# Performance Evaluation of Cluster Head Selection Algorithm for Heterogeneous Wireless Sensor Networks

Veena I Puranikmath<sup>1</sup>, Sridhar Iyer<sup>2</sup>

 <sup>1</sup>Dept. of ECE, S.G. Balekundri Institute of Technology, Belagavi, Karnataka, India – 590010 Visvesvaraya Technological University Belagavi-590018.
 <sup>2</sup>Dept. of CSE(AI), KLE Technological University, Dr. MSSCET, Belagavi, Karnataka, India – 590008 <sup>1</sup>Veenaip@sgbit.edu.in <sup>2</sup>sridhariyer1983@klescet.ac.in

Keywords - WSN, multiple access, clustering, energy-efficiency, throughput

Date of Submission: January 18,2024

Date of Acceptance: May 23, 2024

#### I. INTRODUCTION

In wireless sensor networks (WSNs), autonomous devices i.e., SNs (SNs) are distributed in a spatial manner for monitoring the environmental conditions [1]. The SNs comprise of sensors that collect data which is transmitted via wireless technology to a gateway which serves as interface between WSN and the wired technology. The SN (or mote), is a fundamental component of a WSN which performs multiple tasks such as, processing the collected data, organizing the data into groups, and broadcasting it to other nodes within the network. Each SN comprises of a radio transceiver with an internal antenna, which can also be connected to an external antenna for improved communication range. Additionally, the SN includes a

(i) microcontroller and electronic circuit for interface with the sensors, and (ii) battery for powering the node [2]. Fig. 1 shows that the SNs are deployed in a dense manner to ensure comprehensive coverage of the monitoring area. However, due to the continuous battery operation, the SNs are highly energy-constrained devices [3]. Also, frequent recharging and replacement of batteries is impractical which requires energy-efficient strategies to be implemented in view of prolonging the WSN's lifetime [4].

To address the key issues of energy-efficiency (EE) and stability in WSNs, cluster-based algorithms (see Fig. 2) have been implemented which partition the network into clusters, with every cluster comprising of a designated cluster head (CH) with the responsibility to coordinate cluster functioning [5]. The CH selection is crucial as it determines the nodes with the responsibility of aggregating and relaying the data from other SNs to base station (BS). An effective CH selection strategy significantly impacts the WSNs energy consumption, network lifetime, and overall performance [3]. Specifically, by organizing the nodes into clusters, energy can be conserved by allowing certain nodes to enter low-power sleep modes while the CH manages the communication and data aggregation tasks. Additionally, a key concern in WSNs is network lifetime which refers to the duration until the first node in network exhausts its battery [1].

As frequent recharging and replacement of batteries is not feasible once they are energy depleted, extending network lifetime is key to the WSN's performance. The clusterbased algorithms have been shown to significantly improve network lifetime by minimizing consumed energy via optimized clustering and sleep scheduling [6, 7]. Existing studies have addressed network lifetime issue in WSNs by efficiently managing the CH nodes. In [8], the authors utilized the teaching learning-based optimization (TLBO) method for determining ideal number of CHs in sensor field. The aim is to improve network longevity by minimizing energy requirements. The authors incorporated the Low-Energy Adaptive Clustering Hierarchy based on three layers (LEACH-T) protocol and considered residual energy levels while selecting the CHs. It is shown that LEACH-T method significantly extends the network lifespan by reducing consumed energy for packet transmission. The authors in [9] developed a discrete. version of the TLBO method by incorporating the swap and mutation operators.



Fig. 2: Clustering in WSNs [3].

. This version of TLBO is designed to address power consumption concerns in WSNs. In [10], the authors introduced the Voronoi-Glowworm Swarm Optimization-K-means method in WSNs which aims at improving coverage while minimizing active nodes amount, thereby conserving energy, and extending the network lifespan. The proposed method utilizes Glowworm Swarm Optimization (GSO) in combination with the K-means method and the Voronoi cell structure. Specifically, the Voronoi cell structure aids in determining the optimal sensing radius for effective sensor placement, ensuring efficient coverage of the monitoring area. Additionally, the proposed technique reduces consumed energy by installing SNs using multi-hop transmission and a sleep-wake mechanism. The authors in [11] introduced an effective method for content delivery in the mobile ad hoc networks (MANETs). In this method, every network node is assigned a fitness rating based on its bit- rate, energy level, and delay tolerance. The nodes with highest fitness scores are chosen as cluster leaders. Once the energy requirements are satisfied, a teaching-learningbased optimization approach is used to calculate the fitness scores of nodes. In [12], the authors proposed a method to improve convergence speed of the Artificial Seaweed Optimization (ASO) algorithm by incorporating chaotic maps with Levy flight random walk. The proposed method aims to achieve faster convergence and improve the exploration and exploitation capabilities of the algorithm. Further, the tree-seed algorithm (TSA), which is a complementary technique to ASO, is introduced which is an intelligent meta-heuristic algorithm inspired by the development of trees and the dispersal of their seeds. TSA possesses strong exploratory capabilities, which when combined with ASO, balances exploration and exploitation. The authors in [13] developed a technique that combines particle swarm optimization (PSO) and artificial bee colony (ABC) algorithms to optimize WSNs performance. The proposed method utilizes a software-defined network (SDN) architecture to alleviate the burden on SNs' resources, including their electrical and computational capabilities. By leveraging combined power of PSO, ABC, and SDN, the proposed protocol reduces energy requirements, extends network lifetimes, and minimizes control overhead compared to existing solutions.

In [14], the authors developed a clustering technique which uses map reduction to control the mapping and simplify routing processes in WSNs. The objective is to eliminate unnecessary duplication and overlap to enhance network's performance. The proposed method simplifies the complexity of communication, leading to improved reliability and an extended network lifespan. The authors in [15] presented a novel Learning-Automata (LA)-based hybrid optimization technique that improves the artificial Jellyfish search algorithm (JS) and the Marine Predator Algorithm (MPA) while minimizing their drawbacks. The proposed method enhances LA performance by augmenting the vector of probabilities used in algorithm. The developed LA mechanism is implemented in a modified version of JS and MPA algorithms. In [16], the authors introduced a modified sperm swarm optimization algorithm (MSSO) which is used for both, numerical function optimization and the optimal design of damping controller in power systems. MSSO aims to balance exploitation and exploration by incorporating a chaotic velocity damping factor. The authors in [17] introduced the Modified Distance Vector Hop MDV-TLBO that incorporates a correction factor to adjust hop size of the anchor node. The TLBO, a parameter-free and effective optimization method, is employed to enhance localization precision. After a location upgrade operation, the target nodes estimate their final coordinates. The MDV-TLBO protocol requires only a single communication between anchor and target nodes to broadcast the anchor's position. In [18], the authors applied the process of selecting CHs for specific algorithms until the desired conditions are met. However, few algorithms rely solely on cluster's ID number and distance to determine CHs. It is seen that proposed method results in formation of transmission loops, which leads to higher proportion of death nodes. By incorporating the fitness function into the CH selection process, the proposed algorithm aims to avoid the formation of transmission loops that can lead to emergence of death nodes. The authors in [19] introduced a load-balancing mechanism for fifth generation with the existing Long-Term Evolution Advanced Heterogeneous Network (5GLHNs), incorporating the Constriction Factor approach PSO (CFPSO) and focusing on time synchronization methods and strategies for femtocell networks. The proposed mechanism is tested in a real environment to evaluate resource usage and security

implications, demonstrating its potential to enhance efficiency and performance of 5GLHNs.

In [20], the authors developed an energy-conscious CH selection technique which employed PSO and considered parameters such as, remaining energy, distance, and node density while selecting CHs. While the technique focused on CH selection, it overlooked clustering process which resulted in significant energy wastage throughout network. The authors in [21] presented the PSO-C algorithm which uses sink as a central node in a centralized algorithm for WSNs. The algorithm considers the remaining power and location of SNs during phase of cluster formation and selects CHs depending on energy consumption rates surpassing a specified threshold. In [22], the authors proposed an energy-efficient clustering approach that leverages an optimized version of LEACH protocol to collect data and transmit it in WSNs. The proposed method performs better than existing LEACH protocols considering successful packet delivery ratio (PDR) and energy savings, offering superior performance and EE in WSNs. The authors in [23] proposed clustering-based routing strategy aimed at optimizing energy resources and considering load balancing in WSNs. The study focused on addressing rotation of CHs and calculation of distances simultaneously considering energy utilization at the SNs. In [24], the authors discussed the clustering model based on Modified Distributed Energy Efficient based Clustering (MDEEC) method. Further, MDEEC is tested and compared with existing models, and results show that the MDEECA algorithm is more robust, increases network lifetime, and decreases energy consumption. The authors in [25] presented the method for balancing load between CHs by facilitating the handling of data packets. For routing of data packets across the SNs, network is split into sections of unequal sizes.

## A. Motivation and Contributions

Based on existing studies, it is evident that there is primary focus on developing models with the main aim of enhancing WSNs lifetime. Additionally, considering the fast-paced advancements in WSNs, continuous improvements and optimizations may be necessary to adapt to the evolving technologies and requirements. In addition, in a MANET, a cluster-based approach can be advantageous as it helps in organizing nodes into groups, making it easier to manage and monitor the network. The Certificate Authority (CA) issues and verifies digital certificates for authenticating identity of network nodes. By implementing a cluster-based CA, the CA functionality can be distributed across different clusters, reducing burden on an individual CA and improving the scalability. By integrating a Cluster-based CA scheme with evidence-based validation, security of wireless SNs in MANETs can be enhanced as it will enable the detection of malicious nodes and ensure that only authenticated nodes can communicate within the network. Hence, there is an essential need for formulating advanced methods to address this goal simultaneously provisioning simpler design, faster performance, and low cost. Such a combination will result in a solution which is robust and efficient. This motivates the formulation of CH selection-based algorithm for heterogeneous WSNs.

In this article, an Improved Energy-Efficient Cluster Head Selection (IEECHS) algorithm is proposed which provides a means for dynamic clustering, after which nodes' residual energy is considered for the CH selection. Through this mechanism, it is ensured that CHs have enough energy to perform related activities effectively. Further, alternate cluster members are assigned to clusters using the Cycle Cancelling Algorithm (CCA), which operates via an iterative approach with any valid flow of desired magnitude, and facilitates the transmission of secured data by the CH. The performance of IEECHS method is evaluated through simulations considering key performance metrics viz., throughput, energy consumption, and packet delivery ratio. The results demonstrate that through the proposed algorithm, after completion of 10,000 rounds (iterations), energy depletion rate lowers thereby, resulting in higher stored energy.

The rest of the article is structured as follows..

• Section 2 details proposed model and the IEECHS algorithm.

• Section 3 details the performance evaluation of IEECHS algorithm and discusses the results.

• Section 4 concludes the study.

# II. PROPOSED MODEL

In this section, the IEECHS algorithm is detailed which is a comprehensive approach that addresses the EE and the security challenges in heterogeneous WSNs. Specifically, IEECHS combines rotation-based clustering, energy-saving mechanisms, and a Full Duplex Medium Access Control protocol (FDMAC) protocol, to improve network performance and enhance network lifetime. Next, we detail the key methods of IEECHS, the integration of which provides a solution to address key challenges in heterogeneous WSNs.

**A. Rotation-Based Clustering:** The rotation-based clustering organizes the SNs into clusters. This clustering method ensures that CH's role is rotated among the nodes, preventing any individual node from depleting the energy quickly. By distributing the CH role, consumed energy among SNs can be balanced, leading to increased network lifetime.

**B.Energy-Saving Mechanisms:** To enhance EE, energysaving mechanisms are incorporated which include duty cycling, sleep scheduling, and related methods to allow the nodes to conserve energy during periods of inactivity or low data traffic. By efficiently managing energy consumption, the network can operate for a longer duration before requiring node recharging or replacement.

**C. FDMAC:** In heterogeneous WSNs, types of nodes may have varying capabilities, including FD features. The FDMAC protocol leverages these FD features to enhance channel access prioritization for different traffic classes.

This ensures that nodes with higher priority or critical data obtain improved access to the communication medium, resulting in better Quality of Service (QoS) for the network.

**D. CH Selection depending on Residual Energy:** The algorithm dynamically selects CHs depending on highest energy level among the SNs. By considering the nodes' residual energy, CHs are chosen to have sufficient energy to effectively perform their responsibilities as cluster managers. This energy-aware CH selection process contributes to prolonging the network's operational lifetime.

**E.Cluster Member Assignment using CCA:** After dynamic clustering process, the cluster members are assigned to clusters using the CCA method. This iterative approach helps to find a valid flow with the desired magnitude, ensuring efficient transmission of secured data by the CHs. The CCA method aids in optimizing data routing and reducing communication overhead.

### 2.1 IEECHS Algorithm

The proposed IEECHS algorithm dynamically selects CHs and performs a local search to iteratively update CH selection depending on energy considerations.



Fig. 3. Flow-chart of IEECHS algorithm.

The algorithm's objective is to minimize energy function f(x), where x is a vector representing selection of CHs in network. Hence, preliminary energy sum for the designed

three-level heterogeneous network is given by equations (1) and (2).

**Step 1:** Initially, n SNs are deployed in network, and CHs are randomly selected.

$$E_{total = N(1-m_{R})E_{R} + Nm_{R(1-m_{R})(1-m_{R})E_{R}} + Nn_{R(1+\beta)E_{R}}}$$
(1)  
$$E_{total = NE_{R}(1+m_{R})}(\alpha + n_{0\beta})(2)$$
(2)

**Step 2:** Find the Best CH: In the initial step of CH selection, the algorithm finds the best CH represented by 'g'. This may be based on initial criteria or metric, related to energy efficiency or distance.

**Step 3:** Iterative Local Search: The algorithm performs an iterative local search for improving CH selection depending on energy threshold Th. The process runs until the stopping criterion, 'r < MaxRounds,' is met.

**Step 4:** Threshold-based CH Update: For each SN 'i' in the network, if CH\_ $\epsilon$  (energy of the current CH) is less than threshold T<sub>h+ti</sub>, where t<sub>i</sub> is a per-node threshold value, then the CH selection is updated for SN 'i' as

$$X_i(r+1) = X_i(r) + T_h^*(X_i(r)-g)$$
 (3)

This update might indicate that current CH is not efficient, and node 'i' switches to a better CH.

**Step 5:** Random CH Selection: At this step, two SNs 'j' and 'k' are randomly selected among all solutions, and a local CH selection is performed using.

$$X_{i}(r+1) = X_{i}(r) + \epsilon^{*}(X_{i}(r) - X_{k}(r))$$

$$\tag{4}$$

where,  $\varepsilon$  is drawn randomly from the range [0, 1]. This random selection and update might introduce exploration to search for better solutions.

**Step 6:** Search New CHs: The algorithm searches for new CHs by updating CHs depending on changes made in previous steps.

**Step 7**: Update Best Solution: If the new CHs found are better than current best solution (g), then update the same in network.

**Step 8:** Stopping Criterion: The algorithm continues to iterate until the stopping criterion, 'r < MaxRounds,' is met. The number of rounds denotes maximum number of iterations the algorithm will run.

**Step 9:** Final CH Selection: After the iterations, the algorithm will have selected the CHs based on energy considerations, and the final best CH is represented by 'g'. In the duration of transmitted packet and received packet, energy is dissipated, and this energy is estimated by free space (fs) and multipath (mp). The consumed energy for transmission is given as

$$E_{TX}(k,d) = \begin{cases} E_{\theta} * L + \epsilon_{f\theta} * d^2, \ d < d_0 \\ E_{\theta} * L + \epsilon_{mp} * d^4 * L, \ d \ge d_0 \end{cases}$$
(5)

where, *Ee* denotes amount of energy needed to process 1-bit data.  $\in fs$  and  $\in mp$  are the energies required for transmission of 1-bit data so that acceptable bit error rate can be achieved through fs and mp models, respectively.

The proposed algorithm aims to dynamically adjust CH selection in WSN to optimize consumed energy. However, for a comprehensive evaluation of the algorithm's performance, additional details such as the specific energy function f(x), the criteria for choosing best CH (step 3), and the overall convergence properties need to be considered.

Cycle Cancelling algorithm: The CCA implements the Minimum-Cost Flow Problem (MCFP) which is a fundamental optimization problem in network flow theory [26]. It involves finding the cheapest way to send a certain amount of flow through a flow network. This problem has multiple applications in transportation, logistics, communication networks, and many other real-world scenarios where flow needs to be routed efficiently while considering costs and capacities. For a typical application, such as finding the best delivery route between factory to warehouse, the network represents the road or transportation network. Each edge in the network has a capacity (representing the maximum flow it can carry) and a cost (representing the cost of sending one unit of flow through that edge). It is key to determine the flow to be sent along each edge to minimize total cost while satisfying capacity constraints. The Minimum- Cost Flow Problem can be mathematically formulated as follows:

A directed graph G = (V, E) representing the flow network, where V is nodes set (vertices), and E is edges set. Capacity function c(e) for each edge e in E, representing the maximum flow that edge 'e' can carry. Cost function w(e) for each edge e in E, representing cost of sending one unit of flow through edge e. A source node s and a sink node t representing the start and end points of the flow. In a flow network, the objective is to find a feasible flow that satisfies capacity constraints and sends a certain amount of flow d from source vertex s to sink vertex t. The flow along each edge incurs a cost depending on product of the flow amount f (u, v) and the cost factor a (u, v).

To summarize, the flow network problem is given as:

1. Directed Graph: G = (V, E) is a directed graph representing the flow network.

2. Source and Sink: There are source and sink vertices in graph denoted as s and t, respectively.

3. Edge Capacity: Each edge  $(u, v) \in E$  has a capacity c (u, v) > 0, representing the maximum flow it can carry.

4. Flow Amount: The flow through each edge (u, v) is represented as f(u, v).

5. Cost Function: The cost of sending the flow through an edge (u, v) is given by a (u, v).

6. Flow Conservation: The flow entering a vertex must equal the flow leaving that vertex, except for the source and sink vertices. This ensures flow conservation within the network.

The aim is to find a feasible flow that sends a specific data amount from the source vertex s to sink vertex t while minimizing the total cost of sending flow through the edges. The minimum- cost flow problem aims to find the flow that minimizes the total cost of sending the required amount of flow from source to sink while adhering to the capacity constraints and flow conservation conditions. Solving the minimum-cost flow problem is a fundamental optimization task and has applications in various fields, including transportation, communication networks, and logistics, where the aim is to optimize flow of resources while minimizing associated costs.

Finally, as with any proposed algorithm, thorough testing, and evaluation in real-world or simulated scenarios are essential to assess performance, efficiency, and effectiveness in meeting the desired objectives. In the following section, we detail the simulation setup and discuss the results.

## **III. RESULTS AND DISCUSSIONS**

In this section, we present performance evaluation results of IEECHS algorithm. In the proposed model, 100 nodes are randomly distributed in their orientation in 100m x 100m field. It is assumed that all nodes are in stationary modes, and the BS is placed at the center. The experiments are conducted using MATLAB on a system with a Corei5 processor, 4 GB RAM with window operating system. The key parameters viz., stability period, data packets and network lifetime are considered for performance evaluation. Fig. 4 shows the settings of the radio heterogeneous WSN, and nodes which are distributed in selected field. The key network design parameters are tabulated in Table 1. We compare performance of IEECHS algorithm with the MDEEC algorithm [24].

In Fig. 5, we plot the dead nodes amount with a variation in number of rounds (iterations). It is observed that dead nodes amount starts increasing after approximately 1100 iterations which indicates that network starts to experience node failures after a certain period of operation. At the end of 10000 iterations, there are 92 nodes that remain alive. These nodes have not experienced failure and have continued to operate throughout the simulation. The observation that nodes start dying after 1100 iterations and only 92 nodes remain alive after 10000 iterations suggests that IEECHS model is effective in prolonging network lifetime.

Fig. 6 shows the alive nodes amount with a variation in number of rounds. The existence of alive nodes at simulation end indicates that IEECHS algorithm is suited for lower energy consumption since a considerable number of nodes remain active for the entire 10000 iterations.



Fig. 4. Node distribution in 100m x100m field with BS.

TABLE I. KET NET WORK DESIGN TARAMETERS.	TABLE 1	. KEY NETWORK	<b>CDESIGN PARAM</b>	ETERS.
--	---------	---------------	----------------------	--------

Parameter	Value
Size of WSN	100m x 100m
Number of the Sensor devices	500
Initial energy of sensor devices	0.1 to 0.5 Joules (J)
MAC type	IEEE 802.11
Dissipation energy during transmission and reception	50nJ/bit
Transmission range	5m
Range of Sensing	3m
Radio energy dissipation	50nJ/bit
Data packet length	5000 bits
Data-rate	100 bits/sec
Bandwidth	10000 bits/sec
Processing delay	0.1 sec
Idle energy consumption	50nJ/bit
Amplification energy	100/bit/m2
Maximum number of nodes	12000

This also suggests that the algorithm can effectively manage and conserve energy resources of network nodes. The fact that nodes continue to operate up to 10000 iterations (with only 92 nodes remaining alive) indicates that IEECHS algorithm leads to increase in network lifetime. This in turn implies that network can operate for an extended duration before a considerable number of nodes fail, resulting in network degradation or collapse. Overall, results in Fig. 5 and 6 show that IEECHS algorithm is beneficial for energy-constrained WSNs or similar applications. From Fig. 7, it is seen that maximum packets amount sent to CH occurs at the 10000th iteration in the IEECHS model. This implies that there is a specific point during the simulation where nodes are actively sending the highest number of packets to their respective cluster heads. Also, IEECHS algorithm shows better EE compared to existing MDEEC algorithm. Fig. 8 shows the change in energy with increasing number of rounds. It is evident from the figure that the energy depletion rate is lower for the proposed model, resulting in more energy being stored after completing 10000 rounds. Also, despite completing all the rounds, the SN still retains a small amount of energy when using proposed model which suggests that IEECHS algorithm manages energy consumption more effectively, allowing sensors to maintain better energy reserves for extended operation.



.Fig. 5: Number of Dead Nodes for 100 x 100 m2



Fig. 6: Number of Alive Nodes for 100 x 100 m2

Fig. 9 shows that IEECHS algorithm has higher EE than MDEEC algorithm. It allows the sensor network to operate for a longer duration while retaining more energy after completing certain rounds simultaneously with low power dissipation. This enhanced EE results in prolonged network lifetime and improved performance in resource-constrained environments. Lastly, a comparison of data transmitted to BS by proposed IEECHS model is tabulated in Table 2. From the obtained results it can be inferred that maximum packets amount are transmitted when the IEECHS algorithm is implemented as compared to MDEEC model. This implies that the IEECHS algorithm enables the packets to reach the sink node (BS) which indicates that maximum number of nodes are live after 10,000 iterations.



Fig. 7: Number of packets transmitted to base station for 100 x 100 m2



TABLE 2. COMPARISONS OF DATA TRANSMITTED TO BS FROM MDEEC ALGORITHM AND PROPOSED IEECHS ALGORITHM.

No. of	MDEEC Existing	<b>IEECHS</b> Proposed
Iterations	model [24]	model
1000	9564	9845
2000	12400	13546
3000	16426	18754
4000	17994	19876
5000	19265	20164
6000	21074	23458
7000	22456	27545
8000	24512	27845
9000	28749	29456
10000	29785	29765

## **IV. CONCLUSION**

In the current article, the IEECHS algorithm is proposed which addresses the energy-efficiency and security challenges of the heterogeneous WSNs. The proposed algorithm combines rotation-based clustering and energysaving mechanisms to enhance network performance and extend the network lifetime. To accommodate the heterogeneous nature of network, a full duplex medium access control protocol employed. The CH selection process is based on highest energy level among the SNs in a dynamic manner, using a cluster head rotation-based approach. The nodes' residual energy is considered during CH selection, allowing for more efficient utilization of available energy resources. The remaining cluster members are assigned to clusters using the Cycle Cancelling algorithm.

To evaluate effectiveness of IEECHS, key performance metrics viz., throughput, energy consumption, and packet delivery ratio are considered. The obtained results show that IEECHS algorithm, in conjunction with full duplex medium access control protocol and Cycle Cancelling algorithm, offers a promising solution for improving energy-efficiency, prolonging the network lifetime, and enhancing performance of heterogeneous WSNs. As a scope for future research, we will aim to compare MDEEC and IEECH algorithms with the most recent existing algorithms for heterogeneous WSNs.

## REFERENCES

- GS. Prashanth, P. Manjunatha, Cluster based routing protocols of heterogeneous wireless sensor networks—a survey, J Crit Rev. 7 (2020) 2002-2018.
- [2] R. Alsaqour, ES. Ali, RA. Mokhtar, RA. Saeed, H. Alhumyani, M. Abdelhaq, Efficient Energy Mechanism in Heterogeneous WSNs for Underground Mining Monitoring Applications, IEEE Access 10 (2022) 72907-72924.
- [3] S. Sharmin, I. Ahmedy, R. Md Noor, An Energy-Efficient Data Aggregation Clustering Algorithm for Wireless Sensor Networks Using Hybrid PSO, Energies, 16 (2023) 2487.
- [4] K. Jain, PS. Mehra, AK. Dwivedi, A. Agarwal, SCADA: scalable cluster-based data aggregation technique for improving network lifetime of wireless sensor networks, The Journal of Supercomputing, 78 (2022) 1-29.
- [5] HH. El-Sayed, ZM. Hashem, Comparison of the new version of DEEC protocol to extend WSN lifetime, J Wireless Com Network, 56 (2023).
- [6] MK. Roberts, P. Ramasamy, Optimized hybrid routing protocol for energy-aware cluster heads selection in wireless sensor networks, Digital Signal Processing, 130 (2022) 103737.
- [7] H. Singh, D. Singh D, Hierarchical clustering and routing protocol to ensure scalability and reliability in large-scale wireless sensor networks, The Journal of Supercomputing, 77 (2021) 10165-10183.
- [8] A. Yadav, S. Kumar, A Teaching Learning Based Optimization Algorithm for Cluster Head Selection in Wireless Sensor Networks, International Journal of Future Generation Communication and Networking, 10 (2017) 111-122.
- [9] M. Masdari, S. Barshandeh S, Discrete teachinglearning-based optimization algorithm for clustering in wireless sensor networks, Journal of Ambient Intelligence and Humanized Computing, 11 (2020) 5459-5476.
- [10] A. Chowdhury, D. De, Energy-efficient coverage optimization in wireless sensor networks based on Voronoi-Glowworm Swarm Optimization-K-means algorithm, Ad Hoc Networks, 122 (2021) 102660.
- [11] M. Maiti, S. Mukherjee, PKG Thakurta, An energy efficient teaching learning-based optimization approach for common content distribution in mobile ad hoc networks, Computers and Electrical Engineering, 72 (2028) 296-306.
- [12] S. Barshandeh, M. Haghzadeh M, A new hybrid chaotic atom search optimization based on tree-seed algorithm and Levy flight for solving optimization problems, Engineering with Computers, 37 (2021) 3079-3122.
- [13] L. Sixu, W. Muqing, Z. Min, Particle swarm optimization and artificial bee colony algorithm for

clustering and mobile based software-defined wireless sensor networks, Wireless Networks, 28 (2022) 1671-1688.

- [14] P. Baskaran, K. Karuppasamy, Hybrid teaching learning approach for improving network lifetime in wireless sensor networks, Computers, Materials and Continua, 70 (2022) 1975-1992.
- [15] S. Barshandeh, R. Dana, P. Eskandarian, A learning automata-based hybrid MPA and JS algorithm for numerical optimization problems and its application on data clustering, Knowledge- Based Systems, 236 (2022) 107682, 2022.
- [16] M. Eslami, B. Babaei, H. Shareef, M. Khajehzadeh, B. Arandian, Optimum Design of Damping Controllers Using Modified Sperm Swarm Optimization", IEEE Access, 9 (2021) 145592-145604.
- [17]G. Sharma, A, Kumar, Modified Energy-Efficient Range-Free Localization using Teaching-Learning-Based Optimization for Wireless Sensor Networks, IETE Journal of Research, 64 (2019) 124-138.
- [18]S. Loganathan, J. Arumugam, Energy Efficient Clustering Algorithm Based on Particle Swarm Optimization Technique for Wireless Sensor Networks, Wireless Personal Communications, 119 (2021) 815-843.
- [19] MK. Hasan, TC. Chuah, A A. El-Saleh, M. Shafiq, SA. Shaikh, S. Islam, M. Krichen, "Constriction Factor Particle Swarm Optimization based load balancing and cell association for 5G heterogeneous networks, Computer Communications, 180 (2021) 328-337.
- [20] S. Amanlou, MK. Hasan, KA. Abu Bakar, Lightweight and secure authentication scheme for IoT network based on publish–subscribe fog computing model, Computer Networks, 199 (2021) 108465.
- [21]N. Karasekreter, MA. Şahman, F. Başçiftçi, U. Fidan, PSO-based clustering for the optimization of energy consumption in wireless sensor network, Emerging Material Research, 9 (2020).
- [22] Damayanthi, MR. Belgaum, A Study of Heterogeneity Characteristics over Wireless Sensor Networks, International Journal of Computer Engineering in Research Trends, 9 (2022) 258-262.
- [23] S. Firdous, N. Bibi, M. Wahid, An Energy-Efficient Cluster Based Routing Algorithm for Wireless Sensor Network, in: IEEE International Conference on Frontiers of Information Technology, 2021, pp. 182-187.
- [24] VI. Puranikmath, S. Iyer, SS. Harakannanavar, Performance Evaluation of Modified Distributed Energy Efficient based Clustering Aggregation algorithm in Wireless Sensor Networks, Indian Journal of Science and Technology, 16 (2023) 1-8.
- [25]G. Ravi, MS. Das, K. Karmakonda, Energy Efficient Data Aggregation Scheme using Improved LEACH Algorithm for IoT Networks, International Journal of Intelligent Systems and Applications in

Engineering, 11 (2023) 174.

[26] SAR. Zaidi, M. Hafeez, SA. Khayam, DC. Mclernon, M. Ghogho, K. Kim, On minimum cost coverage in wireless sensor networks" in 2009 43<sup>rd</sup> Annual Conference on Information Sciences and Systems, Baltimore, MD, USA, 2009, pp. 213-218.

#### **Biographies and Photographs**



Veena I Puranikmath, received her B.E., MTech. in the field of Electronics and Communication Engineering from S. G. Balekundri Institute of technology Belagavi and completed master's in digital communication and networking at Godutai College of Engineering for Women Kalaburagi., in 2013, 2015

respectively. Presently she is working as assistant professor with S. G. Balekundri Institute of technology Belagavi. She is pursuing her Ph.D. at Visvesvaraya Technological Univarsity, Belagavi. Since February 2016, she has been working as an assistant professor. Mrs. Veena has authored a book titled "Introduction to Information theory and Coding" and did 15 publications in various high impact factor, peer-reviewed, journals. She is a member of the IEANG, TERA and IFERP. Her current research interests include Wireless Sensor Network and IoT.



Sridhar Iyer (Member IEEE) received the M.S. degree in Electrical Engineering from New Mexico State University, U.S.A in 2008, and the Ph.D. degree from Delhi University, India in 2017. He received the young scientist award from the DST/SERB, Govt. of India in 2013, and Young Researcher Award from Institute of

Scholars in 2021. He is the Recipient of the 'Protsahan Award' from IEEE ComSoc, Bangalore in recognition to his contributions towards paper published / tutorial offered in recognized conferences/journals (during Jan 2020 - Sep 2021). He has completed two funded research projects as the Principal Investigator and is currently involved in on-going funded research projects as the Principal Investigator. He serves on the review panel of high-impact Journals such as, IoT Magazine, IEEE, CCN, Elsevier, PNET, Springer, etc. His current research focus includes semantic communications and spectrum enhancement techniques for 6G wireless networks, and efficient design and resource optimization of the flexi-grid EONs enabled by SDM. He has published over 90 reviewed articles in the aforementioned areas. Currently, he serves as an Associate Professor in the Dept. of ECE, KLE Technological University, Dr MSSCET, Belagavi, Karnataka, India.