ISSN: 2093-5374 / E-ISSN: 2093-5382

A Multi-Faceted Framework to Enhance Lifespan and Optimize Latency in Wireless Sensor Networks

Seethamraju Sudhamsu Mouli[1*], Veeraiah Thalagondapati[2], and T. Raja Rao[3]

[1*]Ecole Centrale School of Engineering Mahindra University, Hyderabad, India.
sudhamsu21pcse002@mahindrauniversity.edu.in,
https://orcid.org/0000-0003-2975-2700

[2]Ecole Centrale School of Engineering Mahindra University, Hyderabad, India.
veeraiah.talagondapati@mahindrauniversity.edu.in
https://orcid.org/0000-0002-8081-0200

[3]Ecole Centrale School of Engineering Mahindra University, Hyderabad, India.
raja.tripuraneni@mahindrauniversity.edu.in
https://orcid.org/0009-0004-9168-1178

Received: November 11, 2024; Revised: December 19, 2024; Accepted: February 11, 2025; Published: March 31, 2025

Abstract

Wireless sensor networks (WSNs) provide huge potential in various applications such as ecological monitoring, healthcare, smart environment and various applications such as robotics. Nevertheless, developing an effective mac protocol for WSNS is challenging due to high energy consumption, scalability issues, and delays. This task introduces an organized Mac protocol to cross these boundaries. The proportional scaling cuttlefish optimization approach (PS-COA) is used by the protocol in order to accomplish the following goals: grouping nodes into groups; balancing energy consumption; and stabilizing network performance. Hebbian Plasticity Neural Networks (HPNN-NAI) are able to plan node activity because they are able to differentiate between active and passive nodes. This allows them to reduce the amount of time and delay that is spent in passive mode, which in turn reduces the amount of energy that is used. The outcomes of the experiments indicate that this method, in contrast to the protocol that is now in use, results in an improvement in energy efficiency, a speeding up of data transmission, and an extension of the network's lifetime. Through the use of the innovative combination of PS-COA, MPNC, RC-FFO, and HPNN-NAI, it has been possible to accomplish the goal of achieving significance in the design and efficiency of the Mac Protocol for WSNS.

Keywords: Wireless Sensor Networks, Cluster Heads, Relay Nodes, Medium Access Control, Network Lifetime.

1 Introduction

As a result of the rapid development of wireless communications technology, wireless sensor networks (WSNs) have seen a rapid growth, demonstrating a remarkable promise for a variety of applications. The term "wireless sensor networks" (WSNs) refers to a kind of distributed network that is dependent on integrated wireless transmission and data processing. Batteries are used to power the sensors, also known as nodes, that are spread over the actual world and together constitute these networks (Nithya &

*Corresponding author: Ecole Centrale School of Engineering Mahindra University, Hyderabad, India.

Narmatha, 2017). With this configuration, wireless sensor networks (WSNs) are able to do localized computations and coordinate amongst nodes with ease. When working in conjunction with a dense array of SNs, wireless sensor networks (WSNs) demonstrate a remarkable level of spatiotemporal accuracy in their continuous detection, tracking, and responsiveness to inputs from the outside world. Numerous industries, such as biomedical technology, precision agriculture, disaster response, infrastructure health monitoring, hazardous environment exploration, and precision agriculture, are all contemplating the use of this capability (Xu et al., 2019; Wang et al., 2019)

The special constraints that wireless sensor networks (WSNs) encounter include their small size, limited energy resources, and the need for collaborative operation. These small sensor nodes are often affordable, have a low impact on the environment in terms of energy consumption, and have very few computing capabilities, memory footprints, and battery lifespan (Hamzah et al., 2019). Therefore, energy efficiency is very necessary for the life of the network. over the use of more traditional techniques, environmental monitoring at a high degree of detail is not always achievable (Srikanth & Shankar, 2020; Raza et al., 2017). However, with a multi-hop communication architecture, sensor nodes collaborate in order to convey data over the network to a central sink.

Yogendra Sahu and Nitish Kumar (2024) developed the ideological framework based on leadership development principles, career progress models, and a merit-based framework to assess the effectiveness of the leadership pipeline model (LPM) in producing healthcare officers and future leaders. Within the context of LPM, this research examines the influence of path-target theory, transformational leadership theory, and leadership development models on the efficacy of healthcare executive leadership (Figure 1).

To avoid collisions, minimize interference, and optimize channel reuse, the MAC protocol deals with node access to the shared wireless medium, making it an essential protocol in WSNs. Although traditional multiple access control (MAC) protocols like CSMA and TDMA have been extensively researched for use in broader wireless networks, WSNs need specialized MAC solutions due to their energy limitations and specific needs (Sahoo et al., 2019). A goal for successful WSN deployments is energy-efficient MAC design, since challenges in WSNs develop from limited energy and bandwidth, variable network topologies, and the requirement for application-specific quality of service (Thoi, 2025). Low Energy Adaptive Clustering Hierarchy (LEACH) (Kavitha, 2024) is one example of a traditional MAC protocol that uses probabilistic CH rotation to spread the energy burden and promote energy-efficient clustering. Nevertheless, in ever-changing settings characterized by fluctuating node energies, base station distances, and traffic loads, these techniques often prove inadequate. According to (Subramanian & Paramasivam, 2017; Swain et al., 2017), adaptive clustering approaches are necessary because include all SNs in each CH selection cycle might speed up energy depletion.

In response to these issues, this research presents a multi-objective optimization framework that integrates state-of-the-art methods for wake-up scheduling, cluster head (CH) selection, and cluster selection. The framework incorporates the following algorithms: PS-COA for energy-efficient clustering and CH selection; RC-FFO for optimal RN selection; and HPNN- NAI for adaptive wake-up scheduling; all developed by Reservoir Computing with Fruit Fly Optimization. By combining these methods, we may create an adaptive, energy-aware MAC protocol that can respond on the fly to changes in the network, enhancing its operational lifespan, reducing latency, and balancing energy usage (Eesa et al., 2015; Xing & Gao, 2015). These techniques handle non-linear and high-dimensional optimization issues without gradient information, adapt to new circumstances and goals, and keep the solution set unique to prevent early convergence.

Because of its capacity to collect data at a finer scale, wireless sensor network deployment is an ideal choice for critical situations in which real-time situational awareness is essential. As an illustration, two instances of such settings are the monitoring of the health of the infrastructure and the investigation of potentially hazardous locations (Urmonov & Kim, 2018; Hu et al., 2017; Liu et al., 2018). When it comes to precision agriculture, wireless sensor networks (WSNs) are used to monitor soil moisture, temperature, and insect population over wide fields. This enables data-driven choices to be made, which in turn increases crop yields while simultaneously reducing resource consumption (Pegatoquet et al., 2018).

In order to provide individualized healthcare, WSNs also provide continuous health monitoring by following patients' vital signs and movements (Madugalla & Perera, 2024; Radha et al., 2018). Nevertheless, for WSNs to reach their maximum potential, communication protocols are needed that optimize resource efficiency while also fulfilling the QoS expectations of certain applications.

To avoid collisions, minimize interference, and optimize channel reuse, the MAC protocol deals with node access to the shared wireless medium, making it an essential protocol in WSNs. Although traditional multiple access control (MAC) protocols like CSMA and TDMA have been extensively researched for use in broader wireless networks, WSNs need specialized MAC solutions due to their energy limitations and specific needs (Odeh & Taleb, 2023). A goal for successful WSN deployments is energy-efficient MAC design, since challenges in WSNs develop from limited energy and bandwidth, variable network topologies, and the requirement for application-specific quality of service. Low Energy Adaptive Clustering Hierarchy (LEACH) (Kavitha, 2024) is one example of a traditional MAC protocol that uses probabilistic CH rotation to spread the energy burden and promote energy-efficient clustering. Nevertheless, in ever-changing settings characterized by fluctuating node energies, base station distances, and traffic loads, these techniques often prove inadequate. According to (Subramanian & Paramasivam, 2017; Swain et al., 2017), adaptive clustering approaches are necessary because include all SNs in each CH selection cycle might speed up energy depletion.

In response to these issues, this research presents a multi-objective optimization framework that integrates state-of-the-art methods for wake-up scheduling, cluster head (CH) selection, and cluster selection. The framework incorporates the following algorithms: PS-COA for energy-efficient clustering and CH selection; RC-FFO for optimal RN selection; and HPNN- NAI for adaptive wake-up scheduling; all developed by Reservoir Computing with Fruit Fly Optimization. By combining these methods, we may create an adaptive, energy-aware MAC protocol that can respond on the fly to changes in the network, enhancing its operational lifespan, reducing latency, and balancing energy usage (Eesa et al., 2015; Xing & Gao, 2015)

These techniques handle non-linear and high-dimensional optimization issues without gradient information, adapt to new circumstances and goals, and keep the solution set unique to prevent early convergence. Because of their multi-objective optimization capabilities, population-based techniques may achieve balanced trade-offs among competing goals, and their inherent parallelism makes them well-suited to issues on an enormous scale.

The structure of this paper is organized as follows: Section 2 presents a review of relevant literature on MAC protocols in WSNs, Section 3 provides a detailed explanation of the problem formulation for the proposed model. Section 4 explains the methodologies and functions employed in the proposed approach, Section 5 illustrates the performance evaluation, highlighting the results obtained Section 6 concludes the work by summarizing the key findings and contributions.

2 Related Work

WSNs have been a key area of research due to their immense potential in various applications one of the most significant challenges in WSNs is the design of energy-efficient protocols, particularly at the MAC layer, which plays a crucial role in managing energy consumption, scalability, and communication delays. Several solutions have been proposed to optimize energy efficiency, CH selection, and routing mechanisms in WSNs.

2.1 Clustering Protocols

LEACH (Low-Energy Adaptive Clustering Hierarchy), proposed by W.B. Heinzelman et al. (Heinzelman et al., 2002), intro- duced a dynamic clustering protocol where any sensor node (SN) can assume the role of a cluster head (CH) based on a predefined threshold. While LEACH effectively balances energy consumption across the network, it suffers from the drawback of excessive energy expenditure as every node is required to participate in the CH selection process. This leads to frequent elections that are power-consuming, especially in larger networks. Building on LEACH's framework, Smaragdakis et al., (2004) proposed the Stable Election Protocol (SEP), which incorporates node heterogeneity to improve energy efficiency. The SEP identifies two distinct categories of nodes, which are referred to as "normal" and "advanced." These individuals have more energy reserves and are in charge of the chores associated with CH. In spite of the fact that SEP is a revolutionary approach for clustering that takes into account energy heterogeneity, it is not particularly flexible when it comes to networks that include sensor nodes that are equally distributed and static. The Virtual Adaptive Partitioning Algorithm (VAP-E) was proposed by Azzedine Boukerche and colleagues (Boukerche & Zhou, 2020) as a solution for clustering heterogeneous wireless sensor networks (WSNs) (Sudhakar et al., 2019) that is energy efficient. This algorithm was developed to address some of the difficulties at hand. Through the optimization of CH selection, VAP-E is able to virtually partition the sensor network and share the load of energy equally across all of the sensors. Despite the fact that this strategy extends the life of the network, it may be challenging to maintain virtual partitions, particularly in large-scale networks that experience unexpected traffic loads. Within the framework of a clustering method that was established by Padmalaya N. et al. (P. N. & A. D., 2016), fuzzy logic is used to optimize the size of the cluster and improve the selection of CHs. This strategy takes a different tack than the others. By using this technology, the network is able to operate for a longer amount of time while consumption of energy is reduced. Adjusting to changing network circumstances, however, is not always a simple task since it is dependent on fine-tuning rules to such a large extent. Using these clustering strategies, considerable gains may be made in terms of regulating energy consumption and improving network efficiency in wireless sensor networks (WSNs). It is necessary to do more research and development since there are a number of important challenges, including energy imbalances, the difficulty of partition management, and the need for flexible and dynamic operations.

2.2 Routing and Energy-Aware Protocols

The Energy-Aware Multi-Hop Clustering Protocol (EAMMH), proposed (Mundada et al., 2012), focuses on enhancing energy efficiency in WSNs through dynamic cluster head (CH) selection and multi- hop routing within clusters. By employing multi-hop communication, the protocol minimizes energy consumption during data transmission. However, frequent CH changes can result in energy imbalances, and the complexity of managing multi-hop paths can lead to higher overhead, particularly in larger net- works. Similarly, the Energy-Efficient Cluster Head Selection (EECH) protocol introduced by Qian Ren et al. (Ren & Yao, 2019) categorizes nodes into distinct roles, including CHs, sensor nodes, and cluster members, to optimize energy usage. While EECH enhances energy efficiency, the protocol's computational com- plexity poses challenges for real-time applications, limiting its practicality in dynamic environments. The Energy-Efficient Trust-Aware Routing Protocol (ETARP), as proposed in (Pu et al., 2015), integrates a trust-based system to ensure secure and energy-efficient data transmission in WSNs. By incorporating trust evaluation into routing decisions, ETARP enhances both data security and energy optimization. However, the protocol may introduce delays, as trust evaluations can be time-consuming, particularly in larger networks with frequent node interactions.

In a different approach, the Bee-Sensor-C Routing Protocol (Cai et al., 2015) leverages the dynamic behavior of bees to enable parallel data transmission. As a result of this protocol's ability to distribute the routing burden over several nodes, it makes effective routing possible and reduces transmission delays in reaction to dynamic changes in the network. Although there is evidence that the approach has the ability to enhance the effectiveness of communication, the extent to which it is effective in networks that are both larger and more complex is still up for discussion. In order to choose cluster leaders, the Regional Energy-Aware Clustering Algorithm (RECA) takes into consideration the weight of each sensor node in addition to the average energy level of the area (as recommended in (Leu et al., 2014)). A clustering method that consumes less energy is provided by this approach. It is particularly useful in networks that include isolated nodes, which are more likely to have energy imbalances. Additionally, the algorithm takes into consideration regional energy levels in order to choose the nodes that are the most energy-efficient as CHs. This is done despite the fact that there may be scaling concerns in larger installations.

Utilizing the Fuzzy C-Means Algorithm, which is presented in (Bouyer et al., 2015), the LEACH approach is improved in order to get a more accurate selection of cluster heads. Through the use of fuzzy logic and the dynamic selection of CHs, this strategy enhances the efficiency with which energy energy is utilized. For improved energy management in heterogeneous networks, fuzzy logic is a great addition to LEACH because of its flexibility to changing network conditions. This makes fuzzy logic an excellent complement to LEACH. As a last point of discussion, the Multi-Level Route-Aware Clustering Technique is an approach that seeks to decrease the amount of power that is used by distributing routing and clustering processes over many levels, as advocated in (Sabet & Naji, 2016). This multi-level technique may enhance data transmission and cluster management, particularly in large networks that are spread out over several locations. The protocol is able to reduce overhead while also maintaining a balanced energy consumption throughout the whole network. This is made possible by the use of hierarchical network segments.

2.3 Medium Access Control Protocols

Numerous Media Access Control (MAC) protocols have been proposed as potential solutions for enhancing the performance of Wireless Sensor Networks (WSNs) as well as their energy efficiency. The TREEM Protocol was introduced by Wang R. and colleagues (Wang et al., 2007). This protocol makes use of a mix of reservation-based and contention-based access in order to adapt to various traffic situations and significantly enhance energy efficiency. On the other hand, there are still instances in which data is lost while it is being sent. The FM-MAC Protocol that was introduced by Zakaria et al. (Hamidi-Alaoui et al., 2020) integrates a multi-channel approach and inter-cluster handover in order to promote mobility in wireless sensor networks (WSNs). However, it has issues with scalability when the size of the network increases. It plans sleep/wake cycles to optimize energy utilization across nodes and was investigated using a Markov chain model by Mahendra Ram et al. (Ram et al., 2019). Timeout MAC (T-MAC) is an alternative protocol that has been effective in a number of traffic circumstances thanks to its ability to schedule sleep/wake cycles. Nevertheless, the technique makes it difficult to find optimal sleep and waking rhythms, which is a computational challenge. Lastly, but certainly not least, the Hybrid MAC Protocol developed by Xin Yang et al. (Yang et al., 2018) combines CSMA/CA and TDMA techniques in order to enhance the energy efficiency of WBAN. Even if it is effective in reducing energy consumption by offloading transmission overhead to the base station, there is room for further optimization since it does not take into account the possibility of energy dissipation that may occur during the sleep states of sensor nodes.

Even though significant breakthroughs have been made, there are still some challenges that need to be overcome. significant challenges include high energy consumption due to frequent CH elections, difficulty with scalability in larger networks, and computational complexity in scheduling and routing. Current solutions often fall short when it comes to combining many optimization objectives, such as maintaining a balance between the lifetime of the network, energy consumption, transmission speed, and node activity. Examples of such goals include maintaining a balance between these four factors. To address the limitations identified in the literature, this work proposes a multi-faceted framework (O'Neil et al., 2017) to enhance the lifespan and optimize latency in wsns and a comparison between existing work and proposed work is shown in below table 1 and annotations used in this paper are shown in table 2

Table 1: Comparison between Existing Works and Proposed Work

Feature	Existing Works	Proposed Work
Energy Efficiency	✓	✓✓
Optimal Cluster Head (CH) Selection	✓	✓✓
Dynamic Clustering	✗	✓
Relay Node Selection	✓	✓✓
Wake-up Scheduling	✓	✓✓
Latency Reduction	✓	✓✓
Data Transmission Efficiency	✓	✓✓
Scalability	✗	✓
Reduced Re-clustering	✗	✓✓
Adaptability to Network Changes	✗	✓

- ✓= Available but limited
- ✓✓= Significantly improved
- ✗= Not available or ineffective

3 Problem Definition

This work aims to devise an energy-efficient MAC protocol for WSNs. Acknowledging the constrained battery capacity of SNs and the necessity for energy-efficient functioning to prolong network lifespan, the energy model considers the primary sources of energy depletion: data transmission, reception, and idle listening. The approach strives to curtail energy consumption during data transmission by optimally selecting CHs and RNs, coupled with implementing an efficient wake-up scheduling mechanism.

Data Transmission: The equation 1 calculates the total energy consumed by summing the product of data packet size, distance, and energy per bit for all transmitted packets. The parameters involved ensure that the energy model accurately reflects the energy expenditure based on packet size and transmission distance.

$$E_{\text{trans}} = \sum_{i=1}^{N} \text{Data\_Size}_i \times \text{Distance}_i \times E_{\text{trans\_per\_bit}} \quad (1)$$

Data Reception: The equation 2 sums the energy consumed per bit for each received data packet, considering the size of each packet to provide a comprehensive view of energy consumption during data reception.

$$E_{\text{recv}} = \sum_{i=1}^{N} \text{Data\_Size}_i \times E_{\text{recv\_per\_bit}} \quad (2)$$

CH Selection: The equation 3 captures the energy consumed by CHs during data aggregation, taking into account the aggregated data size and the energy cost per unit of aggregation.

$$E_{\text{CH}} = \sum_{i=1}^{M} \text{Data\_Aggregation}_i \times E_{\text{CH\_per\_aggregation}} \quad (3)$$

RN Selection: The equation 4 calculates the total energy consumed by RNs, considering the amount of data relayed and the energy cost per unit of relayed data.

$$E_{\text{relay}} = \sum_{i=1}^{K} \text{Relay\_Data}_i \times E_{\text{relay\_per\_data}} \quad (4)$$

Table 2: Annotations

Symbol	Description
N	Number of data packets transmitted or received
Data Size$_i$	Size of the *i*-th data packet
Distance$_i$	Distance traveled by the *i*-th packet
E_trans_per_bit	Energy consumed per bit during data transmission
E_recv_per_bit	Energy consumed per bit during data reception
M	Number of CHs
Data Aggregation$_i$	Aggregated data size by the *i*-th cluster head
E_CH_per_aggregation	Energy consumed per unit of data aggregation
K	Number of RNs
Relay Data$_i$	Data relayed by the *i*-th relay node
E_relay_per_data	Energy consumed per unit of data relayed
Idle Time$_i$	Idle listening time for the *i*-th node
E_idle_per_time	Energy consumed per unit time during idle listening
Wake Time$_i$	Wake-up scheduling time for the *i*-th node
E_wake_per_time	Energy consumed per unit time during wake-up scheduling
E_total	Total energy consumption
E_trans	Total energy consumed during data transmission
E_recv	Total energy consumed during data reception
E_idle	Total energy consumed during idle listening
E_CH	Total energy consumed by CHs

$\bar{E}_{\text{relay}}$	Total energy consumed by RNs
$\bar{E}_{\text{wake}}$	Total energy consumed during wake-up scheduling
SN	Sensor nodes
CH	Cluster Heads
BS	Base station
NLT	Network Life Time
$\bar{E}_{\text{max}}$	Maximum residual energy among all sensor nodes
$\bar{d}_{\text{min}}$	Minimum distance among all sensor nodes
$\mathbf{E}_i$	Residual energy of the *i*-th sensor node
$\mathbf{d}_i$	Distance of the *i*-th sensor node from the base station
Normalized $\mathbf{e}_i$	Normalized residual energy of the *i*-th sensor node
Normalized $\mathbf{d}_i$	Normalized distance of the *i*-th sensor node
$\mathbf{f}_i$	Fitness value of the *i*-th sensor node
$\overline{\text{CH}}_{\text{set}}$	Set of selected CHs
$\bar{E}(\text{CH}_j)$	Residual energy of the *j*-th selected cluster head
$\bar{d}(\text{CH}_j)$	Distance of the *j*-th selected cluster head from the base station
$\mathbf{I}_i$	Color intensity of the *i*-th cuttlefish agent
$\mathbf{w}_1, \mathbf{w}_2$	Weighting factors in the fitness function for color intensity calculation
$\mathbf{x}_i$	Location of the *i*-th sensor node
$\mathbf{E}_i$	Residual energy of the *i*-th sensor node
$\mathbf{d}_i$	Distance of the *i*-th sensor node to the base station
$\mathbf{f}_i$	Cost function for the *i*-th node
$\delta \mathbf{x}_i$	Position update of the *i*-th sensor node
$\mathbf{w}_3, \mathbf{w}_4$	Weighting factors in the position update formula
$\bar{x}_{\text{max}}$	Position of the highest intensity cuttlefish
α, β	Weighting factors used in the fitness function

Idle Listening: The equation 5 addresses the energy wasted while nodes are in an active state without actual communication, by considering the idle time and energy cost per unit time.

$$E_{\text{idle}} = \sum_{i=1}^{N} \text{Idle\_Time}_i \times E_{\text{idle\_per\_time}} \quad (5)$$

Wake-Up Scheduling: The equation 6 sums the energy consumed during wake-up scheduling, considering the time nodes spend transitioning between active and sleep states.

$$E_{\text{wake}} = \sum_{i=1} \text{Wake\_Time}_i \times E_{\text{wake\_per\_time}} \quad (6)$$

Total Energy Consumption: The primary objective of the total energy consumption formula (Etotal) equation 7 is to provide a holistic measure of energy usage in the WSN. This measure helps in identifying and optimizing the various components that contribute to energy depletion, thereby enhancing the overall energy efficiency of the network.

$$E_{\text{total}} = E_{\text{trans}} + E_{\text{recv}} + E_{\text{idle}} + E_{\text{CH}} + E_{\text{relay}} + E_{\text{wake}} \quad (7)$$

Objective 1: The equation 8 maximizes the NLT of the WSN by minimizing energy consumption during data transmission and idle listening.

$$\text{Maximize } NLT = f(E_{\text{trans}}, E_{\text{idle}}) \quad (8)$$

Objective 2: The equation 9 minimizes communication delays and latency by selecting optimal RNs and employing efficient wake-up scheduling.

$$\text{Minimize Delay} = g(\text{RNs}, \text{Wake-up scheduling}) \quad (9)$$

4 Methodology

Energy conservation and delay minimization in WSNs pose key challenges that current researchers aim to address. To overcome these challenges, this work proposes PS-COA and MPNC approach for clustering and cluster head selection, RC-FFOA for optimal Relay node selection, HPNN-NAI for finding active and inactive nodes, and emergent-organized MAC protocol for WSNs that accounts for both energy efficiency and delay considerations is proposed in Figure 1.

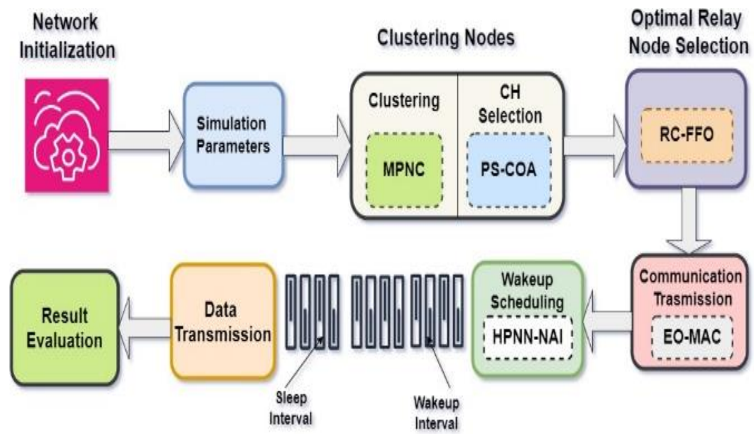

Figure 1: Proposed Framework

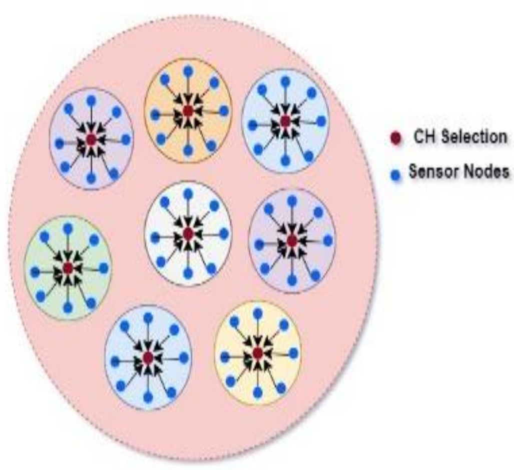

Figure 2: Proposed Framework for Clustering and Cluster Head Selection

4.1 Clustering

The proposed MPNC clustering method of Algorithm 1 forms clusters based on the distance between CH and SNs proposed in Figure 2. This optimization of NLT overcomes limitations of existing approaches which consider factors such as residual energy, node distances, and node degrees when clustering. In the MPNC approach, each SN is grouped into a cluster with the most similar CH according to Mahalanobis distance. Specifically, the Mahalanobis distance and the covariance matrix are first used to assess similarity. Then, SNs deemed similar to a given CH per this distance metric are clustered with that CH. Clustering SNs with their most similar CH in this manner helps save energy efficiently across the network.

To achieve this, the MPNC approach proposed in Figure 2 initially evaluates SN: $[S_{N1}^*, S_{N2}^*, S_{N3}^*, \ldots, S_{NN}^*]$ and CH: $[C_1^*, C_2^*, C_3^*, \ldots, C_N^*]$ form a cluster i.e.

$$E_{DK} = \|C_{K*} - S_{N*K}\|_{S^{-1}} \quad (10)$$

Subsequently, the SN with the minimum distance value is methodically assigned to its corresponding CH based on this evaluation the equation 10, culminating in the formation of a cluster, henceforth designated as. (CK_i) in equation 11, i.e

$$CK_{C\text{New}} = \left[CK_1\left(S_k^1 \cdot (CH_1^*)\right), CK_2\left(S_k^2 \cdot (CH_2^*)\right), \ldots, CK_n(S_k^n \cdot (CH_N^*))\right] \quad (11)$$

Initially focusing on spatial optimization, the MPNC method minimizes the energy spent on communication between nodes and CHs. This reduces the network's overall energy consumption, prolonging its operational lifespan.

4.2 CH Selection

To provide a longer network NLT, CHs are selected based on the node with the highest remaining energy is proposed in Algorithm 2. To achieve this work, we propose a CH selection based on PS-COA. The proposed approach utilizes a cuttlefish algorithm mechanism (Sathish & Ravichandran, 2018) for optimization. This bio-inspired algorithm mimics the camouflage behaviors and mechanisms in cuttlefish to efficiently search complex spaces and converge on near-optimal solutions. The specific workings of the algorithm are modeled on observed cuttlefish adaptations like dynamically adjusting skin patterns and rapidly learning environ- mental contexts. By emulating these natural behaviors, the cuttlefish algorithm can effectively guide the search process despite problem complexity, noise factors, and dynamic constraints. The self-organizing and learning properties of the algorithm allow efficient exploration and leveraging of accumulated in- formation to reach optimized states aligned with the defined objective.The optimization algorithm aims to obtain an optimal solution on a specified objective function. The assessment of fitness values holds paramount importance as it determines the quality of the candidate solutions. We have devised a novel fitness function that integrates the objective function to select CHs based on the highest residual energy and minimizes their distance from the base station, consequently prolonging the network's lifespan and ensuring efficient energy utilization and load distribution among the CHs. The maximum residual energy (E_{max}) and the minimum distance (d_{min}) among all SNs are factored into the equation 12 and 13.

$$E_{\max} = \max(E_1, E_2, \ldots, E_N) \quad (12)$$

$$d_{\min} = \min(d_1, d_2, \ldots, d_N) \quad (13)$$

Normalize the residual energy in the equation 14 and distance in the equation 15 values for each sensor node i using the maximum residual energy and minimum distance, respectively.

Algorithm 1 MPNC Algorithm

Data: Number of nodes N, Network field size, Base station location

Result: CHslocations, SNs assignments, Energy usage

1 **Initialization:**

Initialize simulation parameters: N, network field size, base station location **for** *each node* $i = 1$ *to* N **do**

2 Initialize ID, random location (x_i, y_i), and energy (E_i)

3 **MPNC Clustering:**

Create initial CHs (CH*) at random locations Compute covariance matrix **S** of node positions

for *each sensor node* SN^* **do**

4 **for** *each cluster head* CH^* **do**

5 Compute Mahalanobis distance E^D_K using:

$$E_{DK} = \| C_{K*} - S_{N*K} \|_{S^{-1}}$$

6 Assign SN^* to the closest CH^* based on minimum E^D_K

7 Update CH^* locations as the centroid of the assigned sensor nodes:

$$CK^{New}_{C_k} = [CK_1[S^1_k \cdot (CH^*_1)], CK_2[S^2_k \cdot (CH^*_2)], \ldots, CK_n[S^n_k \cdot (CH^*_N)]]$$

Repeat steps 4-6 until CH locations stabilize or a maximum number of iterations is reached

8 **Simulation**

Communication Phase:

for $t = 1$ *to simulation time* **do**

9 **for** *each node* SN^* **do**

10 SN^* sends data to assigned CH^* Adjust SN^* energy Aggregate and relay CH^* data

11 Evaluate performance metrics

$$\text{Normalized } e_i = \frac{E_i}{E_{\max}} \quad (14)$$

$$\text{Normalized } d_i = \frac{d_{\min}}{d_i} \quad (15)$$

The position of each cuttlefish agent i at iteration, $t+1$ is updated as follows (16)

$$\text{where:} \boldsymbol{X}_i^{t+1} = \boldsymbol{X}_i^t + r_1(\boldsymbol{P}_i^t - \boldsymbol{X}_i^t) + r_2(\boldsymbol{G}^t - \boldsymbol{X}_i^t) + r_3\boldsymbol{N}^t$$

$\mathbf{X}^t_i$ is the position of agent i at iteration t

$\mathbf{P}^t$ is the local best position of agent i at iteration t

$\mathbf{G}^t_i$ is the global best position at iteration t

r_1, r_2, r_3 are random scaling factors representing the influence of local best, global best, and random perturbation, respectively

$\mathbf{N}^t$ is the random perturbation vector

The fitness value (f_i) for each SNs i in equation 17.Selecting the top m SNsas the optimal CHs α and β are the weighting factors that balance the importance of residual energy and distance to the base station for the network based on their fitness values (f_i). The selected CHs are represented by the set in equation 18:

$$f_i = \alpha \cdot \text{Normalized } e_i + \beta \cdot \text{Normalized } d_i (7) \text{ CH set} = \{CH_1, CH_2, \ldots, CH_m\} (18)$$

The total residual energy (E_{total}) in equation 19 and the sum of distances (D_{total}) for the selected CHs in equation 20.

$$E_{\text{total}} = \sum_{j=1}^{m} E(CH_j) \quad (19)$$

$$D_{\text{total}} = \sum_{j=1}^{m} d(CH_j) \quad (20)$$

Where $E(CH_j)$ is the residual energy of the j^{th} selected CH, and $d(CH_j)$ is the distance of the j^{th} selected CH from the base station. The color intensity I_i in equation 21 of each cuttlefish agent can be calculated based on f_i in equation 22that considers the residual energy and distance to the base station of its mapped sensor node.

$$I_i = f_i(E_i, d_i) \quad (21)$$

$$f_i(E_i, d_i) = w_1 \cdot E_i + w_2 \cdot \frac{1}{d_i} \quad (22)$$

x_i is the Location of sensor node,E_i is the residual energy of sensor node,d_{ib} is the distance of node to the base station, I_i is the color intensity of cuttlefish agent and f_i is the Cost function for node.$w1$, and $w2$ are weighting factors. Maximizing f_i maximizes remaining energy and the distance in 23.

$$\Delta x_i = w_3 \sum I_j (x_j - x_i) \quad (23)$$

The movement of the cuttlefish agents can be modeled using the collective response and predation avoid- ance in equation 24

$$\Delta x_i = w_4 (x_{\max} - x_i) e^{-\beta E_i} \quad (24)$$

where x_{max} is the position of the highest intensity cuttlefish, α and β is a constant. So, in each iteration, the location update for each cuttlefish agent combines the collective response and predation avoidance motion vectors. Over the iterations, the cuttlefish agents will cluster around the nodes with higher residual energy and closer to the base station, marked by higher color intensity. The PS-COA algorithm's modeling of color intensity, location updates, and predator avoidance mechanisms ensures the effective selection of CHs. This balance between exploration and exploitation enhances the overall performance and lifespan of the WSN by selecting CHs that are energy-efficient and strategically positioned.

Algorithm 2 PS-COA Clustering Algorithm

Data: Number of nodes N, Network field size, Base station location

Result: CHs locations,SNs assignments, Energy usage

Initialization:

Initialize simulation parameters: N, network field size, base station location **for** *each node* $i = 1$ *to* N

do
Initialize ID, random location (x_i,y_i), and energy (E_i)
Initialize cuttlefish agents with positions and energy levels
PS-COA Clustering: for *each iteration t* **do**
for *each cuttlefish agent i* **do**
Update position using: $\mathbf{X}^{t+1} = \mathbf{X}^t + r_1(\mathbf{P}^t - \mathbf{X}^t) + r_2(\mathbf{G}^t - \mathbf{X}^t) + r_3\mathbf{N}^t$
Evaluate fitness f_i using:
$f_i = \alpha \cdot \text{Normalized RE}_i + \beta \cdot \text{Normalized Distance to BS}_i$ Update local and global best positions
Assign SNs to the closest CH based on minimum Mahalanobis distance Update CH positions as the centroid of the assigned sensor nodes
Repeat steps 4-6 until CH positions stabilize or a maximum number of iterations is reached
Simulation Communication Phase: for $t = 1$ *to simulation time* **do**
for *each node SN* **do**
SN sends data to assigned CH Adjust SN energy Aggregate and relay CH data
Evaluate performance metrics

4.3 RN Selection

Implementing RNs as intermediaries between SNs and CHs through the RC-FFO (Sathish & Ravichandran, 2018) can facilitate energy-efficient data gathering and extend the NLT in WSNs. However, suboptimal RN selection, ineffi- cient deployment strategies, and high communication overheads can adversely impact the NLT of WSNs. The fitness evaluation phase plays a crucial role in assessing the quality of a candidate solution, which encompasses the selected RNs and their deployment parameters. The fitness function aims to minimize the total energy dissipation while considering both communication and deployment costs. The energy consumption of an RN j due to data collection, aggregation, and transmission activities within a single round is represented by the following equation 25.

$$E_{\text{cluster}}(j) = n_j \cdot (E_{\text{receive}} + E_{\text{aggregate}}) + E_{\text{transfer}}(j, \text{NextRelay}(j)) \quad (25)$$

$E_{receive}$ denotes the energy expended in receiving data from a sensor node, while $E_{aggregate}$ represents the energy consumed for data aggregation. E_{transfer}(j,NextRelay(j)) signifies the energy utilized for transmit- ting data from relay node j to its subsequent relay node. Furthermore, the relay node j expends energy to forward data acquired from adjacent RNs. The overall energy consumption of the relay node j is contin- gent upon the cumulative data received by relay node j from other RNs, denoted by $D_{In}(j)$ in equation 26.

$$D_{\text{In}}(j) = \sum D_{\text{In}}(k) \mid \text{NextRelay}(k) = j, k \in R\}, \quad (26)$$

$$\text{if NextRelay}(k) \neq j, \ \forall k \in R$$

$$E_{\text{forward}}(j) = D_{\text{In}}(j) \cdot E_{\text{receive}} + D_{\text{In}}(j) \cdot E_{\text{transfer}}(j, \text{NextRelay}(j)) \quad (27)$$

$$E_{\text{relay}}(j) = E_{\text{cluster}}(j) + E_{\text{forward}}(j) \tag{28}$$

Minimize Energy Loss

$$\text{Lifespan}(j) = \frac{E_r}{E_{\text{relay}}(j)} \tag{29}$$

The energy loss is calculated as the sum of communication and deployment costs, weighted by α and β, respectively in equation 30.

$$f_1 = \alpha \times C_{comm} + \beta \times C_{\text{deploy}} \tag{30}$$

C_{comm} is the communication cost, which can be estimated based on the distances between SNsand RNs. C_{deploy} is the deployment cost, which can be estimated based on the number of RNs and their deployment locations.

The fitness function combines the two objectives using a weighted sum in equation 31

Maximize Lifespan of Relay Node

$$f_2 = \max\,(\text{Lifespan(j)}), \quad \forall j \in R \tag{31}$$

$$\text{Fitness} = w_1 \cdot f_1 + w_2 \cdot f_2 \tag{32}$$

Where $w1$ and $w2$ are weight coefficients that determine the relative importance of the two objectives, and $w1 + w2 = 1$ in equation 32.The objective is to minimize the fitness function, which corresponds to minimizing the total energy loss while maximizing the lifespan of the relay node. During the optimization process, candidate solutions (sets of RNs and their deployment parameters) are evaluated using the fitness function. Solutions with lower fitness values are preferred, as they represent better trade-offs between energy loss and relay node lifespan.The specific implementation details, such as the calculation of communication and deployment costs, the choice of weight coefficients (α, β, $w1$,$w2$), and the optimization algorithm used to search for the best solution, may vary depending on the problem instance and the computational resources available is proposed in Algorithm 3.

4.4 Communication Transmission

The data link layer encompasses the MAC sublayer protocol, orchestrating coordinated access to a shared communication channel. MAC protocols play a pivotal role in systems where multiple nodes can transmit over the same physical medium. Among the prevalent MAC protocols are Carrier Sense Multiple Access (CSMA), CSMA with Collision Detection (CSMA/CD), and CSMA with Collision Avoidance (CSMA/CA). An imperative objective of MAC protocols in WSNs is to facilitate energy-efficient data transmission between sensor nodes, RNs, and the cluster head. However, a significant portion of energy is lost and wasted due to the presence of inactive nodes and non-wake-up nodes. Inactive nodes are those that remain in an awake state within the cluster but do not actively participate in data transmission, unnecessarily consuming energy resources. Conversely, non-wake-up nodes persistently remain in sleep

Algorithm 3 RC-FFO Algorithm

Data: Input data, Reservoir Computing parameters θ_{RC}, Fruit Fly Optimization parameters θ_{FFOA}
Result: Updated Reservoir Computing parameters θ_{RC}, Updated Fruit Fly Optimization parameters
θ_{FFOA}, Updated energy loss E_{loss}

Initialization:
Set initial values for θ_{RC} and θ_{FFOA} **while** *Not Converged or Predefined Iterations* **do**
Reservoir Computing:
$RC(\text{input data}; \theta_{\text{RC}}) \rightarrow C_{\text{Comm}}, C_{\text{Deploy}}$
Fruit Fly Optimization:
Apply FFOA to optimize: $J(\mathbf{D}; \theta_{\text{FFOA}})$
Update Models:
$\theta_{\text{RC}} \leftarrow$ Updated Parameters from RC Optimization
$\theta_{\text{FFOA}} \leftarrow$ Updated Parameters from FFOA Optimization
Update Energy Loss:
Update E_{loss}

Mode, rendering them incapable of sensing data or receiving messages from the CH.To optimize the rout- ing protocol and identify high-throughput and energy-efficient paths, insightful features can be extracted from the network's operational behavior. These informative features, which encapsulate the network's performance characteristics and dynamics, can subsequently be leveraged to train a deep learning model. This data-driven approach can help overcome inefficiencies related to inactive and non-participating nodes in the sensor network. The deep learning system learns to select appropriate communication paths based on metrics indicative of energy usage and data transmission reliability.

4.4.1 Feature Identification

Feature Identification gathers informative data from the various nodes to identify optimal wake-up schedul-ing.It gathers the features namely number of packets received ($\wp_{NR}$), packet reception rate ($\wp_{PRR}$), num-ber of packets lost ($\wp_{PL}$), packet loss rate ($\wp_{PLR}$), throughput rate ($\wp_{TR}$), inter-packet interval ($\wp_{PI}$), network density ($\wp_{D}$) and channel occupancy rate ($\wp_{COR}$). To identify the optimal node, the aforementioned features are aggregated by employing a correlation metric, which is formulated as follows in equation 33:$\wp_{Newext} = \frac{COV(\wp_i, \wp_j)}{\sigma i \sigma_j}$ here,($\wp_{Newext}$) is the extracted feature, σi *and* σ_j are the input features, COV is thecovariance between the input features, and σi and σ_j are the standard deviations of the input features by identifying the active node and inactive node, The features are framed into a data frame that is:

$$\wp\text{Newext} = [\wp\text{NR}, \wp\text{PPIR}, \wp\text{PL}, \wp\text{PLR}, \wp\text{TR}, \wp\text{IPI}, \wp\text{D}, \wp\text{COR}] \quad (33)$$

4.4.2 Node Activation Scheduling

Node Activation Scheduling is an efficient process for maximizing network energy savings. After the formation of clusters within the network topology, each constituted cluster proceeds to implement a dedi-cated sleep/wake scheduling protocol. To optimize energy efficiency, the cluster retains solely one or two nodes with the highest residual energy levels in an active state, while transitioning the remaining nodes into a low-power sleep mode, thereby extending the overall operational lifespan. A Hebbian Plasticity

Neural Network for Node Activ- ity Identification (HPNN-NAI) model schedules energy-efficient data transmission by identifying active and inactive nodes. The model is trained on node features, including the extracted feature which is input into the model. The input features are aggregated with weight and bias values in the hidden layer. The hidden layer is activated using a Prelu activation function in equation 34:

$$\gamma = \sum_{i=1}^{n}(w_i \cdot x_i) + b \quad (34)$$

$$\eta_{\text{hidd}} = \psi_{\text{act}}(\sum_{i=1}^{n}(w_i \cdot x_i) + b) \quad (35)$$

The weight assigned to each input node represents the activation function employed to activate neurons. This work used the Parametric Rectified Linear Unit (PReLU) as the activation function in equation 35 for the hidden neurons, and the sigmoid function for the output neurons in 36.

$$\psi_{\text{act}}(\eta_{\text{hidd}}) = \{ \eta hidd \; if \; \eta hid > 0$$

$$\alpha \eta hidd \; if \; \eta hid \leq 0 \} \quad (36)$$

w_i represents the weight associated with input node i.x_i is the input from node i.b is the bias term.γ is the weighted sum of inputs plus bias. ψ_{act} is the PreLU activation function. α is the learnable parameter.The output layer detects active nodes and inactive nodes, calculating the error loss between predicted (ψ_i) and actual metric(ψ') in eqaution 37:

Overall Loss Function

$$L = \psi_i - \psi \quad (37)$$

$$\eta_{\text{out}} = \sum_{i=1}^{k}(\omega_i - \omega_i') \quad (38)$$

Where (ω_i) and (ω_i') implies the actual value and signifies the observed value in equation 38. Subsequently, a back-propagation process is performed to minimize the loss function, which entails updating the model's weights and biases to better align the predictions with the desired target results. This iterative adjustment of parameters is guided by the Hebbian rule in equation 39.

$$w' = w - \lambda \frac{\partial E}{\partial w} \quad b' = b + \frac{\partial E}{\partial b} \quad (39)$$

Where w and b signify the new weight and bias value. Finally, accurate node scheduling is offered by employing the model for the data's transmission via minimizing the loss, w is a new weight, w is the current weight, b' is the new bias, b is the current bias, λ is the learning rate

5 Results and Discussions

Contrasted with existing methods, the proposed method is validated through numerical evaluations of various performance metrics in this section. The evaluation includes the CH selection technique (PS-COA), the RN selection technique (RC-FFO), and the wake-up scheduling technique (HPNN-NAI). The proposed work is implemented in Python and based on publicly available data (802.15.4 MAC Performance Datasets, 2023) the simulation parameters are shown in Table 3.

Table 3: Simulation Parameters

Parameter	Value
Network Field Area	1500 x 1500 m
Number of SNs	250
Initial Energy of SNs	7J
Distance Between Adjacent Nodes	30 m
Radio Range of Sensor	50 m
Data Packet Size	512 bits
Simulation Time	4200 seconds
Packet Size Range	500 bytes
Node Speed	0 - 20 m/s

5.1 Evaluating the Efficacy of a Proposed CH Designation Approach

An exhaustive comparative study was conducted to evaluate the effectiveness of the newly developed PS-COA cluster head selection method. This innovative approach was benchmarked against several established techniques, including linear scaling social spider optimization (LS-SSOA) (Thalagondapati & Singh, 2023), social spider optimization algorithm (SSOA) (Mirjalili et al., 2015), ant colony optimization (ACO) (Zhao et al., 2018), modified centralized energy- efficient distance (MOD-CEED) (Darabkh & Zomot, 2018), and LEACH (Kavitha, 2024). The assessment focused on two critical performance indicators: energy efficiency and data throughput, measured across various operational cycles. The results, visually represented in Figure 3, provide compelling evidence of PS-COA's superiority. The graph illustrates the correlation between optimal cluster head selection and power consumption over mul- tiple rounds. At the maximum threshold of 2000 rounds, PS-COA demonstrates remarkable efficiency, utilizing only 920J of energy. In stark contrast, competing methods exhibit significantly higher energy demands, ranging from 1290J to 1650J. This disparity can be attributed to their less effective cluster head selection mechanisms. Even at lower operational cycles, PS-COA maintains its edge. For instance, at 400 rounds, PS-COA consumes a mere 180J, while other techniques show higher energy usage: LS- SSOA (200J), SSOA (300J), ACO (370J), MOD-CEED (490J), and LEACH (500J). This trend persists across various round counts, highlighting a clear link between optimal cluster head selection and energy conservation.

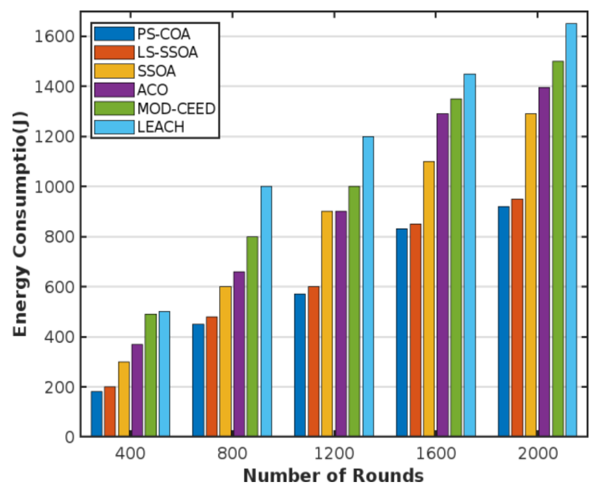

Figure 3: Evaluation Analysis of Proposed PS-COA based on EC

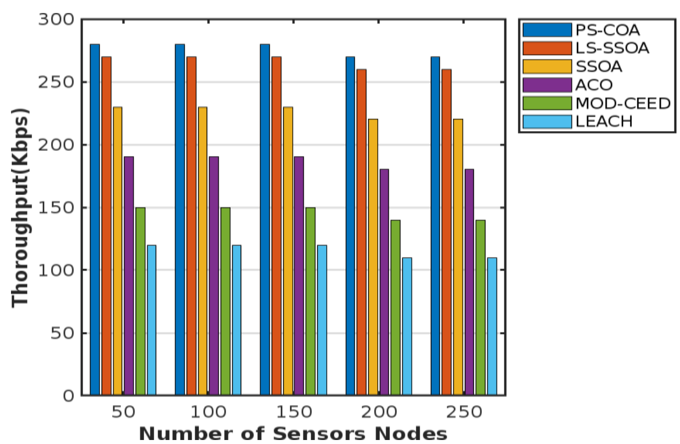

Figure 4: Evaluation Analysis of Proposed PS-COA based on Throughput

Figure 4 denotes the throughput value attained by the proposed PS-COA technique. It can be observed that PS-COA achieves a throughput ranging between 240 kbps SNs varying from 50 to 250 In comparison, the existing methodologies acquire a higher through Figure 4 of 210-280 kbps, indicating some data loss between the CH and BS. Specifically, the throughput achieved by PS-COA for different number of nodes is (50:275Kbps,100:265Kbps,150:260Kbps, 200:250Kbps,250:245Kbps). A declining trend in throughput is evident as the number of SNs increases. Regardless, PS-COA outperforms the other ex- isting systems across all node counts in terms of higher throughput. The reduced data loss enables the proposed technique to reliably sustain higher throughputs even at scale compared to other methods

5.2 Evaluating the Efficacy of a Proposed Optimal RN Selection Approach

Figure 5 presents a comparative analysis of the proposed RC-FFOA RN selection technique against several existing methodologies, including swap displacement And reverse-based Rock optimization (SDR- RHSO) (Bhattacharjee et al., 2022), Efficient RN Selection (ERNS) (Shukla & Tripathi, 2020), particle swarm optimization (PSO) (Kennedy & Eberhart, 1995), MOD- CEED (Shahzad et al., 2024), and LEACH (Kavitha, 2024). The evaluation focuses on Network Lifetime (NLT) performance across varying operational cycles. The graphical representation demonstrates the superior NLT achieved by the RC-FFOA framework. To maximize NLT, optimal RN selection between SNs and CHs is crucial, as it minimizes communication distances. The RC-FFOA technique showcases impressive results: For a 50 node network, the first node death occurs after 695 rounds In a 250 node network, the last SN survives until 615 rounds these figures stand in stark contrast to the performance of existing techniques, which exhibit significant energy depletion and reduced NLT due to suboptimal routing paths between CHs and the BS. For comparison, in a 50-node network scenario ERNS: First node death at 489 rounds, PSO: First node death at 512 rounds, MOD-CEED: First node death at 465 rounds, and LEACH: First node death at 425 rounds. The substantial difference in performance underscores the effectiveness of RC-FFOA in extending network lifetime through more efficient RN selection and routing strategies.

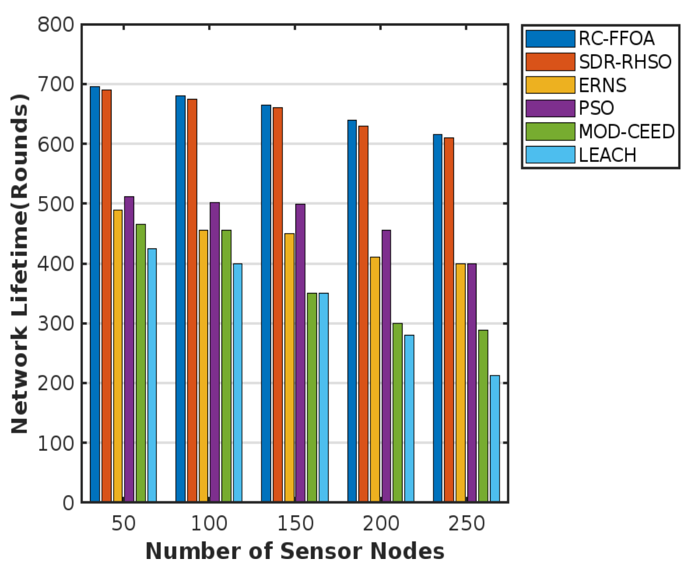

Figure 5: Evaluation Analysis of Proposed RC-FFO based on NLT

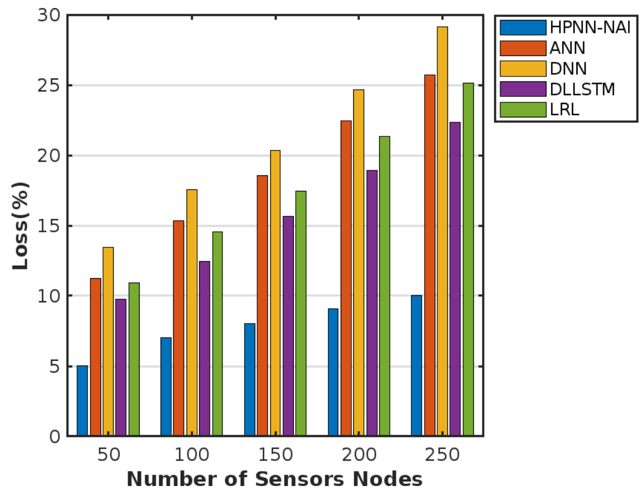

Figure 6: Evaluation Analysis of Proposed HP-NNAI

5.3 Evaluating the Efficacy of Proposed Wake up Scheduling Technique

The proposed HPNN-NAI technique, designed for energy-efficient data transmission by identifying active and non-active nodes, is evaluated against existing methods such as Artificial Neural Network (ANN), Deep Neural Network (DNN), Deep Learning-based Long Short-Term Memory (DLLSTM), and Lightweight Reinforcement Learning (LRL). The evaluation utilizes performance metrics including accuracy, sensitivity, False Positive Rate (FPR), and False Negative Rate (FNR). The results demonstrate that the HPNN-NAI technique achieves effective node activation scheduling by accurately distinguishing active and inactive nodes, with high accuracy of 92.23% and sensitivity of 93.12%, while maintaining low false detection rates (FPR of 13.23% and FNR of 11.32%). In contrast, the existing methods exhibit inferior performance, with accuracy and sensitivity ranging from 79.65% to 87.56%, and FPR and FNR spanning 24.15% to 40.15%. Consequently, the HPNN-NAI technique outperforms existing approaches, proving effective in reducing energy consumption (EC) and prolonging NLT. Table 4 presents the evaluation of the proposed HPNN-NAI for node activation scheduling in WSN.

Table 4: Performance Evaluation of the Proposed HPNN-NAI Technique for Node Activation in WSN

Methods	Accuracy (%)	Sensitivity (%)	FPR (%)	FNR (%)
ANN (Yegnanarayana, 2009)	79.65	80.12	35.65	39.6
DNN (Sze et al., 2017)	81.22	82.13	38.96	40.12
DL-LSTM (Mohanty et al., 2020)	82.35	84.56	32.12	30.11
LRL (Savaglio et al., 2019)	87.56	85.69	24.15	25.65
Proposed HPNN-NAI	92.23	93.31	13.12	10.11

The data transmission loss percentages in Figure 6 of a proposed HPNN-NAI-based wake-up scheduling protocol compared to several existing MAC protocols. The results showed the HPNN-NAI protocol demonstrated substantially lower loss percentages across network sizes from 50 to 250 nodes. Specifically, with 50 nodes, the proposed HPNN-NAI had a transmission loss of only 5.00%, while the existing LRL protocol had over double the loss at 10.93%. The superiority of the HPNN-NAI held for larger networks as well, consistently showing lower losses than current protocols including ANN, DNN, DLLSTM, and LRL. The significantly decreased losses indicate the proposed HPNN-NAI protocol utilizes wake-up scheduling more effectively. By minimizing data loss during transmission, the HPNN-NAI protocol can achieve maximum NLT. In conclusion, the proposed wake-up scheduling approach enables reliable data transmission with minimum loss percentages.

5.4 Evaluating the Efficacy of the Proposed EO-MAC Protocol

The collision probabilities of the proposed Emergent-Organized MAC (EOMAC) protocol in Figure 7 are compared to existing MAC protocols including Self-Organized Priority-based MAC (SPMAC), Hybrid MAC (HyMAC), Timeout MAC (TMAC), and Fast Mobility Adaptive MAC (FMMAC). Simulation re- sults show the collision probability for varying numbers of SNs(SNs) successfully transmitting data in a WSNs. For 50 SNs, the proposed EOMAC protocol has a collision probability of 0.1443, lower than SPMAC (0.1543), HyMAC (0.3201), TMAC (0.5432), and FMMAC (0.7894) over 400 rounds. With

250 SNs, EOMAC's collision probability is 0.5007, significantly lower than the other protocols which approach 1.0. This demonstrates that the EOMAC protocol withstands interference from node collisions and effectively transfers data.The below Table 5 represents the collision probabilities.The energy consumption (EC) characteristics of the proposed EOMAC protocol for SNsare evaluated against existing MAC protocols – SPMAC, HyMAC, TMAC, and FMMAC, as depicted in Figure 8. The EC varies based on the network density, measured by the number of nodes. In a scenario with 50 sensor nodes, EOMAC exhibits an EC of 180J, outperforming SPMAC (200J), HyMAC (320J), and other existing MAC protocols that consume even higher energy. As the network scales to 250 nodes, the EC rises to a maximum of 920J for EOMAC. However, the existing MAC protocols consistently demonstrate sub-substantially higher energy consumption across varying node densities. Therefore, the proposed EOMAC protocol achieves significant reductions in sensor node energy consumption compared to existing proto- cols, thereby demonstrating superior performance in terms of lower EC.

Figure 9 compares the lifetime of SNs(SNs) for the proposed EOMAC protocol and existing MAC protocols, including SPMAC, HyMAC, TMAC, and FMMAC. With a minimum energy consumption (EC) of 200J, the EOMAC protocol achieves an SN lifetime of 140,000ms. As the EC increases to 1,000J, the EOMAC SN lifetime decreases to 46,850ms. For other MAC protocols at the minimum 200J EC, the NLT is lower, with SPMAC exhibiting 135,738ms. The remaining existing protocols follow a similar trend of decreasing lifetime with increasing EC. The results demonstrate that EOMAC achieves lower energy consumption and extended lifetime compared to existing protocols. Consequently, the proposed EOMAC protocol outperforms other techniques and proves more effective in prolonging sensor node lifetime through reduced energy consumption.

Table 5: Analysis of Collision Probability with Varying Number of Nodes: Proposed MAC Protocol vs. Existing Protocols

Collision probabilities	**50**	**100**	**150**	**200**	**250**
Proposed EOMAC	0.1443	0.3056	0.4187	0.4791	0.5007
SPMAC (Bhattacharjee et al., 2022)	0.1543	0.3156	0.4287	0.4891	0.5507
HyMAC (Yang et al., 2018)	0.3201	0.4821	0.5451	0.6691	0.7237
TMAC (Ram et al., 2019)	0.5432	0.6632	0.7132	0.7999	0.8432
FMMAC (Hamidi-Alaoui et al., 2020)	0.7894	0.8901	0.9045	0.9873	1.0000

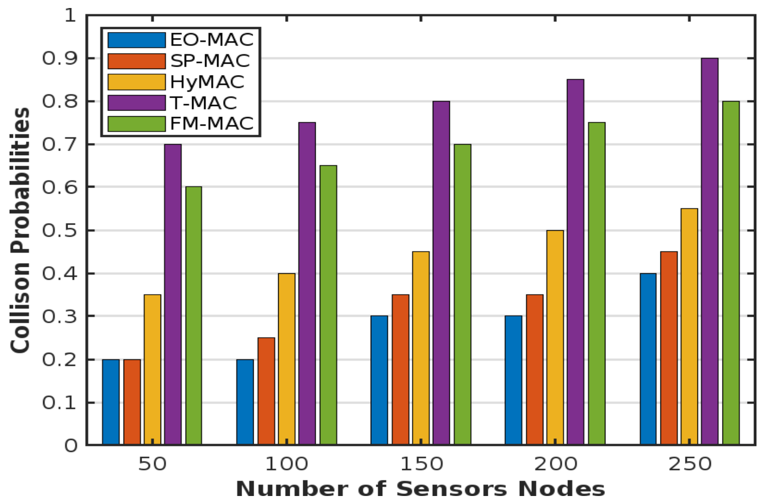

Figure 7: Evaluation Analysis of Proposed EO-MAC Collision Probabilities

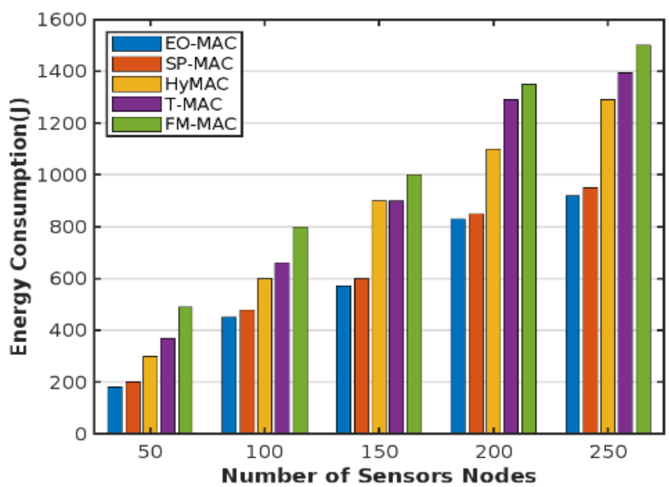

Figure 8: EC of Proposed EO-MAC

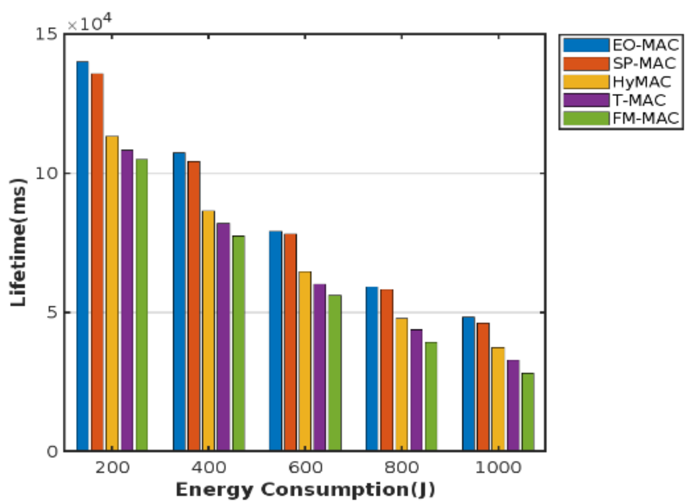

Figure 9: Evaluation Analysis of Proposed EO-MAC

6 Conclusions

A novel emergent-organized MAC protocol has been developed specifically for WSNs to address challenges in energy consumption and latency. This approach leverages the PS-COA method for efficient cluster head selection, minimizing energy usage through the MPNC clustering process. Additionally, optimal relay node selection via the RC-FFOA algorithm reduces transmission loss between sensor nodes and cluster heads, while the HPNN-NAI technique identifies active and inactive nodes, optimizing wake-up scheduling and data transmission. Experimental results validate the framework's superior performance, achieving an energy consumption of 920J over 2000 rounds, a throughput of 240 kbps for 250 sensor nodes, a network lifetime of 615 rounds, and a node activation accuracy of 92.23%. Comparative

analysis with existing methods demonstrates the protocol's energy efficiency and reduced latency. The protocol's low energy demands have practical implications, including lower maintenance costs and enhanced reliability, which is crucial for applications like environmental monitoring and disaster response requiring uninterrupted data flow. Its scalability supports larger WSN deployments in challenging environments, enhancing adaptability and long-term efficiency. Future work will focus on minimizing processing overhead while retaining energy gains, ensuring the system remains efficient and scalable without compromising its strengths.

References

[1] 802.15.4 MAC Performance Datasets, (2023). https://github.com/ewine-project/802_15_4_MAC_perf_datasets.git

[2] Boukerche, A., & Zhou, X. (2020). A novel hybrid MAC protocol for sustainable delay-tolerant wireless sensor networks. *IEEE Transactions on Sustainable Computing*, *5*(4), 455-467. https://doi.org/10. 1109/TSUSC.2020.2973701.

[3] Bouyer, A., Hatamlou, A., & Masdari, M. (2015). A new approach for decreasing energy in wireless sensor networks with hybrid LEACH protocol and fuzzy C-means algorithm. *International Journal of Communication Networks and Distributed Systems*, *14*(4), 400-412.

[4] Cai, X., Duan, Y., He, Y., Yang, J., & Li, C. (2015). Bee-sensor-C: an energy-efficient and scalable multipath routing protocol for wireless sensor networks. *International Journal of Distributed Sensor Networks*, *11*(3), 976127.

[5] Darabkh, K. A., & Zomot, J. N. (2018, June). An improved cluster head selection algorithm for wireless sensor networks. In *2018 14th International Wireless Communications & Mobile Computing Conference (IWCMC)* (pp. 65-70). IEEE. https://doi.org/10.1109/IWCMC.2018.8450425.

[6] Eesa, A. S., Brifcani, A. M. A., & Orman, Z. (2013). Cuttlefish algorithm-a novel bio-inspired optimization algorithm. *International Journal of Scientific & Engineering Research*, *4*(9), 1978-1986.

[7] Gong, P., Chen, T. M., & Xu, Q. (2015). ETARP: An energy efficient trust-aware routing protocol for wireless sensor networks. *Journal of Sensors*, *2015*(1), 469793. https://doi.org/10.1155/2015/469793

[8] Hamidi-Alaoui, Z., & El Belrhiti El Alaoui, A. (2020). FM-MAC: a fast-mobility adaptive MAC protocol for wireless sensor networks. *Transactions on Emerging Telecommunications Technologies*, *31*(6), e3782. https://doi.org/10.1002/ett.3782.

[9] Hamzah, A., Shurman, M., Al-Jarrah, O., & Taqieddin, E. (2019). Energy-efficient fuzzy-logic-based clustering technique for hierarchical routing protocols in wireless sensor networks. *Sensors*, *19*(3), 561. https://doi.org/10.3390/s19030561.

[10] Heinzelman, W. B., Chandrakasan, A. P., & Balakrishnan, H. (2002). An application-specific protocol architecture for wireless microsensor networks. *IEEE Transactions on wireless communications*, *1*(4), 660-670. https://doi.org/10.1109/TWC.2002.804190.

[11] Hu, H., Hu, X., Xiao, J., & Liu, X. (2017, September). CDMA-based MAC protocol for multi-hop WSNs. In *2017 2nd IEEE International Conference on Intelligent Transportation Engineering (ICITE)* (pp. 1-3). IEEE. https://doi.org/10.1109/ICITE.2017.8056922

[12] Kennedy, J., & Eberhart, R. (1995, November). Particle swarm optimization. In *Proceedings of ICNN'95-international conference on neural networks* (Vol. 4, pp. 1942-1948). ieee. https://doi.org/10.1109/ICNN.1995.488968.

[13] Leu, J. S., Chiang, T. H., Yu, M. C., & Su, K. W. (2014). Energy efficient clustering scheme for prolonging the lifetime of wireless sensor network with isolated nodes. *IEEE communications letters*, *19*(2), 259-262. https://doi.org/ 10.1109/LCOMM.2014.2379715

[14] Liu, Y., Ota, K., Zhang, K., Ma, M., Xiong, N., Liu, A., & Long, J. (2018). QTSAC: An energy-efficient MAC protocol for delay minimization in wireless sensor networks. *IEEE Access*, *6*, 8273-8291. https://doi.org/0.1109/ ACCESS.2018.2809501.

[15] Madugalla, A. K., & Perera, M. (2024). Innovative uses of medical embedded systems in healthcare. *Progress in Electronics and Communication Engineering*, *2*(1), 48–59. https://doi.org/10.31838/PECE/02.01.05

[16] Mirjalili, S. Z., Saremi, S., & Mirjalili, S. M. (2015). Designing evolutionary feedforward neural networks using social spider optimization algorithm. *Neural Computing and Applications*, *26*(8), 1919-1928. https://doi.org/10.1007/s00521-015-1856-3.

[17] Mohanty, S. N., Lydia, E. L., Elhoseny, M., Al Otaibi, M. M. G., & Shankar, K. (2020). Deep learning with LSTM based distributed data mining model for energy efficient wireless sensor networks. *Physical Communication*, *40*, 101097. https://doi.org/10.1016/j.phycom.2020.101097.

[18] Mundada, M. R., CyrilRaj, V., & Bhuvaneswari, T. (2012). Energy aware multi-hop multi-path hierarchical (EAMMH) routing protocol for wireless sensor networks. *European Journal of Scientific Research*, *88*(4), 520-530. https://doi.org/ 10.1109/ACCESS.2017.2784542

[19] Nayak, P., & Devulapalli, A. (2015). A fuzzy logic-based clustering algorithm for WSN to extend the network lifetime. *IEEE sensors journal*, *16*(1), 137-144. https://doi.org/10.1109/JSEN.2015.2472970

[20] Nithya, A., & Narmatha, M. (2017). Online Eco-Aware Artificial Fish Swarm Algorithm for Power Management and Load Scheduling in Green Cloud Data Centers. *International Journal of Advances in Engineering and Emerging Technology*, *8*(4), 101-116.

[21] Odeh, A., & Taleb, A. A. (2023). A Multi-Faceted Encryption Strategy for Securing Patient Information in Medical Imaging. *Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications*, *14*(4), 164-176. https://doi.org/10.58346/JOWUA. 2023.I4.012

[22] Pegatoquet, A., Le, T. N., & Magno, M. (2018). A wake-up radio-based MAC protocol for autonomous wireless sensor networks. *IEEE/ACM Transactions on Networking*, *27*(1), 56-70. https://doi.org/10.1109/ TNET.2018.2880797.1mm

[23] Radha, S., Nagabushanam, P., Reddy, T. J., & Sachin, B. (2018, April). Transmission distance in MAC protocol for wireless sensor networks. In *2018 Second International Conference on Inventive Communication and Computational Technologies (ICICCT)* (pp. 1813-1818). IEEE. https://doi.org/10.1109/ICICCT.2018.8473115.

[24] Ram, M., Kumar, S., Kumar, V., Sikandar, A., & Kharel, R. (2019). Enabling green wireless sensor networks: Energy efficient T-MAC using Markov chain-based optimization. *Electronics*, *8*(5), 534. https://doi.org/10.3390/electronics8050534.

[25] Raza, M., Le-Minh, H., Aslam, N., Hussain, S., & Ellahi, W. (2017, March). A control channel-based MAC protocol for time critical and emergency communications in industrial wireless sensor networks. In *2017 International Conference on Communication, Computing and Digital Systems (C-CODE)* (pp. 122-126). IEEE. https://doi.org/10.1109/C-CODE.2017.7918914.

[26] Ren, Q., & Yao, G. (2019). An energy-efficient cluster head selection scheme for energy-harvesting wireless sensor networks. *Sensors*, *20*(1), 187. https://doi.org/10.3390/s20010187.

[27] Sabet, M., & Naji, H. (2016). An energy efficient multi-level route-aware clustering algorithm for wireless sensor networks: A self-organized approach. *Computers & Electrical Engineering*, *56*, 399-417.

[28] Sahoo, P. K., Pattanaik, S. R., & Wu, S. L. (2019). A novel synchronous MAC protocol for wireless sensor networks with performance analysis. *Sensors*, *19*(24), 5394. https://doi.org/10.3390/s19245394.

[29] Savaglio, C., Pace, P., Aloi, G., Liotta, A., & Fortino, G. (2019). Lightweight reinforcement learning for energy efficient communications in wireless sensor networks. *IEEE Access*, *7*, 29355-29364. https://doi.org/10. 1109/ACCESS.2019.2901517.

[30] Shukla, A., & Tripathi, S. (2020). An effective relay node selection technique for energy efficient WSN-assisted IoT. *Wireless Personal Communications*, *112*(4), 2611-2641. https://doi.org/ 10.1007/s11277-020-07063-9.

[31] Smaragdakis, G., Matta, I., & Bestavros, A. (2004). *SEP: A stable election protocol for clustered heterogeneous wireless sensor networks*. Boston University Computer Science Department.

[32] Srikanth, N., & Shankar, T. (2020). Comparison of self-organized tree hierarchy MAC protocol and PP-MAC for energy consideration in wireless sensor networks. *Materials Today: Proceedings*, *33*, 4756-4763. https://doi.org/10.1016/j. matpr.2020.08.359.

[33] Subramanian, A. K., & Paramasivam, I. (2017). PRIN: A priority-based energy efficient MAC protocol for wireless sensor networks varying the sample inter-arrival time. *Wireless Personal Communications*, *92*, 863-881. https://doi.org/10.1007/s11277-016-3581-5.

[34] Sudhakar, R., Rajakumari, J., Poornima, S., & Ramya, V. (2019). A security threats and authentication approaches in wireless sensor networks. *International Journal of Communication and Computer Technologies*, *7*(2), 1-3.

[35] Swain, R. R., Mishra, S., Samal, T. K., & Kabat, M. R. (2017). An energy efficient advertisement based multichannel distributed MAC protocol for wireless sensor networks (Adv-MMAC). *Wireless Personal Communications*, *95*, 655-682. https://doi.org/10.1007/s11277-016-3791-x.

[36] Sze, V., Chen, Y. H., Yang, T. J., & Emer, J. S. (2017). Efficient processing of deep neural networks: A tutorial and survey. *Proceedings of the IEEE*, *105*(12), 2295-2329. https://doi.org/10. 1109/JPROC.2017.2761740.

[37] Thalagondapati, V., & Singh, M. P. (2023). A self-organized priority-based MAC protocol in wireless sensor networks based on SDR-RHSO optimal relay node selection and HL-ANN wake-up scheduling. *Journal of ambient intelligence and humanized computing*, *14*(8), 11093-11102.

[38] Thoi, N. T. (2025). Nanoparticle applications revolutionizing chemical processes. *Innovative Reviews in Engineering and Science, 2*(1), 13-21. https://doi.org/10.31838/INES/02.01.02

[39] Urmonov, O., & Kim, H. (2018). An energy-efficient fail recovery routing in TDMA MAC protocol-based wireless sensor network. *Electronics*, *7*(12), 444. https://doi.org/10.3390/electronics7120444.

[40] Wang, Q., Lin, D., Yang, P., & Zhang, Z. (2019). An energy-efficient compressive sensing-based clustering routing protocol for WSNs. *IEEE Sensors Journal*, *19*(10), 3950-3960. https://doi.org/10. 1109/JSEN.2019.2893912

[41] Wang, R., Liu, G., & Zheng, C. (2007, August). A clustering algorithm based on virtual area partition for heterogeneous wireless sensor networks. In *2007 international conference on*

mechatronics and automation (pp. 372-376). IEEE. https://doi.org/10.1109/ICMA.2007.4303571

[42] Xing, B., Gao, W. J., Xing, B., & Gao, W. J. (2014). Fruit fly optimization algorithm. *Innovative computational intelligence: a rough guide to 134 clever algorithms*, 167-170. https://doi.org/10.1007/ 978-3-319-03404-1_11

[43] Xu, C., Xiong, Z., Zhao, G., & Yu, S. (2019). An energy-efficient region source routing protocol for lifetime maximization in WSN. *IEEE Access*, *7*, 135277-135289. https://doi.org/10.1109/ACCESS.2019.2942321

[44] Yang, X., Wang, L., & Zhang, Z. (2018). Wireless body area networks MAC protocol for energy efficiency and extending lifetime. *IEEE sensors letters*, *2*(1), 1-4. https://doi.org/10.1109/ LSENS.2018.2795566.

[45] Yegnanarayana, B. (2009). *Artificial neural networks*. PHI Learning Pvt. Ltd.

[46] Zhao, H., Gao, W., Deng, W., & Sun, M. (2018). Study on an adaptive co-evolutionary aco algorithm for complex optimization problems. *Symmetry*, *10*(4), 104. https://doi.org/10.3390/sym10040104.

Authors Biography

Seethamraju Sudhamsu Mouli is Pursuing a Ph.D. at the Department of Computer Science and Engineering in Ecole Centrale School of Engineering Mahindra University his research interests are Wireless Sensor Networks and Internet of Things.

Dr. Veeraiah Thalagondapati specialized in soft computing techniques his doctoral research, which was conducted at the Department of Computer Sci- ence and Engineering, National Institute of Technology Patna, focused on maximizing the lifetime of wireless sensor networks. He is currently working as an Assistant Professor at Ecole Centrale School of Engineering Mahindra University.

Dr.T. Raja Rao founded Computer Vision Laboratories (India) Pvt. Ltd. (VI-SIONLABS) in 1986. With his specialization in Artificial Intelligence, he has guided the development of various Expert Systems in the fields of Remote Sensing and Image Recognition, Medical Imaging, and Machine Vision. He is currently working as a Professor at Ecole Centrale School of Engineering Mahindra University.