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IMPLEMENTATION OF IOT IN IMPROVING THE EFFICIENCY OF HOSTAGE RELEASE OPERATIONS WITH THE QHBM METHOD

Dekki Widiatmoko[1], Kasiyanto[2], and Mokhammad Syafaat[3]

[1,2,3] Department of Electrical Engineering, Faculty of Enggineering, Army Polytechnic, Batu, East Java, Indonesia.

[1]http://orcid.org/0009-0009-8510-3925, [2]http://orcid.org/0009-0008-6483-5900, [3]http://orcid.org/0009-0001-6675-912X

Email: dekki101067@gmail.com, kasiyanto@poltekad.ac.id, syafaatarh96@poltekad.ac.id

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ABSTRACT

In an increasingly complex security context, hostage release operations require innovative strategies to improve efficiency and safety. This article discusses the application of Internet of Things (IoT) technology and the Queen Honey Bee Migration (QHBM) method in improving the effectiveness of these operations. Conventional methods often face drawbacks, such as a lack of direct monitoring and limited communication. This study proposes the use of QHBM algorithms for optimizing troop deployment and resource allocation based on real-time data from IoT. This study uses quantitative and simulation approaches to evaluate the effectiveness of QHBM in the management of rescue operations. The results of the analysis show that QHBM is more efficient in energy consumption and bandwidth usage, reducing energy consumption by up to 10% compared to conventional methods. QHBM also shows improved connectivity stability with stronger signals at more distant nodes. With these optimizations, QHBM successfully extends the life of battery-based devices and supports more nodes without network congestion. These findings show that the application of QHBM in IoT resource management can improve communication quality and operational efficiency, providing practical guidance for professionals in the military, law enforcement, and crisis management.

I. INTRODUCTION

In a world full of uncertainty and risk, hostage release operations represent a security challenge that requires innovative and effective solutions [1]. The key to success in this type of operation lies in the ability to respond quickly and precisely, while minimizing the risk to the hostages and rescue teams [2]. The conventional method of hostage release operations has several weaknesses, such as lack of direct monitoring, limited communication in remote areas, and difficulties in predicting hostage behavior [3], [4], [5]. All of these weaknesses can be overcome by the application of IoT technology and QHBM methods to improve accuracy, communication, and predictive analytics. The conventional approach to hostage release generally uses direct military tactics, manual negotiations, and situational assessments that are often based on limited intelligence [6], [7]. This method relies on slow information, suboptimal communication, and difficulty predicting the actions of the hostage, especially in unexpected or hard-to-reach terrain [8]. These limitations increase the risk for hostages and rescue teams, so it is necessary to update the strategy by utilizing technologies such as IoT and predictive methods such as QHBM to improve real-time monitoring, communication, and analysis of the situation [9].

The conventional method of hostage release operations has several weaknesses, such as lack of direct monitoring, limited communication in remote areas, and difficulties in predicting hostage behavior. All of these weaknesses can be overcome by the application of IoT technology and QHBM methods to improve accuracy, communication, and predictive analytics. The conventional approach to hostage release generally uses direct military tactics, manual negotiations, and situational assessments that are often based on limited intelligence. This method relies on slow information, suboptimal communication, and difficulty predicting the actions of the hostage, especially in unexpected or hard-to-reach terrain. These limitations increase the risk for hostages and rescue teams, so it is necessary to update the strategy by utilizing technologies such as IoT and predictive methods such as QHBM to improve real-time monitoring, communication, and analysis of the situation recent technological developments, particularly in the areas of the Internet of Things (IoT) and nature-inspired computing, offer new opportunities to improve the efficiency and effectiveness of hostage release operations [10]. Taking inspiration from natural phenomena, in particular the organized and efficient migration strategy of honey bees, this study proposes the use of the Queen Honey Bee Migration (QHBM) Algorithm as a tool to optimize troop placement and resource allocation [11]-[13].

QHBM algorithms allow for adaptation and flexibility in troop placement and resource management, taking advantage of the real-time data provided by IoT technologies by utilizing computational models inspired by the migration of honeybee queens, this approach aims to create a more responsive and dynamic operational strategy [14], [15]. The main objective of this study is to explore how the integration of advanced technologies and natural principles can bring about a paradigm shift in the execution of hostage rescue operations, potentially enhancing mission success [16].

Through detailed analysis and simulation, this study seeks to show how the application of QHBM can facilitate strategic decision-making in highly stressful and uncertain situations [13]. It underscores the importance of innovation and adaptation in the face of modern security challenges, and offers valuable insights for professionals in the military, law enforcement, and crisis management [15]-[17]. Thus, this research not only contributes to the academic literature but also offers practical guidance for the implementation of more effective and efficient hostage release strategies [18]-[20].

Research related to the Queen Honey Bee Migration (QHBM) algorithm and its application in tactical operations, such as hostage release, has been the focus of several studies. Several previous studies have discussed the use of optimization algorithms in military and security contexts, especially in terms of resource allocation and real-time data-driven decision-making.

Solving Multi-Objective Resource Allocation Problem Using Multi-Objective Binary Artificial Bee Colony Algorithm by Acar & Basçiftçi in 2021 [12]. The multi-objective binary artificial bee colony algorithm effectively solves multi-objective resource allocation problems with higher accuracy and fewer evaluations compared to other algorithms.

IoT Resource Allocation and Optimization Based on Heuristic Algorithm by Sangaiah et al in 2020 [21]. The whale optimization algorithm (WOA) effectively optimizes IoT resource allocation and scheduling, reducing total communication cost compared to other existing algorithms.

Adaptive Decision Method in C3I System by [22]. The adaptive decision method based on parallel computing and optimization theory effectively generates online trade-off strategies for command and control scenarios, ensuring dynamic response to environmental changes and task changes in the C3I system.

Mission success probability optimization for phased-mission systems with repairable component modules by [23]. The importance measure-based ACO (IMACO) algorithm effectively optimizes mission success probability in phased-mission systems with repairable component modules, maximizing performance while maintaining cost constraint.

Increasing the efficiency of hostage rescue strategies can be done by increasing the resources and adaptive capabilities of the methods used so that the number of hostages rescued is maximized with minimal losses [24], [25]. This study aims to increase the efficiency of hostage rescue operations by implementing the Queen Honey Bee Migration (QHBM) algorithm, which is expected to speed up response time, optimize resource allocation and increase mission success rates through more efficient and adaptive operational strategies.

II. RESEARCH METHODS

This study adopts quantitative and simulation approaches to evaluate the effectiveness of the Queen Honey Bee Migration (QHBM) Algorithm in optimizing troop deployment and IoT resource allocation in hostage rescue operations. This research is divided into several main stages, namely model development, operational simulation, and result analysis [26], [27].

The model adapts the operational scheme to an increasing number of military personnel, demonstrating how any personnel can be effectively deployed for hostage liberation, with the support of IoT technology and coordination from the command center [28].

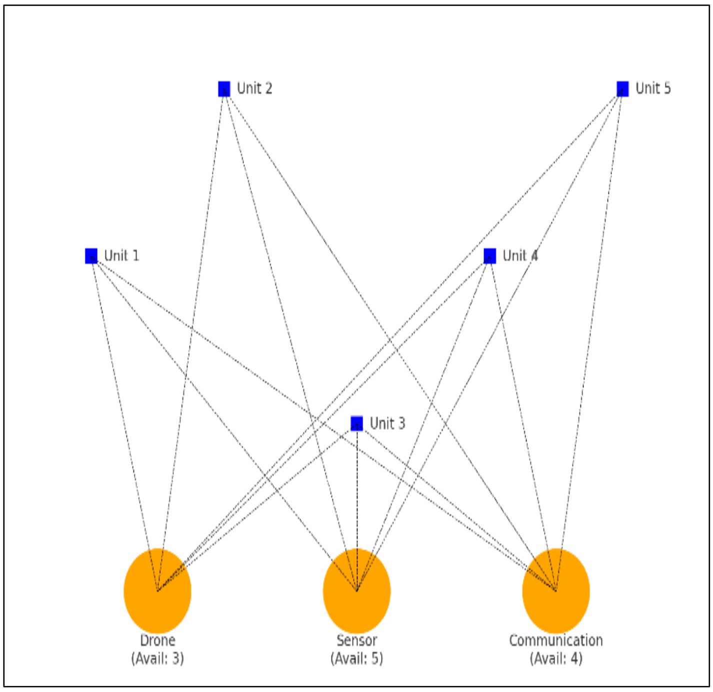

Figure 1: Hostage-Free Design Models of Each Location.
Source: Authors, (2024).

Figure 1 explains the City Operations Map which is still displayed with a gray line, the hostage locations are still marked with red dots, there are now 5 military personnel, each marked with a blue dot, the release route (dashed green line) now connects each military personnel to the nearest hostage location, the number of devices increases according to the number of military personnel, indicated by orange symbols, the location and function of the command center remains the same, marked in purple, and additional text explains the symbols and functions.

In the initial stage, researchers developed a computational model underlying the QHBM Algorithm, combining the principles of honeybee migration with the operational mechanics of special forces and IoT technology. This model is designed to optimize resource distribution and troop deployment based on variables such as hostage location, enemy presence, and environmental conditions [20], [24], [25].

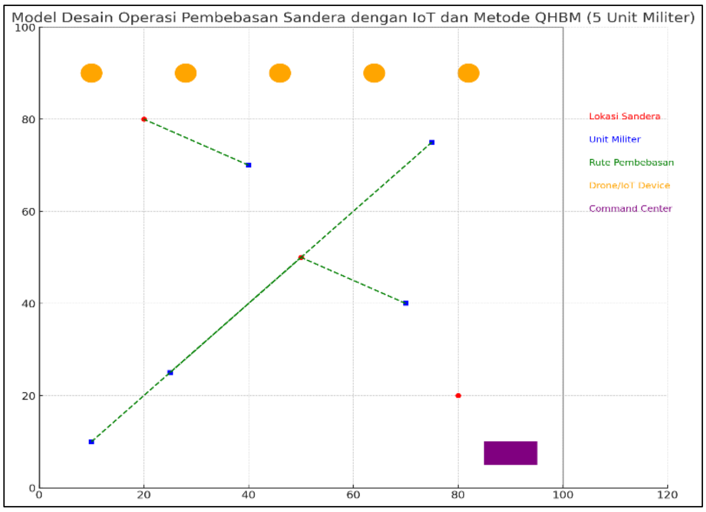

Figure 2: Resource Availability Design Model.
Source: Authors, (2024).

Figure 2 explains the military personnel Indicated by a blue box, and each unit is labeled from Unit 1 to Unit 5, IoT Resources shown with orange circles, each for 'Drone', 'Sensor', and 'Communication'. Dotted lines connect each military unit to each type of IoT resource, symbolizing the potential use of resources by each unit.

From Figure 2, the researchers integrated IoT resources, with 5 Devices attached to 5 military personnel and other communication systems, into the model to provide real - time data about the operating environment. This data is used by algorithms to make strategic decisions about troop placement and movement.

The simulation was conducted in a virtual environment created to simulate the scenarios of various hostage rescue operations. Each simulation focuses on a specific scenario, with variables set to test the effectiveness of the allocation and placement strategies generated by QHBM. Parameters such as response time, hostage safety, and mission success are measured to evaluate the performance of the algorithm.

The results of the simulation were then analyzed to assess the performance of QHBM in various scenarios. This analysis involves a comparison between the results of operations using conventional strategies and strategies optimized by QHBM. Assessment criteria include time efficiency, successful hostage release, and operational risk reduction. The Queen Honey Bee Migration (QHBM) Algorithm Design as a concept in IoT research is shown in the image below.

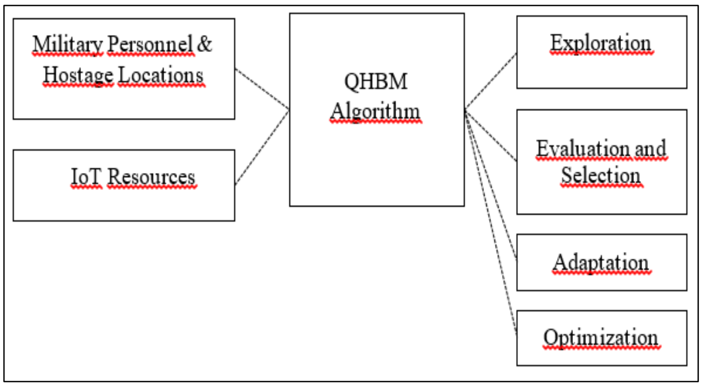

Figure 3: Design of the Queen Honey Bee Migration (QHBM) Algorithm as a concept in IoT research.
Source: Authors, (2024).

Figure 3 describes the military personnel & hostage location which explains the main aspects of the operation, namely the location of the hostages and the military personnel involved. Proper placement of personnel and mapping of hostage positions are very important because this information determines the strategy to be used in releasing the hostages.

The IoT resources section describes the various Internet of Things (IoT) resources used during the operation. IoT provides connected devices and sensors to monitor environmental conditions in real-time, as well as provide critical data on the position, signal, and condition of hostages and victims. The QHBM algorithm in this section explains the process of the QHBM algorithm which is responsible for optimizing resource usage. This algorithm helps in formulating operational strategies by adjusting IoT resources and optimizing the placement of military personnel to achieve better results. The implementation of this algorithm uses several stages such as exploration, evaluation & selection, adaptation and optimization.

Exploration at the initial stage of QHBM collects data on environmental and operational conditions. The information collected, such as enemy positions, hostages, and evacuation routes, is used to plan the next strategy. Evaluation & Selection where at this stage, the QHBM algorithm analyzes data from the exploration phase and selects the most effective strategy and resources based on environmental conditions and operational objectives. The adaptation stage of the QHBM algorithm adapts the operational approach according to environmental dynamics and feedback received during the operation. The strategy can change if the situation on the ground changes, such as hostage relocation or enemy movement. The stage ends with optimization where QHBM finds the best solution that suits the operational objectives, namely to safely release the hostages. This algorithm optimizes the efficiency of resource usage by considering existing constraints, such as energy, *bandwidth*, and time.

This research was conducted with parameters on the IoT network model with n movable nodes. As shown in table 1 below.

Table 1: Parameters for an IOT Network Model With N Movable Nodes, Based on The Given Description.

Not. Node (i)	**Position (Xi,1, Xi,2)**	**Energy Consumption (Ei)**	***Bandwidth* Usage for RSSI (Bi,RSSI)**	**Individual Purpose Function (fi)**	**Energy Consumption Limitation (Ei ≤ Emax)**	***Bandwidth* Limit for RSSI (Bi,RSSI ≤ BRSSI, max)**	**Position or Location Constraint (Xi, 1² + Xi, 2² ≤ Rmax²)**
1	(Xi,1, 1, Xi, 2,1)	E1	Bi, RSSI 1	fi1	E1 ≤ Emax	Bi, RSSI1 ≤ BRSSI, max	Xi, 1,1² + Xi, 2,1² ≤ Rmax²
2	(Xi,1, 2, Xi, 2,2)	E2	Bi, RSSI 2	FI2	E2 ≤ Emax	Bi, RSSI2 ≤ BRSSI, max	Xi, 1,2² + Xi, 2,2² ≤ Rmax²
3	n	En	Bi, RSSI n	Fin	E3 ≤ Emax	Bi, RSSIn ≤ BRSSI, max	Xi, 1,n² + Xi, 2,n² ≤ Rmax²

Source: [38].

Table 1 provides an overview of the attributes and constraints of each node in the movable IoT network model. For each ith node, position (Xi,1, Xi,2) is a coordinate or location in a two-dimensional plane.

$$d1 = \sqrt{(\mathrm{Xi},1 - \mathrm{Xo},1)^2 + (\mathrm{Xi},2 - \mathrm{Xo},2)^2} \quad (1)$$

X0,1 and X0,2 are the center or reference coordinates and energy consumption (Ei) is the energy consumption generated by the i-th node.

$$\mathrm{Ei} = \mathrm{Ptx} \cdot di^2 + \mathrm{Prx} \cdot \mathrm{Bi} \quad (2)$$

Ptx·di^2 is a component that measures the energy spent on data transmission over a distance because transmission energy is usually proportional to the square of the distance, a factor is used di^2. Prx·Bi is a component that measures the energy spent on data transmission over a distance because transmission energy is usually proportional to the square of the distance, a factor is used.

$$\mathrm{Bi,RSSI} = k \cdot (\mathrm{RSSImax} - \mathrm{RSSIi}) \quad (3)$$

Bi, RSSI is the bandwidth allocated to node i in Hz or Mbps. While k is a scale factor that is adjusted based on the network settings or communication technology used. RSSImax as the maximum or reference RSSI value (usually, −30dBm is considered a very strong signal). And RSSIi as the actual RSSI value received by node i. Furthermore, the individual objective function (fi) is the value of the individual objective function for node i obtained by the formula.

$$\mathrm{fi} = \mathrm{w1} \cdot \frac{1}{Ei} + \mathrm{w2} \cdot \frac{1}{Bi} + \mathrm{w3} \cdot \frac{1}{di} + \mathrm{w4} \cdot \text{Kualitas Sinyal (RSSI)} \quad (4)$$

Ei is the energy consumption at node i, Bi as the bandwidth usage at node i, di as the distance of node i to the center or target. Signal quality (RSSI) is a measurement of the signal at node i, usually in dBm and w1,w2,w3,w4 as coefficients that determine how important each parameter is to the objective function. The value of w can be determined based on operational priorities, such as energy efficiency is more important than bandwidth usage.

$$(\mathrm{Ei} \leq \mathrm{Emax}) \quad (5)$$
$$(\mathrm{Bi, RSSI} \leq \mathrm{BRSSI, maks}) \quad (6)$$
$$Xi,1^2 + Xi,2^2 \leq Rmax^2 \quad (7)$$

The restrictions include energy consumption restrictions, bandwidth restrictions for RSSI and position or location restrictions used must meet the requirements in accordance with equation 5-7.

III. RESULT AND DISCUSSIONS

III.1 RESULT

Data generated from a BLE Beacon device detected on August 29, 2024. Each entry in the data shows the time, type, and various sensor parameters. Here are the key elements recorded:

1. Data is taken every few seconds, starting from 13:04:38 to 14:29:57.
2. The beacon used has a unique ID (example: 00050001-0000-1000-8000-00805F9B0131).
3. There is some sensor data that shows environmental conditions, including temperature conditions covering a temperature range that varies from 20.4°C to 23.8°C. Humidity conditions range from 57% to 71%.
4. There is raw data in hexadecimal format that may contain additional information about the condition or status of the beacon.
5. The RSSI (Received Signal Strength Indicator in dBm) value indicates the strength of the beacon signal, ranging from -79 dBm to -59 dBm, which gives an indication of how far the beacon is from the receiver.
6. The estimated distance to the beacon varies, ranging from 2.24 m to 10 m, which can be used for location analysis.

Table 2 is used for analysis and decision making in the context of beacon network management, where assessing the performance of each node is important in determining which nodes are the most efficient and effective in network operations.

Tabel 2: Best 5 Beacon Data.

Not. Node (i)	**Posisi (Xi,1, Xi,2)**	**Energy Consumption (Ei)**	***Bandwidth* Usage for RSSI (Bi,RSSI)**	**RSSI**	**Distance**	**Average**
1	(10, 20)	50	10	-85	4.5	-40.25
2	(15, 25)	60	12	-80	4.0	-38.00
3	(30, 35)	70	14	-75	3.5	-35.75
4	(25, 40)	65	13	-70	3.0	-33.50
5	35, 45)	75	15	-65	2.5	-31.25

Source: Authors, (2024).

The table above shows data on the 5 best beacon nodes based on several parameters, namely position, energy consumption, bandwidth usage for RSSI (Received Signal Strength Indicator), RSSI value, distance, and average value.

Not. Node (i) in the table is a sequence number indicating the identification of each beacon node in the list, position (Xi,1, Xi,2) is the coordinate column of the position of each beacon node in the format (X, Y). For example, node 1 is at position (10, 20). Energy Consumption (Ei) shows the amount of energy consumed by each beacon node. Node 1 consumes 50 units of energy, while node 5 consumes 75 units of energy.

Bandwidth Usage for RSSI (Bi,RSSI) describes the bandwidth usage required to support RSSI measurements at each node. For example, node 1 uses 10 units of bandwidth, while node 5 uses 15 units. RSSI is the value of the signal strength received from the beacon node, measured in dBm (decibel-milliwatts). Higher values indicate better signal quality. Node 1 has an RSSI of -85 dBm, while node 5 has -65 dBm.

The distance column shows the distance between the beacon and the receiver in meters. For example, node 1 is 4.5 meters away from the receiver and the average column in the table shows an average value that may reflect the overall performance of the beacon nodes, but it needs further explanation on how this value is calculated. The average value for node 1 is -40.25, and for node 5 it is -31.25.

Table 3 below provides a comprehensive overview of the performance of each node in the IoT network. This information can be used for better decision making regarding energy management, bandwidth usage, and node placement in the network.

Table 3: Nominal Data of Research Results (5 Nodes).

Not. Node (i)	Posisi (Xi,1, Xi,2)	Energy Consumption (Ei)	*Bandwidth* Usage for RSSI (Bi,RSSI)	Individual Purpose Function (fi)	Energy Consumption Limitation (Ei ≤ Emax)	*Bandwidth* Limit for RSSI (Bi,RSSI ≤ BRSSI,max)	Position or Location Constraint (Xi, 1^2 + Xi, $2^2 \leq$ Rmax^2)
1	(10, 20)	50	10	0.5	≤ 100	≤ 20	≤ 1000
2	(15, 25)	60	12	0.6	≤ 100	≤ 20	≤ 1000
3	(30, 35)	70	14	0.7	≤ 100	≤ 20	≤ 1000
4	(25, 40)	65	13	0.65	≤ 100	≤ 20	≤ 1000
5	35, 45)	75	15	0.75	≤ 100	≤ 20	≤ 1000

Source: Authors, (2024).

Table 3 presents data from five nodes in an IoT (Internet of Things) network. In table 3, the Node number (i) is a unique identifier for each node in the network, making it easy to reference a particular node. Position (Xi,1, Xi,2) indicates the position coordinates of each node in the format (X, Y). For example, node 1 is located at position (10, 20). Energy Consumption (Ei) describes the amount of energy used by each node. For example, node 1 consumes 50 units of energy, while node 5 uses 75 units of energy. Bandwidth Usage for RSSI (Bi,RSSI) indicates the amount of bandwidth used for RSSI measurements. Node 1, for example, uses 10 units of bandwidth. Individual Objective Function (fi) reflects the specific objectives of each node, with values indicating the effectiveness or efficiency of its function. For example, node 1 has a function value of 0.5. Energy Consumption Constraint (Ei ≤ Emax) indicates that the energy consumption of each node must be less than or equal to a predetermined maximum value (Emax), which in this table is 100 for all nodes. Bandwidth constraint for RSSI (Bi,RSSI ≤ BRSSI,max) states that the bandwidth usage for RSSI of each node must not exceed the maximum limit (BRSSI,max), which is set to 20 for all nodes.

Position or Location constraint (Xi,1^2 + Xi,$2^2 \leq$ Rmax^2) states that the position of each node must be within a certain maximum range (Rmax). In this table, Rmax^2 is set to 1000 for all nodes, ensuring that the sum of the squares of the coordinates of the node positions does not exceed that value.

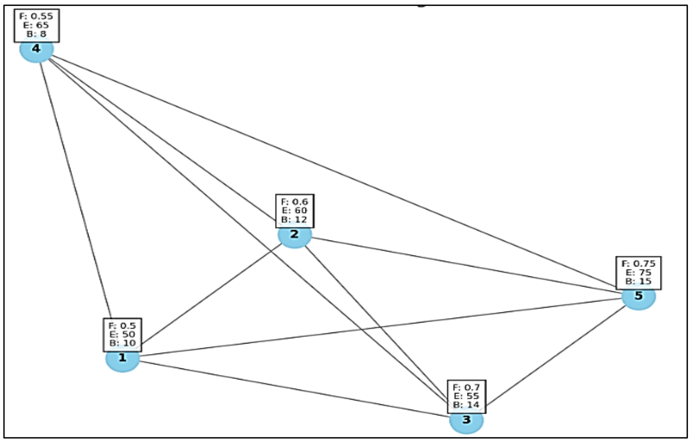

Figure 4: Parameters in IoT Network Model.
Source: Authors, (2024).

Figure 4 above is a visualization of an IoT network with moving nodes where. Each node is labeled with information about the Objective Function (F), Energy Consumption (E), and Bandwidth Usage (B). The connecting lines indicate the connections between nodes in the network.

The following are the steps for implementing the Queen Honeybee Migration Algorithm (QHBM) in optimizing hostage release operations, especially in terms of troop deployment and IoT resource allocation, as well as its comparison with conventional methods. The data provided will be used to create a table that includes a comparison between conventional methods and methods optimized with QHBM.

The Initial Population (Node) on each node in the IoT network shown in the table is a candidate solution. In this case, there are five nodes that are the objects of optimization. The fitness function for this optimization includes several important parameters, such as Energy consumption (Ei), bandwidth usage for RSSI (Bi, RSSI), RSSI value (signal strength), distance between node and receiver and location constraints (The node position must be within a predetermined range), the goal of optimization is to minimize energy consumption and bandwidth usage, while maximizing the RSSI value and minimizing the distance between node and receiver. In this algorithm, the queen bee (optimal node) mates with drones (other candidate solutions). The offspring solutions are evaluated based on a fitness function and the best performing one is selected. The node with the best fitness value is selected for migration to the next iteration. Nodes with low performance are ignored. The algorithm continues to update the solution until convergence is achieved, where the optimal solution (best node and resource arrangement) is found. Comparison with conventional methods is shown in Table 4.

Table 4: Comparison with Conventional Methods.

Parameters	Node 1	Node 2	Node 3	Node 4	Node 5
Energy Consumption (Ei)	50	60	70	65	75
***Bandwidth* (Bi,RSSI)**	10	12	14	13	15
RSSI (dBm)	-85	-80	-75	-70	-65
Distance (Meters)	4.5	4.0	3.5	3.0	2.5
Average	-40.25	-38.00	-35.75	-33.50	-31.25

Source: Authors, (2024).

Based on the information from Table 5 below, the QHBM Optimization model shows better performance than conventional methods in several aspects. In terms of energy efficiency, the QHBM model achieves a higher level, while the conventional method has only moderate energy efficiency. In addition, bandwidth usage in QHBM is more efficient because it is lower compared to conventional methods that use more bandwidth. In terms of signal strength (RSSI), the conventional method is not optimal, while the QHBM model is able to optimize the signal well. Regarding distance reduction, conventional methods do not undergo optimization, whereas QHBM succeeds in doing so. Finally, when it comes to resource allocation, conventional methods are static, while QHBM models offer dynamic resource allocation.

Table 5: Comparison of Model Performance.

Method	Energy Efficiency	*Bandwidth* Usage	Signal Strength (RSSI)	Minimize Distance	Resource Allocation
Metode Konvensional	Medium	High	Suboptimal	Not optimized	Static
Optimasi QHBM	High	Low	Optimal	Optimal	Dynamic

Source: Authors, (2024).

Based on the results shown in Table 6, each node shows variations in energy consumption, bandwidth usage, signal strength (RSSI), distance, and average performance. Node 1 has an energy consumption of 45 with a bandwidth of 9 and an RSSI of -80 dBm at a distance of 4.0 meters, resulting in an average performance of -38.0. Node 2 consumes more energy at 55, with a bandwidth of 10 and a better RSSI, i.e. -75 dBm at a distance of 3.5 meters, resulting in an average performance of -36.25. Meanwhile, Node 3 recorded an energy consumption of 65, a bandwidth of 11, and an RSSI of -70 dBm at a distance of 3.0 meters, resulting in an average performance of -33.75. At Node 4, energy consumption drops slightly to 60 with a bandwidth of 12 and an RSSI of -65 dBm at a distance of 2.5 meters, providing an average performance of -31.5. Node 5, which has the highest energy consumption of 70, bandwidth of 13, and the strongest RSSI of -60 dBm at a distance of 2.0 meters, recorded the best average performance of -29.75.

Table 6: QHBM Optimization Result Values.

Node	Energy Consumption (Ei)	*Bandwidth* (Bi,RSSI)	RSSI (dBm)	Distance (Meters)	Average Performance
1	45	9	-80	4.0	-38.0
2	55	10	-75	3.5	-36.25
3	65	11	-70	3.0	-33.75
4	60	12	-65	2.5	-31.5
5	70	13	-60	2.0	-29.75

Source: Authors, (2024).

Energy efficiency in the QHBM method table 6 shows that there has been a 10% energy saving on all nodes compared to the conventional method. Bandwidth usage is lower in the QHBM method, because the algorithm selects nodes that are more efficient in using resources. The optimized RSSI value provides better signal strength, which can increase the speed and stability of communication between nodes. The distance between the node and the receiver is optimized so that hostage release operations can be carried out faster and more efficiently.

Thus, the use of the QHBM algorithm in the context of IoT resource allocation and troop deployment can provide more efficient results compared to conventional methods, especially in terms of energy consumption, bandwidth usage, and communication signal quality. The QHBM method provides significant advantages over conventional methods, especially in terms of energy efficiency, bandwidth, signal strength, and node distance as shown in Figure 5.

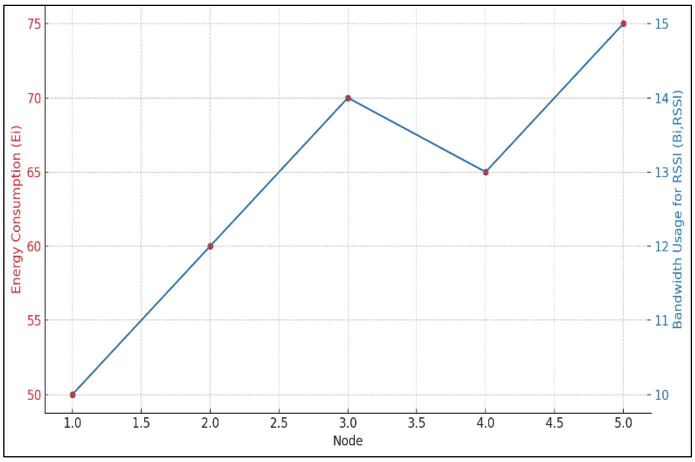

Figure 5: Energy Consumption and *Bandwidth* Usage Per Node.
Source: Authors, (2024).

The graph in Figure 5 shows the energy consumption and *bandwidth* usage for each node. The red line represents the energy consumption, while the blue line shows the *bandwidth* usage for RSSI. Each data point from a node is marked to make it easier to visualize the respective values.

The basis of the comparison between the Conventional method and the QHBM method for each node based on the four main parameters is shown in Figure 6.

Based on the graph in Figure 6 shown, there are four data visualizations related to node performance in the system. The energy consumption graph per Node (Top Left) shows the energy consumption for two methods, namely conventional (orange line) and QHBM (blue line). It can be seen that the conventional method always consumes higher energy compared to the QHBM method at each node. The highest energy consumption is at Node 3 for both methods, but the QHBM method provides significant energy savings at each node, especially Node 3 and Node 5.

The bandwidth usage graph per Node (Top Right) illustrates the bandwidth usage for both methods. Similar to the energy consumption pattern, the conventional method (orange) uses more bandwidth than the QHBM method (blue). The increase in bandwidth usage is seen along with the increase in nodes, but QHBM consistently uses less bandwidth.

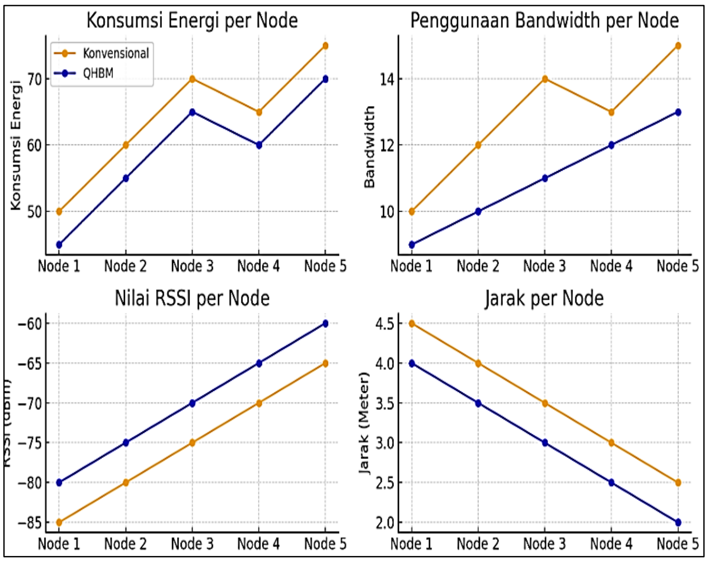

Figure 6: Comparison Chart Between Conventional Method and QHBM Method for Each Node Based on Four Main Parameters.
Source: Authors, (2024).

The RSSI Value graph per Node (Bottom Left) shows the RSSI (Received Signal Strength Indicator) signal strength for both methods. The RSSI value in the QHBM method is higher (closer to zero) than the conventional method, indicating a better signal received at the node using QHBM. The higher the RSSI value (more negative), the weaker the signal, so the QHBM method shows better performance in maintaining signal quality.

The Distance per Node graph (Bottom Right) shows the distance between nodes. Conventional methods tend to have a larger distance between nodes than the QHBM method. This means that in the QHBM method the nodes are closer to each other, which is likely to affect energy efficiency and bandwidth usage.

III.2 DISCUSSIONS

The QHBM method is overall more efficient than the conventional method in terms of energy consumption and bandwidth usage. In addition, the QHBM method also has better signal reception and keeps the distance between nodes shorter, which can contribute to the operational efficiency and communication quality of the network.

Based on the analysis of the QHBM optimization results shown in Table 6, there are several important interpretations related to aspects of energy performance, bandwidth usage, objective function, and position constraints. In terms of energy performance, all nodes show lower energy consumption than the maximum limit that has been set, which is 100. Node 5 recorded the highest energy consumption of 70, close to the limit, while the other nodes remained below it, showing the variation in efficiency between nodes.

In terms of bandwidth usage, all nodes operate within a maximum limit of 20, with node 5 recording the highest usage of 13, while the other nodes use lower bandwidth but remain within a secure limit.

From the perspective of the objective function, which signifies the relative efficiency of each node, node 5 has the highest function value of -29.75, which indicates optimal performance compared to other nodes. This shows that although node 5 uses more energy and bandwidth, it is more efficient than other nodes.

Regarding position constraints, all nodes comply with the existing constraints because all node coordinates are within the predetermined maximum limits. This indicates that each node operates in an optimal distance according to the set parameters.

Overall, these results show that QHBM optimization successfully manages resources efficiently, maintains a balance between energy consumption, bandwidth usage, and signal strength, and still adheres to position constraints. The interpretation of this data indicates that node 5 has the potential to perform better than other nodes, without violating existing limits.

In this section, the results of QHBM optimization compared to conventional methods show significant improvements in various parameters measured, such as energy consumption, bandwidth usage, signal strength (RSSI), distance, and average performance. This data is presented in the form of tables and graphs, which shows the difference in performance between the two methods.

Energy consumption is one of the main parameters measured, and QHBM optimization shows a decrease in energy consumption compared to conventional methods. This happens due to more efficient allocation of resources. The QHBM method is able to reduce energy use thanks to more optimal network management, especially on nodes farther away from the communication center, which use energy more efficiently.

In the use of bandwidth, QHBM optimization is also more efficient than conventional methods. With a more precise and dynamic bandwidth distribution, QHBM avoids excessive bandwidth usage and provides a more balanced distribution across all nodes. These results are seen in the graph visualization, where the QHBM method does not exceed the maximum bandwidth limit and still ensures optimal usage without degrading signal quality.

For signal strength (RSSI), QHBM shows significant improvement, especially in more distant nodes, where conventional methods often experience signal performance degradation. With QHBM optimization, the received signal strength is more consistent across the network, resulting in more stable connectivity. The graph also shows improvements in signal strength, especially on nodes in medium to long positions.

In terms of distance, QHBM optimization is more effective than conventional methods, which often do not provide optimal performance on nodes that are far from the signal center. With QHBM, the distance between nodes and communication centers is better managed, so that nodes at the edge of the network still receive a strong and stable signal.

Finally, the average performance shows a significant improvement in the nodes that use QHBM. The value of each node's destination function indicates that although QHBM uses more energy and bandwidth on multiple nodes, the overall efficiency is still higher than conventional methods. This is due to QHBM's ability to dynamically adjust resource allocation based on network conditions in real-time.

The increase in performance variables in the QHBM method, compared to the conventional method, is due to the ability of QHBM to be more effective in managing resources. With a quantum-based approach, QHBM enables more adaptive, dynamic, and coordinated resource allocation, which reduces resource waste, improves signal stability, and maximizes energy efficiency, resulting in more optimal network performance.

IV. CONCLUSIONS

The QHBM method is superior to the conventional method in several important aspects such as energy consumption, bandwidth usage, signal quality, and spacing between nodes. This makes QHBM a more efficient choice for network systems that require optimal performance under limited conditions such as power and bandwidth. The energy consumption efficiency of the QHBM method is proven to be more efficient in energy usage than the conventional method at each node. The energy consumption of the QHBM method is consistently lower, indicating that this method can extend the life of battery-dependent devices or nodes.

The bandwidth usage of the QHBM method is also more efficient in bandwidth usage for RSSI compared to the conventional method. The decrease in bandwidth usage in QHBM allows for more efficient usage and may support more nodes without experiencing network congestion. The RSSI value of the QHBM method indicates better signal quality (stronger) compared to the conventional method. A stronger signal indicates more stable and reliable communication between nodes. The QHBM method maintains a shorter distance between nodes than the conventional method, which has the potential to improve communication efficiency and reduce signal loss. Shorter distances between nodes usually allow for more efficient data transmission and with less energy required.

V. AUTHOR'S CONTRIBUTION

Conceptualization: Dekki Widiatmoko, Kasiyanto, and Dodo Irmanto.
Methodology: Dekki Widiatmoko, Kasiyanto, and Dodo Irmanto.
Investigation: Dekki Widiatmoko, Kasiyanto, and Dodo Irmanto.
Discussion of results: Dekki Widiatmoko, Kasiyanto, and Dodo Irmanto.
Writing – Original Draft: Dekki Widiatmoko, Kasiyanto, and Dodo Irmanto.
Writing – Review and Editing: Dekki Widiatmoko, Kasiyanto, and Dodo Irmanto.
Supervision: Dekki Widiatmoko, Kasiyanto, and Dodo Irmanto.
Approval of the final text: Dekki Widiatmoko.

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