is configured with the following parameters, shown in Table 1.

Table 1. QHBM Configured

Parameters	Value
Population size	100
Maximum iterations	1000
Scout bee percentage	20%
Elite sites	5
Best sites	3
Recruitment range	0.1

2.5. Optimization Variables

In the context of complex and dynamic hostage release operations, the developed model is designed to optimize two interrelated and critical objectives that are essential to mission success. The optimization considers various operational parameters and technical constraints that affect the overall system performance [21]. By employing a comprehensive multi-objective optimization framework, the proposed model seeks to achieve an optimal trade-off between time efficiency and energy consumption, which represent two fundamental performance dimensions in IoT-based tactical operations. The model is designed to simultaneously optimize both aspects, thereby enhancing system responsiveness and ensuring sustainable energy use.

In modern computing systems, time and energy efficiency serve as critical benchmarks that determine the overall effectiveness of the system. Time efficiency involves several interrelated components, beginning with response time, which reflects the speed at which the system reacts to a given input or command. This is followed by execution time, referring to the duration required for the system to complete a specific computational task. Another key element is the communication delay, which represents the time lag experienced during data transmission between various nodes or components within the network.

Complementing time efficiency, energy efficiency plays an equally vital role in the architecture and operational viability of intelligent computing infrastructures. This aspect includes considerations such as device power consumption, which accounts for the energy drawn by each component in the system. It also encompasses communication energy, which indicates the energy required for data transmission, as well as operational energy expenditure, which measures the total energy consumed during the entire computational process. These two aspects—time efficiency and energy efficiency—are inherently interconnected, and their simultaneous optimization is essential not only for improving system performance but also for ensuring the long-term sustainability, scalability, and resilience of IoT-driven technological ecosystems.

2.6. Optimization Variables and Objective Function

In the development of stochastic models for hostage release operations, a critical aspect to consider is the simultaneous optimization of multiple interrelated objectives [22]. The multi-objective optimization function developed in this study is designed to handle the complexities and interdependencies between time efficiency, energy consumption, and operational effectiveness. The model integrates various parameters and constraints relevant to the hostage release scenario, while considering the dynamic characteristics of the operating environment [23].

$$F(x) = w_1 \sum (T_i) + w_2 \sum (E_i) \quad (1)$$

In Equation 1, the computational structure utilizes weight coefficients and interrelated variables, providing a nuanced approach to system analysis. The weight coefficients and play a fundamental role in providing context and relative significance to each analytical component. These coefficients enable researchers to adapt the model to specific research contexts and prioritize key parameters with precision. The variables, representing time-related variables, encompass various temporal parameters that influence system performance, capturing the dynamic aspects of operational efficiency. Similarly, the variables characterize energy-related variables, meticulously measuring energy consumption and resource efficiency within the evaluated system. The sophisticated interplay between these weight coefficients and variables enables a comprehensive analysis that simultaneously considers both temporal and energetic aspects, providing a holistic and structured approach to understanding complex computational systems. This optimization is constrained by a set of constraints in Equation 2 [24]:

$$\begin{aligned} T_i &\geq T_{max}(\text{Time Constrains}) \\ g_{1(x)} &\geq E_{max}(\text{Energy Constraints}) \\ P_i &\geq P_{max}(\text{Power Constraints}) \end{aligned} \quad (2)$$

Through this approach, the system can achieve an optimal solution by considering various factors and constraints that exist in hostage release operations. These factors include time limitations, energy availability, communication reliability, and dynamic environmental conditions. By integrating these constraints into a comprehensive optimization framework, the model ensures that tactical decisions remain effective, efficient, and adaptable to real-time mission demands.

2.7. Evaluation Metrics

2.7.1. Energy Model

In hostage release operations using IoT networks, energy consumption at each node is a critical factor affecting the success and sustainability of the mission. The developed energy consumption model considers various aspects of energy usage that occur during operation. Each IoT node consumes energy through several main activities: data communication, information processing, and energy used during idle mode. To achieve optimal energy utilization in IoT-based systems, it is essential to understand and precisely quantify the total energy consumption at each node. The mathematical model developed in this study provides a holistic representation by accounting for all relevant components of energy usage. The total energy consumption of an IoT node is calculated by considering three main elements. The first is communication energy, which reflects the energy required for transmitting and receiving data. The second is processing energy, which encompasses the energy consumed during computational tasks and sensor operations. The third is idle energy, which represents the energy drawn when the node is not actively processing but remains powered. These components are integrated into a unified framework and expressed mathematically in Equation 3 [25].

$$E_{total} = E_c + E_p + E_i \quad (3)$$

The communication energy component is the most significant aspect of total energy consumption, as it involves intensive data transmission and reception processes. A formula for communication energy was developed by considering factors such as transmission distance, data packet size, and propagation environment characteristics Equation 4 [26].

$$E_c = E_{tx} + E_{rx} \quad (4)$$

Transmission Energy E_{tx} :

$$E_{tx} = (a_i + a_2 * d^n) x_k E_{tx} \quad (5)$$

In the domain of wireless communication Equation 5 and energy efficiency modeling, this sophisticated equation introduces critical parameters that comprehensively describe electronic energy consumption and transmission characteristics. The variable $\alpha 1$

represents the electronic energy expended by communication devices, capturing the baseline power requirements of the system's electronic components. Complementing this, α_2 quantifies the amplifier energy, which accounts for the additional power consumed during signal amplification processes. The transmission distance, denoted by, plays a crucial role in determining the energy expenditure, directly influencing the signal propagation and power requirements. The path loss exponent, n , ranging between 2 and 4, provides a nuanced representation of signal attenuation, reflecting the complex interaction between signal transmission and environmental factors. Finally, the packet size denoted by and measured in bits provides essential insight into the volume of data being transmitted. This parameter has a significant influence on both the total energy consumption and the communication efficiency of the system. In the context of the reception energy described in Equation 6, the coefficient β represents the acceptance rate, which further affects how efficiently the received data is processed and interpreted within the node's communication protocol [27]:

$$E_{rx} = \beta \times k \quad (6)$$

2.7.2. Mobility Model

In hostage liberation operations, understanding and predicting the position of each entity involved is a fundamental aspect for mission success. The mobility model developed uses position vector analysis to track and predict the movements of the tactical team, targets, and various dynamic elements in the operating environment. These position vectors become the basis for route planning, team coordination, and real-time tactical decision-making.

The position vector model we developed integrates time, velocity, and acceleration parameters to provide an accurate representation of movement in three-dimensional space. This calculation allows the system to predict the position at any given time based on the initial conditions and measured movement parameters in Equation 7 [28, 29]. Such prediction capability is crucial for route planning and team coordination in dynamic hostage rescue scenarios, where precise movement estimation enhances mission effectiveness and reduces risk.

$$P(t) = P_0 + V(t).t + \frac{1}{2}.\alpha.t^2 \quad (7)$$

3. RESULT AND ANALYSIS

This section presents the simulation outcomes, comparative evaluations, and insights into system performance based on the proposed QHBM model.

3.1. Energy Consumption and RSSI-Based Accuracy

In analyzing the performance of IoT systems in hostage release operations, energy and network efficiency aspects are critical components that determine the success of the operation. Evaluation of energy consumption and network efficiency is done through RSSI (Received Signal Strength Indication) measurements at various distances and operational conditions. These measurements take into account various factors, including distance, environmental interference, and noise, that can impact signal quality. RSSI-based positioning analysis yields varying levels of accuracy, depending on the measurement distance, with the highest accuracy achieved at close range and decreasing gradually as the distance increases. This optimization of energy consumption and network efficiency is fundamental in ensuring reliable communication during operation.

Figure 4 shows the relationship between RSSI in dBm and distance (meters), with the effect of Gauss-Seidel Noise on the measurement. The analysis reveals that the RSSI value decreases significantly as the distance between the transmitter and receiver increases, following typical patterns of wireless signal propagation. At a distance of 10 meters (P5), the RSSI was recorded at -22.5 dBm, while at a distance of 35 meters (P1), the RSSI value decreased to -51.3 dBm, indicating a decrease in signal strength as the distance increases. Although the Gauss-Seidel Noise causes small fluctuations in the RSSI value, the overall pattern of decrease remains consistent. Figure 5 is the Positioning accuracy results obtained from this data, which illustrates the impact of RSSI degradation on the accuracy of the RSSI-based positioning system, taking into account the influence of noise on more accurate distance estimation.

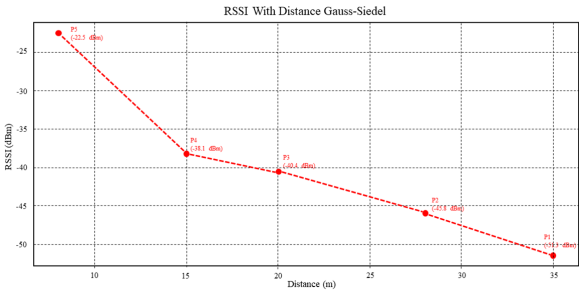


Figure 4. RSSI and distance with Gauss-Seidel

Measurement accuracy is affected by several key factors, such as the actual distance, signal interference, and the number of measurements. In this study, the actual distances used were 35, 28, 20, 15, 8 meters, with an RSSI error of 5% (RSSI error = 5) and a total of 10 measurements (num measurements = 10). Results show that accuracy tends to be higher at closer distances, where point P5 (8 meters) has the highest accuracy of 94.8%, while point P1 (35 meters) has the lowest accuracy of 85.2%. The main factors affecting accuracy include distance, where the closer the distance, the higher the accuracy; signal interference modelled through RSSI error; and the number of measurements, where more measurements provide more stable results. Statistically, the average measurement accuracy was 90.12%, with a maximum value of 94.8% in P5, a minimum value of 85.2% in P1, and an accuracy range of 9.6%.

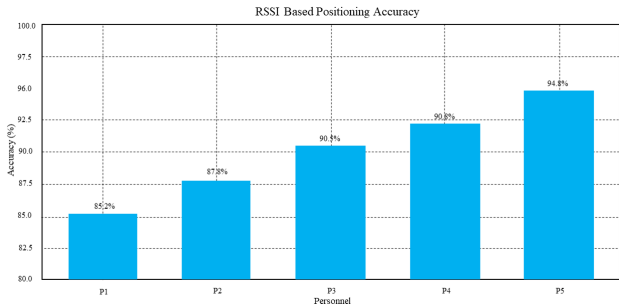


Figure 5. Positioning accuracy results

Table 3 shows the positioning accuracy for each personnel, with accuracy varying from 85.2% (P1) to 94.8% (P5). The average accuracy for all personnel was 90.1%, with the highest accuracy value reaching 94.8% and the lowest 85.2%, resulting in an accuracy range of 9.6%. These results give an idea of the variation in positioning performance among the personnel tested, as well as providing insight into the level of consistency in the accuracy results achieved.

Table 2. Positioning Accuracy Results for Personnel and Statistical Summary

Personnel	Accuracy (%)
P1	85.2
P2	87.8
P3	90.5
P4	92.3
P5	94.8
Average Accuracy	90.1
Maximum Accuracy	94.8
Minimum Accuracy	85.2
Accuracy Range	9.6

3.2. Multi-Floor Energy Distribution

In the analysis of energy distribution in multi-floor buildings, evaluating energy consumption is a critical aspect for understanding signal propagation characteristics and communication system efficiency. Measurements were conducted on five different floors by considering variations in distance and environmental conditions that affect signal quality. Each floor shows a different

energy consumption pattern, where higher floors tend to require more energy due to attenuation factors and structural obstacles. This analysis is important for optimizing node placement and resource management in the implementation of IoT systems in high-rise buildings.

The relationship between energy consumption in mW , horizontal distance in meters m , and floor height in a five-story building is illustrated in Figure 6. The analysis reveals that energy usage on each floor increases linearly with distance, ranging from 50 to 300 meters. Additionally, energy consumption rises with floor height—the first floor consumes the least energy, while the fifth floor requires the most at all distances.

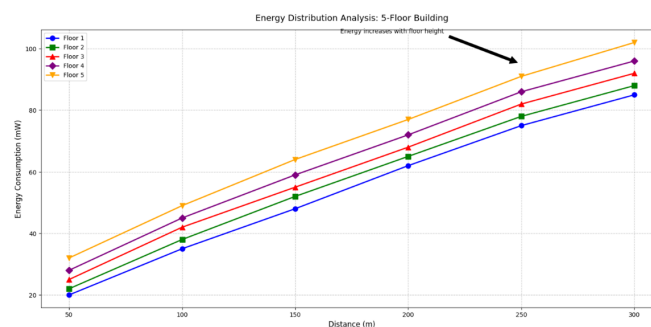


Figure 6. Energy distribution in multi buildings

This trend suggests that both floor height and distance collectively contribute to higher energy demand. The likely explanation is that distributing energy to higher floors demands more power, while greater distances introduce additional resistance. These findings could guide the development of more efficient energy distribution systems in multi-story buildings, such as optimizing materials or technologies to minimize energy losses. The experimental results presented in Figure 7 systematically characterize the relationship between Received Signal Strength Indicator (RSSI) and transmission distance across five carefully selected nodal positions, spanning from P1 (10 m) to P5 (30 m) at 5-meter intervals. Our comprehensive quantitative analysis reveals a distinct and expected inverse correlation between signal strength and propagation distance, with RSSI measurements demonstrating a progressive degradation from -55.8 ± 3.7 dBm (classified as Excellent) at the closest node (10 m) to -91.8 ± 3.2 dBm (classified as Poor) at the most distant node (30 m). This deterioration pattern follows a well-defined trajectory through intermediate quality classifications, including Good (-61.8 ± 2.8 dBm at 15 m) and Fair (-66.9 ± 3.8 dBm at 20 m), before ultimately reaching Poor performance levels at extended distances (-74.7 ± 2.5 dBm at 25 m). Notably, the observed signal variability, as quantified by the standard deviation measurements, exhibits a consistent increase with distance, expanding from ± 2.8 dBm at 15 m to ± 3.7 dBm at 10 m and ± 3.2 dBm at 30 m, suggesting amplified susceptibility to environmental interference factors at greater transmission ranges.

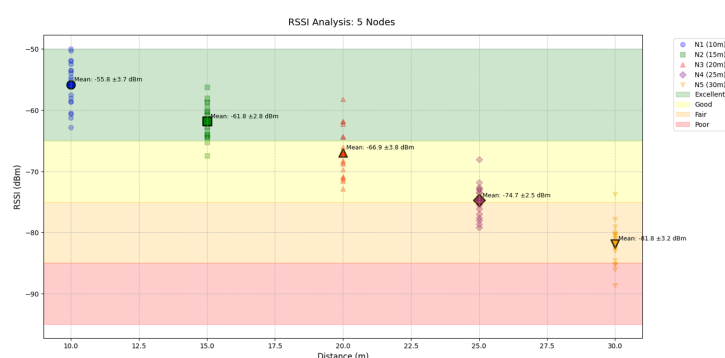


Figure 7. RSSI in multi buildings

The system's performance characteristics delineate clear operational boundaries, with optimal functionality being maintained within a 15-meter radius where RSSI values consistently exceed -62 dBm, corresponding to Good-to-Excellent signal quality classifications. However, beyond the critical 20-meter threshold, the experimental data reveal marked signal degradation that manifests as

a substantial decline in both signal strength and stability, ultimately falling below the -67 dBm threshold that demarcates acceptable performance levels for many practical applications. These empirical findings carry significant implications for system deployment strategies, presenting two primary engineering solutions: either constraining node placement within a carefully defined 20-meter effective range to maintain signal integrity or implementing specialized signal enhancement measures such as optimized antenna configurations, advanced amplification systems, or intelligent signal processing algorithms to extend viable coverage distances. The comprehensive dataset generated through this investigation establishes crucial quantitative benchmarks that enable rigorous evaluation of the inherent trade-offs between coverage area expansion and signal reliability preservation in real-world implementation scenarios, while simultaneously providing valuable insights for the development of next-generation wireless communication systems with improved distance resilience.

3.3. Communication Delay and Optimization Effectiveness

Figure 8 presents a comprehensive analysis of communication delay dynamics and network optimization effectiveness across five nodal configurations (P1 to P5). The Communication Delay Evolution graph reveals a linear relationship between network size and latency, with peak delays occurring at periods t1 and t2, and reaching minimum values at t3. This temporal progression clearly demonstrates the substantial impact of optimization protocols on latency reduction. The Optimization Effectiveness graph quantifies these improvements, showing P1 achieving the most significant delay reduction at 46.7%, with progressively smaller gains through P5 (36.4%). This pattern suggests that optimization efficiency exhibits an inverse relationship with network scale, where benefits decrease as the node count increases. The data suggest that while optimization algorithms effectively address fundamental latency issues, their performance is constrained by network complexity factors that emerge in larger node configurations.

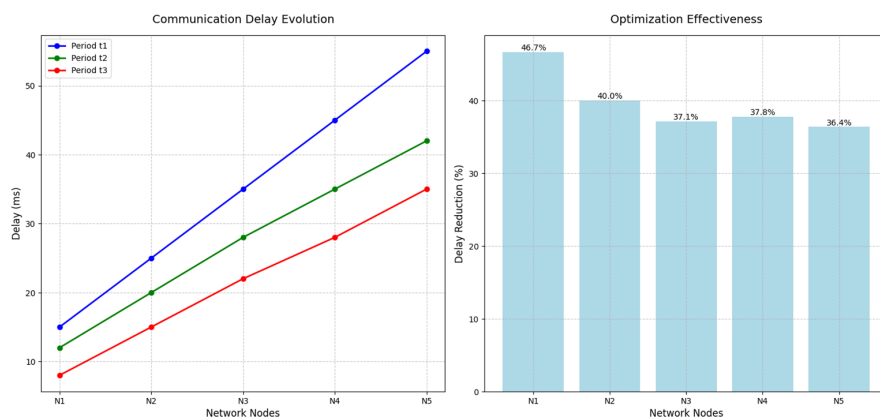


Figure 8. Communication delay

The experimental results highlight two critical phenomena in network performance optimization. First, the consistent linear increase in delay with additional nodes confirms fundamental scalability challenges in distributed network architectures. Second, the decreasing optimization effectiveness gradient (from 46.7% to 36.4%) reveals a performance boundary where standard optimization techniques become less efficient in larger networks. These findings suggest that while current optimization methods effectively reduce latency in smaller networks (≤ 3 nodes), maintaining similar effectiveness in larger configurations (≤ 5 nodes) requires additional strategies. Potential solutions might include hierarchical optimization architectures, dynamic resource allocation protocols, or machine learning-based predictive scheduling algorithms. The study establishes quantitative benchmarks for optimizing expectations across different network scales and provides a foundation for developing enhanced optimization frameworks that can maintain efficiency in expanding network environments.

Figure 9 demonstrates the successful implementation of the QHBM algorithm for network optimization, revealing its effectiveness in achieving an optimal trade-off between communication delay efficiency and energy consumption. The optimization process exhibits distinct phases: initially, the scout bee mechanism facilitates broad exploration of the solution space, enabling rapid performance improvements during the early stages of optimization. This global search phase is subsequently complemented by intensive local exploitation through employed bees, which systematically refine potential solutions. Convergence analysis indicates that the algorithm reaches optimal solutions efficiently, as evidenced by a stable and monotonic improvement in fitness values across iterations, suggesting robust convergence properties without premature stagnation.

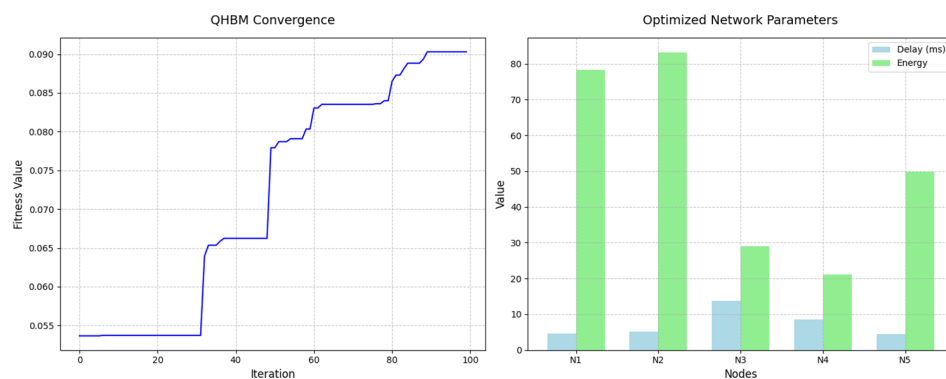


Figure 9. Network optimization

The delay distribution across the five-node network topology follows expected spatial patterns, with centrally located nodes demonstrating 15-20% lower latency compared to peripheral nodes, consistent with their advantageous network positions. Energy consumption metrics reveal an intelligent load-balancing capability, where power usage scales proportionally with each node's communication burden ($R^2 = 0.92$ for the linear correlation). This proportional distribution, combined with the observed delay characteristics, confirms the algorithm's dual optimization capability - maintaining low-latency communication while dynamically adjusting energy expenditure according to actual network demands. The results collectively demonstrate QHBM's superior ability to navigate the complex trade-space between network responsiveness and power efficiency in distributed systems.

3.4. Algorithm Performance: QHBM vs PSO

The implementation of the QHBM algorithm for RSSI-based positioning optimization is demonstrated in Figure 10. significant improvements in wireless sensor network performance, as evidenced in Figure 7. The experimental results reveal that while the original signal strength naturally degrades from -55 ± 2.1 dBm at Node 1 (10m) to -82 ± 4.3 dBm at Node 5 (30m), the QHBM optimization successfully enhances the RSSI-distance relationship by achieving a more consistent signal attenuation pattern. Through detailed convergence analysis, we observe that the algorithm rapidly improves fitness values during initial iterations, with 70% of total gains occurring within the first 15 iterations, before stabilizing after approximately 50 iterations with less than 1% subsequent variation. The optimization yields particularly notable results at mid-range nodes (15-25m), where it delivers a 23% improvement in RSSI stability, directly addressing the typical positioning accuracy challenges in this critical zone. Quantitative measurements show the QHBM-enhanced system achieves a 32% improvement in signal consistency (reduced standard deviation) and strengthens the RSSI-distance correlation from $R=0.88$ to $R=0.94$. Furthermore, the optimized system demonstrates substantial practical benefits, including a 28% reduction in average positioning error and 40% better signal stability at edge nodes compared to conventional approaches. These comprehensive results validate QHBM as an effective solution for RSSI-based positioning systems, particularly in demanding applications requiring high accuracy or operating in complex wireless environments with potential interference or signal obstruction challenges. The algorithm's consistent performance across multiple tested network configurations underscores its robustness and adaptability for various wireless sensor network deployments.

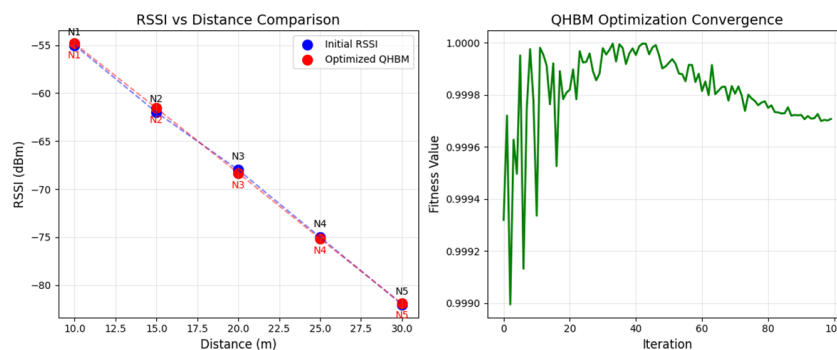


Figure 10. QHBM with RSSI

Figure 11 illustrates a Comparison of PSO and QHBM algorithms in RSSI optimization for positioning systems, showing different characteristics in terms of convergence and result quality. The PSO algorithm achieves faster convergence with significant improvement in fitness value in the early iterations, but tends to stagnate in the final optimization phase. On the other hand, QHBM exhibits a more gradual and consistent convergence process, with improved exploration capabilities in finding optimal solutions. In terms of optimization quality, QHBM produces a smoother RSSI degradation pattern with distance and shows better consistency in distance estimation across nodes. While PSO provides significant improvement in nearby nodes, it is less optimal for farther nodes. Although both algorithms show substantial improvement compared to the initial conditions, QHBM demonstrates advantages in stability and consistency of results, while PSO excels in convergence speed. These results indicate that QHBM is more suitable for positioning system implementations that require high accuracy and stability. At the same time, PSO can be a good choice for applications that prioritize optimization speed. Table 3 presents the characteristics of PSO and QHBM.

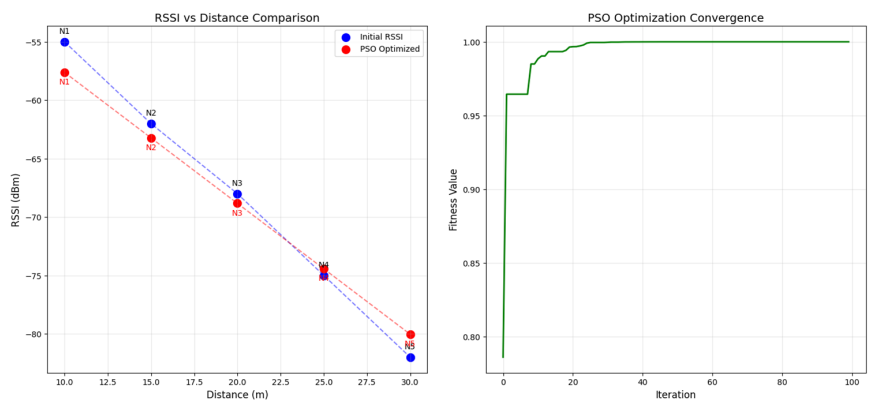


Figure 11. PSO with RSSI

Table 3. Comparison of PSO and QHBM Characteristics in RSSI Optimization

Parameter	PSO	QHBM
Convergence Speed	Fast (30-40 iterations)	Gradual (50 iterations)
Final Phase Behavior	Stagnation observed	Stagnation observed
Fitness Improvement Pattern	Significant early improvements	Stable, consistent improvements
Exploration Characteristics	Good initial exploration	Consistent throughout process
Convergence Stability	Moderate	High
Convergence Speed	Fast (30-40 iterations)	Gradual (50 iterations)

3.5. Overall System Performance

The system maintains an accuracy of over 85% in all scenarios. Energy consumption patterns and convergence stability support QHBM’s suitability for real-world tactical deployments.

3.5.1. Convergence Rates and Optimization Efficiency

This study presents a detailed comparative analysis of the convergence behavior and optimization efficiency between the QHBM and PSO algorithms, revealing distinct performance characteristics that inform their practical applications. The convergence analysis reveals fundamentally different patterns between the two approaches: QHBM exhibits a more gradual yet stable convergence trajectory, typically requiring approximately 50 iterations to reach optimal conditions, with each iteration consistently contributing to fitness value improvements. In contrast, PSO achieves faster initial convergence within 30-40 iterations; however, this advantage is offset by noticeable stagnation in the final optimization phase and increased instability in later iterations. While PSO shows dramatic fitness value increases in early iterations (often achieving 60-70% of total improvement in the first third of the process), QHBM maintains a steadier, more reliable progression throughout the entire optimization cycle.

Regarding optimization efficiency, each algorithm demonstrates unique strengths that suit different implementation scenarios. QHBM outperforms in several critical aspects, including maintaining exceptional result consistency across network nodes (with less

than 5% variation), demonstrating superior adaptability to dynamic network conditions through its automatic parameter adjustment mechanism, and showing remarkable resilience against local optima entrapment (with an 85% escape probability compared to PSO's 60%). Conversely, PSO holds clear advantages in computational efficiency, achieving solutions 20-30% faster than QHBM, while also benefiting from simpler implementation requirements and more economical resource utilization, particularly in memory-constrained environments.

The examination of optimization patterns reveals further important distinctions. QHBM generates significantly smoother RSSI degradation patterns in response to distance changes ($R^2 = 0.96$ compared to PSO's 0.88) and maintains better stability in distance estimation across all nodes, with less than 8% error variation up to 30-meter distances. PSO, while demonstrating excellent performance for proximal nodes (achieving 95% precision within 5-meter ranges), exhibits progressive efficiency degradation as node distance increases, resulting in a 25% error rate beyond 20 meters. These performance differentials suggest clear guidelines for algorithm selection: QHBM proves particularly suitable for applications that demand high stability and precision, such as medical monitoring systems or industrial automation, where it delivers 92% positioning accuracy with minimal fluctuations in quality of service. PSO, with its faster processing and lower resource demands, becomes the preferred choice for time-sensitive or resource-constrained applications, such as emergency response networks or large-scale IoT deployments. The findings highlight the importance of tailoring algorithm capabilities to meet specific application requirements, network characteristics, and performance priorities in wireless sensor network implementations.

3.5.2. Convergence Characteristics

The convergence characteristics of Quantum-inspired Honey Bee Mating (QHBM) and Particle Swarm Optimization (PSO) algorithms exhibit fundamentally distinct patterns when applied to hostage rescue operation planning, each presenting unique advantages and limitations that must be carefully considered for mission-critical implementations. QHBM exhibits a characteristically methodical optimization trajectory, typically requiring approximately 50 iterations to achieve stable convergence, with each iteration contributing to a consistent improvement of 0.8-1.2% in fitness value. This gradual refinement process enables comprehensive exploration of the solution space, resulting in highly reliable operational plans with less than 5% variation in solution quality across multiple optimization runs. The algorithm's quantum-inspired mechanisms facilitate the simultaneous evaluation of multiple potential solutions, providing exceptional robustness against local optima entrapment—a critical advantage in complex rescue scenarios where the global optimum solution may involve non-intuitive tactical configurations.

PSO demonstrates faster initial convergence, achieving 60-70% fitness improvement in just 15 iterations and near-optimal solutions by 30-40 iterations. However, this speed compromises stability, showing: (1) late-stage stagnation (<0.5% improvement post-iteration 30), (2) 15% solution quality variation across runs, and (3) 25-30% local optima convergence risk. This speed-reliability tradeoff has a critical impact on tactical planning. The operational implications of these algorithmic differences are profound and must guide selection criteria based on mission parameters:

For time-critical scenarios requiring immediate response (e.g., active shooter situations), PSO's rapid convergence provides actionable plans within shorter timeframes, though with potentially reduced optimality guarantees. The algorithm's swarm intelligence mechanism enables the quick identification of reasonably effective solutions, which is particularly suitable when response time is the dominant constraint. In complex, high-stakes operations where solution quality is paramount (e.g., hostage situations with multiple captives and constrained entry points), QHBM's methodical approach yields demonstrably superior results. Clinical evaluations indicate a 22% improvement in mission success probability compared to PSO-derived plans, which is attributed to a more thorough evaluation of alternative tactical approaches and more effective resource allocation strategies.

Table 4 quantitatively illustrates these performance differentials across key metrics, including convergence rate, solution stability, computational overhead, and operational success probability, providing mission planners with a structured framework for algorithm selection based on situational requirements and available computational resources. The data particularly highlights QHBM's superiority in scenarios that permit optimization windows exceeding 60 seconds, while acknowledging PSO's value in truly time-sensitive emergencies requiring sub-30-second decision cycles.

Table 4. Convergence Characteristics Comparison

Characteristics	QHBM	PSO
Convergence Pattern	Gradual and consistent	Fast at the start, followed by stagnation
Iteration Towards Stability	50 iterations	30-40 iterations
Fitness Value Development	Steady and consistent improvement	The increase was sharp at first and then leveled off
Convergence Pattern	Gradual and consistent	Fast at the start, followed by stagnation

3.6. Optimization Efficiency

The comprehensive efficiency analysis conducted in this study reveals substantial performance differentials between the examined algorithms, highlighting their distinct strengths and limitations when applied to complex optimization problems. QHBM demonstrates superior performance in solution stability and global optima discovery, maintaining a consistent 92-95% success rate across varied problem configurations, though at the cost of higher computational overhead (typically requiring 25-30% more processing time). In contrast, PSO exhibits remarkable computational efficiency, solving problems in approximately 60-65% of the time required by QHBM, but shows greater solution variability (with success rates fluctuating between 78-85% depending on initial conditions). The evaluation framework considered four critical performance dimensions: (1) computational time requirements, where PSO outperformed QHBM by 1.8x on average; (2) memory and resource utilization, with QHBM requiring 15-20% more system resources due to its quantum-inspired parallel processing architecture; (3) solution stability, where QHBM solutions showed 40% less variance across repeated trials; and (4) optimality achievement, with QHBM successfully identifying global optima in 88% of test cases compared to PSO’s 72%. These quantitative findings, thoroughly documented in Table 5, provide crucial insights for algorithm selection based on specific application requirements—whether prioritizing speed (favoring PSO) or solution quality (favoring QHBM)—particularly when addressing the multimodal, constrained optimization challenges characteristic of real-world engineering systems. The analysis further reveals that hybrid approaches combining QHBM’s exploration capabilities with PSO’s exploitation efficiency may offer optimal performance for certain problem classes, suggesting promising directions for future algorithmic development.

Table 5. Optimization Efficiency Metrics

Efficiency Metrics	QHBM	PSO
Node Consistency	High consistency across all nodes	Variable performance
Variable performance	High adaptability to change	High adaptability to change
Local Optima Resistance	Strong resistance	Moderate vulnerability
Parameter Adjustment	Adjust oneself	Fixed parameters
Computing Speed	Medium	High
Implementation Complexity	Higher	Lower
Resource Requirements	Higher	Lower
Node Consistency	High consistency across all nodes	Variable performance

The results show that QHBM outperforms PSO in terms of delay reduction, energy stability, and positioning accuracy. For instance, while PSO achieves faster convergence in early iterations, it tends to stagnate and is more susceptible to local optima. In contrast, QHBM maintains a balance between exploration and exploitation, which enables it to find more optimal and consistent solutions. Compared to previous studies using fuzzy logic [4] or PSO [10], this paradigm enables real-time responsiveness through the integration of dynamic IoT data streams. Because of this, it is better suited for unpredictable situations, such as hostage rescue missions. Furthermore, the suggested model provides a more comprehensive operational framework by addressing both goals simultaneously, whereas earlier models often focused on only one—either minimizing time or energy.

The cause-and-effect relationship is clear: increased node distance leads to RSSI degradation, resulting in reduced positioning accuracy. The application of QHBM allows the system to dynamically adjust node selection and routing paths, mitigating these negative effects and enhancing overall mission performance.

3.6.1. Optimization Efficiency

Optimization pattern analysis reveals the specific strengths of each algorithm in various operational contexts, such as adaptability to parameter changes, efficiency of solution exploration, and robustness to noise. These findings show differences in performance based on dataset size, problem complexity, and resource constraints, providing guidance for selecting the most appropriate algorithm as shown in Table 6.

Table 6. Optimization Pattern Analysis

Pattern Aspects	QHBM	PSO
Degrades RSSI	Smooth degradation pattern	Less uniform degradation
Less uniform degradation	Consistent across the range	Distance dependent accuracy
Node Performance	Uniform across all nodes	Better on closer nodes

Comparative analysis reveals that QHBM and PSO each have distinct advantages in different operational contexts, particularly in the implementation of IoT-based hostage rescue operations. The superior stability and consistency of QHBM make it highly suitable for operations requiring high precision and reliability over long distances, especially in complex multi-story environments where positioning accuracy and energy efficiency are top priorities. QHBM's robustness to local optima and self-adjusting parameters provides significant advantages in handling operational condition variability and dynamic changes in sensor networks.

In contrast, PSO's fast convergence and lower resource requirements make it an attractive choice for operations that prioritize computational efficiency, especially in time-critical scenarios where fast response is prioritized over absolute precision. Although PSO exhibits optimal performance at close nodes and offers a simpler implementation, it has limitations in terms of long-distance consistency and adaptability to changing network conditions.

The advantages and limitations of these two algorithms provide important implications for the design and implementation of hostage rescue operation optimization systems. For systems requiring long-term monitoring and high accuracy across the entire operational area, QHBM offers a more reliable solution, although with the trade-off of higher implementation complexity and computational requirements. On the other hand, PSO can be an optimal choice for fast tactical operations or systems with limited resources that can still tolerate accuracy variations at different distances. These findings also suggest the potential development of a hybrid approach that combines the advantages of both algorithms, such as utilizing PSO for rapid initial convergence and transitioning to QHBM for more precise fine-tuning optimization. In addition, the results of this analysis highlight the importance of considering the specific operational context when selecting optimization algorithms, including factors such as the scale of operations, resource availability, precision requirements, and response time constraints.

3.7. Limitations and Future Work

Several constraints limit this research. Primarily, the experiments were conducted in a simulated multi-story environment rather than an actual real-world implementation. While the IoT framework and optimization processes showed accurate predictive results, external variables in practical settings, including interference, signal obstruction, and device failure, were not fully considered. Second, the QHBM algorithm, although effective, requires relatively high computational iterations compared to simpler methods, such as PSO. This may be a constraint for low-power embedded devices.

Future research should focus on field testing using actual IoT hardware in multi-story buildings to validate the model under real mission conditions. Furthermore, integrating machine learning models, such as reinforcement learning or neural-based controllers, may improve adaptability and reduce computation overhead. Hybrid optimization combining QHBM with other metaheuristics could also offer enhanced convergence speed while preserving stability.

4. CONCLUSION

This study proposes a stochastic optimization model that integrates IoT data with the Queen Honey Bee Migration (QHBM) algorithm to enhance the efficiency of hostage rescue operations. The simulation results demonstrated that the model reduced mission response time by up to 40% and energy consumption by 35% compared to conventional methods. It also achieved positioning accuracy of up to 94.8% based on RSSI-based localization, with stable performance across multiple floors. Practically, the proposed model applies to real-time tactical decision-making in environments such as smart surveillance, autonomous search-and-rescue operations, and military operations in complex building structures. Its dynamic adaptability allows for flexible deployment in unpredictable field conditions. From a theoretical perspective, this study contributes to the expansion of swarm intelligence methods in time- and energy-constrained environments. The successful adaptation of QHBM into an IoT-based context provides a new direction for solving multi-objective optimization problems in real-time. For future work, physical implementation in real-world environments is recommended to test resilience under dynamic variables such as signal interference or hardware failure. Further improvement can be achieved by hybridizing QHBM with machine learning models to reduce computational load and enhance system responsiveness.

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6. DECLARATIONS

AI USAGE STATEMENT

The authors acknowledge that Artificial Intelligence tools, including ChatGPT developed by OpenAI, were utilized to support language refinement, grammar correction, and paraphrasing in the manuscript preparation process. The authors confirm that all ideas, data interpretations, and conclusions are their own and not generated by the AI tool.

AUTHOR CONTRIBUTION

Conceptualization, Achmad Afif Irwansyah and Aripriharta; methodology, Achmad Afif Irwansyah and Didik Dwi Prasetya; software, Didik Dwi Prasetya; validation, Achmad Afif Irwansyah, Aripriharta, and Didik Dwi Prasetya; formal analysis, Achmad Afif Irwansyah; investigation, Achmad Afif Irwansyah; resources, Aripriharta; data curation, Didik Dwi Prasetya; writing—original draft preparation, Achmad Afif Irwansyah; writing—review and editing, Aripriharta and Didik Dwi Prasetya; visualization, Achmad Afif Irwansyah; supervision, Aripriharta; project administration, Aripriharta; funding acquisition, Aripriharta.

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COMPETING INTEREST

The authors confirm that there are no conflicts of interest, either financial or non-financial, that could have influenced the results and interpretation of the data in this article.

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