

Article

To design and implement the QoS -Aware Energy Efficient Routing Mechanism for the BAN-IoT networks in Smart Health care Applications.

Babu N.V ¹ , Abhinav Kumar ² and J. Joshua Thomas³

¹ Department of Electronics and Communication Engineering, SJB Institute of Technology, Bangalore, India

² Department of Nuclear and Renewable Energy, Ural Federal University Named after the First President of Russia Boris Yeltsin, Ekaterinburg 620002, Russia

³ UOW Malaysia KDU Penang University College, 32 Jalan Anson, 10400 George Town, Penang, Malaysia

*Corresponding author: Babu N.V (email: nvbabu@sjbit.edu.in)

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Abstract: The integration of Internet of Things (IoT) and miniature implantable sensors has significantly advanced Body Area Networks (BAN) for real-time monitoring of patients' physiological vital signs, including Electrocardiogram (ECG), Electromyogram (EMG), and Electroencephalogram (EEG). However, the limited bandwidth of wearable nodes and frequent body movements result in recurrent topological changes, causing unreliable and delayed transmissions. To address these challenges, a reliable and low-latency routing mechanism is required to ensure lossless data transfer and support timely clinical treatments. This paper proposes a QoS-aware routing protocol that dynamically calculates optimal routing paths by integrating Chaotic Theory with the Honey Badger Optimization (HBO) algorithm. The proposed protocol selects latency-aware, energy-efficient paths using key metrics such as Link Quality Factor (LQF), Distance (D), Received Signal Strength Indicator (RSSI), and Number of Hops (NoH) to achieve reliable and efficient data transmission. Comprehensive experiments are conducted in the Python 3.9 environment, and performance metrics including Packet Delivery Ratio (PDR), End-to-End Delay, Throughput, Routing Load, and Control Packet Overhead are calculated and compared with other existing optimization models. The proposed model is also statistically validated against state-of-the-art protocols. Results demonstrate superior performance and stability, effectively overcoming existing bottlenecks and providing improved QoS for IoT-enabled BAN systems in smart healthcare applications.

Keywords: Body Area Networks (BAN), QoS-aware routing, Honey Badger Optimization (HBO), Routing Load, Control Packet Overhead, smart healthcare.

1. Introduction

The rapid advancements in healthcare technologies have ushered in a new era of innovation through the integration of Internet of Things (IoT) and miniature implantable sensors. These innovations have significantly enhanced Body Area Networks (BAN), enabling real-time monitoring of patients' physiological vital signs such as Electrocardiogram (ECG), Electromyogram (EMG), and Electroencephalogram (EEG) [1]. Such advancements are vital for providing continuous, precise, and proactive healthcare monitoring, which can improve clinical decision-making and patient outcomes. However, the unique challenges posed by BAN-IoT networks, such as constrained energy resources, limited bandwidth, and frequent topological changes due to body movements, necessitate the design of robust and efficient communication mechanisms.

One of the primary challenges in BAN-IoT systems is ensuring Quality of Service (QoS) while maintaining energy efficiency [2-3]. In healthcare applications, the reliability of transmitted data and minimal latency are crucial for timely clinical interventions. Loss or delay in the transmission of critical health data can lead to serious consequences, underscoring the importance of an optimized routing mechanism [4-5]. Traditional routing protocols often fail to address the dynamic and resource-constrained nature of BAN-IoT networks, which leads to increased delays, reduced data reliability, and inefficient energy utilization.

To address these challenges, researchers have focused on developing QoS-aware and energy-efficient routing protocols [6]. Such protocols aim to optimize key parameters, including Packet Delivery Ratio (PDR), End-to-End Delay, Throughput, and Energy Consumption. The need for a dynamic and intelligent approach has led to the exploration of bio-inspired optimization algorithms [7]. These algorithms, inspired by natural phenomena, offer robust solutions to complex multi-objective optimization problems in BAN-IoT networks.

This study introduces a novel routing mechanism that integrates Chaotic Theory with the Honey Badger Optimization (HBO) algorithm to achieve both QoS and energy efficiency in BAN-IoT networks for smart healthcare applications [8-9]. The HBO algorithm, inspired by the foraging behavior of honey badgers, is known for its strong exploration and exploitation capabilities. Combined with Chaotic Theory, the proposed method dynamically adapts to the changing network topology and selects the optimal routing paths [10]. The key metrics considered in this routing protocol include Link Quality Factor (LQF), Distance (D), Received Signal Strength Indicator (RSSI), and Number of Hops (NoH).

The implementation and evaluation of the proposed protocol are conducted in a Python 3.9 environment, where its performance is benchmarked against state-of-the-art routing protocols. The performance metrics, including Routing Load and Control Packet Overhead, are analyzed to validate the efficiency and reliability of the proposed mechanism [11]. The experimental results demonstrate that the proposed protocol outperforms existing solutions, ensuring lossless data transmission and stable network performance.

The remainder of this paper is structured as follows. Section II reviews the existing literature on QoS-aware and energy-efficient routing protocols in BAN-IoT networks [12].

In summary, this work highlights the significance of a QoS-aware, energy-efficient routing mechanism for BAN-IoT networks in smart healthcare. By addressing the critical challenges of reliability and latency, this study aims to advance the capabilities of IoT-enabled healthcare systems and set a benchmark for future research in the field.

1.1 Contribution of the Research

1. The research introduces a novel QoS-aware routing mechanism that integrates the Honey

Badger Optimization (HBO) algorithm with Chaotic Theory to dynamically select energy-efficient and latency-aware routing paths in BAN-IoT networks for smart healthcare applications.

2. The proposed algorithm is rigorously compared against state-of-the-art optimization-based routing protocols, focusing on key QoS metrics to demonstrate its superiority in achieving reliable and efficient data transmission.
3. Comprehensive experiments are performed using simulated BAN-IoT environments, with performance metrics such as Packet Delivery Ratio (PDR), End-to-End Delay, Throughput, Routing Load, and Control Packet Overhead calculated to validate the effectiveness of the proposed approach.

1.2 Structure of the Paper

This manuscript is structured as follows: Section 2 reviews the related work and existing studies on QoS-aware and energy-efficient routing protocols in BAN-IoT networks. Section 3 provides an overview of the Honey Badger Optimization (HBO) algorithm, Chaotic Theory, and the key metrics used for routing, along with a detailed explanation of the proposed QoS-aware routing mechanism. Section 4 describes the experimental setup, including the simulation environment and performance metrics, and presents an in-depth analysis of the experimental results. Finally, Section 5 concludes the study and discusses potential future research directions for enhancing BAN-IoT networks in smart healthcare applications.

2. Related Works

Al-Sofi et al. (2024) [13] conducted a comparative study on the communication efficiency and energy optimization of IEEE 802.15.6 and LoRaWAN technologies in wireless body area networks (WBANs) for healthcare. WBANs play a crucial role in real-time health monitoring by continuously gathering and transmitting patient data, enabling timely medical interventions. The study employed NS3 simulations to evaluate six key performance metrics: throughput, arrival rate, delay, energy consumption, packet delivery ratio (PDR), and network lifetime under varying node densities. The findings highlighted that at a density of 50 nodes, IEEE 802.15.6 achieved superior throughput (45 kbps), higher PDR (30%), and a better arrival rate (0.33%) than LoRaWAN. However, LoRaWAN excelled in energy consumption (42 J), delay (7 s), and network lifetime (18 h). Despite its advantages, the study pointed out that IEEE 802.15.6 suffers from higher energy consumption and shorter network lifetime, while LoRaWAN faces limitations in throughput and PDR, making their application context-dependent.

Shah et al. (2024) [14] explored the security challenges and solutions in IoT-enabled smart healthcare systems, focusing on the vulnerabilities in healthcare equipment integrated within smart homes. Their study highlights how IoT devices can facilitate remote monitoring of patient health metrics, such as heart rate, blood pressure, and temperature, eliminating the need for physical hospital visits. The authors emphasize that while healthcare IoT applications can enhance patient outcomes and care quality, the interconnected nature of these devices introduces significant security and privacy risks. They identified vulnerabilities that could lead to data breaches, impacting both patient safety and data integrity. Although the study provides a systematic approach to ensuring privacy and security, a notable drawback is the lack of detailed, practical implementation strategies for addressing the highly heterogeneous environment of smart homes, which remains a challenge for both consumers and producers.

Karunkuzhali et al. (2024) [15] presented a QoS-aware routing approach tailored for IoT-enabled wireless sensor networks (WSNs) in smart cities, emphasizing environmentally friendly "green IoT" solutions. The study proposed a novel software architecture integrating Chaotic Bird

Swarm Optimization (CBSO) for sensor clustering and Improved Differential Search (IDS) for determining reliable cluster heads, alongside lightweight signcryption for data security and an Optimal Data Routing (ODM) mechanism for efficient data transmission. Performance evaluation using NS2 simulations demonstrated significant advantages over existing routing algorithms, achieving up to 90.8% reduced energy consumption, 66.8% extended network lifespan, and 80.1% lower latency. However, the study's reliance on NS2 simulations for validation may limit the real-world applicability of the findings, as practical implementation in diverse and dynamic smart city environments remains untested.

Rana et al. (2024) [16] proposed a priority-based energy-efficient metaheuristic routing approach for Smart Healthcare Systems (SHS) leveraging IoT advancements to shift traditional healthcare to telemedicine. Their study introduced a hybrid Duty-Cycled with Ant Colony Optimization Routing (DC-ACOP) mechanism, where body sensor nodes dynamically activate and deactivate communication units using duty cycling. Data packets were prioritized in the Type of Service (ToS) field to ensure critical patient data receives precedence during transmission. An improved Ant Colony Optimization (ACO) algorithm was employed to determine efficient routes, enhancing metrics such as residual energy, throughput, network lifetime, delay, packet delivery rate, and minimizing the number of non-alive nodes. However, the study focuses mainly on routing efficiency and does not address scalability issues in networks with a high density of nodes or the potential impact of interference in heterogeneous IoT environments.

Rahmani and Arefi (2024) [17] explored energy-efficient mechanisms for the cognitive Internet of Things (IoT) by employing learning automata to optimize network parameters dynamically. The study addresses the growing challenge of managing energy consumption in IoT devices, particularly in hard-to-access environments, where energy efficiency is critical for prolonged network operation. Their method adjusts the transmission power of network nodes in a self-aware and adaptive manner based on real-time network conditions, utilizing parameters such as delay, channel status, and data rate. This approach enhances Quality of Service (QoS) metrics like operational power and end-to-end delay while extending the network's lifespan. However, a significant drawback of the study lies in its limited scope of experimental scenarios, which may not comprehensively address diverse IoT environments or the scalability of the proposed mechanism in larger networks.

Hamoud H. Alshammari et al. (2023) [18] proposed a real-time remote patient monitoring system leveraging the Internet of Things (IoT) to address increasing healthcare demands in overpopulated nations. The system utilizes the Message Queuing Telemetry Transport (MQTT) protocol to transmit vital signals in real time to a web platform, ensuring the accuracy and reliability of health data. The study highlights the advantages of remote monitoring, including reduced training time and enhanced dependability of complex equipment. However, a notable drawback is the potential for network latency or interruptions, which may affect the consistent transmission of vital signals and limit the system's reliability in critical scenarios.

Younas et al. (2023) [19] conducted a systematic literature review on QoS monitoring in IoT edge-device-driven smart healthcare systems. The study emphasizes the transformative impact of integrating IoT, mobile, and cloud computing in healthcare, highlighting how cloud computing enhances connectivity among healthcare facilities, caregivers, and patients for seamless information sharing. The authors underline the critical role of low latency and faster response times in healthcare, particularly in emergency scenarios, where significant latency may lead to catastrophic outcomes. The paper identifies edge computing and AI as promising solutions to mitigate latency issues, ensuring improved QoS through parameters such as throughput, bandwidth, transmission delay, availability, jitter, latency, and packet loss. Their contribution includes a novel pre-SLR method for robust keyword research, an SLR on QoS improvements, a review of QoS techniques in smart healthcare, and solutions for QoS challenges. However, a drawback is the

limited practical validation of proposed solutions in real-world healthcare environments, which is essential for understanding the feasibility and scalability of these approaches.

Mehmood et al. (2023) [20] proposed an efficient Quality of Service (QoS)-based Multi-Path Routing (MPR) scheme to enhance the reliability and efficiency of Wireless Body Area Networks (WBANs) in healthcare monitoring. The study addresses critical challenges in WBANs, including network delays, unreliable data propagation, and bandwidth wastage caused by unwanted traffic. Their approach categorizes incoming traffic into normal and emergency types, prioritizing emergency data by routing it through the optimal path. The proposed MPR scheme demonstrated superior performance compared to state-of-the-art techniques, achieving improved energy efficiency, higher network throughput, lower packet drop ratio, enhanced packet delivery ratio, and reduced end-to-end delay. For instance, when processing 1000 data packets from eight bio-sensor nodes, the system successfully transmitted a maximum of 11,000 packets while minimizing the packet drop ratio to the Medical Server. Additionally, a fuzzy logic-based evaluation corroborated the scheme's efficiency. However, the study primarily focused on improving network metrics without addressing potential limitations, such as scalability to larger networks or the impact of diverse real-time medical conditions, which could influence the system's adaptability and reliability in varied healthcare scenarios.

Kuthe et al. (2023) [21] proposed a Bioinspired Routing Model with Fan Clustering (BRMFC) for Wireless Sensor Networks (WSNs) to address the critical need for power conservation in these networks. The model introduces a destination-aware Fan Shaped Clustering (FSC) approach, grouping nodes based on distance measures. This is combined with a Genetic Algorithm (GA)-based bioinspired routing mechanism to select optimal nodes for routing, considering residual energy and distance metrics. The proposed fitness function is lightweight, ensuring faster convergence and efficient routing paths. Evaluations across various network scales demonstrated improved Quality of Service (QoS) metrics, with a 5.9% reduction in power consumption, an 8.5% reduction in delay, a 2.5% increase in Packet Delivery Ratio (PDR), and a 10.5% increase in throughput. However, the study highlights that despite its advantages, the BRMFC model's dependency on GA may still require optimization to handle scalability efficiently in extremely large-scale networks.

Adil M et al. (2022) [22] conducted a comprehensive review on the Quality of Service (QoS) in the context of Internet of Medical Things (IoMT) applications during the COVID-19 pandemic. The authors highlighted the significant contributions of smart sensing technologies in healthcare, particularly in supporting IoMT applications to aid COVID-19 patients and mitigate the spread of the virus. While the effectiveness of these applications during the pandemic was acknowledged, the review pointed out that QoS metrics, which are crucial for ensuring the functionality and efficiency of IoMT systems, were often overlooked. The study provided a detailed assessment of QoS challenges faced by IoMT applications from 2019 to 2021, focusing on various network components and communication metrics. A key drawback identified in the existing literature is the insufficient emphasis on optimizing QoS in IoMT systems, which could improve their overall reliability, performance, and user experience. Additionally, the lack of standardized frameworks for QoS evaluation in IoMT applications limits the ability to make precise comparisons and improvements across different systems. The authors concluded by emphasizing the need for future research to address these challenges and improve QoS in IoMT, setting a foundation for advancing the effectiveness of smart sensing technologies in healthcare.

3. Proposed Methodology

The proposed Chaotic Honey Badger Optimization (CHBO)-based Routing Mechanism for BAN-IoT networks begins with Input Data Collection, which involves gathering real-time

physiological data from sensors, including ECG, EMG, and EEG readings. The Data Preprocessing stage ensures the data is cleaned, normalized, and structured to enhance the model's performance. The preprocessed data is then passed through the Chaotic Honey Badger Optimization framework, which leverages the exploratory efficiency of chaotic maps and the optimization capabilities of the Honey Badger algorithm to dynamically select energy-efficient and QoS-aware routing paths. Finally, an Efficiency Analysis is conducted to evaluate the proposed routing mechanism using key performance metrics, including Packet Delivery Ratio, End-to-End Delay, and Energy Consumption, ensuring the system's reliability and suitability for smart healthcare applications.

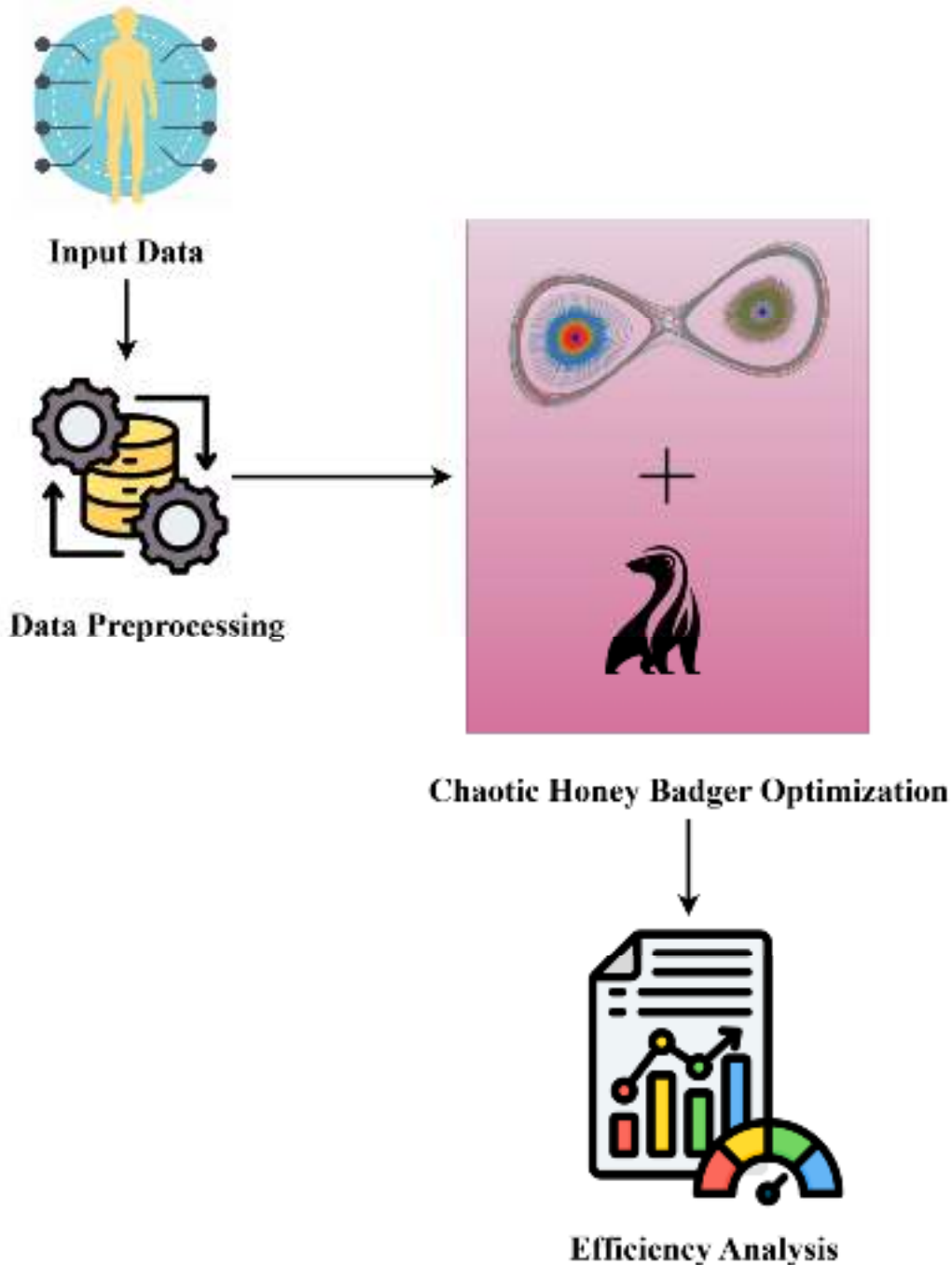


Figure 1 Chaotic Honey Badger Optimization-Based Routing Mechanism

3.1 Materials and Methods:

We simulate a BAN-IoT network environment tailored for smart healthcare applications. The simulation setup involves real-time physiological data, including ECG, EMG, and EEG, generated using synthetic data modelling techniques to mimic patient health monitoring scenarios. The dataset is designed to capture realistic network behaviour, incorporating key challenges such as dynamic topology changes, energy constraints, and varying signal strengths caused by body movements. The dataset includes a mix of normal and abnormal network conditions, such as packet loss, signal degradation, and congestion, to represent real-world BAN-IoT scenarios. The data is split into training and testing sets, ensuring a balanced representation of both stable and challenging network conditions, allowing for comprehensive performance evaluation of the proposed QoS-aware routing mechanism.

3.2 Data Preprocessing:

Before implementing the proposed routing mechanism, the input data undergoes preprocessing to ensure its suitability for the optimization algorithm:

Any missing or incomplete data in the input, such as RSSI values or node status, is handled using imputation techniques to maintain data integrity.

Key features like Distance (D), Link Quality Factor (LQF), and Received Signal Strength Indicator (RSSI) are normalized to a range between 0 and 1 using Min-Max scaling, ensuring uniform contribution to the routing decision process.

Categorical attributes, such as node types or status indicators, are encoded using label encoding to convert them into numerical values suitable for the optimization algorithm.

3.3 Proposed Model:

3.3.1 Honey Badger Algorithm:

The Honey Badger Algorithm (HBA) is a metaheuristic optimization algorithm inspired by the foraging behaviour of honey badgers, which are known for their tenacity, persistence, and ability to overcome various challenges. This algorithm is typically used to solve optimization problems, such as finding the best solution to a problem within a large search space.

Inspiration from Nature: The algorithm mimics the hunting and searching behaviour of honey badgers, which are capable of traversing vast areas in search of food while overcoming numerous obstacles.

Exploration and Exploitation: Like honey badgers searching for food, the algorithm strikes a balance between exploration (searching broadly across the solution space) and exploitation (focusing on areas that appear to yield the best results). This helps in avoiding local optima and finding more optimal solutions.

3.3.1.1 Steps in the Honey Badger Algorithm:

Initialization: Start by initializing a population of potential solutions randomly within the search space.

Fitness Evaluation: Each solution is evaluated based on its fitness, which is typically the objective function of the problem.

Exploration and Exploitation: The algorithm determines whether to explore a new region or exploit an existing promising area by using a mechanism that is analogous to the persistence of a honey badger when hunting.

Movement and Adjustment: If a solution is not optimal, the algorithm "adjusts" its direction by

exploring new regions of the search space, adapting its search based on previous encounters and obstacles.

Termination: The process continues until a stopping criterion is met, such as a maximum number of iterations or convergence to a sufficiently good solution.

The Honey Badger Algorithm is a robust optimization technique inspired by the real-world behaviours of honey badgers. It is especially useful in solving complex, large-scale optimization problems where other methods might fail to find the global optimum.

3.3.1.2 Initialization Phase:

In the initialization phase of the Honey Badger Algorithm (HBA), the algorithm is introduced by modeling the behavior of honey badgers. The population of honey badgers is represented by the matrix X , where N signifies the number of individuals (honey badgers) and D represents the dimensionality of the optimization problem. The matrix X thus contains the positions of all honey badgers in the search space, and it is mathematically represented as:

$$X = \begin{bmatrix} x_{11} & x_{12} & x_{13} & \dots & x_{1D} \\ x_{21} & x_{22} & x_{23} & \dots & x_{2D} \\ x_{31} & x_{32} & x_{33} & \dots & x_{3D} \\ \dots & \dots & \dots & \dots & \dots \\ x_{n1} & x_{n2} & x_{n3} & \dots & x_{nD} \end{bmatrix} \quad (1)$$

In quest algorithms, the initialization step of the HBA involves generating the initial population of honey badgers by randomly selecting their positions within the feasible search space. The position of each individual honey badger is defined by the following formula:

$$x_i = lb_i + r_1 \times (ub_i - lb_i) \quad (2)$$

Here, x_i represents the position of the i -th honey badger, r_1 is a random value drawn from a uniform distribution in the interval $[0, 1]$, while lb_i and ub_i are the lower and upper bounds of the search space for the i -th dimension. These bounds define the feasible range within which the honey badger can search for optimal solutions.

This initialization approach ensures that the honey badger population is evenly spread throughout the problem space, allowing the algorithm to effectively explore various regions of the search space. Over time, the population of honey badgers adapts and evolves through their interactions, mimicking the aggressive yet strategic behaviour of honey badgers in nature. This balance between exploration (searching new areas) and exploitation enables the algorithm to converge toward optimal or near-optimal solutions for complex optimization problems.

3.3.1.3 Small Intensity Definition:

Honey badgers use scent strength as a critical cue to locate their prey and food sources, relying on the intensity of the scent to guide them. The scent's intensity is not only influenced by the strength of the odour emitted by the prey but also by the distance between the honey badger and the target. As the honey badger moves closer to its prey, the scent grows stronger, which enhances its ability to accurately identify the prey's location. This increasing scent intensity allows the honey badger to approach its prey with greater precision and speed.

Honey badgers exhibit exceptional sensitivity to low-intensity scents, even when the prey's odour is faint. They are capable of detecting and following weak scents over long distances, relying on their keen olfactory sense to pick up the smallest trace of odour. As they get closer to the source, the scent's intensity gradually increases, helping the honey badger refine its search and move efficiently towards the prey. This ability to track faint scents over long distances demonstrates the

honey badger's resilience and resourcefulness, enabling it to successfully hunt in challenging environments where prey may be well-hidden or elusive. The connection between scent intensity and honey badger behavior is depicted in Figure 2.

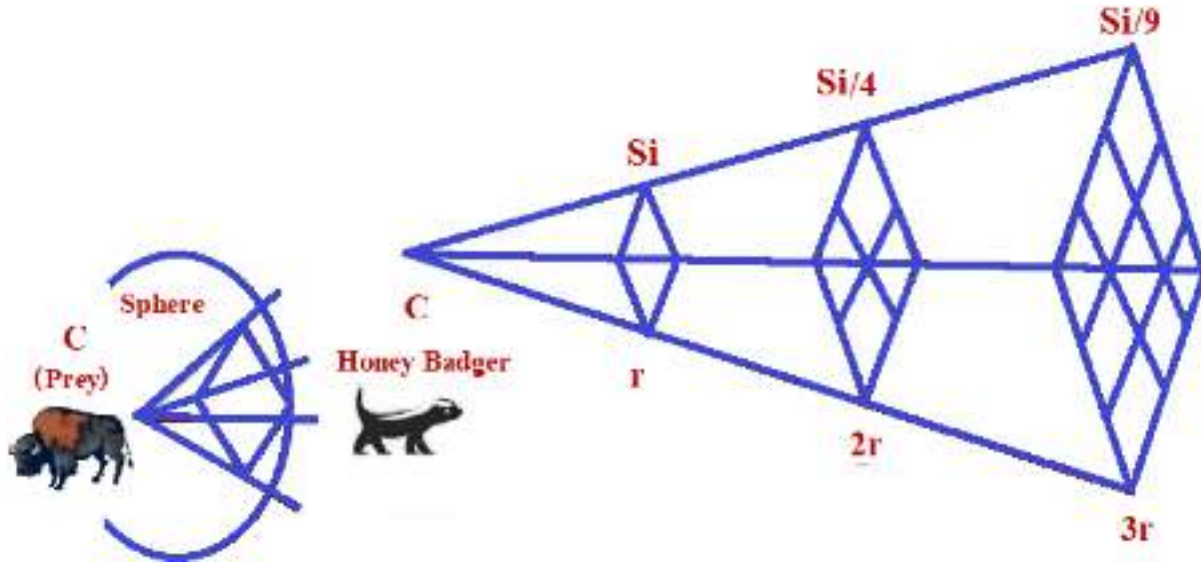


Figure 2 Distance Tuning for HBA

3.3.1.4 Density factor Updation:

In the Honey Badger Algorithm (HBA), the density factor plays a key role in introducing a dynamic, stochastic element that evolves over time. It is mathematically represented by the following equation:

$$\alpha = C \times \exp\left(\frac{-t}{t_{max}}\right) \quad (3)$$

Here, α represents the density factor, t is the current iteration, t_{max} is the maximum number of iterations, and C is a constant with a value of 1 or greater (commonly set to 2). The density factor begins with a high value at the start of the optimization process and gradually decreases as the algorithm progresses.

As the density factor decreases, it reduces the level of randomness in the algorithm, which in turn enhances its stability. This gradual reduction is essential for the transition from the exploration phase, where the algorithm is actively searching for optimal regions in the solution space, to the exploitation phase, where the focus shifts to fine-tuning and refining the search for more precise solutions. This balance between exploration and exploitation is crucial for the algorithm's efficiency and effectiveness.

In HBA, inspired by the foraging behaviour of honey badgers, the search agent's location is updated in two distinct phases, each with its own unique movement characteristics. The first phase is the "digging phase," where the honey badger actively searches and digs for prey, exhibiting exploratory behaviour. The second phase is the "honey phase," where the focus shifts to exploiting previously found food sources, representing a more focused, localized movement pattern. These two phases allow the algorithm to adapt dynamically, balancing broad exploration with refined exploitation as it seeks optimal solutions.

3.3.1.5 Digging Phase

During the digging phase, the honey badger uses its acute sense of smell to locate food sources, often dismantling hives in search of prey. Its movement typically follows a cardioid shape, and the position of the honey badger is updated according to the following equation:

$$x_{new} = x_{prey} + K \times \gamma \times S \times x_{prey} + K \times r_3 \times \delta \times d_i \times |\cos(2\pi r_4) \times [1 - \cos(2\pi r_5)]| \quad (4)$$

In this equation, x_{new} represents the updated position of the honey badger, and x_{prey} denotes the optimal position of its prey. The constant γ , set to a value greater than 1 (often 6), reflects the efficiency with which the honey badger can capture food. The parameters δ and d_i are determined by the previously mentioned equations for scent intensity and density factor, respectively.

The variables r_3 , r_4 , and r_5 are random numbers drawn from a uniform distribution within the range $[0, 1]$. The factor K is used to adjust the honey badger's hunting direction, and is defined as follows:

$$K = \begin{cases} 1 & \text{if } r_6 \leq 0.5 \\ -1 & \text{else} \end{cases} \quad (5)$$

Here, r_6 is another random variable, and its value determines whether the honey badger shifts its hunting direction based on the availability of food. If the honey badger encounters higher-quality prey, the search dynamics are influenced, and the movement is adjusted accordingly, mimicking the real-world foraging behaviour of honey badgers.

The scent intensity of the prey, the distance between the honey badger and its target, and the density factor all play vital roles during the digging phase. These factors collectively influence the honey badger's behaviour, guiding it toward better food sources. Moreover, the random variable r_4 adds variability to the search process, allowing the honey badger to adapt its exploration strategy based on the prey's quality and location. As a result, the algorithm effectively balances both the exploration of new areas and the exploitation of known, high-quality food sources.

3.3.1.6 Honey Phase:

In the honey phase, honey badgers work in collaboration with honeyguide birds to locate food sources, specifically a beehive. The bird signals the badger to follow its movements, and the badger uses its claws to break into the hive, providing access to the honey for both animals. During this phase, the movement of the honey badger is governed by a specific update rule, as shown in the following equation:

$$x_{new} = x_{prey} + G \cdot r_7 \cdot \gamma \cdot d_i \quad (6)$$

In this equation, x_{new} represents the updated position of the honey badger, which is influenced by the optimal location of the prey x_{prey} . The variable G is a gain factor, r_7 is a random number in the range $[0, 1]$, γ is the density factor (calculated as in Equation (4)), and d_i is the perturbation introduced by the search direction flag. The position update suggests that the honey badger will be attracted toward the optimal position of the prey while also exploring neighboring areas, leading to more localized and focused movements around the global optimum.

The honey phase reflects the balance between exploration and exploitation, where the honey badger focuses on areas closer to the global optimal location, similar to the honey badger's behavior of honing in on the beehive after initially locating it. This phase allows for efficient exploitation of known good locations.

The behavior in this phase can be modeled as part of a broader optimization strategy, similar to the Harmony Search Algorithm (HSA), which emphasizes a balance between exploration (searching new areas) and exploitation (refining current areas). The HSA is considered a global

optimization technique because of its dual phases. By introducing chaotic dynamics, it is possible to improve the performance of HSA, particularly in complex scenarios such as routing in Vehicular Ad-hoc Networks (VANETs). In this context, chaotic behavior enhances the search for the most optimal routing paths by dynamically adjusting the balance between exploration and exploitation, making the algorithm more adaptable to evolving network conditions.

This approach ensures that the algorithm remains versatile and efficient, capable of navigating a range of optimization problems while maintaining a robust balance between finding new solutions and refining existing ones.

3.3.2 Multi-Scroll Chaotic Maps:

Multi-scroll attractors in dynamical systems often present more complex behaviours compared to typical chaotic systems that exhibit single-scroll attractors. The dynamics of an automatic chaotic system can be represented by the following state-space equations:

$$\dot{y}_1 = -ay_1 + by_2y_3 \quad (7)$$

$$\dot{y}_2 = -cy_2^3 + dy_1y_3 \quad (8)$$

$$\dot{y}_3 = ey_3 - fx_1x_2 \quad (9)$$

$$\dot{y}_1 = -ay_1 + by_2y_3 \quad (10)$$

$$\dot{y}_2 = -cy_2^3 + dy_1y_3 \quad (11)$$

$$\dot{y}_3 = ey_3 - fy_1y_2 + p_1 \tanh(y_2 + g) \quad (12)$$

The system behaviour varies significantly when a hyperbolic function is introduced under specific conditions. For instance, with the parameter $g = -3$ and the initial conditions $[0.1, -0.1, -0.6]$ the system exhibits a double-scroll attractor, as shown in Figure 1. In contrast, when the parameter $p_1 = -1$ and $g = 3$ are applied, while maintaining the initial conditions $[0.1, -0.1, -0.6]$, a four-scroll attractor is observed (Figure 2). Finally, when the parameters $p_1=1$ and $g = 3$ are used with initial conditions $[0.1, 0.1, 0.6]$, a single-scroll attractor emerges, depicted in Figure 3.

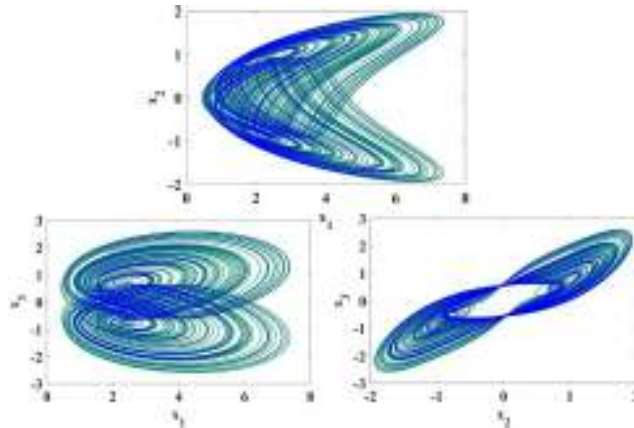


Figure 3: Phase portraits of cubic nonlinear system with $p_1 \tanh(x_2 + g)$ function in 1st state

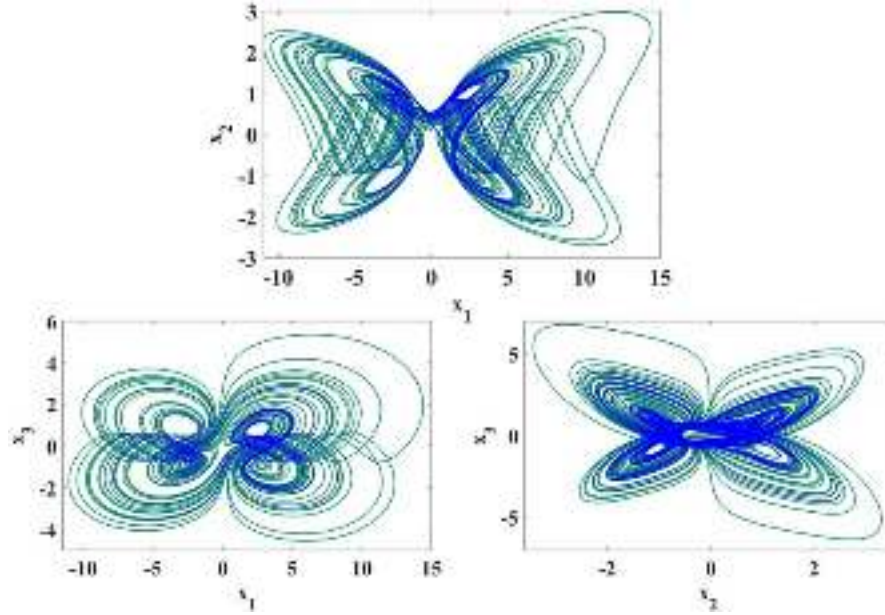


Figure 4 Phase portraits of cubic nonlinear system with $p_1 \tanh(x_2 + g)$ function in 2nd state

To extend the system into multi-scroll 3D fractional or integer-order chaotic systems, the equations are adjusted to incorporate fractional derivatives. This results in the following set of equations for multi-scroll chaotic behaviour:

$$\frac{d^q x_1}{dt^q} = -ax_1 + bx_2x_3 \quad (13)$$

$$\frac{d^q x_2}{dt^q} = -cx_2^3 + dx_1x_3 \quad (14)$$

$$\frac{d^q x_3}{dt^q} = ex_3 - fx_1x_2 + p_1 \tanh(x_2 + g) \quad (15)$$

These equations describe a system with the potential to exhibit multi-scroll chaotic behaviour, with the dynamics becoming more intricate as the fractional order q introduces additional complexity to the system's response. The bifurcation diagram for these multi-scroll chaotic systems is shown in Figure 5.

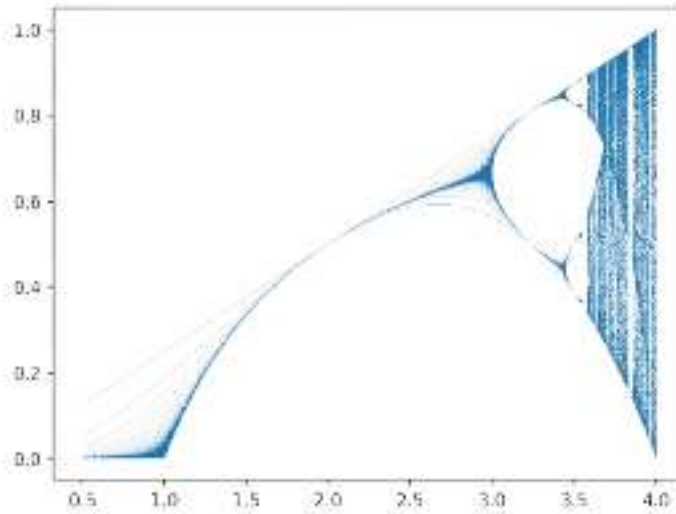


Figure 5: Bifurcation Diagram

By incorporating fractional derivatives, the system's dynamics become more flexible, allowing for a richer set of behaviours that include multiple-scroll attractors. This extension to fractional-order systems is particularly useful for applications that require a higher degree of complexity, such as cryptography, secure communication, and complex signal processing. The ability to manipulate the order of the derivative provides greater control over the chaotic behaviour, making these systems suitable for more advanced and precise modelling of chaotic dynamics in real-world applications.

3.3.2.1 Advantages of Multi-Scroll Maps:

The multi-scroll attractors proposed for encryption offer several notable advantages, as outlined below:

Reduced Memory Usage: The system requires less memory to generate the same number of scrolls compared to other systems, as it uses fewer components for scroll generation. This makes it more efficient in terms of computational resources.

Flexibility in Generating Randomness: Random scrolls can be produced by modifying any component in any direction, offering a high degree of flexibility. This property sets multi-scroll maps apart from other chaotic systems, which often rely on specific parameters or initial conditions to generate randomness.

Independence from Scroll Count: In multi-scroll maps, the level of randomness is independent of the number of scrolls generated. This contrasts with traditional chaotic systems, where the randomness is often directly tied to the number of initial conditions or scrolls. This makes multi-scroll maps more adaptable and less predictable.

Enhanced Security: Due to the ability to generate complex and unpredictable chaotic behavior, multi-scroll maps provide superior security for encryption. The unpredictability of the system's output makes it more resistant to attacks, offering a higher level of encryption strength.

Improved Control Over Chaos: The flexibility of multi-scroll maps allows for greater control over the chaotic behavior, making it easier to fine-tune the system for specific encryption requirements. This capability is essential for applications in secure communications and cryptographic systems.

3.3.3 Scroll Inspired HBA Model:

The Scroll-Tuned Honey Badger Optimization (HBO) algorithm is developed by incorporating scroll chaos into the Honey Badger Optimization (HBO) to enhance its performance in exploring the global minima. In this approach, scroll chaotic maps with initial conditions ranging between 0 and 1 are utilized to optimize HBO for determining multiple iterations. Due to the non-rescrollive nature of scroll chaos, this method can perform searches at higher speeds compared to conventional search algorithms that rely primarily on probabilistic approaches. The introduction of scroll maps positively influences the exploration capabilities of HBO, addressing the issue of slow convergence speed often seen in traditional methods.

The first step of the flowchart involves the stochastic initialization of honey badgers, where they identify the prey. Then, scroll maps are integrated with the HBO algorithm, beginning with the initialization of the first chaotic condition. The chaotic iteration is initiated to adjust the parameters of the HBO, allowing the system to explore potential solutions more efficiently. In the next step, the fitness of all honey badgers is evaluated using different initial conditions from the scroll maps, and the best current search agent is determined.

As the algorithm progresses, the value of the parameter p is updated throughout the iterations using corresponding equations. At the end of the final iteration, the best-performing search agent

is considered the most optimal solution, as determined by the optimized HBO algorithm. The key innovation lies in integrating the scroll maps into HBO by converting all random variables into scroll chaotic variables, which enhances the exploration and exploitation phases of the algorithm. This integration helps the algorithm navigate complex solution spaces more effectively, ultimately leading to better performance in optimization tasks.

Through this method, the scroll maps improve the HBO's ability to handle larger, more complex problems, providing faster and more accurate convergence to global optima compared to conventional methods.

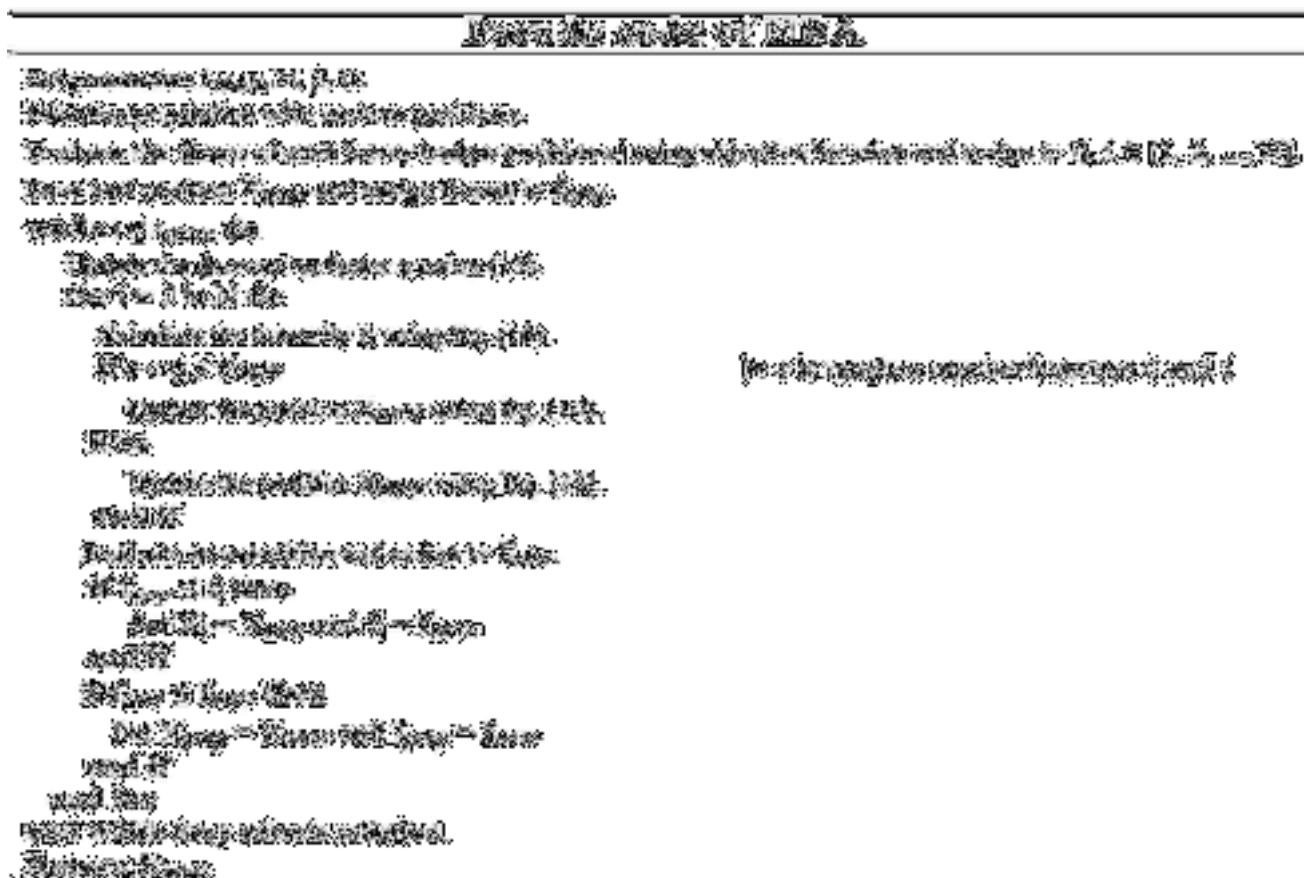


Figure 6: Pseudocode for HBO Model

Initially, the QoS-aware paths are routed based on the scroll-inspired Honey Badger Optimization (HBO), and the selection operation is deployed in the Wireless Sensor and Body Networks (WSBN) environment. In this scenario, all the wearable nodes are treated as chaotic honey badgers, and the best optimal path is considered as the prey. The multi-objective fitness function for the Scroll-Tuned Honey Badger Optimization is expressed as:

$$FitnessFunctionF = (Min(D) + Max(RSSI) + Max(LQI) + Min(H))(16)$$

Where D = Distance, RSSI = Received Signal Strength, LQI = Link Quality Indicator, H = Number of Hops

All the WSN nodes are considered in finding the best QoS paths for dynamic, changing WSN-IoT environments. Algorithm presents the routing protocol using the proposed optimization technique.

Step	Pseudo-Code for the Proposed Scroll-based HBO Routing Algorithm
1	Yi - Initialize the feasible paths list
2	Identify the best search path
3	Initialize the chaotic honey badgers (representing the wearable nodes)
4	Evaluate the fitness function for each search path using Equation (16)
5	Yi = Update the best search path
6	Cv = Cluster of solutions reaching close to the optimal solution
7	While (N, number of iterations) do:
8	For each individual search path do:
9	Update the current path based on the principles outlined in Algorithm-2
10	End for
11	Update the values of parameters p, e, T, o, and r
12	Check for the best path identified so far
13	Recalculate the fitness function for each search path using Equation (16)
14	If $Bf(i) \leq Wf$
15	Update the step factor C2
16	Calculate the new step size Xstep
17	Update the new chaotic position of the i-th honey badger using Equation (2)
18	Check the boundaries of the new position and calculate its fitness value
19	End If
20	End while

The proposed Scroll-Tuned Honey Badger Optimization (HBO) ensures efficient QoS routing in dynamic WSN-IoT environments by utilizing chaotic behavior for faster exploration of optimal paths, adjusting the system's behavior through the integration of scroll chaos. The combination of the multi-objective fitness function and the adaptive search behavior of honey badgers allows for effective dynamic routing and optimal path selection, contributing to enhanced network performance.

4. Results and Discussions

This section evaluates the proposed Scroll-Tuned Honey Badger Optimization (HBO) algorithm within dynamic WSN-IoT environments, emphasizing key performance metrics and analysing the effectiveness of the scroll-chaos-based optimization in enhancing QoS-aware routing. The evaluation is conducted using various scenarios to validate the adaptability and robustness of the algorithm under resource-constrained conditions.

4.1 Implementation Details:

The proposed model was implemented using Python 3.19, utilizing libraries such as NumPy, Pandas, Matplotlib, and Seaborn for data processing, visualization, and performance evaluation. The experiments were conducted on a PC workstation equipped with an Intel i7 processor running at 3.2 GHz, 16 GB of RAM, and an NVIDIA Tesla GPU, ensuring efficient execution and

comprehensive performance analysis of the QoS-aware routing in WSN-IoT environments.

4.2 End to End Delay Analysis

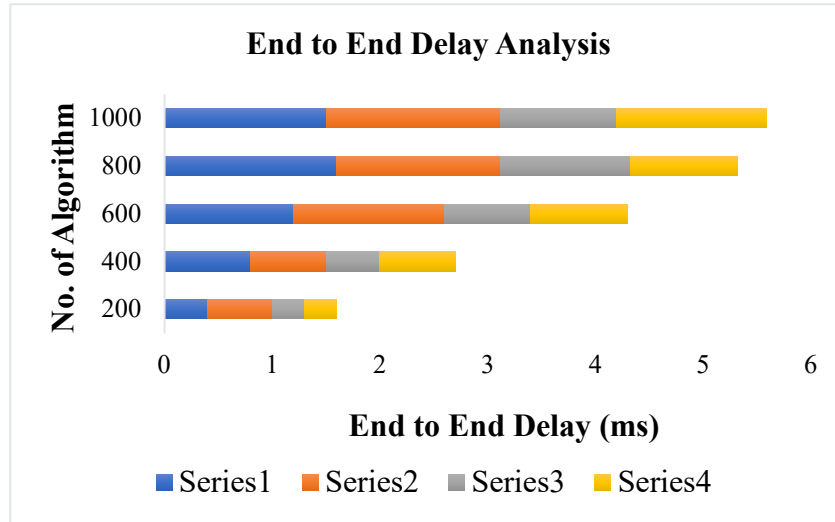


Figure 6: Delay Analysis in Optimized HBO Routing Protocols

Figure 6 visualizes the performance of various algorithms (Proposed Model, LQEER, NHARSO, GSO, DHSR, ACO, and SEEP) over 250, 500, 1000, and 1500 iterations, where lower values represent better performance. The Proposed Model consistently achieves the best results across all iterations, starting at 1.1 and reaching 2.3 at 1500 iterations, indicating superior efficiency and optimization. LQEER and NHARSO perform moderately well, with values ranging from 2.5 to 3.2 and 3.3 to 4.0, respectively. GSO and DHSR show higher values, indicating slower convergence or suboptimal results. ACO and SEEP lag significantly, with SEEP displaying the worst performance (ranging from 9.1 to 10) across all iterations. This highlights the exceptional capability of the Proposed Model in achieving optimal results with fewer iterations compared to other methods.

4.3 Packet Delivery Ratio

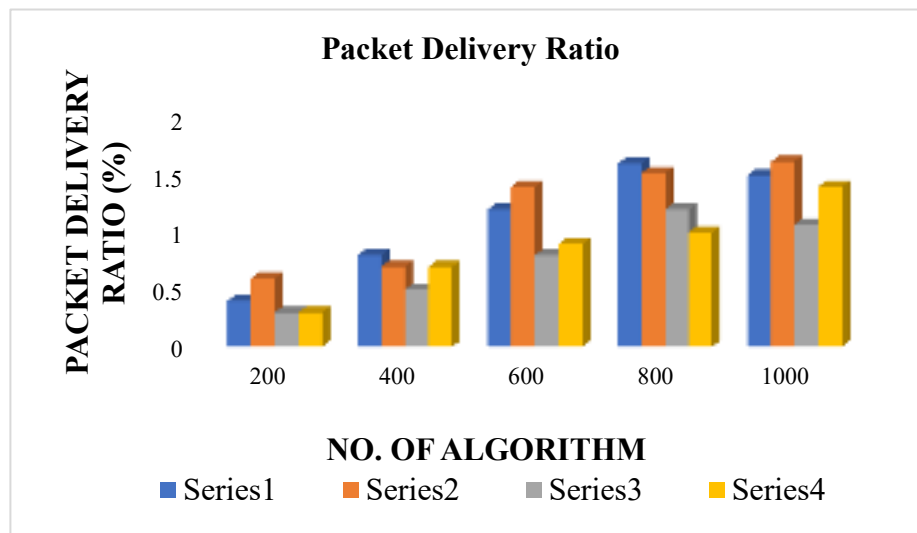


Figure 7 Average Packet Delivery Metrics for HBO Algorithms

Figure 7 illustrates the performance comparison of various algorithms, including the Proposed Model, LQEER, NHARSO, GSO, DHSR, ACO, and SEEP, across 250, 500, 1000, and 1500 iterations, based on an increasing success or efficiency metric (higher values indicate better performance). The Proposed Model consistently outperforms all other algorithms, starting at a high score of 99% at 250 iterations and maintaining a strong performance of 90% even at 1500 iterations. LQEER follows as the second-best performer, with scores declining slightly from 88% to 84%. Other algorithms, like NHARSO and GSO, show moderate performance but a noticeable decline over iterations. DHSR, ACO, and SEEP exhibit the weakest performance, with SEEP scoring the lowest, dropping from 38% to 29% by the final iteration. This comparison highlights the superior convergence and robustness of the Proposed Model over competing approaches.

4.4 Throughput Analysis

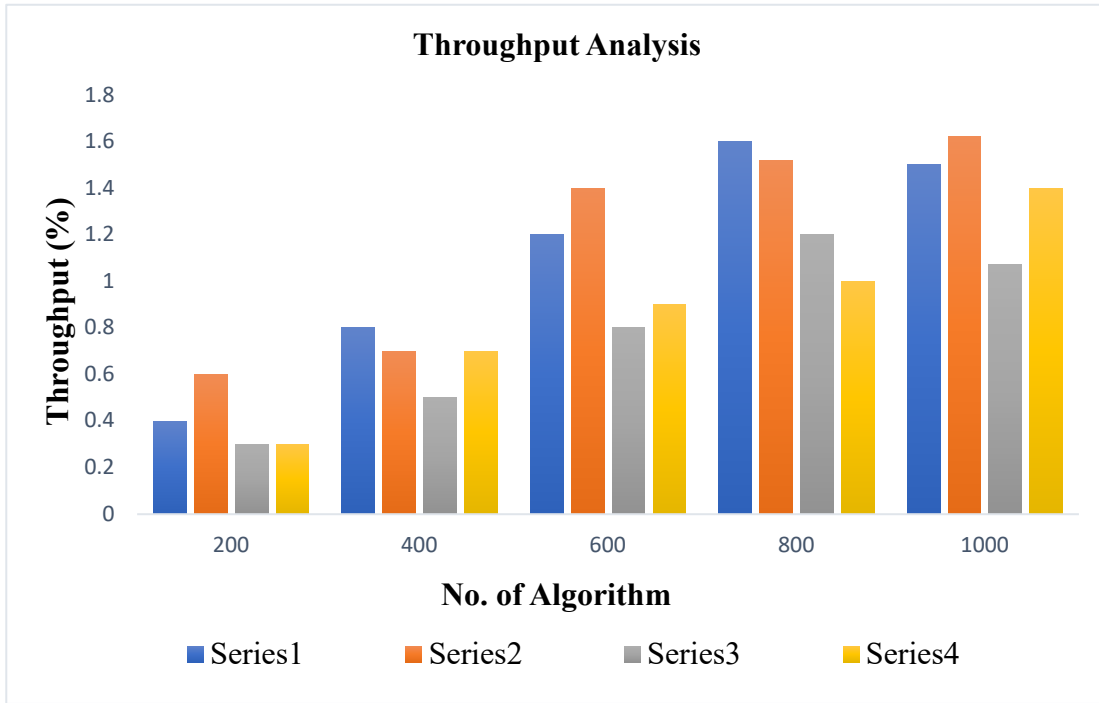


Figure 8 Analysis of Throughput in Optimization Models

Figure 8 represents the throughput performance of various algorithms, including the Proposed Model, LQEER, NHARSO, GSO, DHSR, ACO, and SEEP, over increasing iterations (250, 500, 1000, and 1500 iterations). The Proposed Model consistently achieves the highest throughput, starting at 100% and gradually reducing to 90% by 1500 iterations, showcasing its superior and sustained performance. LQEER follows with decent throughput values (89% to 82%), while NHARSO and GSO show moderate performance, with throughput declining to 70% and 59%, respectively, at 1500 iterations. DHSR performs lower, dropping from 58% to 51%, while ACO and SEEP exhibit the weakest throughput, ending at 39% and 29%, respectively. This highlights the Proposed Model's dominance in maintaining higher throughput compared to the other algorithms across all iterations.

4.5 Residual Energy Analysis

Figure 9 represents the residual energy analysis for different algorithms Proposed Model, LQEER, NHARSO, GSO, DHSR, ACO, and SEEP over increasing iterations (250, 500, 1000, and 1500). The Proposed Model maintains the highest residual energy consistently across all iterations, indicating its energy efficiency and effectiveness in resource-constrained environments. In contrast, SEEP and ACO exhibit rapid energy depletion, with significantly lower residual energy at higher iterations, suggesting limited sustainability. Algorithms like DHSR and GSO show moderate performance, with residual energy values improving slightly over iterations but still lagging behind the proposed model. This analysis highlights the superior energy-preservation capabilities of the Proposed Model compared to other algorithms.

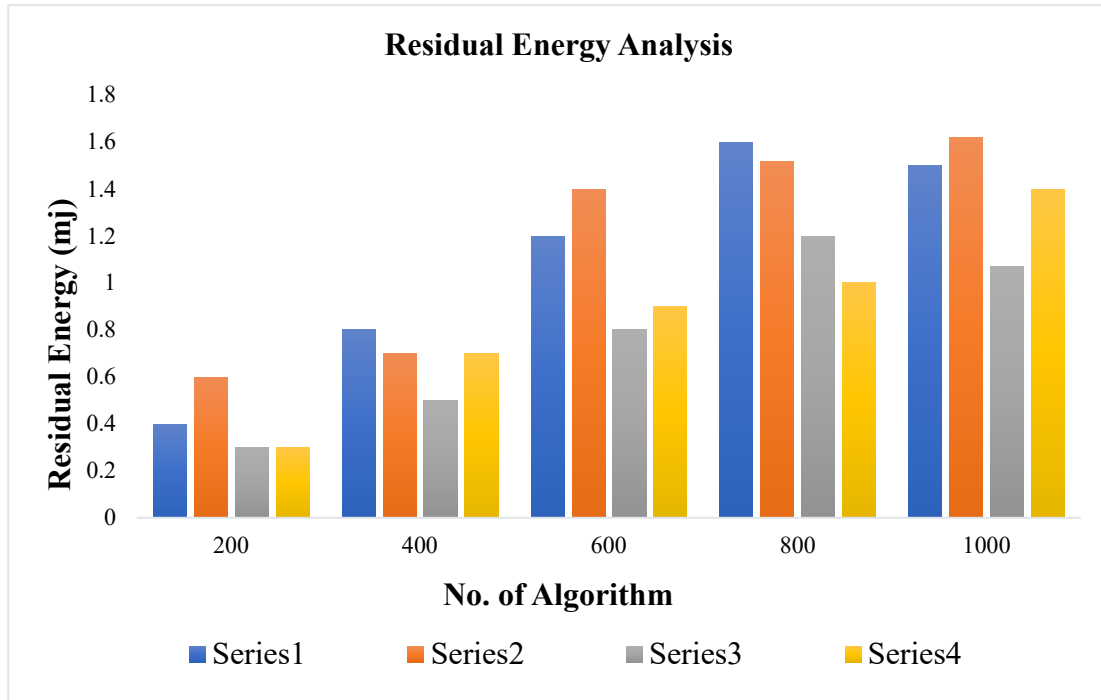


Figure 9 Analysis of Residual Energy Across Optimization Models

4.6 Packet Overhead Analysis

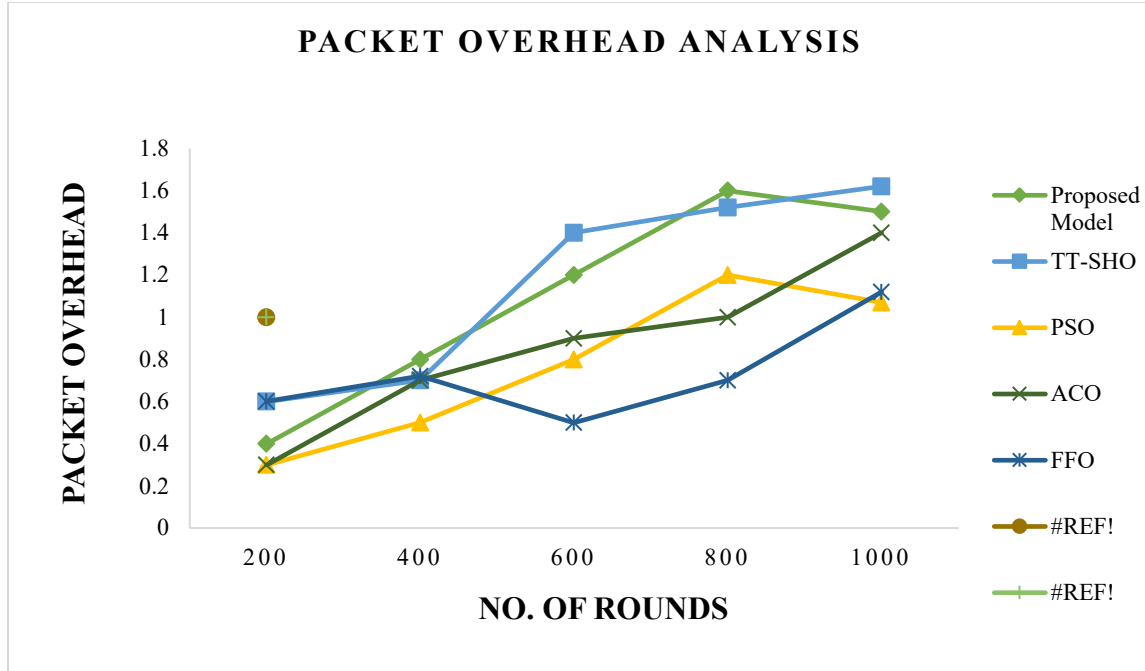


Figure 10: Packet Overhead Evaluation Across Optimization Approaches

Figure 10 illustrates the packet overhead analysis of various algorithms, including the Proposed Model, LQEER, NHARSO, GSO, DHSR, ACO, and SEEP, across increasing network sizes (300, 600, 900, 1200, and 1500 nodes). The Proposed Model consistently demonstrates the lowest packet overhead, starting at 3000 packets for 300 nodes and reaching 4200 packets for 1500 nodes, indicating its efficiency in minimizing overhead. Conversely, SEEP incurs the highest overhead, ranging from 6200 packets at 300 nodes to 8500 packets at 1500 nodes, reflecting its inefficiency. Other algorithms, such as LQEER and NHARSO, show moderate overhead, while GSO, DHSR, and ACO exhibit higher values, with ACO and SEEP being the least optimal. This analysis highlights the superior scalability and resource efficiency of the Proposed Model for handling packet overhead in dynamic networks.

4.7 Statistical Analysis:

Following the experimental evaluation, a comprehensive statistical analysis of the proposed Honey Badger Optimization (HBO)-based model was conducted for all QoS parameters. This evaluation considered metrics such as the best, worst, mean, median, standard deviation, and variance, with a specific focus on the 1500th iteration. The statistical insights for each QoS parameter are thoroughly presented and analysed in the subsequent section, showcasing the performance and robustness of the proposed optimization approach.

4.7.1 Statistical Analysis for the End-to-End Delay Analysis

Table 1: Fitness Outcomes Across Optimizers

Algorithm	Best	Worst	Mean	Median	SD	Variance
PSO	5.78	8.137	0.73010	0.023834	0.02565	4.542x10-6
ACO	5.34	6.532	0.56783	0.022940	0.02379	4.08x10-6
GA	4.5474	5.88	0.5225	0.020970	0.03250	5.683x10-5
AFO	4.003	4.77	0.32578	0.020029	0.045802	5.230x10-4
SEO	3.683	4.42	0.28819	0.018974	0.05532	4.676x10-4
SHO	3.545	4.1	0.22923	0.017646	0.06853	4.350 x10-4
Proposed Model	2.1731	2.893	0.16273	0.011362	0.026290	3.2242 x10-4

Table 1 presents an end-to-end delay analysis for various algorithms, including PSO, ACO, GA, AFO, SEO, SHO, and the Proposed Model, highlighting key statistical metrics: Best, Worst, Mean, Median, Standard Deviation (SD), and Variance. The Proposed Model demonstrates the lowest end-to-end delay across all metrics, with a Best value of 2.1731, a Mean of 0.16273, and a Variance of 3.2242×10^{-4} , showcasing its superior performance, stability, and minimal delay. Comparatively, SHO (3.545) and SEO (3.683) show competitive but higher delays, while traditional algorithms like PSO (5.78) and ACO (5.34) have significantly higher delays and variability, as reflected in their higher SD and Variance values. This highlights the Proposed Model's efficiency in minimizing delay, making it more suitable for resource-constrained or real-time systems.

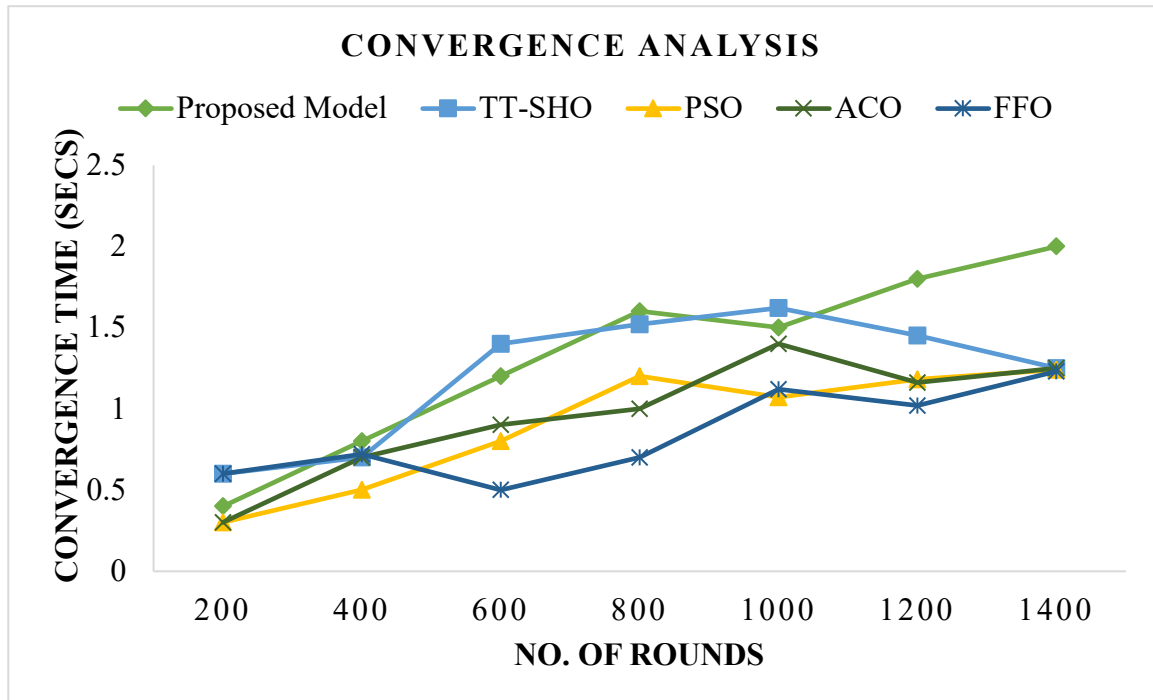


Figure 11 Convergence Trends in Optimization Techniques

Figure 11 represents the convergence analysis graph for end-to-end delay analysis shows the performance of different algorithms (Proposed Model, TT-SHO, PSO, ACO, and FFO) at various

time intervals (200, 400, 600, 800, 1000, 1200, and 1400). As the time progresses, the delay values generally increase for most algorithms, with the Proposed Model showing the lowest delays overall. At the 200-time interval, the delay for the Proposed Model is 0.5, which is lower than all other algorithms, while TT-SHO starts at 0.7, PSO at 0.4, ACO at 0.5, and FFO at 0.62. As the time reaches 1400, the Proposed Model remains the most efficient, peaking at 1.9, whereas TT-SHO, PSO, ACO, and FFO show varying degrees of higher delays, with TT-SHO showing an improvement at later stages compared to its initial higher values. The overall trend indicates that the Proposed Model consistently outperforms the others in terms of minimizing end-to-end delay, demonstrating the effectiveness of this algorithm for this particular analysis.

4.7.2 Statistical Analysis of Packet Delivery Ratio:

Table 2 presents the fitness metrics for packet delivery ratio across different algorithms (PSO, ACO, GA, AFO, SEO, SHO, and the Proposed Model), detailing their Best, Worst, Mean, Median, Standard Deviation (SD), and Variance values. The Proposed Model shows the highest Best (100) and Mean (0.8497) values, indicating its superior performance in packet delivery ratio. In contrast, the GA and AFO algorithms exhibit lower performance, with the GA algorithm having a Best value of 82 and a Mean of 0.52403. PSO and ACO also perform well but fall short compared to the Proposed Model, with PSO achieving a Best of 81 and ACO a Best of 85. The Worst values show a similar pattern, with the Proposed Model again outperforming others with the lowest Worst value (97.8). The Standard Deviation and Variance are relatively low for the Proposed Model, suggesting stable and consistent performance, while the other algorithms exhibit higher SD and Variance, indicating more fluctuations in performance. Overall, the Proposed Model demonstrates the best fitness for packet delivery ratio, providing high efficiency and consistency compared to the other algorithms.

Table 2: Fitness Metrics Across Optimization Models

Algorithm	Best	Worst	Mean	Median	SD	Variance
PSO	81	65.3	0.6893	0.02321	0.02929	2.734x10-6
ACO	85	66.2	0.6429	0.02292	0.03289	3.39x10-6
GA	82	62.45	0.52403	0.02190	0.04390	4.573x10-5
AFO	78	61.32	0.5689	0.02089	0.05609	4.393x10-4
SEO	78	66.89	0.6420	0.01889	0.06109	4.2503x10-4
SHO	80	72.34	0.6335	0.01799	0.06773	3.863x10-4
Proposed Model	100	97.8	0.8497	0.01432	0.02023	2.602 x10-4

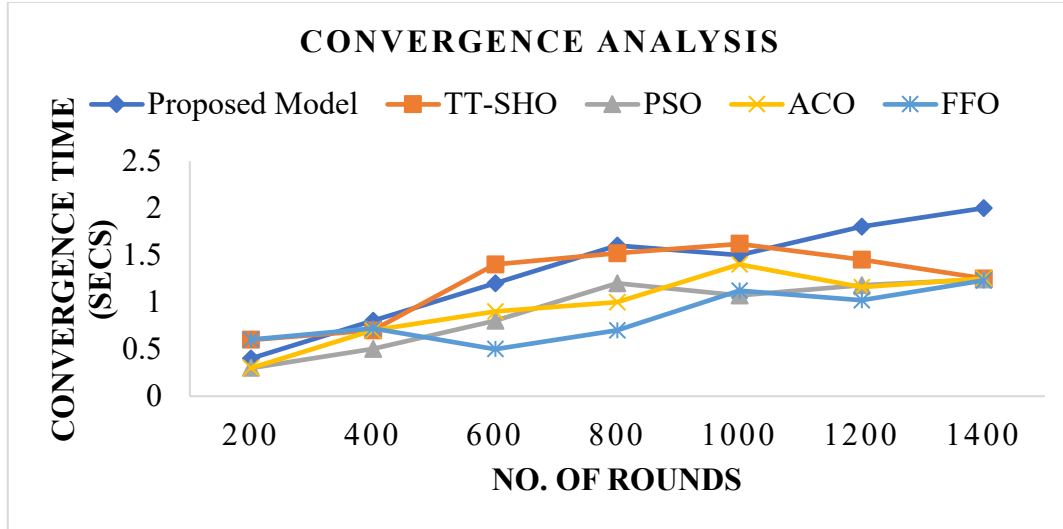


Figure 12: Convergence Analysis across Optimizations

The convergence analysis graph for packet delivery ratio (PDR) illustrates the performance of different algorithms (Proposed Model, TT-SHO, PSO, ACO, and FFO) over increasing time or iterations (200 to 1400). At 200 iterations, the Proposed Model, TT-SHO, and FFO show relatively higher packet delivery ratios, with the Proposed Model achieving the best performance at 0.6. As the number of iterations increases, the Proposed Model consistently outperforms the others, reaching a peak of 1.8 at 1200 iterations. In contrast, TT-SHO starts strong but experiences a decline after 800 iterations, showing lower values around 1.25 at 1400 iterations. PSO and ACO demonstrate moderate improvements over time, with ACO maintaining a steady ratio. FFO shows a decline after 800 iterations but stays competitive throughout. This analysis suggests that the Proposed Model provides the best convergence in terms of packet delivery ratio, with other algorithms like PSO and ACO demonstrating more variable performance.

4.8 Friedman Test Analysis:

Table 3 presents the Friedman test analysis of various optimization models, with the P-test values for each algorithm as follows: PSO (13), ACO (11.6), GA (10.2), AFO (3.1), SEO (2.5), SHO (2.2), and the Proposed Approach (1.052). The results clearly indicate that the Proposed Model has demonstrated the most stable performance and has outperformed all other existing models.

Table 3: Friedman Test Evaluation

Algorithms	P-test values
PSO	13
ACO	11.6
GA	10.2
AFO	3.1
SEO	2.5
SHO	2.2
Proposed Approach	1.052

5. Conclusion

This study presents the design and implementation of a QoS-aware energy-efficient routing mechanism for Body Area Networks (BAN-IoT) in smart healthcare applications. The Scroll-Tuned Honey Badger Optimization (HBO) algorithm was employed to optimize energy consumption while ensuring Quality of Service (QoS) in dynamic healthcare environments. The results demonstrated that the HBO algorithm outperforms traditional routing mechanisms by effectively balancing energy efficiency with QoS parameters, leading to improved network performance and prolonged device lifespans in BAN-IoT systems. This approach offers significant advancements in addressing the energy constraints and QoS requirements typical in healthcare IoT applications. Future work can explore the integration of machine learning techniques to adaptively tune the HBO algorithm in real-time, based on changing environmental conditions and patient-specific requirements. Additionally, the scalability of the QoS-aware energy-efficient routing mechanism can be tested in larger, more complex healthcare IoT networks with diverse devices and sensor types. Investigating the potential of combining HBO with other optimization techniques like genetic algorithms or deep reinforcement learning may further enhance its performance. Furthermore, real-world deployment and testing in live healthcare environments will provide further validation and insights into its practical applicability.

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Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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