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Integrated QHBM-IoT Framework for Multi-Objective Optimization of Emergency Rescue Operations in Urban Combat Zones

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Abstract

Emergency rescue operations in urban combat zones face critical challenges in maintaining reliable communication networks under conditions of high mobility, limited energy, and dynamic topologies. This study proposes an integrated Queen Honey Bee Migration (QHBM) and Internet of Things (IoT) framework for multi-objective optimization in tactical rescue communication. The framework utilizes a bio-inspired algorithm without clustering, employing polar-spatial sector analysis to enable adaptive routing in mission-critical environments. Simulation results demonstrate that the proposed QHBM-IoT framework outperforms conventional heuristic algorithms, namely Particle Swarm Optimization (PSO) and Grey Wolf Optimizer (GWO). Specifically, QHBM achieves up to 25% longer network lifetime than PSO, and 30% higher throughput while maintaining a packet delivery ratio above 92% in networks with up to 300 nodes. It also achieves the lowest energy consumption (0.87–1.21 Joules), minimal end-to-end delay (105–179 ms), and reduced control overhead (5.2–11.2 packets/s). In addition, QHBM exhibits the fastest and most stable convergence, achieving optimal fitness within fewer than 100 iterations. A prototype wearable device integrating RSSI, distance, and GPS further validates the framework's real-time implementation feasibility. These findings demonstrate the practical potential of QHBM-based swarm intelligence for energy-efficient and reliable communication in emergency rescue operations under highly dynamic urban conditions.

Keywords: Energy Efficiency, Emergency Rescue, Network Optimization, Tactical Communication, QHBM-IoT.

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1 Introduction

The rapid advancement of Internet of Things (IoT) technology has opened up unprecedented opportunities across diverse mission-critical applications, such as military operations, healthcare systems, surveillance infrastructures, and intelligent transportation (Schiller et al., 2022; Seyyed Abbasi et al., 2023; Satra et al., 2024). However, a persistent challenge in IoT deployment lies in maintaining efficient and reliable data transmission while optimizing energy consumption, especially in environments characterized by high mobility and dynamic topologies (Sujito et al., 2022; Sugiono et al., 2023). Conventional routing protocols like the Low Energy Adaptive Clustering Hierarchy (LEACH) have been widely adopted to prolong network lifetime through energy-saving strategies (Noh et al., 2020; Daanoune et al., 2021; Sathish Kumar et al., 2022). Nevertheless, these protocols often fall short in highly dynamic and mobility-intensive scenarios, such as emergency rescue operations in urban combat zones (Li et al., 2022; Ouldzira et al., 2019).

Inspired by the biological behavior of honey bees, Queen Honey Bee Migration (QHBM) is an optimization framework that simulates the migration phenomenon of queen honey bees, which occurs when worker bees have found a food source in the surrounding area (Irmanto et al., 2025; Bormann, 1982; Kasiyanto et al., 2024). QHBM works by not looking at the entire target area but dividing it into several regional sectors that will help find the fastest and most effective delivery route. This concept is expected to apply the same when applied to wireless sensor networks (WSN) in IoT systems (Rahim, 2024; Boopathy et al., 2024). QHBM can adapt quickly if the network structure changes and is unstable, so that it finds the best reliable delivery route (Pękala-Wojciechowska et al., 2021; Irmanto et al., 2024). It is very suitable for application in applications that require high accuracy and mobility that require fast data delivery such as hostage rescue in military operations in unpredictable urban environments (Du et al., 2022; Hoang et al., 2023; Hoang et al., 2023).

The application of QHBM in previous research has attempted to combine the use of Received Signal Strength Indicator (RSSI), Residual Energy to reveal that this strategy can improve the stability of routes between nodes in IoT networks (Joshua & Sidik, 2021; Dewi, 2019). This finding proves that energy use can be reduced, reducing transmission delays between end nodes, increasing the operational life of IoT devices, and avoiding overhead on hardware (Aripriharta et al., 2020; Jong et al., 2017). The use of QHBM in urban hostage rescue conditions is suitable for testing with the assumption that data dissemination can be done quickly, saving time and being able to adapt to complex operational environments (Falk & Grey, 2021). The grouping of sector areas carried out by the QHBM algorithm is expected to meet the desired results with not excessive computational support (Jensehaugen, 2021; Jong et al., 2019; Wibowo et al., 2019). This research proposes QHBM as a method that works independently without the need for clustering, unlike previous methods, while simultaneously achieving maximum efficiency in connection stability and data transmission quality, as well as energy savings (Peng et al., 2021; Vinayakumar et al., 2019; Wirawan et al., 2020).

The integrated QHBM-IoT framework, enabling optimal multi-objective optimization in military operations such as hostage rescues in extreme environments like urban combat, is a novelty offered in this research. This is the first work to deploy QHBM in a decentralized, non-clustered manner for tactical communication, demonstrating notable advantages over conventional algorithms. Compared to Particle Swarm Optimization (PSO) and Grey Wolf Optimizer (GWO), QHBM achieves up to 25% longer network lifetime, 30% higher throughput, and over 92% packet delivery ratio in dense networks, while reducing energy consumption and control overhead (Mertes et al., 2021).

This research makes several key contributions to the advancement of IoT systems for critical operations. First, it introduces a cluster-free, bio-inspired optimization framework that enhances tactical communication in real-time. Second, through rigorous simulation, it presents comparative analysis against PSO and GWO, providing insights into system-level advantages in energy savings and transmission reliability. Third, it demonstrates the feasibility of integrating QHBM with practical IoT hardware by developing a wearable rescue device capable of real-time monitoring using RSSI, distance, and GPS. The results of this research will provide a theoretical foundation for the development of a communication infrastructure that has high resilience and adaptability, specifically aimed at addressing challenges in emergency scenarios such as hostage rescues in urban environments.

2 Experimental Process

This study uses the QHBM framework as a framework in an effort to achieve multi-objective optimization in emergency hostage rescue applications in urban environments. The use of QHBM is carried out in challenging tactical conditions, such as rescues in high-rise buildings, dense urban environments, requiring energy efficiency, network stability, and smooth communication performance. Simulation conditions using variations in node density and mobility change dynamics will assess the feasibility of this framework. Similar simulations are also carried out on two optimization methods, namely Grey Wolf Optimizer (GWO) and Particle Swarm Optimization (PSO), as a comparison to assess the superiority of each algorithm used.

Research Framework Overview

Hostage rescue in urban areas presents a challenging communication challenge: maintaining smooth, battery-efficient, and reliable communication in dense, building environments. This research creates an intelligent system by combining the QHBM algorithm and IoT devices. This system is then thoroughly tested through simulations under various conditions (many or few devices, moving or stationary). When the results are compared with other methods (PSO and GWO), the results show that the proposed QHBM system is superior in energy saving and ensuring robust communication networks and secure data transmission.

Using a quantitative simulation-based approach, this study designs and tests an innovative communication system. This system has four fundamental elements working together: a QHBM-based optimization engine, an IoT sensor network as its physical layer, an intelligent module for multi-objective decision-making, and an adaptive routing mechanism. This strategy aims to simultaneously meet three important goals: maximizing energy efficiency, ensuring a stable network connection, and maintaining high communication quality during critical missions. To achieve this, the research workflow is carried out in five structured phases, starting with the preparation of theoretical foundations, followed by model design, implementation, simulation preparation, and finally a comprehensive performance evaluation.

Unlike traditional methods that are often slow due to the need to group devices conventionally, the proposed QHBM-IoT architecture operates completely autonomously (decentralized). The system divides the search area into eight sectors to simplify communication route discovery. Each device intelligently determines the best path by assessing its surroundings, such as battery life and signal strength from nearby devices, without needing to know the entire network map. This capability makes the system highly flexible and adaptable to changing device locations, such as in buildings or at urban

environmental rescue sites. Because it does not rely on a single command center, the system is more resilient, easily scalable, and reliable for energy-efficient emergency communications in critical times.

System Model

This section will discuss a system model for emergency rescue missions in the midst of urban battles, and its performance will combine QHBM and IoT technologies. The design features a network of distributed tactical nodes operating within a flexible and adaptive communication topology, supported by a bio-inspired optimization protocol tailored to address the challenges of high-mobility conditions and stringent energy constraints.

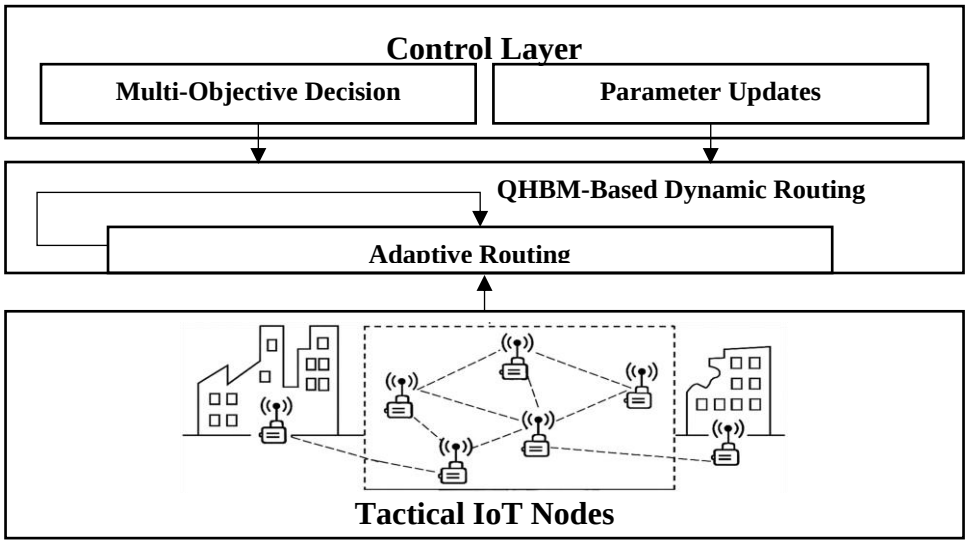

Figure 1: System design of QHBM-IoT in rescue missions

Figure 1. Shows that there are three main layers of the system architecture shown in Figure 1: the QHBM-Based Dynamic Routing layer, which controls adaptive routing based on the queen bee migration principle; the Control Layer, which handles multi-objective decision making and parameter updates; and the Tactical IoT Node layer, which is responsible for real-time sensing and communication in urban environments. Decentralized wireless communication between tactical nodes enables reliable and energy-efficient data transfer across highly dynamic topologies.

Table 1: Simulation parameters for the QHBM-IoT framework

Parameter	Value and Description
Deployment Area	500 m × 500 m urban grid
Number of IoT Nodes	50 – 200 nodes
Node Initial Energy	2 Joules
Communication Range	30 meters
Mobility Model	Random Waypoint
Simulation Duration	1000 seconds
Energy Model	First Order Radio Model
Optimization Algorithm	QHBM
Comparative Algorithms	Particle Swarm Optimization (PSO) and Grey Wolf Optimizer (GWO)
Routing Update Interval	Every 20 seconds

Tactical nodes are used in complex urban topologies, including high-rise buildings, with varying densities and mobility patterns. The nodes use multi-hop wireless communication under an ad-hoc protocol, and energy efficiency is prioritized due to limited electrical resources in the field.

To evaluate the proposed QHBM-IoT framework under realistic urban conditions, a simulation environment is developed with the following key parameters.

Table 1. The selection of PSO and GWO as baseline algorithms allows a balanced comparison between group-based and evolutionary optimization strategies, both of which are widely adopted in energy-aware routing for IoT networks.

Queen Honey Bee Migration (QHBM) Algorithm

The Queen Honey Bee Migration (QHBM) algorithm serves as the core optimization engine in the proposed QHBM-IoT framework for enhancing tactical decision-making in emergency rescue operations within urban combat zones. Inspired by the natural migratory behavior of queen bees and the spatial scouting of worker bees, the algorithm is designed to support multi-objective optimization under high-mobility, energy-constrained, and infrastructure-challenged environments.

In the context of urban rescue missions, QHBM enables tactical IoT nodes to dynamically discover and maintain optimal communication paths by evaluating multiple directional sectors, minimizing energy usage, and maximizing data transmission reliability. The search around the queen is divided into eight customized directional sectors. Each scout agent samples potential routes by exploring different sectors based on polar coordinates, and reports fitness values associated with signal quality and energy availability.

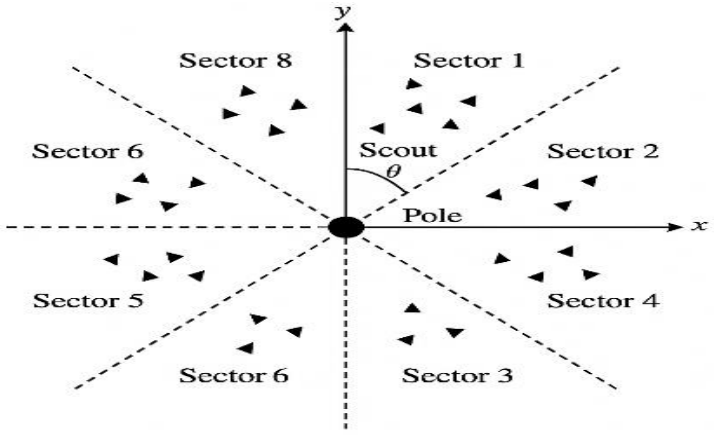

Figure 2: Directional migration scheme of QHBM in urban

Figure 2. Shows that the QHBM divides the model into eight sectors around the queen node. A scout agent monitors the position of the target in each sector. The assessment of each scout is determined by the angular direction, which serves as a reference for the appropriate direction for efficient migration. The QHBM adaptively optimizes routing by relying on energy availability and signal quality.

1 Sector Classification and Scout Generation

Each iteration begins with the queen node. $Q^{(k)} = \left(x_Q^{(k)}, y_Q^{(k)}\right)$ generating a set of *N* scout nodes S_i, randomly distributed within a search radius $r^{(k)}$ in equations (1) (Apripriharta et al., 2023):

$$S_i=Q^{(k)}+ r^{(k)}\cdot S_i=(x_i,y_i),\theta_i\sim \text{Uniform}(0,2\pi) \quad (1)$$

Each scout is assigned to one of eight sectors $s_j \in \{1, 2\ldots,8\}$ based on the angle in equations (2) (Apripriharta et al., 2022):

$$\theta_i=\left(\frac{180}{\pi}\cdot \text{atan2}\left(y_i-y_Q^{(k)},x_i-x_Q^{(k)}\right)+360\right) \text{mod} 360 \quad (2)$$

2 Sector Fitness and Attraction Probability

The fitness of each scout $f(S_i)$ is evaluated based on a weighted function combining residual energy and signal strength. The attraction c_j of each sector is computed as the average fitness of scouts within that sector in equations (3) (Wang et al., 2021):

$$c_j=\frac{1}{n_j}\sum_{i\in s_j} f(S_i) \quad (3)$$

Then, the normalized sector probability p_j is given by in equations (4) (Sikarwar et al., 2025):

$$p_j=\frac{c_j}{\sum_{j=1}^{8} c_j} \quad (4)$$

3 Sector Selection and Migration Direction

The dominant sector s_d is selected as the one with the highest probability in equations (5) (Nagaraju et al., 2022):

$$s_d= \arg \max_j (p_j) \quad (5)$$

The migration angle $\theta^{(k)}$ is then derived from the pole direction associated with sector s_d, possibly adjusted by neighboring comparisons.

4 Queen Position Update

The queen's new position is updated as follows1 revisited in equations (6) (Apripriharta & Horng, 2023):

$$\begin{aligned} x_Q^{(k+1)}&=x_Q^{(k)}+r^{(k)}\cdot m^{(k+1)}\cdot\cos(\theta^{(k)}) \\ y_Q^{(k+1)}&=y_Q^{(k)}+r^{(k)}\cdot m^{(k+1)}\cdot\sin(\theta^{(k)}) \end{aligned} \quad (6)$$

Where $m^{(k+1)}$ is a movement factor influenced by sector contrast and confidence level.

To adapt to mission-critical scenarios, the confidence factor γ is also updated dynamically to maintain a balance between exploration (seeking new paths) and exploitation (refining known routes). Termination conditions include convergence based on position change, maximum iteration limits, or insufficient improvement in sector performance. The QHBM algorithm applies the working principle of a bee swarm, with movement initiation from the queen. Therefore, under the same ideal conditions, the algorithm is capable of offering decentralized, adaptable routing paths. This makes QHBM an ideal algorithm for extreme missions such as IoT-based hostage rescues, where it can provide direct and reliable communication under complex conditions.

Integrated QHBM-IoT Framework Implementation

The QHBM-IoT framework is expected to optimally integrate IoT communications directly, enabling it to support hostage rescue operations in extreme urban combat zones. The absence of clustering and adaptive decision-making with the help of decentralized swarm-based routing ensures decision responses adapt to the environment and network dynamics. This is achieved through four key elements in the proposed framework:

1 **IoT Tactical Node Layer**
The nodes used will form a scalable network, adapting to the needs of adapting to complex urban conditions. All nodes are equipped with sensors and communication devices that enable the network to dynamically reconfigure connections to avoid obstacles such as trees, buildings, houses, and other potential obstructions.

2 **QHBM Optimization Engine**
QHBM works by analyzing three key factors: node energy reserves, connection reliability between nodes, and path availability. Furthermore, a polar-spatial mechanism is used to guide node selection, resulting in efficient and adaptable routes.

3 **Multi-Objective Decision Module**
The QHBM system works by simultaneously optimizing three metrics: energy efficiency, network reliability, and communication quality. The process involves normalizing the values of each objective. These values are then integrated into a single score (the global fitness function). This final score is used to evaluate and rank the best routes.

4 **Adaptive Routing Layer**
QHBM will manage the routing table by evaluating the fitness of each sector. It dynamically discards inefficient paths and redirects data flow. Data is then routed through nodes located along the calculated optimal vector, referring to the fitness evaluation formula in equation (7) (Wirawan et al., 2020).

$$f_{Total}=w_1 \cdot f_1+w_2 \cdot f_2+w_3 \cdot f_3 \quad (7)$$

Equation 7, the evaluation of the system equation is carried out using 3 main metrics, namely energy efficiency to measure the remaining energy on a device or the energy used when sending data. Network reliability metrics will assess how reliable the connection is, usually calculated from the percentage of successful data packet delivery, and communication metrics that will reflect the quality of the connection, such as how low the latency or time delay is, or how strong the received signal is. Each metric will be given a priority weight, where, if added together, it is worth 1. This weighting makes the system very flexible, because the priority can be changed according to mission needs. By combining all these metrics, the system can operate efficiently in difficult environments such as urban rescue sites without the need to rely on fixed infrastructure (Sikarwar et al., 2025).

Performance Evaluation Metrics

The QHBM-IoT performance evaluation uses several performance metrics to assess the system's ability to maintain energy efficiency, reliability, and response speed. Furthermore, these metrics provide an objective and consistent basis for comparison with other algorithms such as PSO and GWO.

Table 2. explains the role and definition of each metric. These metrics provide a balanced assessment of system performance, both from a network and algorithm perspective. The combination of delivery ratio and throughput data illustrates the robustness of established communications. Meanwhile, power

efficiency is measured by energy consumption and network lifetime. Control overhead and convergence time metrics are used to evaluate the efficiency and scalability of the algorithm.

Table 2: Performance metrics used in simulation evaluation

Metric	**Definition**	**Objective**
Network Lifetime	Time until the first node exhausts its energy	Maximize
Packet Delivery Ratio (PDR)	Ratio of successfully received packets to total transmitted packets	Maximize
Average Energy Consumption	Average energy used per node throughout the simulation	Minimize
End-to-End Delay	Average time taken for a data packet to travel from source to destination	Minimize
Throughput	Total amount of successfully delivered data per unit time	Maximize
Control Overhead	Ratio of control packets to total packets transmitted	Minimize
Convergence Time	Number of iterations needed for the algorithm to stabilize	Minimize

Through a comparative simulation analysis that focuses on the effectiveness of algorithm performance, it will be known whether the QHBM-IoT framework is superior to other conventional optimization methods.

3 Results and Discussions

Comparative Performance Analysis

After the simulation, the performance results of three different optimization methods, QHBM, PSO, and GWO, were compared. The assessment focused on three fundamental aspects: network lifespan, or network survivability; successful data packet delivery; and energy consumption, or energy usage rate.

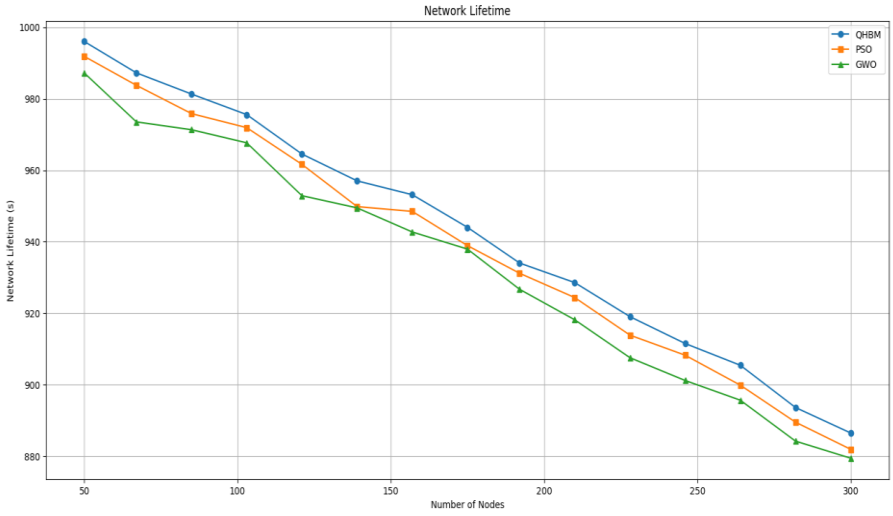

Figure 3: Network lifetime comparison of QHBM, PSO, and GWO algorithms over increasing number of nodes

In Figure 3. There is a significant performance difference between QHBM and PSO, and GWO. QHBM exhibits excellent stability; even when the number of nodes increases to 300, its lifetime only decreases gradually from 995 to 888 seconds. In contrast, the network lifetimes in PSO and GWO drop

significantly with the addition of nodes, with GWO being the weakest. These results underscore the superiority of QHBM in energy resource management.

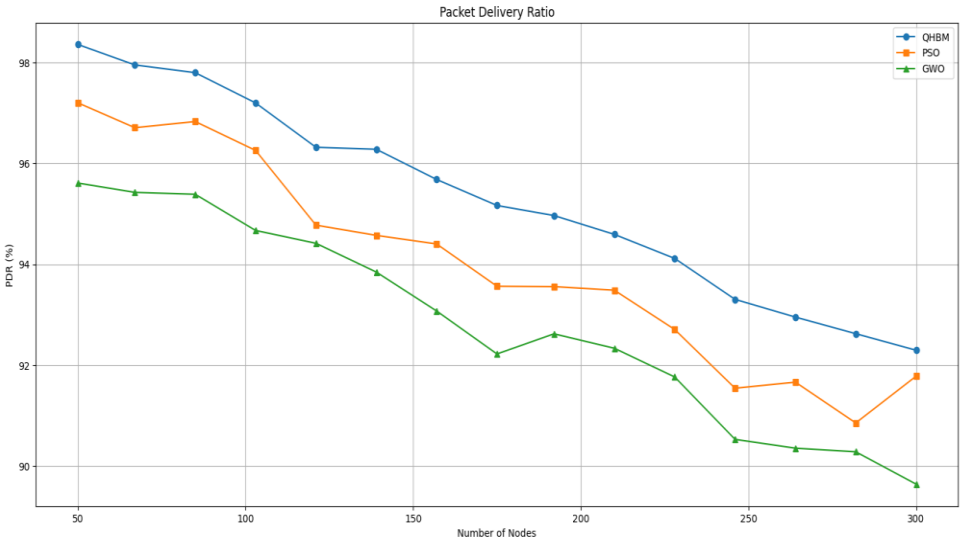

Figure 4: Packet delivery ratio (PDR) performance of QHBM, PSO, and GWO under varying network densities

In Figure 4. It's extremely high Packet Delivery Ratio (PDR) performance. This algorithm demonstrates strong resilience to packet loss, with a PDR consistently above 92% even in highly congested networks. This capability far surpasses PSO and GWO, whose PDRs drop to 91% and 89%, respectively. This stability makes QHBM a more reliable solution for ensuring vital information reaches its destination.

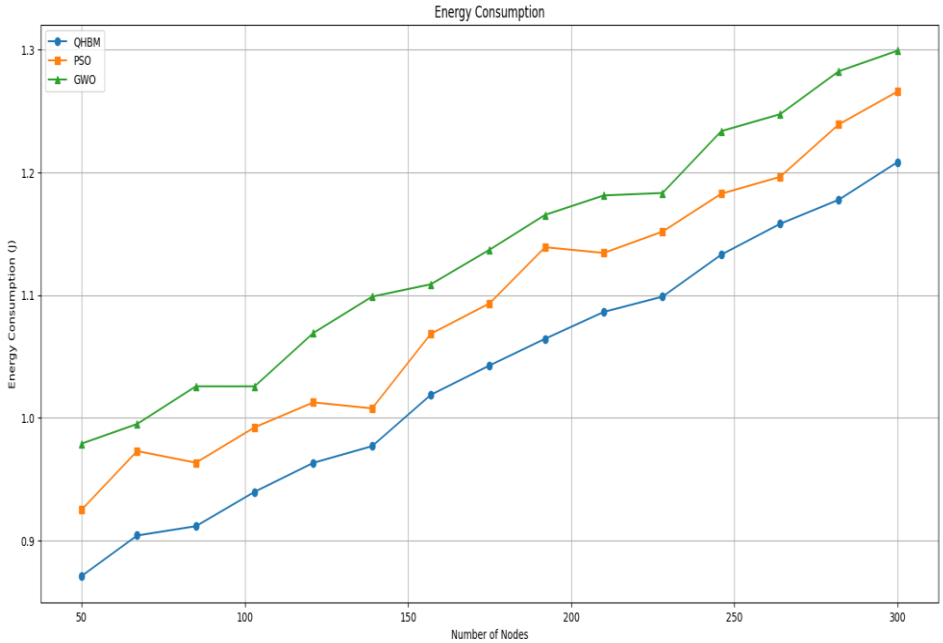

Figure 5: Energy consumption trends of QHBM, PSO, and GWO with respect to network scale

In Figure 5. There is a clear performance difference. QHBM emerges as the most power-efficient, with energy usage only moving from 0.87 J to 1.21 J. In comparison, PSO and GWO are significantly more energy-intensive, with GWO even exceeding 1.3 J in the densest scenario. This difference highlights how QHBM is more intelligent in optimizing its network to conserve resources.

Based on all the experimental data presented, QHBM consistently performs optimally. This finding holds across all three evaluation criteria, demonstrating that QHBM is the only algorithm capable of achieving the best balance between maximizing network lifetime, maintaining communication reliability, and minimizing energy consumption. Therefore, QHBM can be considered a superior and adaptive solution for implementing smart IoT systems in dynamic and demanding urban environments, such as in tactical rescue operations.

Communication Efficiency Metrics

In the End-to-End Delay metric, the QHBM algorithm demonstrated the best performance with consistently lower delay values compared to PSO and GWO across the entire range of node numbers. As the number of nodes increased from 50 to 300, QHBM only experienced a moderate increase in delay, from around 105 ms to 179 Ms. In contrast, PSO and GWO exhibit more significant and fluctuating delay increases, with GWO reaching nearly 200 ms at the maximum number of nodes.

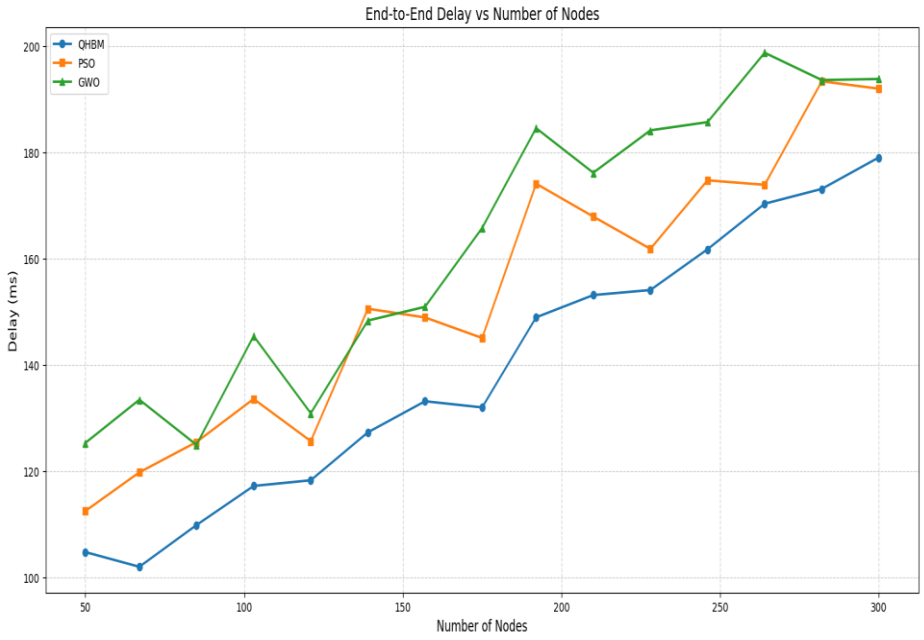

Figure 6: End-to-End delay comparison across QHBM, PSO, and GWO with varying network sizes

Figure 6. shows that the vector-based direct path finding mechanism in QHBM is able to minimize latency in communication without requiring a complex clustering process. The trend in this graph shows that as the number of nodes increases, the delay time for all methods tends to increase. It can be seen that QHBM, with the blue line in the graph, is consistently at the bottom. This indicates that QOHM has the lowest delay time in almost all conditions, so it can be concluded that it is the fastest method in sending data from sender to receiver.

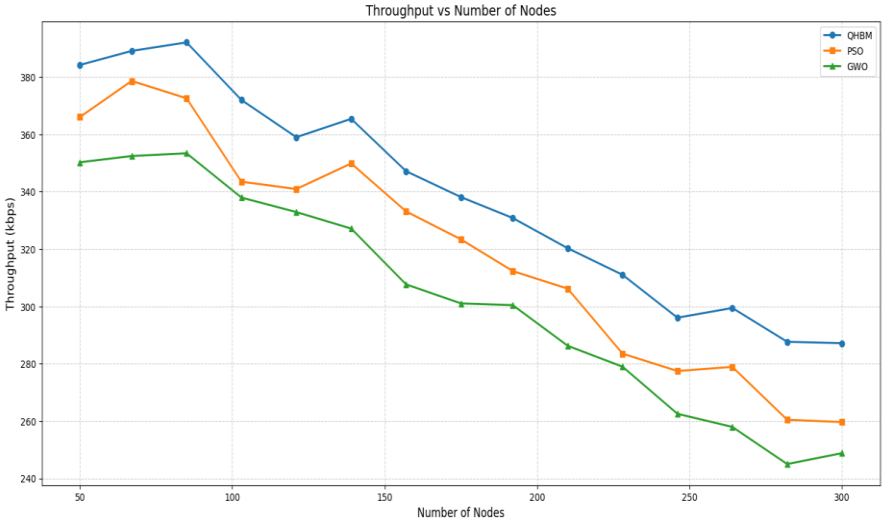

Figure 7: Throughput performance of QHBM, PSO, and GWO over increasing number of nodes

Figure 7. QHBM's throughput once again demonstrates its superiority with consistently high data transfer rates even as the number of nodes increases. Although all three algorithms experience a decrease in throughput as network density increases, QHBM still maintains a throughput of around 288 kbps at 300 nodes, which is higher than PSO (~260 kbps) and GWO (~248 kbps). QHBM is efficient in routing and stable data transmission, especially in highly dynamic topologies. Although its performance decreases with increasing network density, its performance still makes it superior to the other two methods, PSO and GWO.

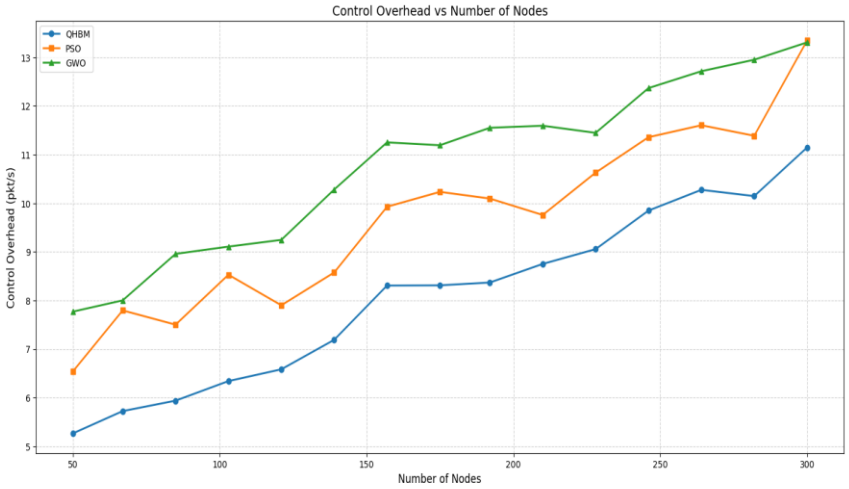

Figure 8: Control overhead analysis for QHBM, PSO, and GWO in dynamic and dense topologies

Figure 8. Shows that QHBM manages the network efficiently without burdening the system with excessive routing information exchange. The Control Overhead metric records the lowest overhead value for QHBM. The number of control packets sent per second by QHBM ranges from 5.2 packets/second to 11.2 packets/second, significantly lower than PSO and GWO, which reach 13.3 and 13.4 packets/second, respectively, at the highest node condition. QHBM can manage the network efficiently without burdening the system with excessive routing information exchange.

Algorithm Convergence and Stability

In the Convergence Comparison metric, QHBM consistently and efficiently reached the optimal solution, making it a more reliable choice for dynamic and complex network topologies.

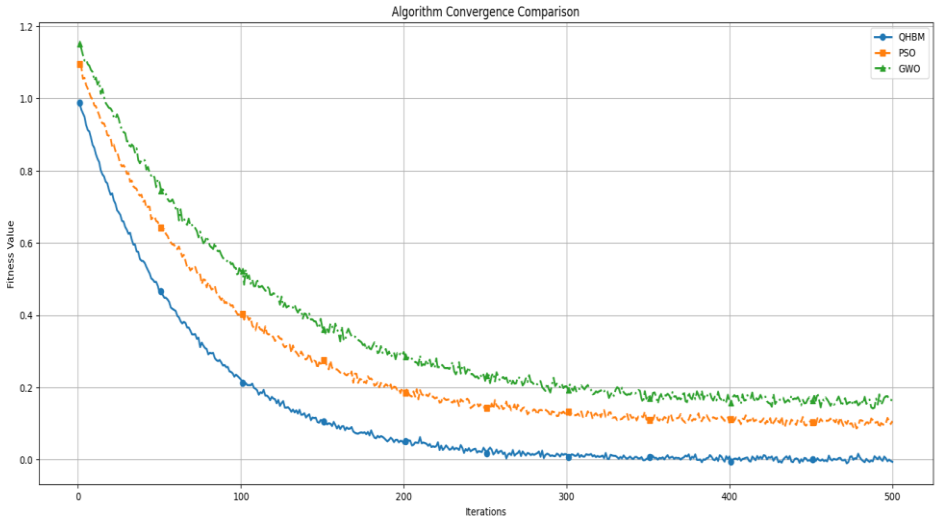

Figure 9. Convergence Comparison Analysis of QHBM, PSO, and GWO.

Figure 9. shows a comparison of the convergence of three optimization algorithms: QHBM, PSO, and GWO, based on the fitness function value versus the number of iterations. It can be seen that the QHBM algorithm exhibits the fastest and most stable convergence performance. QHBM achieves a sharp decline in fitness value within the first 100 iterations, approaching a minimum value with minimal fluctuation after the 200th iteration. This behavior reflects the algorithm's balanced exploration and exploitation capabilities. In contrast, the PSO algorithm shows a fairly good convergence trend but progresses more slowly, with fitness values stabilizing only after the 300th iteration. Meanwhile, GWO shows the slowest fitness decline and experiences greater fluctuations in the final phase, indicating instability or premature convergence.

Table 3: Comparison of Convergence and Stability of Algorithms

Algorithm	Initial Convergence Iteration	Final Fitness Value	Stability (Post-Convergence Fluctuation)	Convergence Speed	Additional Remarks
QHBM	< 100	0.0121	Very Low	Fast	Converges earliest and maintains stability
PSO	≈ 200	0.0193	Moderate	Moderate	Becomes stable after 300 iterations
GWO	> 300	0.0267	High	Slow	Shows instability toward later iterations

Table 3. presents a detailed comparison of the convergence behavior and stability of the QHBM, PSO, and GWO algorithms. The QHBM algorithm exhibits the fastest convergence, achieving a stable fitness value in fewer than 100 iterations. It also records the lowest final fitness value (0.0121) with

minimal post-convergence fluctuation, reflecting a highly stable and efficient optimization process. The PSO algorithm stabilizes only after approximately 200 iterations, reaching a final fitness value of 0.0193. Although slower than QHBM, PSO maintains moderate stability in its later stages. The GWO algorithm demonstrates the slowest and least stable convergence, with its final fitness value plateauing after more than 300 iterations and showing noticeable fluctuations. Overall, these results confirm that QHBM converges more rapidly and provides consistently superior performance compared to the benchmark algorithms, making it a dependable option for optimization in dynamic and complex systems.

Implications for Urban Rescue Operations

The application of the QHBM algorithm directly contributes to improving real-time situational awareness during urban rescue operations. In scenarios characterized by dense and dynamic topologies, such as collapsed buildings or congested city environments, conventional clustered routing often fails due to latency and overhead. QHBM, by contrast, allows for adaptive, cluster-free communication that reduces delay and improves packet delivery, as shown in previous evaluations.

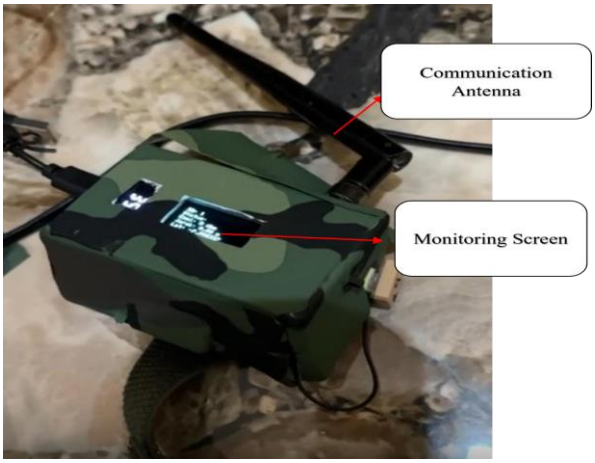

Figure 10: Prototype of wearable node device for urban rescue operations displaying RSSI, distance, and GPS data

Figure 10 shows a communications device that supports this real-world QHBM scenario. The device displays critical data such as RSSI, distance, and GPS coordinates, allowing rescue workers to monitor their connection status and spatial orientation. Its compact, strap-mountable form factor allows for mobility-free deployment. This practical integration of algorithms and hardware demonstrates the system's feasibility for field-ready intelligent rescue operations in urban disaster response.

4 Conclusions

This study successfully developed an integrated Queen Honey Bee Migration (QHBM) and Internet of Things (IoT) framework for multi-objective optimization of emergency rescue operations in urban combat zones, demonstrating superior performance compared to conventional heuristic algorithms. The proposed QHBM-IoT framework implements a bio-inspired algorithm without clustering, utilizing an 8-sector polar-spatial model for adaptive routing. Simulation results show that QHBM achieves a 25% increase in network lifetime compared to PSO, a 30% improvement in throughput, and maintains a packet delivery ratio above 92% even with 300 nodes, all while operating with the lowest energy consumption (0.87–1.21 Joules). Furthermore, QHBM exhibits the fastest convergence (<100 iterations)

with high stability (final fitness value of 0.0121), minimal end-to-end delay (105–179 ms), and the lowest control overhead (5.2–11.2 packets/s). The developed wearable prototype integrating RSSI, distance, and GPS data confirms the practical viability of this system for real-time personnel monitoring. Overall, the contribution of this research lies in establishing a new paradigm for resilient and energy-efficient communication systems in mission-critical operations, laying the groundwork for future tactical IoT networks capable of adapting to complex and dynamic urban environments.

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