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RESEARCH ARTICLE

ENERGY-EFFICIENT MANTIS SEARCH OPTIMIZATION FRAMEWORK FOR ENHANCED WIRELESS SENSOR NETWORK PERFORMANCE IN IOT APPLICATIONS

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Abstract – Wireless Sensor Networks (WSNs) play a critical role in Internet of Things (IoT) applications that offer automation and data exchange across various domains such as environmental monitoring, healthcare, and agriculture. WSN frequently suffers from unstable topology, energy limitations, and communication overhead that damage the network performance. To overcome these issues, this study introduced the Energy-efficient Mantis Search Optimization for Wireless Sensor Networks (EMSO-WSN) framework to enhance the routing efficiency in WSN-IoT. This model includes Fuzzy C-Means (FCM) for adaptive clustering, Adaptive Walrus Optimization (AWO) for efficient Cluster Head Selection (CHS), and Mantis Search Algorithm (MSA) for robust route optimization. This research focuses on improving the WSN in IoT applications that will enhance the network lifetime and energy efficiency. The proposed EMSO-WSN emphasizes multi-phase decision making, behavioral modelling, and soft clustering, ensures high scalability, and reduces latency. Finally, the experimental framework was simulated by Python using NS2 for fine-grain throughput and computational efficiency. The EMSO-WSN model is evaluated using key metrics such as Network Lifetime (NL), Energy Consumption (EC), delay, number of CH, Data Packet Delivery (DPD), and throughput. This shows the comparison of the proposed EMSO-WSN reduces less EC of 6 Joules at 100 nodes than that of other existing methods like SWARAM of 9 J, HHO-CFR of 10 J, and ECEEC of 11 J, respectively. The throughput of proposed EMSO-WSN achieves 58.75% higher than that of other existing like SWARAM, 45.11% higher than HHOCFR, and 22.73% higher than ECEEC. Thus, the EMSO-WSN framework is validated as a scalable and energy-efficient solution for modern WSN-IoT infrastructures.

Keywords *– Wireless Sensor Networks, Internet of Things, Energy Efficiency, Cluster Head Selection, Mantis Search Algorithm, Routing Optimization.*

1. INTRODUCTION

WSNs are widely used in many different industries, including the IoT, agriculture, and environmental monitoring [1]. A key component of these applications is wireless communication between WSN nodes [2]. It provides devices with perception, computation, and decision-making abilities and links them via wireless communication technologies [3]. This makes it possible for the IoT to receive and send data instantly, automate data exchange and collaboration, increase operational and production efficiency, and reduce expenses. In addition, the IoT uses predictive maintenance and big data analysis to give businesses insight into customer demands and market trends, enabling them to make better informed decisions [4]. Furthermore, the use of IoT in domains like health monitoring and smart homes is enhancing people's quality of life and advancing sustainable development [5]. Thus, the Internet of Things offers substantial benefits in terms of increasing productivity, cutting expenses, gaining new insights, raising standards of living, and encouraging sustainable growth [6]. A network is important and faces several challenges, such as sensor nodes' limited energy, their vast and random dispersion, and other features [7].

By maximizing network lifespan, decreasing EC, choosing the best pathways, and ensuring low latency, WSN routing optimization aims to increase network performance and energy use efficiency [8]. Transmission scheduling and path selection are two methods and systems that are used to guarantee accurate and efficient data transfer between nodes [9]. In WSNs, research on routing optimization is crucial for enhancing network performance, prolonging NL, ensuring dependable data transfer, and enabling real-time applications [10]. WSN systems can become more intelligent, dependable, and efficient by implementing efficient route optimization methods and techniques. In the IoT, WSN routing optimization is crucial because it can increase network lifespan, boost energy efficiency and performance, offer dependable data transmission, and enable real-time applications across a range of application domains.

Consequently, the advancement and use of animal networking are greatly aided by routing optimization in WSNs [11,12]. Routing optimization for WSNs is challenged by several issues such as bandwidth and capacity limitations, network topology dynamics, and energy constraints [13]. To tackle these challenges, a novel Energy-efficient Mantis Search Optimization for Wireless Sensor Networks (EMSO-WSN) framework has been proposed to minimize the EC and increase the NL in the WSN. The major contributions of the proposed EMSO-WSN techniques are as follows:

- The primary goal of the research is to develop the EMSO-WSN framework to enhance NL and reduce EC in IoT-enabled WSNs.
- The Fuzzy C-Means algorithm is used for adaptive soft clustering, improving energy balance and data aggregation among sensor nodes.
- An Adaptive Walrus Optimization algorithm is proposed to select optimal CH based on energy and coverage efficiency.
- A MSA is employed for dynamic routing, ensuring reduced latency and improved throughput in dense IoT networks.
- The EMSO-WSN approach achieved a 40% increase in throughput and extended NL up to 350 rounds compared to existing methods.

The organization of the paper is structured as follows. Section 2 covers the details of the literature review. Section 3 offers a description of the developed EMSO-WSN model. Section 4 presents the experiment's findings. Section 5 contains the future work and conclusion

2. LITERATURE REVIEW

Recent advancements in WSN-IoT routing optimization have focused on improving energy efficiency, cluster stability, and data transmission reliability. Techniques such as fuzzy clustering with Particle Swarm Optimization (PSO), osprey-based optimization, federated deep reinforcement learning, and Harris hawk's optimization have been explored to address challenges like high message overhead, frequent re-clustering, and limited NL. Despite these efforts, existing approaches still face issues with scalability, dynamic adaptation, and secure data transfer.

In 2024, Lei [14] suggested a novel hybrid energy-aware IoT routing method that combined fuzzy clustering with the PSO algorithm. However, multi-hop data transfers, communication, and the inherent challenges of wireless networks are critical to the IoT infrastructures' lifespan and efficacy.

In 2024, Somula et al., [15] designed an osprey optimization algorithm based on energy-efficient cluster head selection (SWARAM) to select the optimal CH in a WSN-based IoT. This approach increased the 10% NL and the packet delivery ratio by 10%, respectively. In contrast, the SWARAM performance was evaluated in real-time factors such as load balancing, mobility, security, and fault tolerance.

In 2024, Suresh et al., [16] provided an energy-efficient and adaptable routing system that considered a message overhead, temporal complexity, data sum rate, communication delay, and scalability. In dynamic network scenarios, the suggested study method makes use of Federated Deep Reinforcement Learning (FDRL), which permits adaptive routing and distributed decision-making.

In 2024, Jing [17] identified hot spot issues, high message overhead for cluster formation, and frequent cluster maintenance remain the primary clustering and routing protocol difficulties. To improve the NL, their study suggested a novel protocol called Harris Hark Optimization Clustering with Fuzzy Routing (HHOCFR), which combined fuzzy routing and Harris Harks Optimization Clustering. Additionally, neighborhood centroid opposition-based learning mechanisms and excellent point set-based population initialization are employed to speed up convergence and prevent becoming stuck in local optima.

In 2024, Aravind [18] offered a geographic routing protocol that is energy-efficient (EEG) based on the specified six-fold objective function. In this case, the optimal route selection considers overhead, latency, Quality of Service (QoS), energy, distance, and trust. Nevertheless, their research expanded by gathering data in real time and adding other restrictions like time and temperature.

In 2024, Phalaagae et al., [19] suggested a new security method called the Randomized Bi-Phase Authentication Scheme (RBAS), which strengthened internal and external network security by integrating digital watermarking techniques. Successful deployment in the real world depends on improved security measures to counter emerging threats and researched, cost-effective deployment techniques.

In 2024, Karim et al., [20] created a protocol called Serverless Wireless Sensor Networks (SWSN) called Enhanced Centroid-based Energy Efficient Clustering (ECEEC). The suggested method offered stateless execution, automated scalability, and economical services. However, the suggested protocol added the security feature of other networks, such as Wireless Body Area Networks (WBAN) and the IoT.

Despite significant advances in routing protocols and optimization strategies for WSNs within the IoT domain, several persistent challenges remain. Existing approaches often struggle with issues such as high EC, limited NL, communication overhead, scalability in dynamic environments, and security vulnerabilities. To tackle these challenges, a novel Energy-efficient Mantis Search Optimization for Wireless Sensor Networks (EMSO-WSN) has been proposed, which will be covered in the next section.

3. PROPOSED METHODOLOGY

In this section, the proposed Energy-efficient Mantis Search Optimization for Wireless Sensor Networks (EMSO-WSN) framework is described in detail. It consists of three key phases such as clustering via Fuzzy C-Means (FCM), CHS through Adaptive Walrus Optimization (AWO), and routing optimization using MSA. Each phase contributes to minimizing EC, enhancing CHS, and optimizing route discovery to ensure efficient and prolonged network operation. Figure 1 shows the EMSO-WSN framework

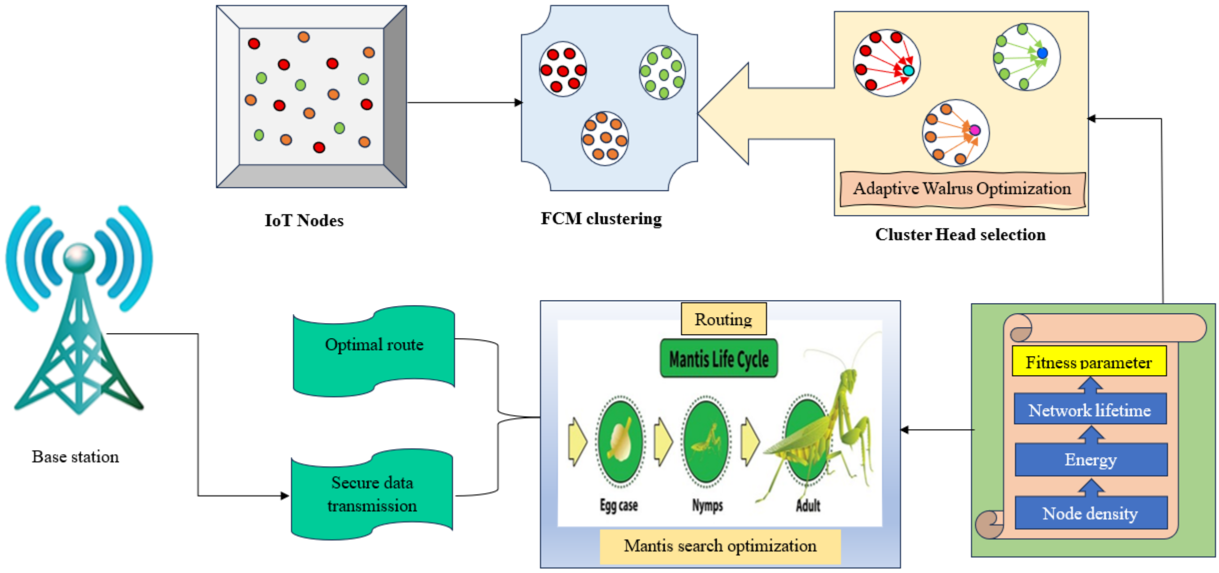

Figure 1. Overall architecture of EMSO-WSN

3.1. Clustering Via Fuzzy C-Means (FCM)

FCM is employed to handle node clustering with uncertainty and vagueness, typical in WSN deployments. It assigns sensor nodes to multiple clusters based on membership values, minimizing the distance between nodes and cluster centers. This soft clustering method enhances data aggregation and balances network load, reducing EC. The fuzzy C-means (FCMs) algorithm is the most popular fuzzy clustering technique. The aim of FCM is to minimize the total distance between the instances and the cluster centers. The objective of WSNs is to group sensor nodes of N into distinct clusters of k. It is possible to formulate the FCM objective function for clustering in WSNs as follows:

$$W = \sum_{u=1}^{n}\sum_{w=1}^{k}\mu^{m}\, d(x_u, x_c)^2, u = 1,2,\ldots,n \quad w = 1,2\ldots,k \tag{1}$$

$$\mu_{uw} = \frac{1}{\sum_{w=1}^{k}\frac{d(x_u,c_w)}{d(x_u,c_k)}^{\frac{2}{m-1}}} \tag{2}$$

$$\mu_{uw} \in [0,1] \tag{3}$$

$$C_w = \frac{\sum_{1}^{n}(\mu_{uw})^m x_u}{\sum_{1}^{n}(\mu_{uw})^m} \tag{4}$$

Most applications use Equation (2), where m is the value of the fuzzifier and μ is the membership of node u to cluster w. Moreover, C_w stands for cluster centroid. FCM Clustering ensures flexible and adaptive clustering for data uncertainty which leads to more stable and energy-efficient groupings of sensor nodes

3.2.Cluster Head Selection via Adaptive Walrus Optimization

AWO simulates walrus behavioral strategies feeding, migration, and escaping predators, to exploit and explore the space search for optimal CH. It dynamically balances local and global search to identify nodes with maximum coverage and minimum energy usage, ensuring effective cluster leadership and improved network stability. AWO consists of three phases such as exploration, Migration, and exploitation are discussed below

Phase 1: Strategy of feeding (exploration): This is a basic feeding strategy to serves as the mathematical model to update the walrus position into a new position, and it is generated by Equation (5) to enhance the objective function value.

$$Z_{d,a}^{U_1} = z_{d,a} + rand_{d,a}.(WX_a - I_{d,a}.z_{d,a}) \tag{5}$$

$$Z_d = \begin{Bmatrix} z_d^{U_1}, F_d^{U_1} < F_d:, \\ Z_d, else, \end{Bmatrix} \tag{6}$$

According to the initial phase, the newly generated d^{th} walrus is located at $z_d^{U_1}$, $F_d^{U_1}$ is the value of the fitness function, WX is the best candidate solution, $z_{d,a}^{U_1}$ is the a^{th} dimension, [0,1] is the internal of random values $rand_{d,a}$, $I_{d,a}$ is the algorithm capacity that enhances the use of exploration.

Phase 2: Migration: As the weather warms, the AWO algorithm uses the walrus's natural migration pattern to drive the exploration of search regions by moving to rocky beaches or into late-summer outcrops. Equation (7) created a new location. The walrus' original location is replaced by Equation (8). This new position produces a value for the improved objective function.

$$z_{d,a}^{U_2} = \begin{Bmatrix} z_{d,a} + rand_{d,a}.(z_{m,a} - I_{d,a}..z_{d,a}), F_m < F_d \\ z_{d,a} + rand_{d,a}.(z_{d,a} - z_{m,a}), else, \end{Bmatrix} \tag{7}$$

$$Z_d = \begin{Bmatrix} z_d^{U_2}, F_d^{U_2} < F_d; \\ Z_d, else, \end{Bmatrix} \tag{8}$$

Where z_d^U is the second phase for the newly generated location for the d^{th} walrus, $F_d^{U_2}$ is the value of the fitness function, $z_{d,j}^{U_2}$ is the a^{th} dimension, $m \neq d$, and $Z_m, m \in \{,2,\ldots,N\}$ are the walrus selected position to migrate the d^{th} term, F_m is the fitness function value, and $z_{m,a}$ is a j th dimension.

Phase 3: Escaping from predators and fighting off (exploitation): AWO can exploit the local search of the problem-solving space around the candidate solution to enhance the natural behavior simulation. Equations 9 & 10a re used to generate the random new position within the neighbourhood, and these positions improve the objective function values and replace the previous position in Equation (11):

$$z_{d,a}^{U_3} = z_{d,a} + \left(le^t{}_{local,a} + \left(ue^t{}_{local,a} - rand.\, le^t{}_{local,a}\right)\right) \times LF \quad (9)$$

$$localbounds: \begin{Bmatrix} le^t{}_{local,a} = \frac{le_a}{t}, \\ ue^t{}_{local,a} = \frac{ue_a'}{t} \end{Bmatrix} \quad (10)$$

$$Z_d = \begin{Bmatrix} z_d^{U_3}, F_d^{U_z} < F_d; \\ Z_d, else, \end{Bmatrix} \quad (11)$$

In the third phase of the walrus $z_d^{U_3}$ is the newly generated location of d^{th}. Where $z_{d,a}^{U_3}$ is the a th dimension, the iteration contour represented by t, F_d^z is its fitness function value, ue_a and le_a are the local lower bounds and local upper bound of d^{th} variable allowance respectively, for the candidate solution neighbourhood is a local search simulation. WaOA is equipped levy distribution to enhance the Levy movement of LF vector. The formation of the levy flying function is described in Equation (12):

$$LF = 0.01 \times \frac{u \times \sigma}{|v|^{\frac{1}{r}}} \quad (12)$$

$$\sigma = \left(\frac{\Gamma\left(1+\gamma \times sin\left(\frac{\pi\gamma}{2}\right)\right)}{\Gamma\left(\frac{1+\gamma}{2}\right) \times \gamma \times 2^{\left(\frac{\gamma-}{2}\right)}}\right)^{\frac{1}{\gamma}} \quad (13)$$

Thus, the AWO for CHS leverages bio-inspired strategies for selecting optimal CH, which enhances energy distribution and extends NL

3.3. Routing via Mantis search optimization

Mantis search optimization (MSA) optimizes routing paths through the behavioral modeling of mantis hunting strategies, combining exploration, exploitation, and sexual cannibalism phases. By integrating Lévy flights and strike velocity adaptations, MSA ensures efficient route discovery and robust data delivery, reducing latency and maximizing throughput in dynamic WSN environments.

3.3.1. Initial Population

In MSA, each mantis stands for a possible fix for an optimization issue. It is possible to generate a size of N solutions × D and x is a two-dimensional matrix. Moreover, an arbitrary vector initializes the upper and lower bound optimization explained in Equation (14).

$$\vec{x}_i^t = \vec{x}^l + \vec{r} \times (\vec{x}^u - \vec{x}^l) \quad (14)$$

where $\vec{x}_i^t$ represent Mantis i's location at the t[th] assessment function; t; $\rightarrow \vec{x}^l$, and $\vec{x}^u$ are the upper and bottom bounds of j-dimension; and $\vec{r}$ is a vector that generate random values among 0 and 1 of the uniform distribution.

3.3.2. Exploration Stage

In MSA, normal distribution and Lévy flight are combined to encompass the size of both large and small step, which symbolizes the predators' search for victims outside of their hiding spots. Lévy flights are randomized with a step length that is determined by the Lévy distribution. The power-law formula of an index are typically expressed as $(x) \sim |x|^{-1-\beta}$, where $0 < \beta \leq 2$. The following equation (15) represents a mathematical expression for the Lévy distribution in its simplified form:

$$L(x,\gamma,\phi) = \begin{cases} \sqrt{\frac{\gamma}{2\pi}} exp\left(-\gamma/(2x-2\varphi)\right) \frac{1}{(x-\varphi)^{1.5}} & if 0 < \varphi < x < \infty \\ 0 & if x < 0 \end{cases} \quad (15)$$

where γ is a scaling parameter, and $\varphi > 0$ indicates a minimum step. The model is obviously changed to Equation (16) as $\gamma \rightarrow \infty$:

$$L(x,\gamma,\phi) = \frac{1}{x^{1.5}} \sqrt{\frac{\gamma}{2\pi}} \quad (16)$$

3.3.3. Exploitation Stage

With a constant value, the sigmoid curve is used to determine the mantis size that strike the velocity of prey attacking. The magnitude of the striking velocity (v_s) of a mantis's front legs in the direction of its prey can be quantitatively determined using Equation (17):

$$v_s = \frac{1}{1+e^{1\rho}} \quad (17)$$

Where ρ is the gravity of Mantis Strike acceleration to ensure the constant value of experimental findings. (l) is a number that generates between -1 and -2 to control the rate of gravitational acceleration; 0 and 1 are the velocity of hitting magnitude that maximize and minimize the value of -1 and -2. The following formula modifies the behavior of each mantis as it grasps its prey in Equation (18):

$$x_{i,j}^{t+1} = \frac{\left(x_{i,j}^t + x_j^*\right)}{2.0} + v_s \times (x_j^* - x_{i,j}^t) \quad (18)$$

where the prey's location is indicated by $x_{i,j}^t$ to speed the attacking process and minimize the distance; $x_{i,j}^{t+1}$ indicates a new position of the evaluation function, and $t+1$ shows the j[th] dimension of i[th] mantis; x_j^* shows the best solution for the present location.

3.3.4. Sexual Cannibalism

Mantises pray for females to eat males in immediate copulation, known as sexual cannibalism. During or after mating, the female consumes the male, is expressed in Equation (19):

$$\vec{x}_i^{t+1} = \vec{x}_a^t \times cos(2\pi l) \times \mu \quad (19)$$

where μ denotes the portion of the male that was eaten, $\vec{x}_a^t$ stands for the male, and the phrase $(cos\ (2\pi l))$ denotes the freedom for females and moves to males for the eating process. Finally, MSA for Routing delivers reliable and dynamic route optimization through predator-prey-inspired behavior, which improves data delivery and reduces network congestion

4. RESULTS AND DISCUSSION

Experimental findings of the proposed EMSO-WSN are presented in this section. The Network Simulator (NS2), equipped with 4 GB of RAM and an Intel Core CPU, was utilized for implementation

4.1. *Performance Metrics*

The EMSO-WSN model is evaluated using key metrics such as NL, EC, delay, number of CH, DPD, and throughput. Simulations show that EMSO-WSN significantly outperforms existing protocols like SWARAM [15], HHOCFR [17], and ECEEC [20].

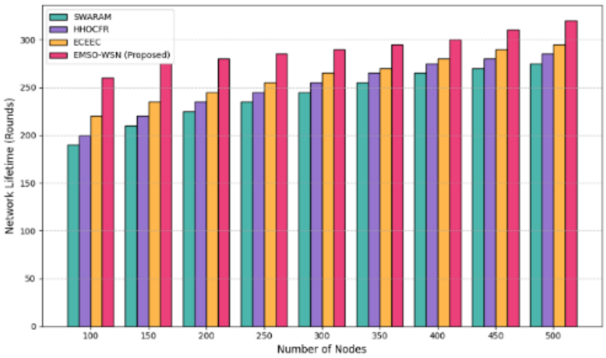

Figure 2. Comparison of NL with different nodes

In Figure 2, the NL steadily increases with the number of nodes. The proposed EMSO-WSN achieves higher performance than that of other existing methods, SWARAM [15], HHO-CFR [17], and ECEEC [20]. Specifically, EMSO-WSN achieves an NL of 260 rounds with 100 nodes and reaches up to 320 rounds with 500 nodes. In contrast, SWARAM ranges from 190 to 280 rounds, HHO-CFR from 200 to 290 rounds, and ECEEC from 220 to 300 rounds as node count increases. This demonstrates the superior energy-aware CH optimization capability of EMSO-WSN.

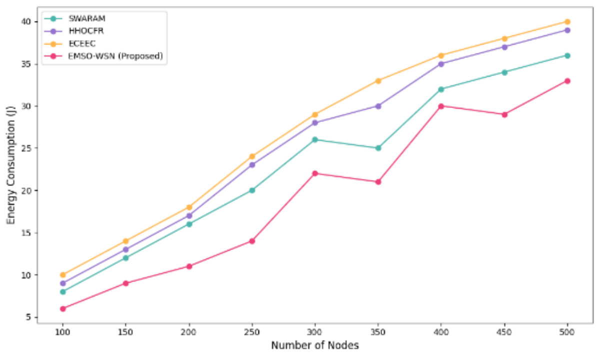

Figure 3. Performance based on EC

Figure 3 presents the EC, where the proposed EMSO-WSN shows better performance than existing methods like SWARAM [15], HHOCFR [17], and ECEEC [20]. It starts with the lowest energy usage of 6 joules at 100 nodes and gradually increases to only 33 joules at 500 nodes. On the other hand, SWARAM's EC ranges from 9 J to 36 J, HHO-CFR from 10 J to 40 J, and ECEEC from 11 J to 39 J. These result shows that the proposed EMSO-WSN ensures reduce the energy usage, high NL, and make high efficient with scalable solution for WSN-IoT environments.

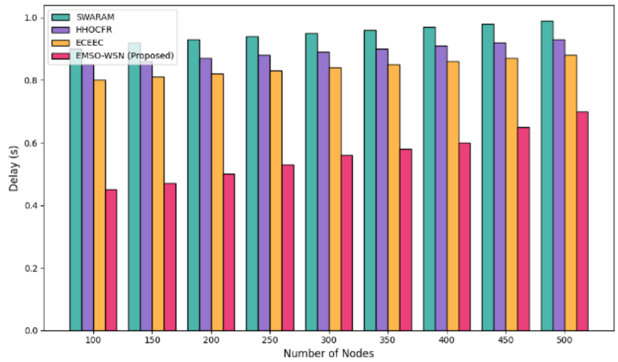

Figure 4. Delay Comparison

Figure 4 shows the delay (in seconds) versus the number of nodes for four protocols. The proposed EMSO-WSN protocol consistently exhibits the lowest delay, starting at 0.46s (100 nodes) and rising to 0.69s (500 nodes). In contrast, SWARAM shows the highest delay, increasing from 0.88s to 0.99s. HHOCFR and ECEEC have intermediate delays, ranging from 0.84s–0.93s and 0.81s–0.89s, respectively.

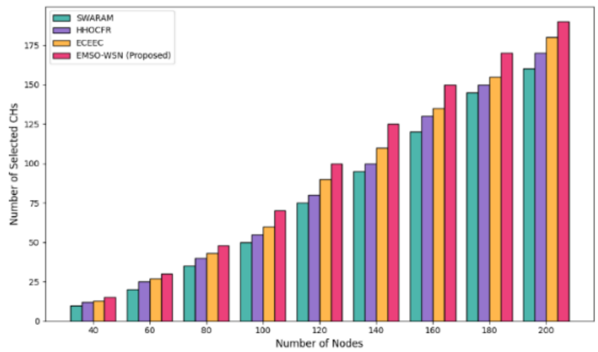

Figure 5. Number of selected CHs

Figure 5 shows CHS that increase the number of nodes range from 40 to 200. In that Proposed EMSO-WSN consistently selects more CHs and reach 190 CHs at 200 nodes, while SWARAM selects the least (about 160 CHs). HHOCFR and ECEEC peaks around 170–180 CHs.

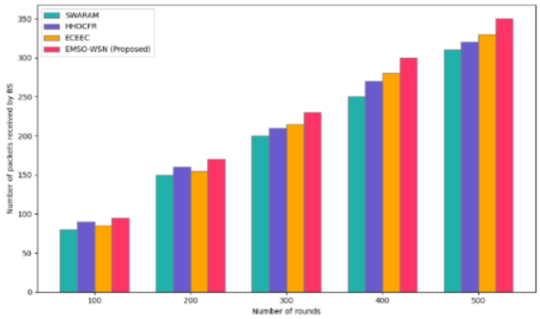

Figure 6. Packets Received by Base Station (BS) over Transmission Rounds for Different Methods

The performance of packets received by the BS is displayed in Figure 6. At 500 rounds, EMSO-WSN delivers about 350 packets, whereas SWARAM only manages around 310 packets. HHOCFR and ECEEC perform moderately, with about 320–330 packets received. This shows that the proposed EMSO-WSN improved delivery reliability

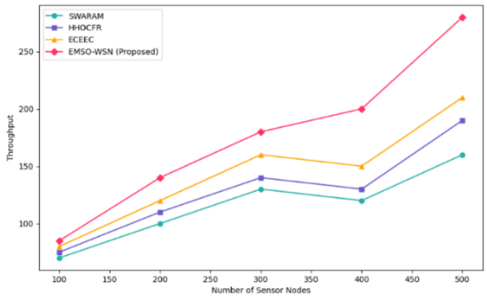

Figure 7. Throughput Vs Number of Sensor Nodes

The Proposed EMSO-WSN achieves the highest throughput, among other existing approaches, SWARAM [15], HHOCFR [17], and ECEEC [20]. At a network size of 500 sensor nodes, EMSO-WSN delivers a throughput that is 58.75% higher than SWARAM, 45.11% higher than HHOCFR, and 22.73% higher than ECEEC. Figure 7 shows EMSO-WSN network performance, with superior scalability and data transmission efficiency.

5. CONCLUSION

This research presented an Energy-efficient Mantis Search Optimization for Wireless Sensor Networks (EMSO-WSN) framework to enhance the routing efficiency in WSN-IoT. It included the FCM clustering, AWO-based CHS, and MSA routing to minimize the EC, ensure reliable data transmission, and extend the NL. The experimental framework was simulated by Python using NS2 for fine-grain throughput. The EMSO-WSN model is evaluated using key metrics such as NL, EC, delay, number of CH, DPD, and throughput. This shows the comparison of the proposed EMSO-WSN reduces less EC of 6 Joules at 100 nodes than that of other existing methods like SWARAM of 9 J, HHO-CFR of 10 J, and ECEEC of 11 J, respectively. The throughput of proposed EMSO-WSN achieves 58.75% higher than that of other existing like SWARAM, 45.11% higher than HHOCFR, and 22.73% higher than ECEEC. Despite this achievement, the proposed EMSO-WSN lacks reliance on static assumptions and real-time mobility handling. Future research focuses on mobile nodes, adapting real-time algorithms, a security layer to handle the cyber-physical threats, and large-scale deployments to further improve scalability and resilience.

CONFLICTS OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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