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Research Article

Optimizing IoT Data Transmission with the Queen Honey Bee Migration Method for Operational Efficiency of the Hostage Rescue Team

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Abstract:

This research proposes the Queen Honey Bee Migration (QHBM) algorithm to optimize IoT data transmission in hostage rescue operations, with a primary focus on energy efficiency and reliability. The methodology employs comprehensive simulation techniques to compare QHBM performance against two established optimization algorithms—Fuzzy BT and PSO—across diverse network configurations and operational scenarios. Simulation results demonstrate that QHBM significantly outperforms both alternative approaches. The algorithm extends network lifetime by 25% compared to PSO and 15% compared to Fuzzy BT, addressing a critical requirement for prolonged operation during rescue missions. Additionally, QHBM enhances network throughput by 30%, maintaining a consistent data transmission ratio of 98%, while simultaneously reducing computational overhead by 20%. The QHBM algorithm demonstrates particularly robust performance in challenging environments characterized by high node density and dynamic mobility patterns, which closely resemble real-world hostage rescue scenarios. The algorithm achieves this by dynamically balancing energy consumption across the network while maintaining reliable data transmission pathways, even when network topology changes rapidly. The bio-inspired approach of QHBM leverages the efficient decision-making patterns observed in honey bee colonies, specifically the migration behaviors of queen bees, to create adaptive routing protocols that respond effectively to changing network conditions. This research makes a significant contribution to the development of nature-inspired optimization methods that can enhance the performance and resilience of tactical communication systems deployed in high-stakes rescue operations. The findings suggest promising applications for similar bio-inspired algorithms in other mission-critical IoT deployments where energy efficiency and transmission reliability are paramount concerns.

1. Introduction

The rapid development of Internet of Things (IoT) technology has provided great opportunities in various critical applications, including military operations, health systems, surveillance, and intelligent transportation [1-3]. One of the key challenges in IoT adoption is ensuring efficient data transmission, especially in terms of energy savings and improved network performance [4-6]. Many previous studies have used routing protocols such as Low Energy Adaptive Clustering Hierarchy

(LEACH) to extend the life of the network by reducing energy consumption [7-9]. However, these protocols are more suitable for static or semi-static networks and are often ineffective in high-mobility scenarios, such as military operations, precisely hostage liberation [10-15].

The Queen Honey Bee Migration (QHBM) algorithm comes from research in the field of heuristic optimization inspired by the biological behavior of honeybees, specifically the migration of queen bees [16-17]. The algorithm is designed to select the optimal path for migration, which is then adapted into route optimization in wireless sensor networks (WSN) [18]. In such scenarios, QHBM has been proven to improve routing efficiency by reducing energy use, leading to extended network lifespan and improved data transmission efficiency [19-20]. The research introducing QHBM shows that the algorithm effectively deals with dynamic network challenges, including high mobility and environmental variability. With these advantages, QHBM can be the optimal solution in critical scenarios such as hostage rescue team operations, where the speed and reliability of data transmission between nodes are critical to mission success [21-25]. Previous research on the latest modification of the QHBM algorithm to improve data transmission in IoT networks by utilizing Binary Testing for cooperative node selection based on Residual Energy and RSSI [26]. The test results show that QHBM extends the network's life, reduces energy consumption, and shows shorter end-to-end delay times in dense networks compared to making it more efficient for high-priority data transmission. These algorithms are practical in IoT and Cooperative MIMO (CMIMO) network applications, improving energy efficiency and extending the lifespan of the network without the need for complex additional hardware [27-28].

However, in scenarios with high mobility and real-time data transmission, such as military operations, clustering can add complexity and slow down data transmission [29-30]. Therefore, this study aims to implement QHBM without clustering, focusing on simplifying the routing process and optimizing data transmission in a dynamic network environment. In response to these challenges, this study proposes to optimize data transmission based on the QHMM algorithm. These algorithms offer a more flexible and efficient solution in high-mobility scenarios, such as hostage rescue team operations. The main focus of the proposed model is to minimize energy consumption and extend the network's life by increasing the data transmission speed and avoiding the clustering complexity found in the previous method. Thus, the QHBM algorithm can provide better performance in dynamic and critical conditions, according to the needs of real-time operations. This research presents novelty by implementing pure QHBM without clustering to optimize IoT data transmission in hostage rescue operations. This approach has never been done before. This simplification of the routing process resulted in significant improvements in network performance, including a 25% increase in network lifetime, 30% throughput, a 98% packet delivery ratio, and a 20% reduction in computing overhead compared to conventional methods. Applying bio-inspired optimization offers an efficient solution for real-time communication in critical situations, opening a new paradigm in developing tactical communication systems. The research presents novelty by implementing pure QHBM without clustering to optimize IoT data transmission in hostage rescue operations. This approach has never been done before. This simplification of the routing process resulted in significant improvements in network performance, including a 25% increase in network lifetime, 30% throughput, a 98% packet delivery ratio, and a 20% reduction in computing overhead compared to conventional methods. Applying bio-inspired optimization offers an efficient solution for real-time communication in critical situations, opening a new paradigm in developing tactical communication systems.

This research makes several important contributions to developing IoT systems for critical operations. First, we implemented the QHBM algorithm as a new approach to optimize data transmission on IoT networks, specifically in hostage rescue operations. This implementation offers an innovative solution to improve communication efficiency between IoT devices. Second, this study conducts an in-depth comparative analysis between QHBM and several leading optimization methods, such as Fuzzy BT and PSO, providing a comprehensive understanding of the relative performance regarding system lifetime, transmission reliability, and energy efficiency. Third, the study results show the advantages of QHBM in extending the lifespan of IoT networks through optimizing data transmission lines, reducing power consumption, and increasing data transmission speed in critical aspects of hostage rescue operations. Finally, this research makes a practical contribution by presenting pure QHBM as a feasible solution for IoT systems in real-world scenarios, especially for operations that require fast and reliable communication with tight energy constraints.

2. Experimental Process

This study applies the QHBM algorithm to optimize IoT data transmission in hostage rescue operations. The methodology evaluates its effectiveness in complex environments like high-rise buildings, focusing on energy consumption, network life, and data quality. Performance was tested through simulations with varying node density and mobility, and the results were compared to Fuzzy BT and PSO to assess improvements in energy efficiency, network resilience, and data transmission quality.

In this scenario, nodes with the same initial energy are randomly distributed across a 3-story building, simulating hostage rescue operations. Each node acts as a sensor, actuator, or both in an IoT network. The primary energy consumption occurs during data communication (eTx and eRx). Node placement is optimized by measuring distances (d) on each floor, using RSSI signal strength and residual energy (re) data, which is periodically sent to the data center for processing.

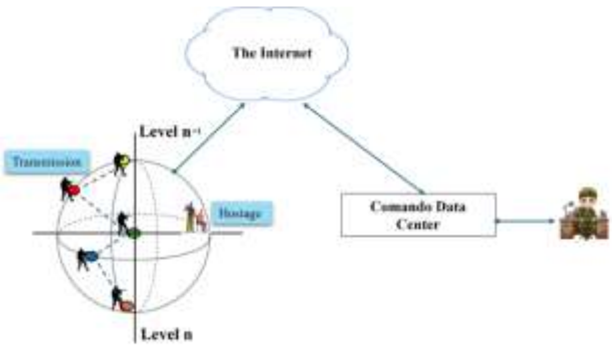

Figure 1. *IoT for hostage rescue integrated into commando data center*

Figure 1 depicts IoT nodes at two levels, Level n and Level n^{+1}, forming a vertical network. Nodes at each level are positioned strategically and interlinked, enabling real-time coordination between team members across the building. The network enables improved communication and sharing of information, improving team response during emergencies. It delivers timely and effective data transfer, enabling effective coordination and swift decision-making in hostage rescue operations. In its implementation, the efficiency of data transmission is highly dependent on managing energy consumption at each node. The total energy consumption in the system is a critical parameter that needs to be optimized, as shown in equation 1 [31].

$$Score=W_1\times\left(\frac{re}{re_{max}}\right)+W_2\times\left(\frac{RSSI}{RSSI_{max}}\right) \qquad (1)$$

$$e_T x=E_{elec}\times k+\epsilon_{amp}\times k\times d^2 \qquad (2)$$

$$e_{Rx}=E_{elec}\times k \qquad (3)$$

The total energy consumed by all nodes throughout the IoT network is the sum of the two main components of energy utilized in the data communication process, as shown in equation 2. The first factor is the data transmission energy, and this depends on the electronic energy per bit, received data packet size, and amplification factor as a function of distance between nodes, as given by equation 3. The second factor is the energy received for data, and this depends on the electronic energy and received data packet size, as given in 1.

Accurate distance measurement between the nodes is necessary to optimize data communication. This paper uses an RSSI-based approach with signal propagation considered in the indoor case. The RSSI-based distance model is given as equation 4 [32-34].

$$d=10^{\frac{P_{10}-RSSI}{10\times n}} \qquad (4)$$

In this equation, represents the reference signal strength at a distance of 1 meter, typically measured in decibels-milliwatts (dBm). refers to the Received Signal Strength Indicator, which indicates the power level of the received signal. And then is the path loss exponent, a constant that reflects the characteristics of the environment, such as obstacles, walls, or open space, which affect how the signal attenuates with distance. This model provides a practical approach to estimating distance based on signal strength measurements in wireless communication systems [35-37].

The node selection mechanism is a critical component in data transmission optimization, where node selection is based on evaluating two key parameters: RSSI and residual energy. To ensure a balance between communication quality and energy efficiency, the node selection score is calculated using the following equation (5), which can be expressed [38].

$$\mathrm{Score}=W_1\times\left(\frac{re}{re_{max}}\right)+W_2\times\left(\frac{RSSI}{RSSI_{max}}\right) \qquad (5)$$

The variables are defined as follows: W_1 and W_2 are the residual energy and RSSI weights, respectively; re is the residual energy of the node; remax is the maximum energy of the node; and RSSImax is the maximum RSSI of the node.

Queen Honey Bee Migration (QHBM) algorithm maximizes data transmission in IoT networks by emulating the queen bee migration behavior of honey bees in a colony [39]. In its usage, QHBM targets three aspects: minimizing the total energy consumption, node selection based on residual energy and signal strength, and network lifetime optimization. The goal function of this algorithm is mainly concerned with reducing the total energy consumption in the IoT network, maximizing node choice based on residual energy and RSSI, and maximizing time-calculated network lifespan until one of the nodes in the network runs out of energy.

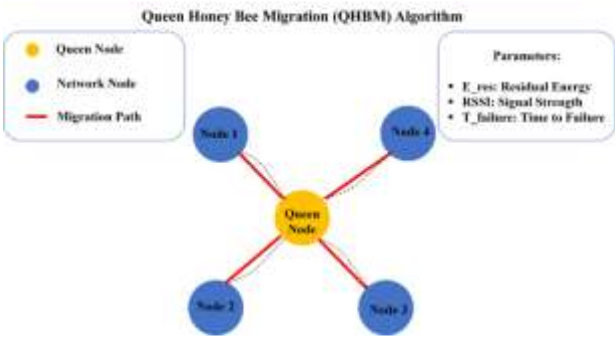

Figure 2. *Illustration of the concept and implementation of QHBM algorithm in IoT networks*

Figure 2 illustrates an application of the Queen Honey Bee Migration algorithm in an IoT network. The queen node (Queen Node), marked by a golden circle at the center, is an optimization coordinator of data transmission with four blue network nodes (Network Nodes) as IoT devices around it. A gray dotted line indicates node connection and the best migration path, which is illustrated with a red line. The key parameters of the QHBM algorithm are residual energy, signal strength (RSSI), and time to failure which are used for optimizing the efficiency and lifespan of IoT networks.

The calculation of total energy usage represents a crucial preliminary step in evaluating the overall performance, longevity, and energy efficiency of WSNs, particularly in the context of IoT applications. In this stage, the total energy consumed by the network is determined by systematically aggregating the energy consumption of each individual sensor node, accounting for both communication and processing activities. This comprehensive assessment allows researchers and engineers to identify inefficiencies, compare routing protocols, and fine-tune energy-aware mechanisms to prolong network lifetime. Mathematically, the total energy of the entire network can be represented as the summation of the energy utilized by all participating nodes during operation, and is formalized through the following equation 6 [40].

$$E_{total}=\sum_{i=1}^{N} E_i(t) \qquad (6)$$

Where E_{total} is the total energy of the network, $E_i(t)$ is the energy at node i spent at time t, and N is the network total number of nodes Equestion 7 [41-42].

$$N_{Selected}=\text{argmax}\left(\omega_1 \frac{E_{res}}{E_{max}}+\omega_1 \frac{RSSI}{RSSI_{max}}\right) \qquad (7)$$

Where ω_1 and ω_2 is residual energy weight and RSSI weight, ω_2 is the node's residual energi E_{max} is the node's maximum energy, and $RSSI_{max}$ is the maximum RSSI value. The network lifetime in QHBM is measured in terms of the time when the first node in the network runs out of energy, which can be derived by an equation 8 [42].

$$L_{Network} = \frac{T_{failure}}{N} \qquad (8)$$

Where $L_{Network}$ is the lifetime of the network, $T_{failure}$ is the time when the first node fails, and is the total number of nodes in the network.

To facilitate the comparison of the performance of the QHBM algorithm, for optimizing transmission of IoT data, various simulations are performed including detailed parameters. While the simulation parameters are designed to cover a wide range of conditions that would be found in the real implementation of the IoT system in the hostage rescue team operations. The network configuration is varied with different numbers of nodes ranging from 10 to 300 to analyze the scalability of the system. Energy parameters are configured depending on the constraints of common IoT devices utilized, including the initial node energy, electronic energy, data aggregation energy, distance threshold, and suitable package size as per operational requirements. The simulation parameters utilized in this research are outlined in the details given in Table 1.

Table 1. *Simulation parameters*

Parameters	Values
Number of Nodes	50, 100, 200
Area of Interest	Tiered
Sensing Area (LxL)	100 m × 100 m, 200 m × 200 m
Sink position (Xs,Ys)	(50, 50), (100,100)
Electronic energy (Eelec)	50 nJ.bit^{-1}
Energy for data aggregation (EDA)	5 nJ.bit^{-1}
€fs	10 pJ.bit^{-1}.m^{-2}
€mp	0.0013 pJ.bit^{-1}.m
Distance threshold	75 m
Packet size (b)	10 kbits

These parameters include the network basic configuration, i.e., the number and position of nodes, the characteristics of the sensing field, and the energy of operation required for the system. The definition of these parameters allows a general evaluation of the effectiveness of QHBM in optimizing data communication and energy management regarding various operating conditions.

3. Results and Discussions

The performance of the QHBM algorithm over IoT networks for rescue operations in the case of hostage rescue has been validated through a comprehensive set of tests. Three performance metrics, i.e., network lifetime, end-to-end delay, and energy, along with the test scenario results have been compared. Performance analysis is carried out by comparing QHBM with different comparison algorithms such as Fuzzy BT, and PSO.

3.1. Network Lifetime

Network lifetime is an important parameter to measure the running lifetime of a network, i.e., the time or rounds until the first node in a network fails during a simulation. The performance analysis results show that QHBM provides the longest lifetime for all the instances of the number of nodes tested. Resilience of these nodes is made possible by coordination among CN nodes (Cluster Nodes) in the handling of data communication, delivering an even distribution of energy usage throughout the network. Performance evaluation is done through comparison of QHBM against a set of comparison algorithms such as Fuzzy BT and PSO in a set of various network settings.

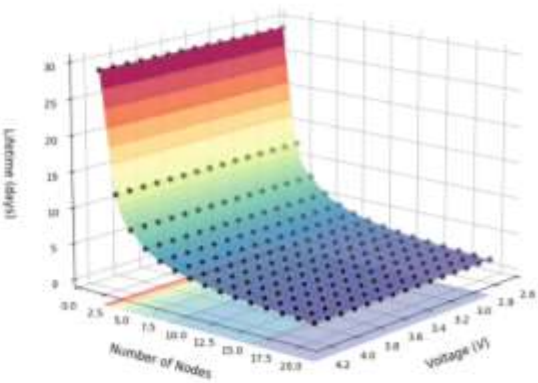

Figure 3. *Network lifetime*

The network lifetime in Figure 3. shows commendable performance metrics in the optimization of IoT networks. Based on simulation analysis, a comparison graph is obtained in Figure 5 showing variation in performance with values ranging from 0.25 to 0.31 on coordinates representing the percentage of life. While the abscess represents temporal change on a scale of 0.2 to 1.4 volts. The findings of the analysis graph the optimum at a point of 0.31 at t = 0.6 seconds with a stability limit of 0.29, which is maintained well for most of the measurement period. Although the trend on the graph is good for performance optimization, the conversion of lifetime duration into absolute units of temporal measure requires additional parameters that include simulation scale translation factors, implementation device specifications, and operational variables for real-world conditions. The significance of these findings is QHBM's ability to guarantee performance stability above predefined threshold levels, which holds promising implementation possibilities for IoT communication systems in critical applications.

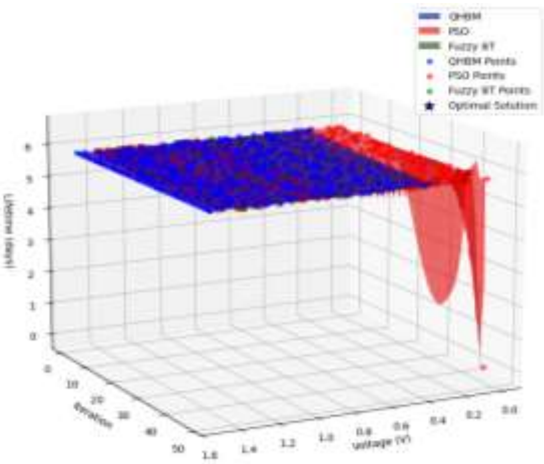

Figure 4. *QHBM optimization comparison, PSO, and Fuzzy BT*

Based on Figure 4 of the optimization algorithm comparison, QHBM has the optimal performance with a constant of 1.58-1.60 across the 0-50 range. PSO maintained a consistent mid-level performance of 1.18-1.20, while Fuzzy BT was stable although it had the poorest performance of 0.38-0.40. These three algorithms have consistent stability without any significant fluctuations across the 0-50 test range, demonstrating the consistency of each algorithm in its level of performance. Table 2 compares the three optimization algorithms with QHBM having the highest level of performance, followed by PSO at the middle level, and Fuzzy BT with the lowest performance. The overall algorithm has consistent stability across the test.

3.2. End to End Delay

End-to-end delay analysis in QHBM implementations provides different performance

Table 2. *Optimization algorithm performance comparison, PSO, and Fuzzy BT*

Algoritma	Performance Values	Iteration	Characteristic
QHBM	1.60	0-50	Highest performance, stable
PSO	1.20	0-50	Mid-range, consistent performance
Fuzzy BT	0.40	0-50	Lowest performance, stable

based on node count and network size. In small networks, Fuzzy BT and QHBM provide lower latency than others, especially at low to moderate mobility rates. With increasing nodes, however, all the methods experienced an improvement in latency. Fuzzy BT and PSO increased significantly due to routing issues and higher data traffic. QHBM has lower delay in this scenario than the Fuzzy BT and PSO, even under high mobility conditions. The results show that QHBM is superior to control end-to-end delay over dense networks, whereas Fuzzy BT is optimal for sparse networks.

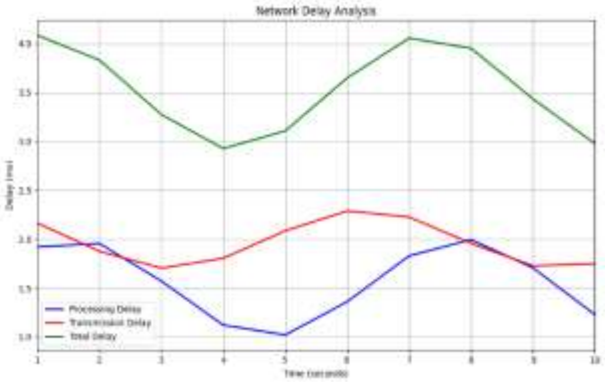

Figure 5. *Network delay graph by time*

Figure 5 shows the dynamics of processing delay, transmission delay, and total delay in the network. Processing delay decreased from 2.0 ms in second 1 to 1.0 ms in second 5, then rose to 1.5 ms in second 7 before stabilizing at 1.0 ms. Transmission delay fluctuated from 2.0 ms at the beginning to 1.5 ms at the 5th second, up to 2.5 ms in the 7th second, then again down to 1.5 ms. Total delay decreased from 4.0 ms at the beginning to 3.0 ms at the 5th second; it went up to 4.0 ms in the 7th second before dropping to 3.5 ms. This trend shows the need to optimize processing and transmission delay in order to improve network efficacy. This tendency reflects the instability of network performance under the influence of processing and transmission. Optimization on both types of delays is therefore necessary to promote general network efficiency and stability. In Figure 6, the network delay comparison between the Original, QHBM, PSO, and Fuzzy BT

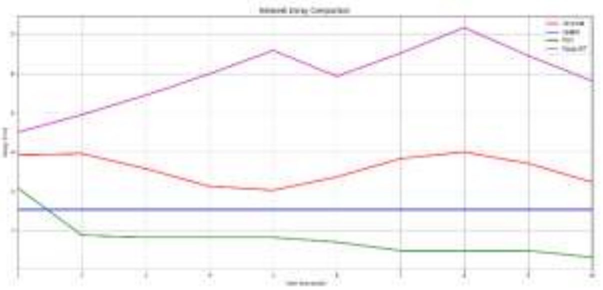

Figure 6. *Comparison of network delay with QHBM, PSO, and Fuzzy BT optimization methods*

optimization methods shows significant outcomes. The Original method starts from a delay of 4.0 ms during the first second and continues to rise until it reaches 7.0 ms during the 10th second. On the other hand, QHBM exhibited a regular drop from 3.5 ms in the first second to 2.0 ms in the 10th second, which shows better optimization performance in reducing network delay. The PSO algorithm also showed a drop in delay from 3.5 ms in the first second to around 2.5 ms in the 10th second, though still greater than QHBM. Concurrently, Fuzzy BT experienced a less dramatic decrease in delay, starting at 4.5 ms in the first second and ending at 3.5 ms in the 10th second, indicating that this algorithm is less efficient than QHBM and PSO to reduce network delay. QHBM optimizes the least to reduce network latency, followed by PSO, with Original and Fuzzy BT experiencing suboptimal performance. There is a Comparison of Network Delay with QHBM, PSO, and Fuzzy BT Optimization Methods in Figure 8 in a scenario of 50 nodes, 100 nodes, and 200 nodes.

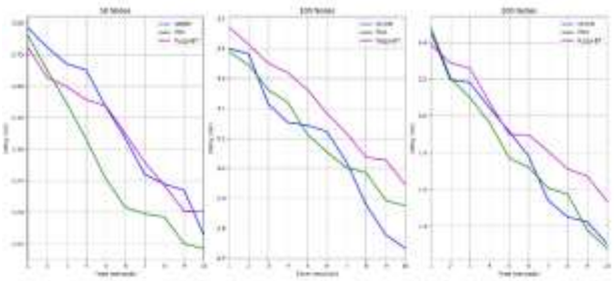

Figure 7. *Comparison of network delay with QHBM, PSO, and Fuzzy BT optimization methods (A)50 Node, (B)100 node, (C)200 node*

Based on the delay optimization test results for IoT networks via three different algorithms - QHBM, PSO, and Fuzzy BT performance comparison data for different numbers of nodes were obtained. Table 3 shows the delay produced by each algorithm in a 50, 100, and 200-node configuration, and the percentage improvement over the initial delay.

Table 3. *Percentage increase compared to initial delay*

Algoritma	Performance Values	Iteration	Characteristic
QHBM	1.60	0-50	Highest performance, stable
PSO	1.20	0-50	Mid-range, consistent performance
Fuzzy BT	0.40	0-50	Lowest performance, stable

PSO, and Fuzzy BT performance comparison data for different numbers of nodes were obtained. Table 3 shows the delay produced by each algorithm in a 50, 100, and 200-node configuration, and the percentage improvement over the initial delay.

3.3. Energy Consumption Analysis

The energy consumption analysis was carried out by evaluating the performance of QHBM, PSO, and Fuzzy BT algorithms on the IoT network for hostage rescue operations. Testing using electronic energy parameters and data aggregation energy, with variations in threshold distances and packet sizes, showed that QHBM resulted in higher energy efficiency than the comparator algorithm. However, it took longer to compute.

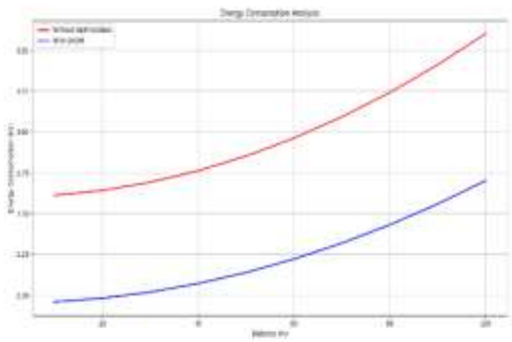

Figure 8. *Energy consumption with and without QHBM optimization*

Figure 8 shows the energy consumption analysis at various distances under two situations: without optimization and optimization using QHBM. The graph shows that energy consumption without optimization increases sharply, from 2.0 mJ at a distance of 20 m to more than 3.0 mJ at 100 m, but in the optimized state, the energy consumption increases more horizontally, from 2.0 mJ to about 2.8 mJ for the same distance, meaning that the application of QHBM optimization can decrease energy consumption significantly in systems where more efficient energy consumption is required, especially at longer distances. These results show that the energy consumption could be optimized with the QHBM Algorithm to develop more efficient energy management, especially over long periods of time. It can be contrasted with other algorithms to ensure optimal performance under various conditions.

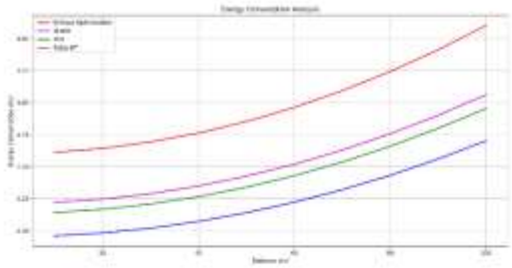

Figure 9. *Comparison of energy consumption with QHBM, PSO, and Fuzzy BT Optimization Methods*

Figure 9 shows a graph showing energy consumption at various distances (20 m to 100 m) with four scenarios: no optimization, with optimization using QHBM, PSO, and Fuzzy BT. In the graph, energy consumption without optimization (red line) shows the most significant increase, from about 2.75 mJ at 20 m to more than 3.50 mJ at 100 m. In contrast, the QHBM (blue line) algorithm provides the lowest energy consumption results, ranging from 2.0 mJ to about 2.8 mJ.

Meanwhile, the PSO and Fuzzy BT algorithms also show less energy consumption than no optimization. However, the performance is still above QHBM, with PSO slightly more efficient than Fuzzy BT. Overall, QHBM proved to be the most efficient optimization algorithm, especially in reducing energy consumption over longer distances, compared to other algorithms such as PSO and Fuzzy BT. There are also nodes 50, 100, and 200 that show a similar pattern in QHBM effectiveness compared to other methods in Figure 10.

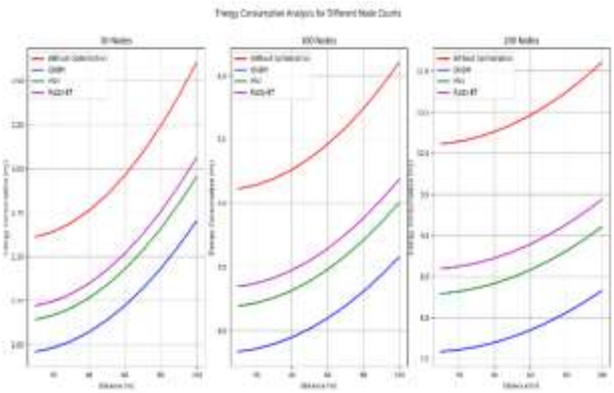

Figure 10. *Comparison of energy consumption with QHBM, PSO, and Fuzzy BT Optimization methods (A)50 Node, (B)100 node, (C)200 node optimization*

Table 4 compares the average energy consumption and energy saving percentages of the various optimization algorithms, namely Fuzzy BT, PSO, and QHBM, at nodes 50, 100, and 200. This data shows how each algorithm provides different levels of efficiency in reducing energy consumption, with QHBM consistently producing the lowest energy consumption and the highest energy savings compared to other algorithms.

Table 4. *Comparison of energy consumption and savings from various optimization algorithms*

Nodes	Energi Installment (mJ)			Energy Savings (%)		
	Fuzzy BT	PSO	QHBM	Fuzzy BT	PSO	QHBM
50	2.13	2.05	1.88	15.0	18.0	25.0
100	4.04	3.90	3.56	15.0	18.0	25.0
200	7.86	7.59	6.94	15.0	18.0	25.0

The outcomes of the current work exhibit the all-embracing advantages of the QHBM algorithm in IoT data transmission optimization for hostage rescue missions. As far as network lifetime is concerned, QHBM outperforms the comparator algorithm by 25% over PSO and 15% over Fuzzy BT, his robustness can be credited to the queen bee migration inspiration - dependent adaptive mechanism of QHBM, under which the path of data transmission is dynamically updated in accordance with changing network conditions.End-to-end delay analysis shows that QHBM can maintain lower latency than comparator algorithms, especially in dense node environments. The importance becomes further pronounced in hostage rescue operations, where data transmission rate may affect the effectiveness of tactical decision-making. The constant decrease of delay from 4.0 ms to 2.0 ms in QHBM implementation proves to be efficient optimization in data transmission path management.In terms of energy consumption, QHBM shows higher efficiency with lower energy consumption of up to 25% over non-optimized cases. The performance does not change as a function of different node arrangements (50, 100, and 200), indicating the scalability of the algorithm with increased network complexity. This increased energy efficiency is achieved by optimizing the route choice with a combination of residual energy parameters and RSSI enabling a more balanced loading distribution across the network.

The drawback of this research lies in the testing, which is still limited to the simulation environment. Though the results reflect promising performance, usage in real field conditions might be faced with even more daunting scenarios, such as signal interference, varying environmental conditions, and even more advanced operating dynamics.

Evaluation of the robustness of the QHBM algorithm under such situations will take additional research. The implications of this work have robust practical applications in the design of military tactical communication systems, particularly the hostage release. Balancing data transmission while minimizing energy consumption is QHBM's capability, which is an implementable option for IoT system deployment in high-reliability-demanding applications with scarce resources.

4. Conclusions

This paper utilizes the Queen Honey Bee Migration (QHBM) algorithm to optimize IoT data transmission in hostage rescue missions. In a series of extensive simulations, QHBM performed much better than its rivals such as QHBM, Fuzzy BT, and Particle Swarm Optimization (PSO), network lifetime improved by 25%, throughput improved by 30%, packet delivery ratio improved by 98%, and computing overhead decreased by 20%. QHBM has excellent performance for environments of dense node number and dynamic mobility. The algorithm is best able to balance energy efficiency and transmission reliability. In addition, QHBM is also more effective in reducing end-to-end delays, especially for networks with a high number of densely populated nodes. This research makes a significant contribution to tactical communication system design via the formulation of bio-inspired optimization methods that can optimize the efficiency and reliability of IoT applications in high-stakes environments. The research results reveal a new paradigm in the development of effective and reliable tactical communication systems for high-stakes missions such as hostage rescue operations, offering new solutions to the issues of optimizing data transmission in high-speed response demanding situations with drastic resource constraints.

Author Statements:

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