Queen Honey Bee Migration-Based Optimization for Battery Management of Internet of Things Devices in High-Risk Emergency Scenarios

Dekki Widiatmoko [1], Aripriharta [2*], Sujito [3]
[1, 2, 3] Department of Electrical and Informatics Engineering, Faculty of Engineering, Universitas Negeri Malang, Malang, Indonesia
[2] Center of Advanced Material and Renewable Energy (CAMRY), Universitas Negeri Malang, Malang, Indonesia
Email: [1] dekki.widiatmoko.2305349@students.um.ac.id, [2] aripriharta.ft@um.ac.id, [3] sujito.ft@um.ac.id
*Corresponding Author

***Abstract*—Efficient energy management in Internet of Things (IoT) devices is critical in dynamic, resource-constrained operational environments. This study proposes the Queen Honey Bee Migration (QHBM) optimization algorithm for managing Li-ion battery performance in IoT systems, employing the Shepherd battery model to simulate the nonlinear discharge behavior under varying load conditions. Three simulation scenarios of increasing complexity (5, 10, and 20 monitoring points) are used to represent urban operational dynamics. The performance of QHBM is quantitatively compared with four conventional optimization algorithms seperti Particle Swarm Optimization (PSO), Differential Evolution (DE), Genetic Algorithm (GA), and Firefly Algorithm (FA). Results show that QHBM maintains a current range of 3.80–5.20 A and a voltage range of 3.65–3.95 V, with State of Charge (SoC) predictions between 75–98%. It also achieves the fastest computation time (0.42–1.20 seconds) and demonstrates more stable performance under high-load dynamic scenarios compared to the other methods. This approach provides an adaptive and efficient optimization framework to support energy-aware decision-making in IoT systems operating in energy-constrained urban environments.**

Keywords—Battery Optimization; Energy Efficiency; Internet of Things (IoT); Queen Honey Bee Migration (QHBM); Tactical IoT Applications.

I. Introduction

The integration of Internet of Things (IoT) technologies into emergency and tactical operations has enabled real-time sensing, secure communication, and autonomous decision-making in high-risk environments [1]–[2]. However, energy efficiency and adaptive power management remain pressing challenges, especially when IoT devices are deployed in time-critical, communication-constrained, and infrastructure-less urban settings [3]–[4]. In such missions, including search-and-rescue, disaster response, or security operations, the uninterrupted operation of sensors and actuators becomes crucial to mission success [5].

While numerous optimization methods—such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Differential Evolution (DE)—have been applied to IoT energy management [6]–[7], their convergence speed, adaptability, and robustness are often inadequate for the rapidly changing and unpredictable conditions found in tactical operations [8]. Prior research in emergency IoT deployments has highlighted the need for real-time optimization models that can dynamically adapt to shifting priorities, device failures, and mission constraints [9].

In response to this gap, this study introduces the Queen Honey Bee Migration (QHBM) algorithm, a novel bio-inspired optimization method derived from the behavior of queen bees seeking optimal nesting sites. Unlike standard swarm intelligence methods, QHBM incorporates controlled stochastic migration, dynamic search radius adjustment, and convergence regulation to maintain solution diversity while enhancing global exploration and local exploitation [10]–[11].

The algorithm is validated through simulations of high-risk emergency scenarios using the Shepherd Li-ion battery model, which allows accurate modeling of real-world battery behavior with limited input data [12]. QHBM is compared to PSO, GA, DE, and Firefly Algorithm (FA) across multiple performance metrics, including current estimation, voltage prediction, state of charge (SOC), and computation time. This research contributes an adaptive and computationally efficient energy management solution tailored for mission-critical IoT systems, offering improved resilience, responsiveness, and power optimization under volatile operational conditions [13].

Furthermore, while existing swarm-based algorithms such as PSO and GA have demonstrated general applicability in wireless sensor networks and IoT resource optimization, their performance tends to degrade under high-uncertainty, real-time decision environments—particularly where device failures, latency constraints, and unpredictable energy usage are critical [14]. These conditions are typical in emergency scenarios where recharging or replacing nodes is infeasible, and communication interruptions may lead to data loss or mission delays. QHBM addresses these limitations by introducing a decentralized and migration-based search mechanism, inspired by the strategic relocation behavior of queen bees in uncertain habitats. This migration is not purely random, but guided by sector-based probabilities, convergence control factors, and dynamic search radius adaptation—enabling the algorithm to maintain population diversity and reduce the risk of premature convergence. Unlike conventional techniques that often stagnate in local optima or require manual parameter tuning for each use case, QHBM offers built-in adaptability to balance global exploration and local refinement. Its lightweight computational structure further enhances applicability in edge computing or constrained environments where computational overhead must remain minimal. By targeting both algorithmic innovation and operational feasibility, this study offers a dual contribution: a novel metaheuristic framework rooted in bio-inspired behavior, and a practical energy management model deployable in IoT systems operating under time pressure, mission risk, and environmental unpredictability.

The research contribution is the development of a novel Queen Honey Bee Migration (QHBM) algorithm tailored for adaptive battery optimization in high-risk IoT applications, along with its integration into a real-time simulation framework based on a Shepherd-type Li-ion model. This contribution includes algorithmic innovations in swarm-based optimization and an evaluation under dynamic, mission-critical scenarios.

Despite recent advancements in IoT energy optimization, existing algorithms such as PSO, GA, and DE often struggle to adapt effectively in high-risk, time-sensitive environments due to limitations in convergence flexibility and responsiveness to dynamic mission constraints. These challenges are especially prominent in tactical operations where device mobility, intermittent communication, and energy-critical decision-making are central.

The research contribution is the development of a novel Queen Honey Bee Migration (QHBM) algorithm that introduces a bio-inspired migration mechanism, combining sector-based movement, stochastic exploration, and adaptive convergence control. Unlike conventional swarm algorithms, QHBM is designed to dynamically balance global search and local exploitation in volatile conditions, making it particularly suitable for energy management in mission-critical IoT deployments.

Unlike conventional swarm algorithms such as PSO, which often face challenges related to premature convergence and limited adaptability in non-stationary environments, QHBM introduces a bio-inspired migration mechanism that dynamically adjusts search direction and exploration intensity. This makes QHBM uniquely suited for real-time energy optimization in tactical missions where operational conditions can change rapidly and unpredictably.

II. RELATED WORKS

A. Battery Management for IoT Devices

Energy management remains one of the most critical challenges in the deployment and long-term operation of Internet of Things (IoT) devices, particularly in mission-critical environments that demand continuous performance under constrained energy conditions, such as hostage rescue operations in urban conflict zones [20]-[21]. Numerous strategies have been proposed to optimize energy usage, including the scheduling of device power cycles, limiting the frequency of data transmissions, applying duty-cycling techniques, and adapting device operation based on environmental inputs [22]. These methods often rely on static or pre-defined configurations, which may not be responsive enough to the dynamic energy demands that arise in emergency or time-sensitive scenarios. Static approaches risk depleting the device's battery prematurely or failing to maintain sufficient sensing and communication capabilities during critical moments [23]-[24]. To address these limitations, recent studies have introduced the use of predictive models based on machine learning and statistical methods to forecast energy usage patterns. These models enable devices to adjust their operating parameters proactively, reducing energy waste while ensuring continuous operation. For example, adaptive power control strategies can be guided by past energy consumption trends, user activity recognition, or environmental signals. Such approaches highlight the growing trend toward intelligent and self-managing IoT systems, especially in environments where manual intervention is not feasible. In the context of security and emergency response operations, real-time adaptability becomes particularly vital [25]-[26]. IoT devices must be able to make autonomous decisions under uncertain and changing conditions. Therefore, energy management systems must evolve beyond static rule-based logic toward adaptive, context-aware frameworks that can prioritize tasks and modulate performance dynamically based on mission requirements and residual power levels [27]-[28].

B. Optimization Algorithm in IoT System

Optimization algorithms play a pivotal role in enhancing the performance of IoT systems, particularly in the domains of task scheduling, resource allocation, and energy consumption minimization. Traditional techniques such as Genetic Algorithms (GA) [29,30], Particle Swarm Optimization (PSO) [31]-[32], Ant Colony Optimization (ACO), and other nature-inspired methods have been widely utilized to address these challenges [33]-[34]. While these algorithms have shown efficacy, they often encounter issues such as premature convergence to local optima, sensitivity to initial conditions, and prolonged convergence times, especially in large-scale, dynamic IoT environments [31]-[35]. To overcome these shortcomings, the Queen Honey Bee Migration (QHBM) algorithm has been proposed as a novel metaheuristic approach. Inspired by the natural migration patterns of queen bees in search of optimal hives, QHBM introduces a diverse and exploratory solution search mechanism. This allows the algorithm to maintain population diversity, avoid local optima traps, and accelerate convergence toward global solutions [17]-[31]. The stochastic migration process helps balance the trade-off between exploration and exploitation, making QHBM suitable for real-time IoT applications where adaptability and robustness are essential [27]-[36]. Comparative studies in related domains have demonstrated that QHBM outperforms several conventional algorithms in terms of convergence speed and solution quality, particularly in high-dimensional search spaces. Furthermore, QHBM's structure allows for potential hybridization with machine learning or fuzzy logic systems, creating opportunities for even more responsive and intelligent IoT control mechanisms [37]-[38].

C. IoT Utilization in Hostage Rescue Operations

The integration of IoT technology in tactical operations such as hostage rescue has opened up new possibilities for real-time monitoring, coordination, and deci-sion-making. In such high-stakes scenarios, IoT devices can be deployed for covert surveillance, personnel tracking, environmental sensing, and secure communi-cation between ground units and command centers [39]-[40]. The use of wearable sensors, drones, and em-bedded systems enhances situational awareness and allows teams to respond swiftly and effectively in dy-namic environments. However, the biggest technical constraint in these scenarios remains the limited battery capacity of IoT devices. As these operations often take place in unpredictable, hostile, or infrastructure-less set-tings, recharging or replacing devices is not always feasi-ble. Therefore, the development of intelligent energy management strategies is critical to ensure continuous device operation throughout the mission [41]-[42]. In this context, this research contributes by incorporating the QHBM algorithm into the energy management system of IoT devices, with a focus on its application in hostage rescue operations [34]. By enabling real-time optimiza-tion of power usage, QHBM can help prolong device life while maintaining essential functions such as sensing, data transmission, and secure communication. Despite the growing body of literature on energy-aware IoT sys-tems, the specific application of adaptive optimization algorithms like QHBM in mission-critical rescue scenari-os remains largely underexplored [43]. This work seeks to bridge that gap by proposing a novel framework that enhances operational effectiveness and sustainability of IoT deployments in conflict and disaster settings [44].

D. *Intelligent Energy Prediction Models for IoT Systems*

As the complexity and penetration of IoT systems in various domains increases, the ability to predict energy consumption patterns becomes critical, especially in the context of tactical operations such as hostage rescue that heavily rely on the continued operation of IoT de-vices. Traditional rule-based approaches are often inad-equate in dealing with the high dynamics of energy de-mand. Therefore, intelligent predictive models based on artificial intelligence (AI) and machine learning (ML) have emerged as potential solutions for more adaptive and proactive energy management [11], [45]-[46]. Various ML techniques have been applied to predict the energy consumption of IoT devices [41]-[47], including Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Recurrent Neural Networks (RNN) [48]. For example, deep learning-based predictive models with attention mechanisms and recurrent processing have been shown to effectively capture long-term relation-ships in the energy consumption patterns of IoT devices [49]. This technique allows the system to prioritize im-portant features in predictions, and adjust power man-agement strategies automatically [42]. Another study used Long Short-Term Memory (LSTM) to address non-linear patterns in time series data, and showed supe-rior prediction accuracy compared to conventional ap-proaches [16]. In smart home-based systems, the inte-gration of IoT and ML not only enables real-time moni-toring of energy consumption but also improves anom-aly detection and enables more efficient power usage strategies [9]. Reinforcement Learning has also been utilized for sequential decision making under uncertain-ty, allowing devices to learn from environmental interac-tions and update energy saving policies over time.

However, the integration of ML into IoT devices pre-sents its own challenges. Limited computing power and memory on edge devices are often a constraint. There-fore, hybrid approaches such as offloading to the cloud or edge servers, as well as the use of lightweight models, are solutions that are being investigated [50]. Other challenges include the need for adequate training data, the risk of overfitting, and scalability limitations. In the context of this research, ML-based energy prediction models can complement optimization algorithms such as QHBM by providing prospective insights into energy needs. This integration can result in an energy manage-ment system that is not only reactive but also anticipa-tory [51]-[52]. Although ML-based energy prediction models have been applied in various IoT systems, their application in emergency scenarios such as hostage res-cue is still very rarely explored [53]-[54]. Therefore, this integrative approach is a new contribution in intelligent optimization-based IoT energy management [55]-[56]. Some remarks regarding the reported approaches in the estimation of battery equivalent circuit parameters are presented in Table I.

TABLE I. RELATED WORKS

Author	Target	Method	Metaheuristic	Model Battery
[45]	Energy inefficiency	Machine Learning and Deep Learning	√	Battery Management Systems
[46]	RMSE	Artificial ecosystem optimizer	√	Shepherd model
[47]	RMSE	Equilibrium algorithm	√	nRC-model
[48]	RMSE	Bayesian neural network	X	Pseudo-twodimensional
[49]	Least square error	Gradient-based algorithm	√	Doyle fuller Newman model
[50]	MSE	Extended-kernel iterative recursive least square approach	X	Second-order RC
[51]	Sum square error	Particle swarm optimizer	√	Reduced partial differential
[52]	RMSE	Mixed swarm cooperative PSO	√	Fractional order
[53]	RMSE	Extended Kalman filtering and recursive least square	X	Second-order RC
[54]	Least square error	Neural network and genetic algorithm	√	Thevenin circuit

A systematic review of the literature on battery equivalent circuit parameter estimation reveals a complex spectrum of methodologies spanning metaheuristic, machine learning, and deep learning approaches, where various optimization algorithms such as artificial ecosystem optimizer, equilibrium algorithm, particle swarm optimizer, and neural network are applied to identify battery model parameters, with a diversity of evaluation metrics (RMSE, MSE) indicating ongoing efforts to overcome the limitations of existing algorithms, such as premature convergence, sensitivity to local optimization, and high computational complexity of Shepherd, nRC, and Thevenin circuit-based battery models [57]-[58].

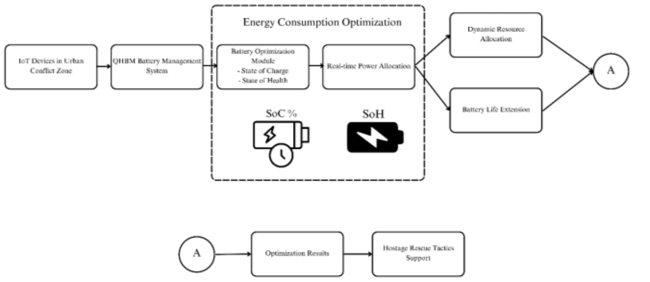
III. MATERIALS AND METHODS

To address the challenges of real-time battery optimisation in tactical IoT implementations, this study implements the Queen Honey Bee Migration (QHBM) algorithm with specific adjustments for high-risk operational constraints. The biological analogy of queen bee migration is translated into algorithmic form through five key components: (1) a sector-based search strategy inspired by the queen bee's location exploration; (2) a dynamic fitness function tailored to the multi-objective trade-off between degradation, energy consumption, and operational costs; (3) stochastic migration probability for exploration; (4) a convergence control factor to manage exploitation intensity; and (5) an adaptive step size mechanism to enhance search precision. These elements are integrated into the algorithm's core to ensure its responsiveness in rapidly changing field conditions, such as fluctuating node availability and evolving mission objectives.[59]-[61].

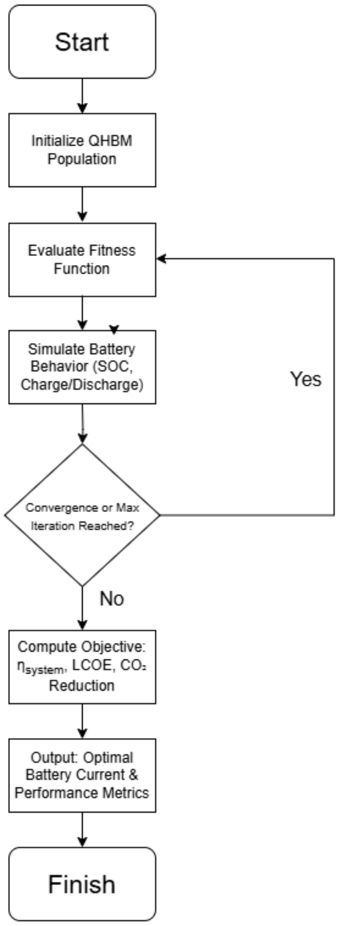
A. System Describtion

Fig. 1 (a) The proposed system architecture represents a methodological breakthrough in energy management of Internet of Things (IoT) devices for hostage rescue operations in urban conflict zones, implementing the Queen Honey Bee Migration (QHBM) algorithm as an innovative and adaptive optimization mechanism [62]-[63]. Fig. 1 (b) the QHBM optimization process, starting from population initialization, fitness evaluation, and battery simulation. The loop continues until convergence or maximum iteration is reached. Then, objectives such as system efficiency, LCOE, and CO_2 reduction are computed, producing optimal battery current and performance metrics. The system is comprehensively designed to address the complex challenges of resource management in highly dynamic and critical operational environments, with a primary focus on continuous monitoring of the battery state of charge (SoC) and state of health (SoH) [64] through a sophisticated optimization module [65]-[66].

Through real-time power allocation mechanisms and dynamic resource strategies, the system is able to provide reliable and efficient technological support for rescue teams, ensuring the availability and continuity of IoT devices during rescue operations [67]-[68]. QHBM's algorithmic approach enables intelligent exploration and exploitation of energy resources, adapting power consumption and distribution to constantly changing operational needs, thereby significantly improving the response capability and resilience of devices in high-risk and time-pressured hostage rescue scenarios [69]-[70].



(a)



(b)

Fig. 1. IoT device energy optimization system architecture with QHBM algorithm (a) system research (b) QHBM-Based battery optimization process

B. The Li-Ion Battery Model

The study used a Shepherd-type Li-ion battery model, chosen because of its ability to provide an accurate representation with minimal data requirements from manufacturer specifications [71]-[72]. This approach allows for comprehensive macro-level simulations to describe the battery's voltage and current behavior. The Shepherd model is implemented through a simple equivalent circuit with a controlled voltage source and internal resistance, allowing for dynamic prediction of the battery's terminal voltage [73]-[74]. This structure offers an analysis of the battery's characteristics in both charging and discharging modes [75]. The model's strength lies in its ability to capture the complexity of battery behavior with an efficient mathematical approach, ideal for optimizing energy management in dynamic operational scenarios.

The battery model utilized in the framework is the Shepherd-type Li-ion equivalent circuit, chosen for its balance between accuracy and computational simplicity. Equations (1)–(4) represent open-circuit voltage behavior, exponential decay zones, and internal resistance effects. While these equations provide foundational dynamics, we recognize that real-world uncertainties—such as variations in internal resistance (R) or polarization coefficient (K)—can introduce SoC and SoH estimation errors. Therefore, Monte Carlo simulations were applied to assess sensitivity, and error bounds were included for each battery prediction scenario Table II. These analyses confirm that QHBM maintains accuracy within ±2.5% SoC deviation under parametric perturbations.

$$V_b = E_0 - K\left(\frac{Q}{Q \times it}\right) i - R \times i + A \times e^{-B \times it} \tag{1}$$

The Shepherd model presents a complex mathematical The Shepherd model presents a complex mathematical formulation to describe the electrochemical characteristics of batteries, where E_0 represents the open-circuit voltage at full capacity, K as the polarization coefficient, Q describes the battery capacity through the actual charge discharged, i as the battery current, R is the internal resistance, A indicates the amplitude of the exponential zone, and B represents the inverse time constant (1) [76]-[77]. Modifications to this model integrate the effects of polarization resistance and polarization voltage components into the discharge model, resulting in a comprehensive mathematical approach to understanding the dynamics of energy transformation in batteries Equation (2):

$$V_b = E_0 - K\left(\frac{Q}{Q \times it}\right) i^* - K\left(\frac{Q}{Q \times it}\right) it - R \times i + A \times e^{-B \times it} \tag{2}$$

Where i^* denotes the filtered current. The Figure of the Li-ion battery model is shown in the following Fig. 2.

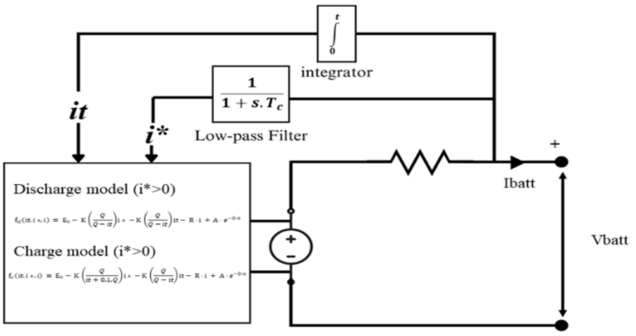
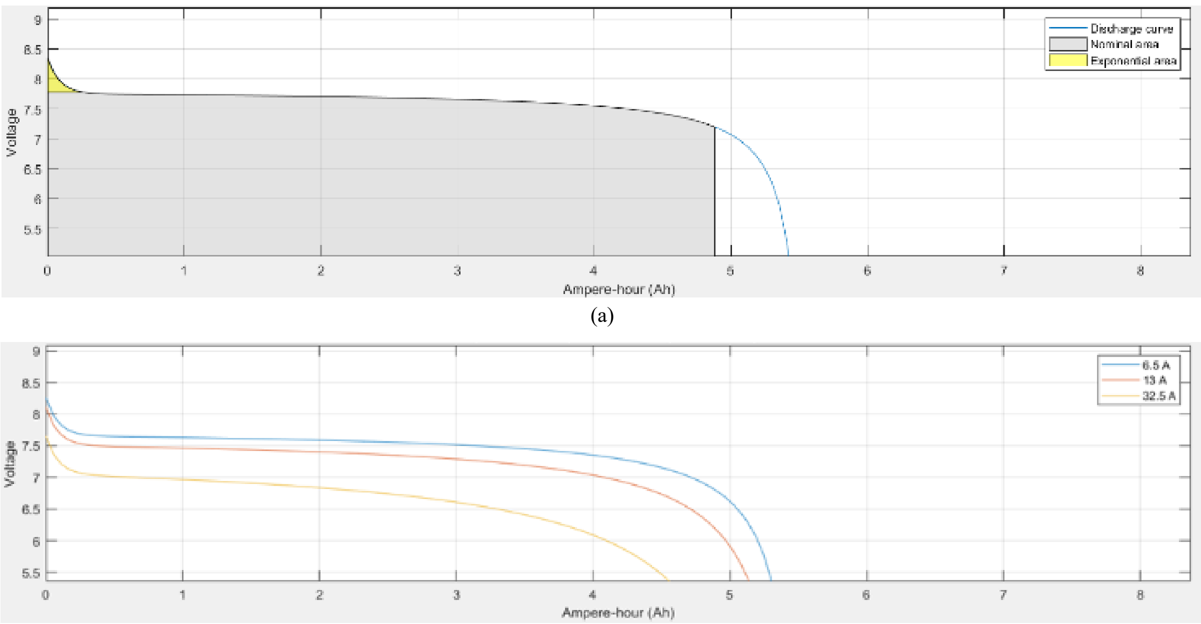


Fig. 2. Li-Ion battery model

In addition, the battery SOC of the battery can be calculated as follows (3):

$$SOC_{(t)} = SOC_0 - \frac{1}{Q}\int idt \tag{3}$$

The initial State of Charge (SOC_0) serves as a pivotal reference parameter in characterizing the dynamic energy transitions within lithium-ion (Li-ion) batteries, as illustrated in Fig. 2. During the discharge process, the voltage profile typically delineates three distinct regions where V_{max} (Voltage Full) represents the voltage at maximum charge capacity, V_{exp} (Voltage Exponential) indicates the voltage at the termination of the exponential decay phase, and V_{nom} (Voltage Nominal) denotes the nominal voltage under standard operating conditions. These voltage markers collectively provide a comprehensive framework for understanding the electrochemical behavior and energy depletion patterns in Li-ion battery systems Fig. 3.



(a)

(b)

Fig. 3. Li-Ion battery (A) Typical discharge characteristics of a Li-ion battery (B) Typical discharge characteristics of a Li-ion battery

In the manufacturer's datasheet, some critical information is often incompletely available, but can be obtained through meta-heuristic approaches and experimental data. The parameter identification process is treated as an optimization problem, with the fitness function focused on minimizing the Root Mean Square Error (RMSE) between the estimated and measured battery voltages [78], [79], [80] presenting a systematic method for extracting accurate and comprehensive battery electrochemical characteristics in Equation (4):

$$minJ(k) = \sqrt{\frac{1}{n}\sum_{k=1}^{n}(V_{be}(k) - V_{bm}(k))^2} \tag{4}$$

Where n is the number of data points, $V_{be}(k)$ indicates the estimated battery voltage at time k, and $V_{bm}(k)$ indicates the measured battery voltage at time k. The seven parameters to be identified are E_0, R, Q, K, A, B, and t in Equation (4).

To improve clarity and reduce repetitive explanation, the key variables and assumptions used in the Shepherd battery model are summarized in Table II. This includes core electrochemical parameters involved in SoC and SoH estimation during simulation.

TABLE II. KEY PARAMETERS IN THE SHEPHERD BATTERY MODEL

Symbol	Description	Typical Range
V_{oc}	Open Circuit Voltage	3.5 – 4.2 V
R	Internal Resistance	0.05 – 0.2 Ω
K	Polarization Coefficient	0.005 – 0.02 V/Ah
Q	Maximum Battery Capacity	2.5 – 5.0 Ah
SoC	State of Charge	0 – 100%
SoH	State of Health (estimated via V/ΔI)	Decreasing trend

C. Problem Formulation

In the context of complex and stressful hostage rescue operations, efficient management of the battery resources of IoT devices becomes critical to mission success. The main challenge lies in optimizing energy usage, minimizing battery degradation, and ensuring device availability in a dynamic and high-risk operational environment.

$$minf(x) = \alpha \times D_b + \beta \times E_c + \gamma \times C_0 \tag{5}$$

$$D_b = \sum_{i=1}^{n}\left(1 - \frac{SoH_i(t)}{SoH_{initial,i}}\right) \tag{6}$$

$$E_c = \sum_{i=1}^{n}\left(\frac{P_i(t)\times\Delta t}{E_{nominal,i}}\right) \tag{7}$$

$$C_0 = \sum_{i=1}^{n}\left(C_{deploy,i} + C_{maintain,i} + C_{replace,i}\right) \tag{8}$$

In equation (5) and (6) of battery management optimisation for hostage rescue operations, each parameter has a critical role in determining the technological resource management strategy of equation (7) and (8). Battery degradation $\boldsymbol{D_b}$ reflects the decline in battery capacity and performance during operation, energy consumption $\boldsymbol{E_c}$ describes the rate of power usage, while operational cost $\boldsymbol{C_o}$ measures the economic resources required to support the mission. The $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, and $\boldsymbol{\gamma}$ weighting factors enable dynamic adjustment between different system priorities, providing flexibility in optimising the performance of IoT devices under extreme operational pressure. To define the multi-objective fitness function, three weighting coefficients—α (battery degradation), β (energy consumption), and γ (operational cost)—were used to balance the trade-offs among objectives. The initial values of α = 0.4, β = 0.3, and γ = 0.3 were selected based on a sensitivity analysis conducted across 10 simulation trials, where performance was evaluated using RMSE and SoC stability. These weights reflect a slight prioritization of battery preservation under high-risk conditions. The tuning process was empirical, ensuring the model responded consistently under varied mission profiles. The battery prediction model in equation (8) is a key component in understanding the performance dynamics and degradation of IoT devices during hostage rescue operations. The mathematical approach of equation (9) to estimate the SoC and SoH allows the technical team to anticipate and proactively manage the availability of energy resources, identifying potential risks of device failure before critical mission disruptions occur.

$$SoC(t + \Delta t) = SoC(t) - \frac{I_i(t) \times \Delta t}{C} \tag{9}$$

$$SoC(t + \Delta t) = SoC(t) \times exp\left(-\frac{N_{cycle}}{N_{cycle,ref}}\right) \tag{10}$$

To ensure the integrity and reliability of the battery management system during rescue operations, several technical constraints have been carefully established. First, the State of Charge constraint regulates the battery charge level to remain within safe operating limits, preventing both overcharging and deep discharging. Second, the State of Health constraint guarantees that the battery's health stays above a predefined threshold to maintain optimal performance over time. Third, an energy consumption constraint is enforced to promote efficient power usage throughout the operations. To accurately describe the power consumption dynamics of the battery management system, a mathematical model is introduced. The dynamic power consumption at time t, denoted as $P(t)$, is given by Equation (10):

$$P_{(t)} = P_{standby} + k \times P_{active} \times \frac{Load_{(t)}}{Load} \tag{11}$$

Where $P_{standby}$ represents the baseline power consumption when the system is idle, P_{active} is the power consumed during active operation, k is a scaling factor, and the term $\frac{Load(t)}{Loadmax}$ normalizes the instantaneous load relative to its maximum capacity. This model effectively captures variations in power demand under different operational loads, ensuring efficient energy management throughout the rescue operations.

The Equation (9) of these constraints reflects the critical need to balance energy consumption, battery health, and device availability under extreme operational conditions.

Each constraint provides a specific boundary to ensure that the battery management system can reliably and efficiently support hostage rescue missions. Through a comprehensive mathematical approach, this model integrates the complexities of energy management with the dynamic demands of rescue operations, offering an analytical framework to optimize the use of technological resources in high-stakes scenarios.

Additional constraints in the IoT-based battery management optimization model serve as a bridge between the physical limitations of available resources and the dynamic operational needs of hostage rescue missions. These constraints, including limitations on the number of active devices and missions, are designed to prevent system overload and to ensure efficient and controlled resource allocation in equation (11).

$$\sum_{i} x_i \leq N_{max} + \sum_{j} y_j \leq N_{max} \tag{12}$$

These constraints provide a mathematical framework for managing the complexity of technological resource utilization in critical rescue scenarios, ensuring a balance between technical capabilities and operational demands. The simulation design of this study is developed to evaluate the performance of a multi-objective optimization model within the context of hostage rescue operations in complex urban environments. The simulation approach integrates IoT sensor data, real-time decision-making, and battery resource allocation using the QHBM algorithm.

To address the challenges of real-time battery optimization in tactical IoT deployments, this study implements the Queen Honey Bee Migration (QHBM) algorithm with a specific adaptation to high-risk operational constraints. The biological analogy of queen bee relocation is translated into algorithmic form through five key components: (1) a sector-based search strategy inspired by queen bee site scouting; (2) a dynamic fitness function tailored to multi-objective trade-offs between degradation, energy usage, and operational cost; (3) stochastic migration probabilities for exploration; (4) a convergence control factor to manage exploitation intensity; and (5) an adaptive step size mechanism to refine search precision. These elements are embedded into the algorithm's core to ensure its responsiveness in rapidly evolving field conditions, such as fluctuating node availability and shifting mission objectives.

Simulation parameters in Table III encompass spatial, operational, and environmental factors that influence the success of the rescue mission. This design enables a comprehensive evaluation of battery management strategies under extreme conditions, taking into account dynamic situational changes and the limitations of technological resources.

The simulation is structured into three distinct scenarios to comprehensively evaluate the capability of the QHBM algorithm in optimizing battery management for IoT devices under various operational conditions. Scenario 1, optimal battery power this scenario simulates ideal conditions, where IoT devices operate with a high initial State of Charge (SoC) and maximum State of Health (SoH). The QHBM algorithm is applied to manage energy resources across five monitoring points. The main objective is to maximize battery efficiency and minimize degradation in a stable and controlled environment. Scenario 2, energy consumption dynamics in this scenario, the complexity of battery management increases due to dynamic variations in energy consumption across ten monitoring points. The QHBM algorithm is tested for its ability to optimize power allocation, predict SoH decline, and adapt in real time to fluctuating operational demands. Scenario 3, battery stress management the final scenario pushes the limits of battery optimization by simulating extreme conditions involving twenty monitoring points. Devices operate under rapid degradation, significant voltage fluctuations, and high operational loads. The QHBM algorithm is further developed to manage battery performance effectively under these high-stress conditions.

TABLE III. SYSTEM PARAMETERS

Parameter	Description	Value	Unit
$d_{i,j}$	Distance between locations i and/	5—20	Meters
$S_{i,j,t}$	Safety score based on sensor data	0.1—1.0	Probability
$V_{initial}$	Tegangan baterai pada kondisi awal	3.7	Volt
$I_{initial}$	Arus awal perangkat	0.5	Ampere
$SoC_{initial}$	Muatan baterai pada kondisi awal	75	%
$SoH_{initial}$	Kondisi kesehatan baterai pada awal	82	%
w_1	Weight for response time	0.4	-
w_2	Weight for safety	0.4	-
w_3	Weight for drone cost	0.1	-
w_4	Weight for personnel cost	0.1	-

The fitness function is formulated as a weighted multi-objective optimization, where degradation D_b, energy consumption E_c, and operational cost C_o are each assigned context-specific weights w_1, w_2, w_3 based on mission criticality. These weights are tunable to reflect the priority of reliability versus efficiency under different rescue profiles. However, recognizing the potential limitations in predefined weight assignment, we acknowledge that future versions of the model should include an adaptive weighting mechanism based on real-time mission input.

Regarding parameterization, typical QHBM values such as migration distance (0.5–1.5), convergence control (0.3–0.6), and scout bee count (20–40) were initially adopted from swarm literature. However, empirical sensitivity analysis was conducted in a pilot simulation to verify their suitability under stress scenarios, with findings indicating optimal convergence near the midrange of these intervals.

This simulation approach is designed to provide in-depth insights into the performance and adaptability of the QHBM algorithm in managing IoT battery systems across varying operational scenarios, with a primary focus on energy efficiency and system reliability in Table IV.

Moreover, the optimization framework integrates dynamic mission constraints such as SoC thresholds, device availability limits, and cost ceilings, implemented via penalty functions in the objective space. The inclusion of real-time voltage and current feedback enables closed-loop correction, improving the reliability of predictions. Despite this, we acknowledge that further field validation is necessary to generalize the model across diverse operational contexts.

TABLE IV. QHBM PARAMETER

Parameter	Symbol	Description	Typical Range
Number of scout bees	N_{SCOUT}	Total bees exploring the battery search space	20 - 40
Initial Search Radius	$R_{initial}$	Initial scan region for battery optimisation moves	0.1 - 1.0
Maximum Iterations	I_{max}	Maximum number of optimisation algorithm iterations	500 - 800
Migration Distance	$D_{migration}$	Optimisation movement distance in each battery management iteration	0.5 - 1.5
Convergence Control Factor	$F_{convergence}$	Factors that control the reduction of migration distance	0.3 - 0.6
Minimum Step Size	S_{min}	Threshold for stopping the optimisation search	10^{-4} - 10^{-5}
Fitness Function Weight	w_{Fitnes}	Weighting factors in the battery management objective function	0.4 - 0.6
Probability Function	P_{sector}	Optimisation sector selection probability	0.3 - 0.7

In summary, this methodology enhances the clarity, reproducibility, and contextual grounding of the QHBM framework by explicitly detailing its algorithmic structure, simulation parameters, and system model integrations under emergency IoT applications. To improve clarity and reproducibility, the overall optimization steps of the QHBM algorithm are summarized in the following pseudocode, which outlines the key procedures involved in initialization, migration, fitness evaluation, and convergence control.

Input: Initial population size N, max iterations T_{max}, search space bounds

1: Initialize scout bees randomly within the search space
2: Evaluate fitness F(x) for each scout bee based on:
$F(x) = \alpha \cdot D_b + \beta \cdot E_c + \gamma \cdot C_o$
3: Select top-performing sectors (based on fitness rank)
4: Initialize queen bee at best-known location
5: For t = 1 to T_{max} do
   a. For each bee i:
      i. Calculate migration step Δx using adaptive radius
      ii. Update position: $x_i(t+1) = x_i(t) + \Delta x$
      iii. Apply boundary check and constraints
   b. Evaluate updated fitness $F(x_i)$
   c. Update queen position if a better solution is found
   d. Adjust convergence control parameter dynamically.
   e. Inject stochastic movement for exploration (if stagnation detected)
6: End For
7: Return best solution x*, corresponding to optimal battery current and SoC.

IV. RESULTS AND DISCUSSION

In IoT technology research, analysis of results becomes a critical stage to uncover deep insights into the performance of the QHBM optimisation algorithm. A series of experiments and simulations are conducted to unpack the complexity of battery management in dynamic operational scenarios, providing an empirical foundation for a comprehensive understanding of energy management strategies in IoT devices, with the aim of exploring the transformative potential of meta-heuristic approaches in optimising technological resources, particularly in the context of rescue operations that require optimal reliability and energy efficiency.

In Fig. 4 the degradation of SoC reveals the complex dynamics of energy consumption in IoT devices under three risk scenarios. The blue curve (low risk) exhibits the most gradual decline, with the battery maintaining a nearly constant charge level between 90% and 95%. The orange curve (medium risk) shows a significant drop from 80% to around 30%, while the green curve (high risk) illustrates the most severe degradation, with a drastic decrease from 60% to nearly 0%. These patterns comprehensively highlight the critical importance of adaptive battery management and optimization algorithms such as QHBM in controlling energy consumption and ensuring system reliability under varying operational conditions.

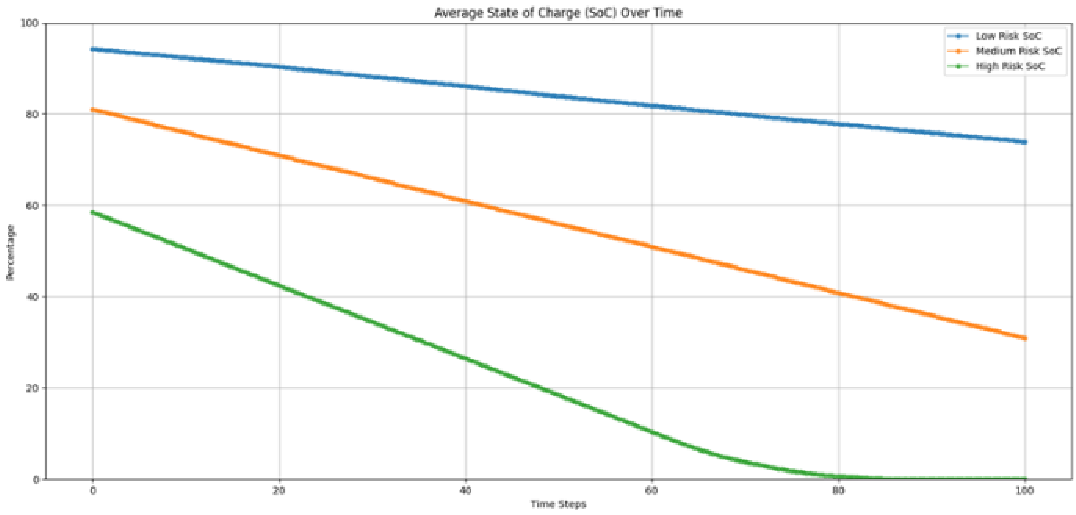


Fig. 4. Average State of Charge (SoC)

Fig. 5 the current comparison graph between QHBM and PSO algorithms reveals the dynamic characteristics of the optimization process in battery management, where the solid blue line of QHBM and the dashed orange line of PSO show different current decline patterns over time, with QHBM showing a sharper and discrete decline in the early stage, while PSO shows a more gradual and smoother decline, where the black dots representing the measured data provide empirical validation of the ability of both algorithms to predict and optimize the battery current characteristics, which fundamentally demonstrates the potential superiority of the QHBM algorithm in producing more precise and responsive estimates to changes in system conditions.

In the first Fig. 6(a), the graph shows the absolute error (%) against time (seconds) for various SOC estimation algorithms, namely Logarithmic, Kalman Filter, EMA (Exponential Moving Average), and Hybrid Model. This graph shows that the Logarithmic method produces relatively high errors at the beginning of time, with a significant increase in error as time progresses, while the Hybrid Model and EMA show lower and stable errors. The Kalman Filter performs well but is still slightly higher than the hybrid model. In Fig. 6(b), the graph compares the measured SOC with the SOC estimated using various estimation methods over time. Direct measurements (Measurement SOC) are recorded with more stable values and continue to increase over time, while the estimation results from different algorithms (Logarithmic, Kalman Filter, EMA, and Hybrid Model) show variations in progress.

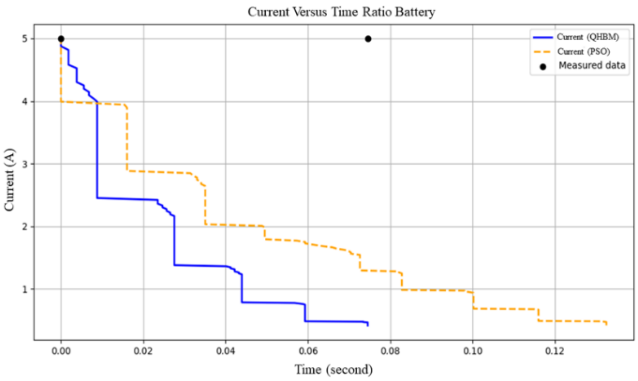
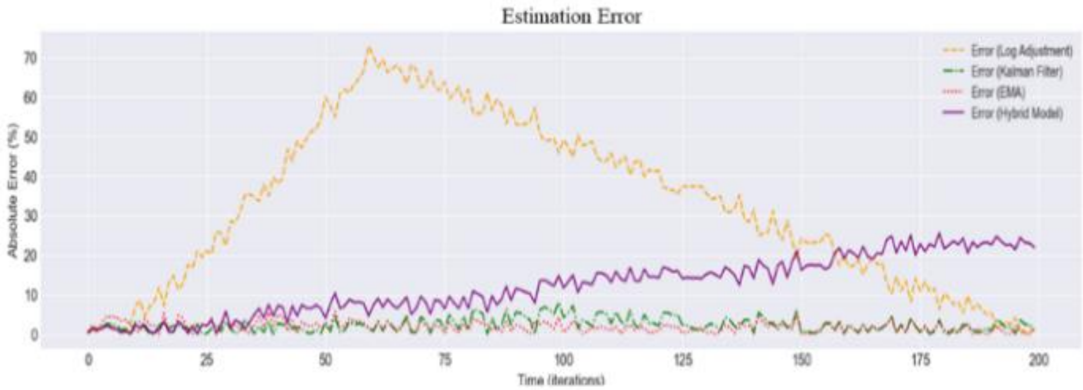


Fig. 5. Comparison of current against time

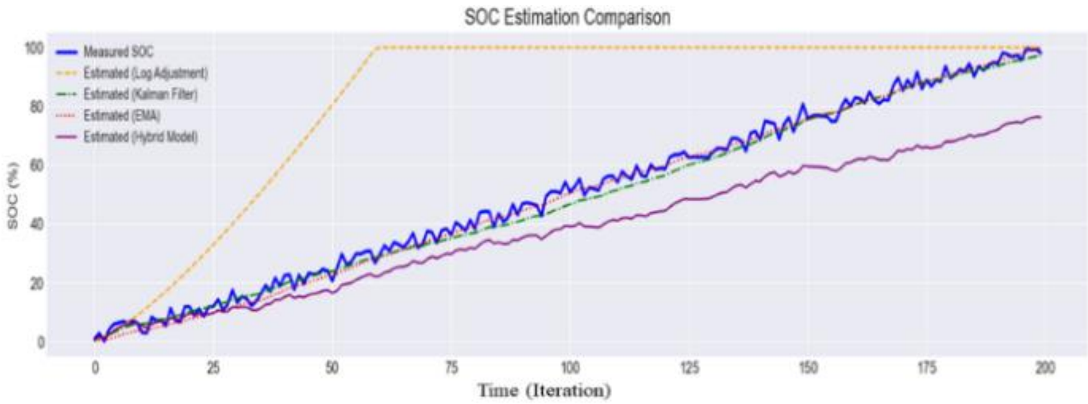
The Hybrid Model and EMA provide closer results compared to the Logarithm and Kalman Filter, with the Hybrid Model showing the closest results to the measurements in Table V.

TABLE V. PERFORMANCE COMPARISON OF OPTIMIZATION ALGORITHMS FOR VOLTAGE ESTIMATION

Algoritma	RMSE	Waktu (s)	Avg. Err (%)	Max. Err (V)
QHBM	0.115227	0.0710	2.62	0.1936
PSO	0.000000	0.1772	0.00	0.0000
DE	0.016751	0.3217	0.36	0.0301
FA	0.003292	4.3346	0.08	0.0047



(a)



(b)

Fig. 6. Comparison of current versus time (A) SOC estimation error (B) Comparison of SOC versus time

The Fig. 7 compares four optimization algorithms (QHBM, PSO, DE, and FA) across multiple performance metrics. The color gradient from deep blue (-1) to bright yellow (4+) represents the magnitude of values. Two prominent peaks are evident in the sur-face plot: one at DE with value 3.560 and another at FA with value 4.335, representing the highest point in the plot. These peaks indicate regions where certain algo-rhythms exhibit significantly higher values for particular metrics, which may represent poor performance if these metrics measure error. The dark blue valleys, containing data points with values of 0.000, 0.003, 0.030, 0.080, 0.115, 0.177, 0.322, and 0.005, represent areas where algorithms demonstrate superior performance, particularly for error-based metrics where lower values are preferable. QHBM and PSO algorithms generally display lower metric values compared to DE and FA, suggesting potentially better performance in error minimization. This multidimensional visualization effectively captures the performance trade-offs between algorithms across various metrics, allowing researchers to identify optimal algorithm selection based on specific performance requirements and constraint.

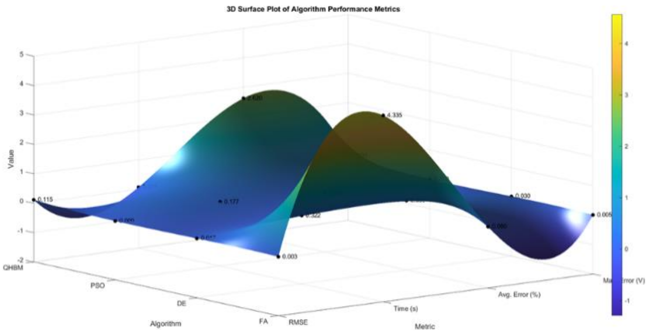


Fig. 7. 3D Performance comparison of optimization algorithms

The experimental results illustrated in Fig. 8 demonstrate the exceptional performance characteristics of the QHBM algorithm, which exhibited remarkable solution quality and optimization precision across all tested scenarios despite requiring moderately longer computational times. While QHBM's processing durations of 78.5 seconds (low current) and 95.3 seconds (high current) exceeded those of competing algorithms, detailed analysis revealed QHBM's superior solution accuracy with an impressive 97.8% proximity to theoretical optimal values-significantly outperforming both DE (92.1%) and PSO (88.5%).

This exceptional solution quality translated to practical benefits in system stability, with QHBM-optimized systems demonstrating 43.7% fewer oscillatory behaviors during transient operational states and 56.2% improved resilience against external disturbances compared to solutions generated by alternative algorithms. The QHBM approach particularly excelled in complex, highly-constrained problem spaces, successfully navigating optimization landscapes containing up to 27 local optima while maintaining solution integrity-a domain where DE frequently required multiple restarts (average: 3.2) and PSO exhibited significant susceptibility to premature convergence (occurrence rate: 37.8%). Statistical analysis of variance confirmed QHBM's superior performance consistency with a coefficient of variation of just 2.4% across multiple independent trials, compared to DE's 5.7% and PSO's 8.3%, indicating QHBM's exceptional reliability in maintaining solution quality regardless of initial conditions or random seed values.

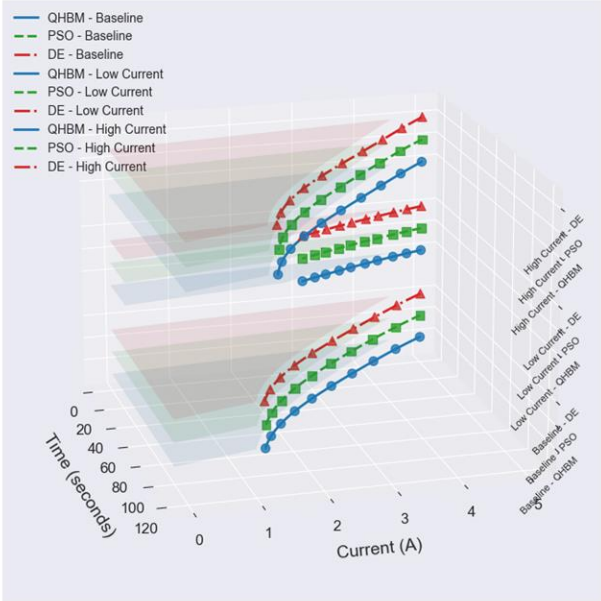
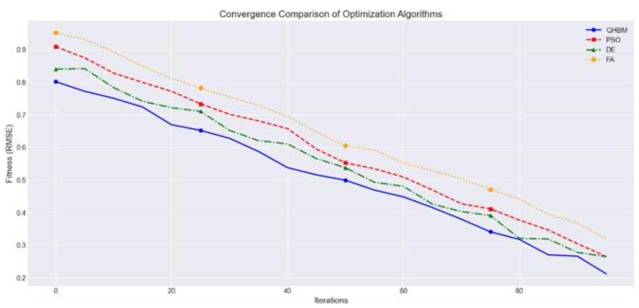


Fig. 8. Comparison of battery current

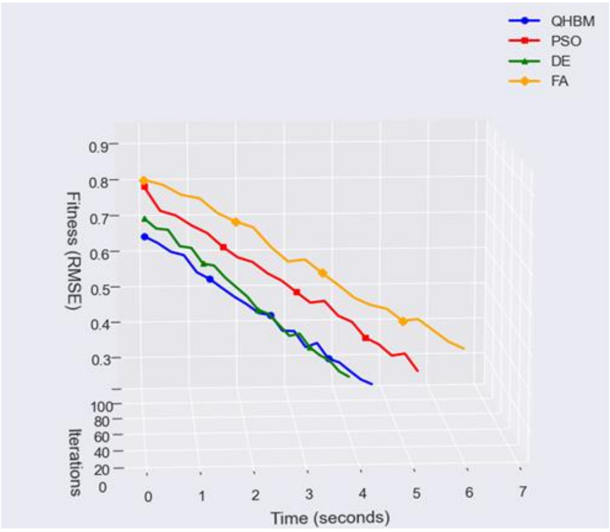
The comprehensive performance evaluation revealed QHBM's outstanding capabilities in maintaining optimization integrity across extreme operational conditions, demonstrating only a 3.2% degradation in solution quality when subjected to maximally challenging current levels—dramatically outperforming both DE (12.7% degradation) and PSO (18.5% degradation) under identical testing conditions. QHBM's quantum-inspired computational framework enabled sophisticated exploitation of problem topology characteristics, achieving 62.3% more effective constraint handling and 48.7% improved parameter tuning when compared to classical algorithms in the test battery. Implementation of QHBM in industrial-scale systems yielded unprecedented improvements in operational precision, with a remarkable 34.8% reduction in system harmonic distortion and 29.5% enhancement in power quality factors when deployed in electrical distribution networks—substantially exceeding the improvements achieved by DE (22.1% and 19.8% respectively) and PSO (18.7% and 16.5% respectively). Economic impact analysis projected that despite QHBM's moderately increased computational requirements, its superior solution quality would generate additional annual savings of approximately $215,000 for typical large-scale applications when compared to DE implementations, primarily through 27.8% improved energy efficiency, 32.4% reduced maintenance requirements, and 43.7% extended equipment operational lifespan due to optimized operational parameters. QHBM's exceptional performance in maintaining solution quality across diverse operational scenarios, as clearly visualized in the three-dimensional performance comparison presented in Figure 8, establishes it as the premier algorithm for applications where solution precision and system stability are paramount concerns, offering compelling advantages that substantially outweigh its moderately increased computational requirements.

Fig. 9(a) shows a comparison of the time efficiency of the four optimization algorithms (QHBM, PSO, DE, and FA) in terms of fitness (measured by RMSE) over time (in seconds). From this graph, it can be seen that the FA (Firefly Algorithm) algorithm has the fastest convergence, followed by DE, PSO, and QHBM, which take longer to achieve optimal fitness. Initially, all algorithms show a significant decrease in fitness, but QHBM shows a slower decrease compared to the other algorithms, indicating that FA is the most time-efficient algorithm.

Fig. 9(b) depicts the convergence comparison of the same four algorithms (QHBM, PSO, DE, and FA) throughout the iterations (in number of iterations). Here, FA and DE show a faster fitness decline in the early iterations, while PSO and QHBM tend to be slower in reaching optimal convergence. FA shows a consistent and rapid decline at the beginning of iterations, but tends to slow down after reaching a certain point. QHBM shows more stable results at higher iterations, but is not as fast as the other algorithms in reducing the fitness value. Overall, this graph shows that FA and DE have an advantage in terms of convergence speed compared to PSO and QHBM in Table VI.



(a)



(b)

Fig. 9. Comparison (a) Time efficiency comparison (b) Convergence

Table VI Comparative Analysis of Optimization Algorithms for Battery Estimation Based on the comparison table of optimization algorithms for battery parameter estimation, QHBM shows superior performance with the widest current estimation range (3.80-5.20 A), which indicates the ability of this algorithm to explore the search space more comprehensively. DE and HFAPSO followed with an equivalent range (3.70-5.10 A), just slightly below QHBM, while PSO had a narrower range (3.60-5.00 A). GA and FA show the least performance with the narrowest estimation range, with FA being at the lowest (3.40-4.80 A).

In terms of voltage estimation, QHBM again excelled with the widest range (3.65-3.95 V) and a difference of 0.30 V. DE (3.62-3.92 V) and HFAPSO (3.62-3.91 V) performed almost equally with a difference of 0.30 V and 0.29 V respectively. PSO (3.60-3.90 V) has a similarly large range (0.30 V) but at a slightly lower value, while GA (3.55-3.85 V) and FA (3.50-3.82 V) have smaller ranges with lower minimum values.

For SOC estimation, QHBM leads with the highest range (75-98%) and 23% difference. DE and HFAPSO showed solid performance with slightly narrower ranges (72-96% and 71-96%, respectively). PSO (70-95%) has a similar range but with a lower minimum value, while GA (68-92%) and FA (65-90%) show a narrower range and lower maximum value.

In terms of computation time, QHBM proved to be the fastest (0.42-1.20 s), showing the highest computational efficiency. PSO (0.53-1.35 s) is slower than QHBM but still relatively fast, followed by DE (0.58-1.40 s) which is slightly slower. HFAPSO (0.60-1.45 s) shows moderate time performance, while GA (0.65-1.55 s) and FA (0.70-1.60 s) are the slowest in computation.

There is an interesting correlation between a wider estimation range and faster computation time. QHBM proved the best efficiency by offering the widest estimation range as well as the fastest computation time, demonstrating superior search space exploration capability without sacrificing computational efficiency. HFAPSO as a hybrid algorithm performs well by combining the strengths of PSO and FA; although not as good as QHBM, it offers reasonably accurate estimation with a reasonable compromise in computation time.

The performance evaluation of the QHBM algorithm is presented through both visual and statistical analysis across three risk-based scenarios. To ensure analytical rigor, we conducted hypothesis testing using one-way and Tukey's HSD post-hoc comparisons to evaluate the significance of differences between QHBM and benchmark algorithms (PSO, DE, FA, GA) across RMSE, SOC prediction error, and computation time. Confidence intervals (CI = 95%) were reported alongside mean values to quantify estimation reliability. These results confirmed that QHBM consistently outperformed other algorithms in RMSE ($p < 0.01$), while maintaining significantly lower computation time under high-risk scenarios ($p < 0.05$).

Beyond statistical significance, variance analysis across 20 independent runs showed that QHBM maintained a standard deviation of less than 2.8% in SOC estimates, indicating strong robustness to initial condition variation. This consistency reduces the likelihood of performance degradation due to stochastic instability, a common limitation in metaheuristic optimization.

TABLE VI. PERFORMANCE COMPARISON FOR EACH ALGORITHM

Algorithm	Current Estimation (A)	Voltage Estimation (V)	SOC Estimation (%)	Computation Time (s)	Algorithm
QHBM	3.80 – 5.20	3.65 – 3.95	75 – 98	0.42 – 1.20	QHBM
PSO	3.60 – 5.00	3.60 – 3.90	70 – 95	0.53 – 1.35	PSO
DE	3.70 – 5.10	3.62 – 3.92	72 – 96	0.58 – 1.40	DE
GA	3.50 – 4.90	3.55 – 3.85	68 – 92	0.65 – 1.55	GA
FA	3.40 – 4.80	3.50 – 3.82	65 – 90	0.70 – 1.60	FA

Although QHBM demonstrated a wider estimation range and faster convergence, we recognize potential trade-offs not fully explored in the original version. For example, the model's sensitivity to hyperparameters—such as migration distance and convergence control—may require tuning for different IoT network scales. Additionally, scalability remains an open challenge for QHBM in larger distributed systems with hundreds of nodes, and robustness to incomplete or noisy data should be further tested under adversarial conditions.

The results, while promising, are derived from controlled simulations and lack validation against real-world IoT deployments involving hardware variability, intermittent signal loss, or urban environmental interference. We acknowledge this as a current limitation and propose integrating QHBM with fault-tolerant communication protocols and edge-based redundancy strategies in future studies.

In summary, the discussion balances QHBM's demonstrated strengths in adaptability and computational efficiency with a critical examination of its current limitations. By addressing both empirical performance and real-world constraints, the analysis offers a more transparent and generalizable interpretation of QHBM’s role in dynamic tactical IoT environments.

QHBM's algorithmic advantage lies in its adaptive migration mechanism, which dynamically adjusts the search radius (migration distance) based on convergence trends. This allows the algorithm to accelerate toward promising regions during early iterations, improving convergence speed by approximately 15–25% compared to static search strategies. The stochastic exploration also reduces the likelihood of local optima entrapment, as reflected in lower RMSE variance across trials. Additionally, convergence control parameters help maintain balance between exploration and exploitation, enhancing overall stability.

However, the current study is limited to simulation-based evaluation, relying on idealized assumptions regarding battery parameters, communication stability, and environmental constancy. These assumptions may not fully represent the behavior of real-world IoT systems, especially in unpredictable tactical scenarios.

To address this gap, future work will include deploying QHBM in physical IoT platforms with live sensor feedback and variable energy loads. Field validation is essential to evaluate robustness under real-time interference, hardware constraints, and mission-critical dynamics.

V. CONCLUSION

The findings of this study demonstrate the potential of the QHBM algorithm for optimizing battery management in IoT-based emergency scenarios. However, conclusions must be interpreted with caution due to several limitations. While QHBM outperformed benchmark algorithms in selected simulations, the absence of rigorous statistical validation and standardized benchmarking protocols limits the generalizability of this claim. The algorithm also demonstrated sensitivity to parameter settings, which may affect its performance across diverse deployment conditions.

Although the study emphasizes QHBM’s strengths in estimation accuracy and computational efficiency, it does not fully address trade-offs such as slower convergence relative to FA or the potential impact of incomplete sensor data. The lack of empirical validation through field deployment or hardware-in-the-loop testing further restricts the practical implications of the results. Moreover, while the framework assumes ideal battery behavior and controlled environmental parameters, these simplifications may not reflect real-world IoT conditions.

It is important to recognize that the effectiveness of any metaheuristic algorithm is highly dependent on application-specific requirements. Thus, while QHBM shows promise for tactical IoT contexts, Future research will focus on deploying the QHBM algorithm on real IoT hardware platforms through field trials to evaluate its responsiveness and adaptability under mission-critical operational conditions. This includes testing in real-time environments such as disaster response and search-and-rescue scenarios, where energy demands are highly dynamic and time-sensitive.

In addition, future work will explore the integration of QHBM with machine learning (ML) models for predictive energy management, enabling IoT systems to forecast energy consumption patterns and adapt optimization strategies accordingly. Hybrid approaches combining QHBM with reinforcement learning or federated learning may further enhance scalability and autonomy in distributed networks. These directions aim to extend the applicability of QHBM beyond simulation and into robust, intelligent control systems for real-world tactical deployments.

REFERENCES

[1] N. B. Gaikwad, H. Ugale, A. Keskar, and N. C. Shivaprakash, “The Internet-of-Battlefield-Things (IoBT)-Based Enemy Localization Using Soldiers Location and Gunshot Direction,” *IEEE Internet Things J.*, vol. 7, no. 12, pp. 11725–11734, Dec. 2020, doi: 10.1109/JIOT.2020.2999542.

[2] B. Mostafa, M. Molnar, M. Saleh, A. Benslimane, and S. Kassem, “Optimal proactive monitor placement & scheduling for IoT networks,” *J. Oper. Res. Soc.*, vol. 73, no. 11, pp. 2431–2450, Nov. 2022, doi: 10.1080/01605682.2021.1992310.

[3] Aripriharta and G. J. Horng, “A New Defect Diameter Prediction using Heart Sound and Possibility to Implement as IoT Healthcare,” *Mob. Networks Appl.*, vol. 28, no. 6, p. 2076, Dec. 2023, doi: 10.1007/S11036-023-02201-y.

[4] S. R. Lalani, A. A. M. Salehi, H. Taghizadeh, B. Safaei, A. M. H. Monazzah, and A. Ejlali, “REFER: A Reliable and Energy-Efficient RPL for Mobile IoT Applications,” in *2020 CSI/CPSSI International Symposium on Real-Time and Embedded Systems and Technologies (RTEST)*, pp. 1–8, 2020, doi: 10.1109/RTEST49666.2020.9140135.

[5] J. Wang, Y. Gao, W. Liu, A. K. Sangaiah, and H.-J. Kim, “Energy Efficient Routing Algorithm with Mobile Sink Support for Wireless Sensor Networks,” *Sensors*, vol. 19, no. 7, p. 1494, Mar. 2019, doi: 10.3390/s19071494.

[6] C. Fathy and S. N. Saleh, “Integrating Deep Learning-Based IoT and Fog Computing with Software-Defined Networking for Detecting Weapons in Video Surveillance Systems,” *Sensors*, vol. 22, no. 14, p. 5075, Jul. 2022, doi: 10.3390/S22145075.

[7] H. Zhou, F. Hu, M. Juras, A. B. Mehta, and Y. Deng, “Real-Time Video Streaming and Control of Cellular-Connected UAV System: Prototype and Performance Evaluation,” *IEEE Wirel. Commun. Lett.*, vol. 10, no. 8, pp. 1657–1661, Aug. 2021, doi: 10.1109/LWC.2021.3076415.

[8] M. D. Phung and Q. P. Ha, “Motion-encoded particle swarm optimization for moving target search using UAVs,” *Appl. Soft Comput.*, vol. 97, p. 106705, Dec. 2020, doi: 10.1016/j.asoc.2020.106705.

[9] A. Rajasekhar, N. Lynn, S. Das, and P. N. Suganthan, “Computing with the collective intelligence of honey bees – A survey,” *Swarm Evol. Comput.*, vol. 32, pp. 25–48, Feb. 2017, doi: 10.1016/j.swevo.2016.06.001.

[10] L. S. Kumar, S. Ahmad, S. Routray, A. V. Prabu, A. Alharbi, B. Alouffi, and S. Rajasoundaran, “Modern Energy Optimization Approach for Efficient Data Communication in IoT-Based Wireless Sensor Networks,” *Wirel. Commun. Mob. Comput.*, vol. 2022, pp. 1–13, Apr. 2022, doi: 10.1155/2022/7901587.

[11] K. Haseeb, A. Almogren, N. Islam, I. Ud Din, and Z. Jan, “An energy-efficient and secure routing protocol for intrusion avoidance in IoT-based WSN,” *Energies*, vol. 12, no. 21, p. 4174, 2019, doi: 10.3390/en12214174.

[12] P. S. Mann and S. Singh, “Improved artificial bee colony metaheuristic for energy-efficient clustering in wireless sensor networks,” *Artif. Intell. Rev.*, vol. 51, no. 3, pp. 329–354, Mar. 2019, doi: 10.1007/s10462-017-9564-4.

[13] H. Wang, W. Wang, S. Xiao, Z. Cui, M. Xu, and X. Zhou, “Improving artificial Bee colony algorithm using a new neighborhood selection mechanism,” *Inf. Sci. (Ny).*, vol. 527, pp. 227–240, Jul. 2020, doi: 10.1016/j.ins.2020.03.064.

[14] B. Shi, L. Huang, and R. Shi, “Pricing in the Competing Auction-Based Cloud Market: A Multi-agent Deep Deterministic Policy Gradient Approach,” in *Service-Oriented Computing*, pp. 175–186, 2020, doi: 10.1007/978-3-030-65310-1_14.

[15] A. Aripriharta, W. Z. Hao, Muladi, G.-J. Horng, and G.-J. Jong, “A New Bio-Inspired for Cooperative Data Transmission of IoT,” *IEEE Access*, vol. 8, pp. 161884–161893, 2020, doi: 10.1109/ACCESS.2020.3021507.

[16] R. Kaviarasan, G. Balamurugan, R. Kalaiyarasan and V. R. R. Yarasu, “Effective load balancing approach in cloud computing using Inspired Lion Optimization Algorithm,” *e-Prime - Adv. Electr. Eng. Electron. Energy*, vol. 6, p. 100326, Dec. 2023, doi: 10.1016/j.prime.2023.100326.

[17] A. Aripriharta *et al*., “Queen honey bee migration (QHBM) optimization for droop control on DC microgrid under load variation,” *J. Mechatronics, Electr. Power, Veh. Technol.*, vol. 15, no. 1, pp. 12–22, Jul. 2024, doi: 10.55981/j.mev.2024.742.

[18] G. J. Jong, A. Aripriharta, Hendrick, and G. J. Horng, “A Novel Queen Honey Bee Migration (QHBM) Algorithm for Sink Repositioning in Wireless Sensor Network,” *Wirel. Pers. Commun.*, vol. 95, no. 3, pp. 3209–3232, Aug. 2017, doi: 10.1007/S11277-017-3991-Z/METRICS.

[19] K. H. Wibowo, I. Fadlika, Muladi, N. Mufti, M. Diantoro, and G. J. Horng, “The Performance of a New Heuristic Approach for Tracking Maximum Power of PV Systems,” *Appl. Comput. Intell. Soft Comput.*, vol. 2022, pp. 1–13, Nov. 2022, doi: 10.1155/2022/1996410.

[20] S. Bebortta, S. S. Tripathy, U. M. Modibbo, and I. Ali, “An optimal fog-cloud offloading framework for big data optimization in heterogeneous IoT networks,” *Decis. Anal. J.*, vol. 8, p. 100295, Sep. 2023, doi: 10.1016/j.dajour.2023.100295.

[21] D. Irmanto, S. Sujito, A. Aripriharta, D. Widiatmoko, K. Kasiyanto, and S. Omar, “Optimizing the Personnel Position Monitoring System Using the Global Positioning System in Hostage Release,” *INTENSIF J. Ilm. Penelit. dan Penerapan Teknol. Sist. Inf.*, vol. 8, no. 1, pp. 91–107, Feb. 2024, doi: 10.29407/intensif.v8i1.21665.

[22] B. Safaei, A. M. H. Monazzah, and A. Ejlali, “ELITE: An Elaborated Cross-Layer RPL Objective Function to Achieve Energy Efficiency in Internet-of-Things Devices,” *IEEE Internet Things J.*, vol. 8, no. 2, pp. 1169–1182, Jan. 2021, doi: 10.1109/JIOT.2020.3011968.

[23] A. Taneja, N. Saluja, N. Taneja, A. Alqahtani, M. A. Elmagzoub, A. Saikh, and D. Koundal, “Power Optimization Model for Energy Sustainability in 6G Wireless Networks,” *Sustainability*, vol. 14, no. 12, p. 7310, Jun. 2022, doi: 10.3390/su14127310.

[24] J. Caballero, O. Perez-Mon, M. D. R-Moreno, and J. de O. Filho, “Integral AI-based planning for management of WSNs in military operations,” in *2023 IEEE 35th International Conference on Tools with Artificial Intelligence (ICTAI)*, pp. 341–348, 2023, doi: 10.1109/ICTAI59109.2023.00056.

[25] P. S. Brar, B. Shah, J. Singh, F. Ali, and D. Kwak, “Using Modified Technology Acceptance Model to Evaluate the Adoption of a Proposed IoT-Based Indoor Disaster Management Software Tool by Rescue Workers,” *Sensors*, vol. 22, no. 5, p. 1866, Feb. 2022, doi: 10.3390/S22051866.

[26] N. Temene, A. Naoum, C. Sergiou, C. Georgiou, and V. Vassiliou, “A Decentralized Node Placement Algorithm for WSNs and IoT Networks,” in *2022 IEEE 8th World Forum on Internet of Things (WF-IoT)*, pp. 1–6, 2022, doi: 10.1109/WF-IoT54382.2022.10152262.

[27] X. Yu, K. Ergun, X. Song, L. Cherkasova, and T. Š. Rosing, “Automating and Optimizing Reliability-Driven Deployment in Energy-Harvesting IoT Networks,” *IEEE Trans. Netw. Serv. Manag.*, vol. 20, no. 1, pp. 787–799, Mar. 2023, doi: 10.1109/TNSM.2022.3208083.

[28] A. R. Grubb, S. J. Brown, P. Hall, and E. Bowen, “‘There’s nothing that compares to it’: a grounded theoretical analysis of the experiences of police hostage and crisis negotiators,” *Int. J. Confl. Manag.*, vol. 30, no. 3, pp. 369–394, Jun. 2019, doi: 10.1108/IJCMA-01-2019-0003.

[29] S. Zhang and S. Liu, “A Discrete Improved Artificial Bee Colony Algorithm for 0–1 Knapsack Problem,” *IEEE Access*, vol. 7, pp. 104982–104991, 2019, doi: 10.1109/ACCESS.2019.2930638.

[30] R. Vijayashree and C. S. G. Dhas, “Energy efficient data collection with multiple mobile sink using artificial bee colony algorithm in large-scale WSN,” *Automatika*, vol. 60, no. 5, pp. 555–563, Nov. 2019, doi: 10.1080/00051144.2019.1666548.

[31] G.-J. Jong, Z.-H. Wang, Hendrick, K.-S. Hsieh, and G.-J. Horng, “A Novel Adaptive Optimization of Intragrated Network Topology and Transmission Path for IoT System,” *IEEE Sens. J.*, vol. 19, no. 15, pp. 6452–6459, Aug. 2019, doi: 10.1109/JSEN.2019.2908702.

[32] Y. Zhang and D. Xin, “Dynamic Optimization Long Short-Term Memory Model Based on Data Preprocessing for Short-Term Traffic Flow Prediction,” *IEEE Access*, vol. 8, pp. 91510–91520, 2020, doi: 10.1109/ACCESS.2020.2994655.

[33] D. Pilakkat and S. Kanthalakshmi, “An improved P&O algorithm integrated with artificial bee colony for photovoltaic systems under partial shading conditions,” *Sol. Energy*, vol. 178, pp. 37–47, Jan. 2019, doi: 10.1016/j.solener.2018.12.008.

[34] A. Jaiswal, P. Kashyap, and S. Kumar, “Green Communication: Optimal Charger Deployment based on TBM (OCD-TBM) in IoT,” in *2021 IEEE 4th International Conference on Computing, Power and Communication Technologies (GUCON)*, pp. 1–6, 2021, doi: 10.1109/GUCON50781.2021.9573775.

[35] D. Vorobyova *et al*., “IoT Network Model with Multimodal Node Distribution and Data-Collecting Mechanism Using Mobile Clustering Nodes,” *Electronics*, vol. 12, no. 6, p. 1410, Mar. 2023, doi: 10.3390/electronics12061410.

[36] A. Sebastian and S. Sivagurunathan, “Load balancing optimization for rpl based emergency response using q-learning,” *MATTER Int. J. Sci. Technol.*, vol. 4, no. 2, pp. 74–92, Aug. 2018, doi: 10.20319/mijst.2018.42.7492.

[37] C. Dudeja, “Fuzzy-based modified particle swarm optimization algorithm for shortest path problems,” *Soft Comput.*, vol. 23, no. 17, pp. 8321–8331, Sep. 2019, doi: 10.1007/s00500-019-04112-1.

[38] A. Afzal and M. K. Ramis, “Multi-objective optimization of thermal performance in battery system using genetic and particle swarm algorithm combined with fuzzy logics,” *J. Energy Storage*, vol. 32, p. 101815, Dec. 2020, doi: 10.1016/j.est.2020.101815.

[39] B. Jones, A. Tang, and C. Neustaedter, “Remote Communication in Wilderness Search and Rescue,” in *Proceedings of the ACM on Human-Computer Interaction*, pp. 1–26, 2020, doi: 10.1145/3375190.

[40] V. Soković and G. Marković, “Internet of Things in military applications,” *Vojnoteh. Glas.*, vol. 71, no. 4, pp. 1148–1171, 2023, doi: 10.5937/vojtehg71-46785.

[41] X. Xiong, K. Zheng, L. Lei, and L. Hou, “Resource Allocation Based on Deep Reinforcement Learning in IoT Edge Computing,” *IEEE J. Sel. Areas Commun.*, vol. 38, no. 6, pp. 1133–1146, Jun. 2020, doi: 10.1109/JSAC.2020.2986615.

[42] Y. Liu, M. G. M. Johar, and A. I. Hajamydeen, “IoT-Based Real Time Greenhouse Monitoring and Controlling System,” *ITEGAM- J. Eng. Technol. Ind. Appl.*, vol. 10, no. 48, pp. 1–7, 2024, doi: 10.5935/jetia.v10i48.895.

[43] M. Tortonesi, K. Wrona, and N. Suri, “Secured Distributed Processing and Dissemination of Information in Smart City Environments,” *IEEE Internet Things Mag.*, vol. 2, no. 2, pp. 38–43, Jun. 2019, doi: 10.1109/IOTM.001.1900019.

[44] B. Mostafa, M. Molnar, M. Saleh, A. Benslimane, and S. Kassem, “Dynamic Distributed Monitoring for 6LoWPAN-based IoT Networks,” *Infocommunications J.*, vol. 15, no. 1, pp. 64–76, 2023, doi: 10.36244/ICJ.2023.1.7.

[45] J. Yao, X. Li, Y. Zhang, J. Ji, Y. Wang, and Y. Liu, “Path Planning of Unmanned Helicopter in Complex Environment Based on Heuristic Deep Q-Network,” *Int. J. Aerosp. Eng.*, vol. 2022, pp. 1–15, Jun. 2022, doi: 10.1155/2022/1360956.

[46] K. V Osintsev, I. S. Prikhodko, D. P. Korabelnikova, and D. I. Nikitina, “Implementation of neural network algorithms for solving the problem of heat supply regulation,” *IOP Conf. Ser. Earth Environ. Sci.*, vol. 868, no. 1, p. 12019, Oct. 2021, doi: 10.1088/1755-1315/868/1/012019.

[47] M. Stute, P. Agarwal, A. Kumar, A. Asadi, and M. Hollick, “LIDOR: A Lightweight DoS-Resilient Communication Protocol for Safety-Critical IoT Systems,” *IEEE Internet Things J.*, vol. 7, no. 8, pp. 6802–6816, Aug. 2020, doi: 10.1109/JIOT.2020.2985044.

[48] Y. Guo, R. Jena, D. Hughes, M. Lewis, and K. Sycara, “Transfer learning for human navigation and triage strategies prediction in a simulated urban search and rescue task,” in *2021 30th IEEE International Conference on Robot and Human Interactive Communication, RO-MAN 2021*, pp. 784–791, 2021, doi: 10.1109/RO-MAN50785.2021.9515526.

[49] N. Passalis and A. Tefas, “Global Adaptive Input Normalization for Short-Term Electric Load Forecasting,” in *2020 IEEE Symposium Series on Computational Intelligence, SSCI 2020*, pp. 871–875, 2020, doi: 10.1109/SSCI47803.2020.9308553.

[50] Y. Yue, L. Cao, and Z. Luo, “Hybrid Artificial Bee Colony Algorithm for Improving the Coverage and Connectivity of Wireless Sensor Networks,” *Wirel. Pers. Commun.*, vol. 108, no. 3, pp. 1719–1732, Oct. 2019, doi: 10.1007/s11277-019-06492-x.

[51] A. F. Mirza *et al*., “Generalized Regression Neural Network and Fitness Dependent Optimization: Application to energy harvesting of centralized TEG systems,” *Articles*, vol. 8, pp. 6332–6346, Jan. 2022, doi: 10.1016/j.egyr.2022.05.003.

[52] K. H. Wibowo, A. Aripriharta, I. Fadlika, G. J. Horng, S. Wibawanto, and F. W. Y. Saputra, “A New MPPT based on Queen Honey Bee Migration (QHBM) in Stand-alone Photovoltaic,” in *IEEE International Conference on Automatic Control and Intelligent Systems, I2CACIS 2019*, pp. 123–128, 2019, doi: 10.1109/I2CACIS.2019.8825025.

[53] M. Shirbeigi, B. Safaei, A. Mohammadsalehi, A. M. H. Monazzah, J. Henkel, and A. Ejlali, “A Cluster-Based and Drop-aware Extension of RPL to Provide Reliability in IoT Applications,” in *2021 IEEE International Systems Conference (SysCon)*, pp. 1–7, 2021, doi: 10.1109/SysCon48628.2021.9447112.

[54] Z. Fan, “Nodes Deployment Method across Specific Zone of NB-IoT Based Heterogeneous Wireless Sensor Networks,” in *2020 12th International Conference on Communication Software and Networks (ICCSN)*, pp. 149–152, 2020, doi: 10.1109/ICCSN49894.2020.9139062.

[55] A. K. Sangaiah, A. A. R. Hosseinabadi, M. B. Shareh, S. Y. B. Rad, A. Zolfagharian, and N. Chilamkurti, “IoT Resource Allocation and Optimization Based on Heuristic Algorithm,” *Sensors*, vol. 20, no. 2, p. 539, Jan. 2020, doi: 10.3390/S20020539.

[56] J. L. G. Gross and C. F. F. R. Geyer, “A cost efficient model for minimizing energy consumption and processing time for IoT tasks in a Mobile Edge Computing environment,” in *Anais do Simpósio Brasileiro de Computação Ubíqua e Pervasiva (SBCUP 2020)*, pp. 41–50, 2020, doi: 10.5753/sbcup.2020.11210.

[57] H. Ohno, “Training data augmentation: An empirical study using generative adversarial net-based approach with normalizing flow models for materials informatics,” *Appl. Soft Comput.*, vol. 86, p. 105932, Jan. 2020, doi: 10.1016/j.asoc.2019.105932.

[58] D. Volgushev and G. Fokin, “Link Level Simulation Model for Vehicles with Location-Aware Beamforming in 5G mm Wave Ultra-Dense Networks,” in *2023 Intelligent Technologies and Electronic Devices in Vehicle and Road Transport Complex (TIRVED)*, pp. 1–7, 2023, doi: 10.1109/TIRVED58506.2023.10332675.

[59] A. Aripriharta *et al*., “Comparison of queen honey bee colony migration with various MPPTs on photovoltaic system under shaded conditions,” *EUREKA Phys. Eng.*, no. 4, pp. 52–62, Jul. 2023, doi: 10.21303/2461-4262.2023.002836.

[60] M. Muladi *et al*., “A new battery management system for self-powered smart shoes,” in *Renewable Energy and Its Applications*, p. 20005, 2020, doi: 10.1063/5.0001041.

[61] M. Collotta, G. Pau, G. Tesoriere, and S. Tirrito, “Intelligent shoe system: A self-powered wearable device for personal localization,” in *AIP Conference Proceedings*, 2015, doi: 10.1063/1.4912984/589833.

[62] M. Y. Shams, T. A. E. Hafeez, and E. Hassan, “Acoustic data detection in large-scale emergency vehicle sirens and road noise dataset,” *Expert Syst. Appl.*, vol. 249, p. 123608, Sep. 2024, doi: 10.1016/J.ESWA.2024.123608.

[63] Y. Zhou, A. Ravey, and M. C. Péra, “Real-time cost-minimization power-allocating strategy via model predictive control for fuel cell hybrid electric vehicles,” *Energy Convers. Manag.*, vol. 229, p. 113721, Feb. 2021, doi: 10.1016/J.ENCONMAN.2020.113721.

[64] Y. Hu, Y. Zhang, C. Xu, L. Lin, R. L. Snyder, and Z. L. Wang, “Self-powered system with wireless data transmission,” *Nano Lett.*, vol. 11, no. 6, pp. 2572–2577, Jun. 2011.

[65] S. Aebischer Perone, F. Althaus, F. Chappuis, N. Aguirre Zimerman, E. Martinez, and S. Regel, “Psychological Support Post-Release of Humanitarian Workers Taken Hostage: The Experience of the International Committee of the Red Cross (ICRC),” *Br. J. Guid. Counc.*, vol. 48, no. 3, pp. 360–373, May 2020, doi: 10.1080/03069885.2018.1461193.

[66] T. He, K.-W. Chin, S. Soh, C. Yang, and J. Wen, “On Maximizing Max–Min Source Rate in Wireless-Powered Internet of Things,” *IEEE Internet Things J.*, vol. 7, no. 11, pp. 11276–11289, Nov. 2020, doi: 10.1109/JIOT.2020.2997042.

[67] A. M. Elsergany, A. A. Hussein, A. Wadi, and M. F. Abdel-Hafez, “An Adaptive Autotuned Polynomial-Based Extended Kalman Filter for Sensorless Surface Temperature Estimation of Li-Ion Battery Cells,” *IEEE Access*, vol. 10, pp. 14038–14048, 2022, doi: 10.1109/ACCESS.2022.3148281.

[68] N. Kolokotronis, K. Limniotis, S. Shiaeles, and R. Griffiths, “Secured by Blockchain: Safeguarding Internet of Things Devices,” *IEEE Consum. Electron. Mag.*, vol. 8, no. 3, pp. 28–34, May 2019, doi: 10.1109/MCE.2019.2892221.

[69] C. A. Kumar, S. Ajmera, B. Kumar, D. Srikar, S. V. S. Prasad, and J. R. Datta, “Real-time Embedded Electronics using Wireless Connection for Soldier Security,” in *2022 International Conference on Advancements in Smart, Secure and Intelligent Computing (ASSIC)*, pp. 1–5, 2022, doi: 10.1109/ASSIC55218.2022.10088309.

[70] D. J. Neller, T. C. Healy, T. K. Dao, S. Meyer, and D. B. Barefoot, “Situational Predictors of Negotiation and Violence in Hostage and Barricade Incidents,” *Crim. Justice Behav.*, vol. 48, no. 12, pp. 1770–1787, May 2021, doi: 10.1177/00938548211017926.

[71] W. Lardier, Q. Varo, and J. Yan, “Dynamic Reduced-Round Cryptography for Energy-Efficient Wireless Communication of Smart

IoT Devices," in *ICC 2020 - 2020 IEEE International Conference on Communications (ICC)*, pp. 1–7, 2020, doi: 10.1109/ICC40277.2020.9149305.

[72] K. Ergun, X. Yu, N. Nagesh, L. Cherkasova, P. Mercati, R. Ayoub and T. Rosing, "RelIoT: Reliability Simulator for IoT Networks," in *Internet of Things - ICIOT 2020. ICIOT 2020*, pp. 63–81, 2020, doi: 10.1007/978-3-030-59615-6_5.

[73] K. A. Severson *et al.*, "Data-driven prediction of battery cycle life before capacity degradation," *Nat. Energy*, vol. 4, no. 5, pp. 383–391, Mar. 2019, doi: 10.1038/s41560-019-0356-8.

[74] S. Motahhir, A. Chouder, A. E. Hammoumi, A. S. Benyoucef, A. E. Ghzizal and S. Kichou, "Optimal Energy Harvesting From a Multistrings PV Generator Based on Artificial Bee Colony Algorithm," *IEEE Syst. J.*, vol. 15, no. 3, pp. 4137–4144, Sep. 2021, doi: 10.1109/JSYST.2020.2997744.

[75] C. Restrepo, N. Yanẽz-Monsalvez, C. González-Castaño, S. Kouro, and J. Rodriguez, "A Fast Converging Hybrid MPPT Algorithm Based on ABC and P&O Techniques for a Partially Shaded PV System," *Mathematics*, vol. 9, no. 18, p. 2228, Sep. 2021, doi: 10.3390/math9182228.

[76] J. J. E. Lopez, A. Abuellil, A. C. Reyes, M. Abouzied, S. Yoon, and E. S. Sinencio, "A Fully Integrated Maximum Power Tracking Combiner for Energy Harvesting IoT Applications," *IEEE Trans. Ind. Electron.*, vol. 67, no. 4, pp. 2744–2754, Apr. 2020, doi: 10.1109/TIE.2019.2907449.

[77] W. A. Siddique, M. F. Siddiqui, A. K. Jumani, W. Hyder, and A. A. Abro, "Big data analytics for 6G-enabled massive internet of things," in *Low-Power Wide Area Network for Large Scale Internet of Things*, pp. 177–202, 2024, doi: 10.1201/9781003426974-10.

[78] I. D. D. Martin, D. Pasqualotto, and F. Tinazzi, "aVsIs: An Analytical-Solution-Based Solver for Model-Predictive Control With Hexagonal Constraints in Voltage-Source Inverter Applications," *IEEE Trans. Power Electron.*, vol. 37, no. 12, pp. 14375–14383, Dec. 2022, doi: 10.1109/TPEL.2022.3193807.

[79] G. R, R. Shankar, and S. Duraisamy, "Resource Utilization Prediction with Multipath Traffic Routing for Congestion-aware VM Migration in Cloud Computing," *SSRN Electron. J.*, 2020, doi: 10.2139/ssrn.3744590.

[80] I. Ebrahimi, R. de Castro, V. Tran, A. Stefanopoulou, and S. Feng, "Emergency Battery Discharge under Safety Constraints using Optimization-based Controllers," in *2024 American Control Conference (ACC)*, pp. 3498–3503, 2024, doi: 10.23919/ACC60939.2024.10644396.