International Journal of Reconfigurable and Embedded Systems (IJRES)
Vol. 13, No. 3, November 2024, pp. 774~785
ISSN: 2089-4864, DOI: 10.11591/ijres.v13.i3.pp774-785

Energy-efficient clustering and routing using fuzzy k-medoids and adaptive ranking-based wireless sensor network

Haritha K. Sivaraman, Rangaiah Leburu
Department of Electronics and Communication Engineering, RajaRajeswari College of Engineering, Bangalore, India

Article Info

Article history:

Received Feb 19, 2024
Revised Mar 21, 2024
Accepted Apr 19, 2024

Keywords:

ARanEOR
Cluster head
Energy
Fuzzy k-medoids
Routing
Wireless sensor network

ABSTRACT

The wireless sensor network (WSN) is a vital component of infrastructure that is seeing tremendous demand and quick expansion in a variety of industries, including forestry, airports, healthcare, and the military. Increasing network lifetime and reducing power consumption (PC) are now major goals in WSN research. This research proposes a unique energy-efficient cross-layer WSN design that aims to maximize network lifetime while maintaining quality of service (QoS) criteria to address these challenges. The research initially utilizes the fuzzy k-medoids (FKMeds) clustering technique to group sensor nodes (SN) to improve resilience, scalability, and minimize network traffic. Following that, the hybrid improved grey wolf and ant colony (HIGWAC) optimization approach is applied to choose cluster heads (CH), minimizing distances, reducing latency, and optimizing energy stability. Finally, data is transmitted through the shortest pathways using the adaptive ranking-based energy-efficient opportunistic routing (ARanEOR) protocol, which ensures effective and energy-conserving routing in WSN while dynamically lowering network overhead. Compared to existing approaches, the proposed method in this study outperforms them in terms of energy efficiency, latency, and network longevity.

Corresponding Author:

Haritha K Sivaraman
Department of Electronics and Communication Engineering, RajaRajeswari College of Engineering
Ramohalli Cross, Mysore Rd, Kumbalgodu, Bangalore, Karnataka, India
Email: haritharesearchscholar@gmail.com

1. INTRODUCTION

The energy efficient clustering protocol addresses the critical problem of energy consumption (EC) in wireless sensor network (WSN), where resource-constrained sensor nodes (SN) are critical. It is widely employed in several applications, WSNs need energy-saving methods to extend the life of their networks [1]. The protocol attempts to cluster SN and optimize the selection of the cluster head (CH) by considering node density, residual energy, and distance, among other variables. Through the use of efficient clustering algorithms to enable data aggregation at the cluster level, the protocol reduces the energy needed for data transmission to a central base station (BS) [2]–[4]. Reducing EC and extending network lifetime are the primary goals, and they ensure the long-term and dependable operation of WSNs [5].

The CH-based cross-layer routing protocol is a smart solution for major issues in WSNs. The protocol offers a novel approach to routing by utilizing CH as the main decision-makers and integrating information from the physical, data link, and network levels for effective routing. CH are critical to data transmission because they make smart decisions that optimize energy efficiency and minimize congestion [6]. The cross-layer integration ensures the data transmission paths that use the least amount of energy. CH-based decision-making at various network layers, which is the protocol's main focus, is anticipated to significantly improve WSN performance. The integration of energy efficient clustering and CH-based cross-layer routing provides a holistic solution to the challenges inherent in WSNs. The protocol aims to strike a balance between energy conservation and effective data communication. This paper presents an innovative approach for energy-efficient cross-layer WSN design in response to these demands, to maximize network lifetime and ensure rigorous quality of service (QoS) standards simultaneously [7]–[9].

2. LITERATURE REVIEW

This section examined some recent studies on energy-efficient clustering and cluster CH-based cross-layer routing protocols in WSNs. The study being conducted on energy efficiency and carbon reduction (EECR) in WSNs utilizing fuzzy k-medoids (FKMeds) and an adaptive ranking-based cross-layer routing protocol would benefit greatly from this review, which will also set theoretical groundwork for future research in this area. In 2020, Deepa and Suguna [10] examined the routing protocol difficulties and solutions in WSN. It proposed an optimized QoS-based clustering with multipath routing protocol (OQoS-CMRP) to enhance network lifespan, data dependability, and energy preservation. It highlights the importance of balancing energy usage and data quality in QoS-based routing protocols. OQoS-CMRP is compared with existing protocols. It maximizes network routing and clustering efficiency in WSNs [11], [12]. In 2020, Doostali and Babamir [13] discussed the WSN EC issues and provided an energy-efficient CH selection technique. It focuses attention on the shortcomings of current methods and presents clustering as a distributed energy management strategy. The technique, based on learning automata and sleep-awake mechanism, enhances network endurance and energy usage compared to previous methods. Mehbodniya *et al*. [14] in 2022, introduced the energy-aware proportional fairness multi-user routing (EPFMR) architecture in WSN, an energy-efficient routing system. The first phase in EPFMR framework's design to lower the rate of EC is the request time submitted for route finding. The greedy instance fair method (GIFM) was used to quantify energy on multi-user route paths when a route path for packet flow was found. Throughput is increased by GIFM in EPFMR, which creates node-dependent, energy-efficient localized route paths.

3. SYSTEM MODEL

An advanced network architecture known as WSNs is intended to continuously observe and collect information on the physical condition of the area in which they are located. The BS and many SNs are two main parts of this infrastructure that are usually available. The BS acts as the hub or main control unit for the WSN. It serves as an interface between end users or data analysis systems and the field-deployed SN [15], [16].

3.1. Network model

WSN clustering splits sensors into clusters to use as little energy as possible. The CH receives sensory input from common nodes that regularly scan the surroundings. Among the common nodes, the CH node is perpetually selected. An essential role of CH is to collect data from each cluster node and forward it to BS. Grouping helps to prevent direct connection between sensors and receivers. Figure 1 is an illustration of WSN system model.

3.2. Concept of energy

If the threshold distance $'d_{th}'$ is larger than the value of 'd_p', then node's energy is precisely proportionate to propagation distance, 'd_p'. The (1) represents the total energy required by each node to transport M-bit data packet.

$$E_T(M, d_p) = E_R(M) + \varepsilon_{am} \times M \tag{1}$$

Where, E_T indicates energy required for data transmission; E_R represents the energy consumed for receiving data; ε_{am} denotes energy used for amplification; M is number of bits.

The EC in receiver end is given in (2).

$$E_R(M) = E_{dis} \times M \tag{2}$$

Where, E_{dis} indicates energy dissipation per bit.

The amplification energy can be expressed as (3).

$$\varepsilon_{am} = \begin{cases} \varepsilon_{fs} \times {d_p}^2, \ when\ d_p \leq d_{th} \\ \varepsilon_{mp} \times {d_p}^2, \ when\ d_p > d_{th} \end{cases} \tag{3}$$

Where, ε_{fs} represents energy utilized for amplification in free space; ε_{mp} indicates amplification energy used in multi path [17]-[19].

The overall loss of energy for WSN is represented as E_{Total} and the expression of total energy is given in (4).

$$E_{Total} = E_T + E_R \tag{4}$$

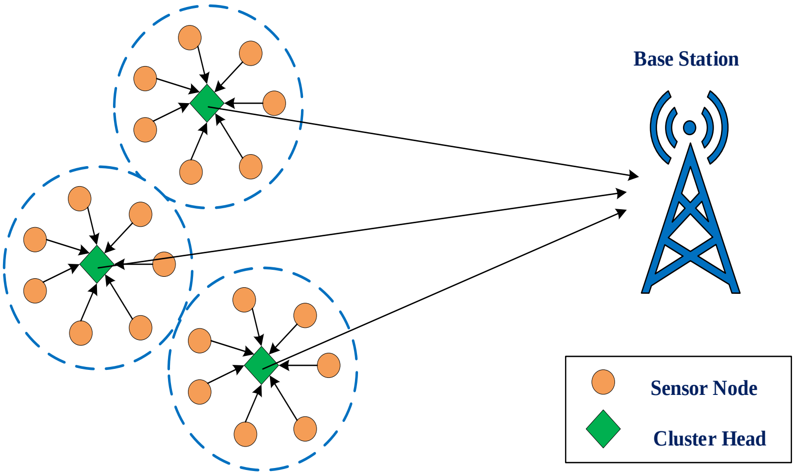


Figure 1. General structure of WSN

4. PROPOSED METHOD

This section discusses in detail the proposed EECR using FKMeds and adaptive ranking-based cross layer routing protocol for WSN. The proposed method has three methods: initially, FKMeds method is used for clustering to achieve robustness, scalability, and reduced network traffic SN and it is briefly discussed in section 4.1. Secondly, hybrid improved grey wolf and ant colony (HIGWAC) optimization technique is proposed to select CH through distance reduction, energy stabilization, and latency minimization between nodes and this technique is covered in section 4.2. Finally, adaptive ranking-based energy-efficient opportunistic routing (ARanEOR) protocol is applied to transmit data across the shortest channels for efficient and energy-preserving routing in WSN and dynamically lowering network overhead and this approach is discussed in section 4.3.

4.1. Clustering using FKMeds

In this study, the SN are grouped using clustering approach called FKMeds method, which calculates the distance criteria by computing the values of cluster center of data. The updated membership matrix M_u is first determined using the fuzzy c means (FCM) approach in the FKMeds in order to obtain the medoid value [20]-[23]. The index data from each cluster with the greatest membership value is then used to choose the medoid. The FKMeds objective function is represented in (5).

$$F_{obj} = \sum_{i=1}^{m} \sum_{k=1}^{n} (d^2(c_k, x_i)(\delta_{ik})^r) \tag{5}$$

Where, F_{obj} is objective function in t-th iteration; ω_{ik} represents degree in M_u membership matrix; r denotes fuzzy rank ($r \geq 2$); $d(c_k, x_i)$ indicates distance between i^{th} data value and the k^{th} cluster center.

The initial membership degree value 'δ_{ik}' in M_u membership matrix is created using the (6) and (7) when using FKMeds approach for cluster center computations.

$$M_u = [\delta_{ik}]_{m \times n, \sum_{k=1}^{c} \omega_{ik}=1, \quad 1 \leq i \leq n} \tag{6}$$

$$\delta_{ik} = [0,1], \ \ i = 1,2,\dots,m; k = 1,2,3,4,\dots,c \tag{7}$$

Each iteration updated the membership matrix, represented by δ_{ik}, which is calculated using (8).

$$\delta_{ik} = \frac{[d^2(c_k,x_i)]^{\frac{-1}{r-1}}}{\sum_{j=1}^{c}[d^2(c_j,x_i)]^{\frac{-1}{r-1}}} \tag{8}$$

The cluster center is computed using the (9) once the M_u membership matrix has been obtained.

$$C_k = \frac{\sum_{i=1}^{m}(\omega_{ik})^r y_i}{\sum_{i=1}^{m}(\omega_{ik})^r} \tag{9}$$

4.2. Cluster head selection using hybrid improved grey wolf and ant colony

In WSN, CH is a node that serves as coordinator for other cluster nodes. It is responsible for collecting data from each cluster node and forwarding it to BS. Data from other nodes within the cluster is gathered by the CH. The data may include of any measurement made by the sensors. The CH may compile and analyze the gathered data before forwarding it to minimize the volume of information sent. The CH sends the processed data to BS, the WSN's central hub. This might be accomplished directly or in a multi-hop manner via other CH. A crucial component of WSNs is CH selection, which has an impact on energy efficiency and the lifespan of network. Although existing CH selection methods have a great deal to offer WSNs, they frequently have issues with node delay, energy stability, and distance reduction. To overcome these limitations, this study introduces HIGWAC optimization approach which is a combination of improved grey wolf optimization (IGWO) and ant colony optimization (ACO) algorithm [24], [25].

4.2.1. Improved grey wolf optimization

The information on optimizing CH choice process to maximize network lifetime is offered to IGWO algorithm. CH selection is carried out by BS using IGWO algorithm to eliminate unpredictability inherent. Based on fitness values, all SNs are separated into four subgroups, roughly, of which sixteen SN locations are designated as fixed to accommodate multi pathways. The method is stated in terms of rounds. An SN's fitness value is calculated using its distance from BS and leftover energy.

$$Fit = \begin{cases} 0.8 \times \left(\frac{E_{res}}{E_{init}}\right) + 0.2 \times \left(\frac{D_{max}-D}{D_{max}-D_{min}}\right), E_{res} < 0 \\ 0.2 \times \left(\frac{E_{res}}{E_{init}}\right) + 0.8 \times \left(\frac{D_{max}-D}{D_{max}-D_{min}}\right), E_{res} < d_{th} \end{cases} \tag{10}$$

Where, E_{res} represents residual energy at SN after every cycle, E_{init} indicates initial energy of SN, D is distance between SN and BS, D_{min} and D_{max} are minimum and maximum distance between BS and SN respectively.

The initial position of BS is calculated using (11).

$$\overrightarrow{P_{CH}} = \left|W_\alpha \overrightarrow{P_\alpha} + W_\beta \overrightarrow{P_\beta} + W_\gamma \overrightarrow{P_\gamma}\right| \tag{11}$$

Where, W_α, W_β, W_γ are initial weights and it can be expressed as (12).

$$W_\alpha = \frac{Fit_\propto}{Fit_\propto + Fit_\beta + Fit_\gamma}, W_\beta = \frac{Fit_\beta}{Fit_\propto + Fit_\beta + Fit_\gamma}, W_\alpha = \frac{Fit_\gamma}{Fit_\propto + Fit_\beta + Fit_\gamma} \tag{12}$$

Where, $Fit_\propto$, Fit_β, and Fit_β indicates first three optimal values of SNs. The IGWO technique is utilized to improve global search capabilities. The weights W_α, W_β, and W_γ are dynamically updated with the help of the vectors $\overrightarrow{D}, \vec{C}$ at i^{th} iteration, the weights are computed as (13) to (15).

$$W_\alpha^{i+1} = \frac{\overrightarrow{D_\alpha^{i+1}} \times \overrightarrow{C_\alpha^{i+1}}}{\overrightarrow{D_\alpha^{i+1}} \times \overrightarrow{C_\alpha^{i+1}} + \overrightarrow{D_\beta^{i+1}} \times \overrightarrow{C_\beta^{i+1}} + \overrightarrow{D_\gamma^{i+1}} \times \overrightarrow{C_\gamma^{i+1}}} \tag{13}$$

$$W_\beta^{i+1} = \frac{\overrightarrow{D_\beta^{i+1}} \times \overrightarrow{C_\beta^{i+1}}}{\overrightarrow{D_\alpha^{i+1}} \times \overrightarrow{C_\alpha^{i+1}} + \overrightarrow{D_\beta^{i+1}} \times \overrightarrow{C_\beta^{i+1}} + \overrightarrow{D_\gamma^{i+1}} \times \overrightarrow{C_\gamma^{i+1}}} \tag{14}$$

$$W_{\gamma}^{i+1} = \frac{\overrightarrow{D_{\gamma}^{\iota+1}} \times \overrightarrow{C_{\gamma}^{\iota+1}}}{\overrightarrow{D_{\alpha}^{\iota+1}} \times \overrightarrow{C_{\alpha}^{\iota+1}} + \overrightarrow{D_{\beta}^{\iota+1}} \times \overrightarrow{C_{\beta}^{\iota+1}} + \overrightarrow{D_{\gamma}^{\iota+1}} \times \overrightarrow{C_{\gamma}^{\iota+1}}} \tag{15}$$

During CH selection process, α, β, and γ wolves are used to identify the position of CH while other SNs compute their distances in relation to BS. In $(i+1)^{\text{th}}$ iteration, the revised location of SN is calculated as (16).

$$\overrightarrow{P^{\iota+1}} = \overrightarrow{P_{CH}^{\iota}} - \vec{D} \times \vec{C} \tag{16}$$

Where, $\vec{C}$ indicates convergence vector and it is calculated as $\vec{C} = 2\ \vec{\propto} \times \vec{r_1} - \vec{\propto}$, The CH location from the previous iteration, or i^{th} iteration is represented by $\overrightarrow{P_{CH}^{\iota}}$.

4.2.2. Ant colony optimization

The probability algorithm for identifying optimization pathways is called ACO. The ant system has three components: Initialization is the beginning phase. Every ant needs a taboo table to keep track of notes that are transferred throughout the procedure. Reduce the starting value of the pheromone on either side. Set the initial value of taboo table to the ant's notice that it is l in length. Set the initial value of pheromone that the ant releases at each side to zero. Step two is building the route. Ants use a specific probability to decide the CH’s future location. Probabilities are computed using the (17).

$$P_{ij}(t) = \begin{cases} \frac{[\pi_{ij}(t)]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{w\epsilon allowed}[\pi_{ij}(t)]^{\alpha}[\eta_{ij}]^{\beta}} & if\ j\epsilon allowed \\ 0 & otherwise \end{cases} \tag{17}$$

In the (17) mentioned above α is a weight calculation of pheromone and indicates the probability of selecting nodes at time t from CH i to CH j. The pheromone that helps ants choose which node to target next is more efficient the higher α. The inspiration factor, denoted by β, plays a crucial role in the probability calculation process. A higher value of β indicates that the ants will have an easier time selecting the next target CH. A list of CHs not on the ant's forbidden table is permitted. The pheromone's role comes in third. According to ACO model, the pheromone is updated as (18) after every ant discovers.

$$\tau(t+1) = \rho \cdot \tau_{ij}(t) + \Delta\tau_{ij}(t, t+1) \tag{18}$$

Where, $\tau_{ij}(t)$ indicates the pheromone of edge ij at time t. ρ defines maintenance factor. In (18) ρ, α, and β are the optimal parameters. These parameters are used to enhance the performance of model by tuning the parameters. The ρ and α are robust at 0.6 and 0.2, respectively. When more precise solutions are required, lower values of parameter β are more suitable. It ranges from 6 to 12.

4.2.3. Hybrid improved grey wolf and ant colony optimization

A hybrid technique that combines the advantages of IGWO and ACO can be very beneficial for CH selection in WSNs, especially when it comes to stability, latency minimization, and distance reduction. To improve the efficiency of CH selection in WSN, the ACO is fused with IGWO. Therefore, the adaptability of ACO's pathfinding allows it to adapt to changes in the network, while the effective optimization of IGWO ensures near-optimal performance. To select the optimal CH, the optimal parameter values $\alpha = 0.2$, $\beta = 6$, and $\rho = 0.6$ of ACO is applied to the weight parameters W_{α}, W_{β}, and W_{γ} of IGWO respectively. The optimal CH of HIGWAC can be expressed as (19).

$$\overrightarrow{P_{CH}} = \left|\left(0.2 \times \overrightarrow{P_{\alpha}}\right) + \left(6 \times \overrightarrow{P_{\beta}}\right) + \left(0.6 \times \overrightarrow{P_{\gamma}}\right)\right| \tag{19}$$

By applying optimal parameters of ACO with IGWO will tune the optimal CH effectively.

4.3. Routing using ARanEOR protocol

ARanEOR protocol uses node ranking based on energy and distance for adaptive route selection. The WSN routing protocol known as ARanEOR grades forwarder nodes (FNs) and CH using an adaptive ranking mechanism and employs an opportunistic forwarding technique to maximize EC for each SN. The major purpose of this mechanism is to dynamically rank nodes, and then utilize that ranking to determine FN in ARanEOR. The two main components that influence dynamic ranking are node's location and residual energy. ARanEOR selects collection of possible nodes and creates a ranking table to determine which node should be the forwarder. Therefore, by employing refined selection method that is covered in the sections below, ARanEOR seeks to prevent any needless energy loss, which might increase WSN efficiency and lower EC.

4.3.1. Architecture and layout

The FN is chosen among source node's neighbors depending on variables like residual energy of node and distance between nodes. The value of parameter determines how CH and all neighbors of source node are arranged or given priority in table given below. The process of selecting FN, which is a node nearest to source node and has the maximum residual energy, is shown in Figure 2.

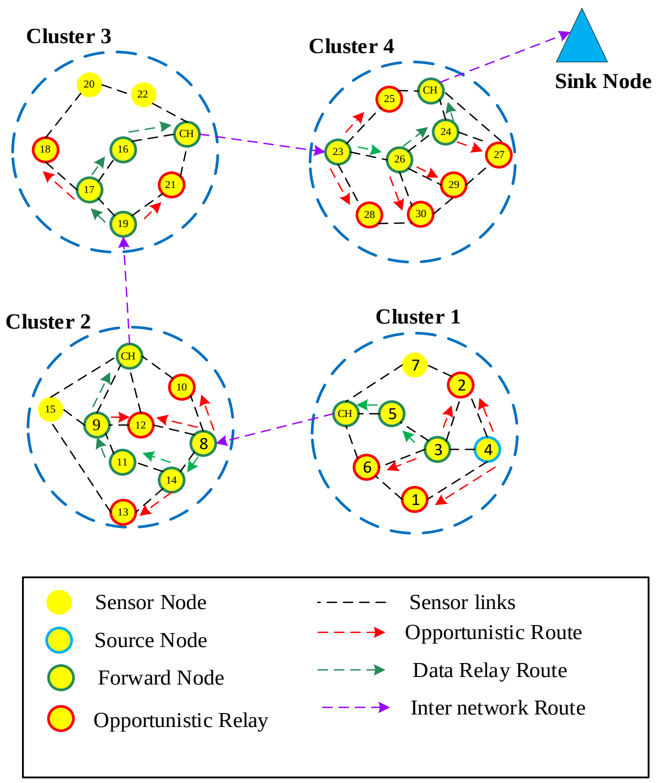


Figure 2. Volunteer routing scheme with opportunistic approach using adaptive node ranking

4.3.2. Routing table

The ARanEOR routing table differs from the one used in conventional opportunistic routing networks. This change results from the next forwarder node in ARanEOR being chosen depending on rank. As demonstrated in Figure 2, the next forwarder node in opportunistic and relay routes will be chosen with the use of a rating table. The example that follows illustrates this:

– Example 1: FN section for Node ID 4 next hop in cluster 1. Table 1 indicates that node with ID 3 has the highest rank based on residual energy and distance from source node. The next FN is selected from source node.
– Example 2: Selecting next hop and locating FN in cluster 1 for ID 2. The node with node ID 5 has highest rank, as indicated by Table 2, based on its distance and residual energy from source node. It has been selected as FN by relay node with ID 3.

Table 1. Neighbor node ranking from source node

ID of node	Range	Residual energy (%)	Distance
3	1	90	0.45 m
1	3	88	0.78 m
2	2	89	0.49 m
CH	4	85	1.32 m

Table 2. Adjacent nodes ranked by the preceding forwarder node

Node ID	Range	Residual energy (%)	Distance
5	2	87	0.81m
6	1	89	0.69m
CH	3	85	1.2m

4.3.3. Algorithm of ARanEOR

The adaptive node ranking method determines a rank of node based on its distance parameter and residual energy level. The FNs are chosen based on determined rank. Two factors are recorded for each communication from each node: distance between nodes ($D(\delta_i, \delta_j)$ and net residual energy of nodes ($E_{res}(\delta_i)$). Each node's net residual energy is calculated from its residual energy following packet delivery. Subsequently, among the candidate nodes, the node with the highest net residual energy is taken into consideration for top ranking, and so on. The nodes with lowest rank are selected to become CH. Once CH has been located, nodes and their positions are determined with respect to source node. Consequently, the ranking system helps establish a relay channel for data packets, Algorithm 1 depicts the details of optimization. Furthermore, the rankings are changed based on updated remaining energy after every relay round.

Algorithm 1. ARanEOR - Adaptive ranking for FNs

Inputs:
  $D(\delta_i, \delta_j), E_{res}(\delta_i), M_r, M_t, P_{txp} = 0.9\, J/bit,\ E_{init}(\delta_i), N_s, P_{rxp} = 0.8\, J/bit$
Outputs:
  $E_{max}(\delta_i), D_N(\delta_i, \delta_k)$
Step 1: Calculate residual energy for each node
  for i = 1 to N *do*
    $E_{res}(\delta_i) = M - \left(\left(M_r * P_{rxp}\right) + \left(M_t * P_{txp}\right)\right);$
    $E_{max}(\delta_i) = max\left(E_{res}(\delta_i), E_{res}(\delta_i - 1)\right)$
  end for
Step 2: Identification of CH
  if $E_{max}(\delta_k)\ occurs; k \in \{1,2, \dots M\}$ *then*
    $\delta_k \in CH$
  end if
Step 3: Calculate distances between present and forwarder node
  $\forall\ \delta_i \in N_s\ and\ \delta_j \in F_n$
  $D(\delta_i, \delta_j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$
Step 4: Update routing table
return

5. RESULTS AND DISCUSSION

This section presents simulation setup and analyses the performance of suggested strategy based on significant factor results. To evaluate proposed procedure, experiments are carried out in simulation environment that can imitate wireless network data transmission circumstances in almost real time. For this purpose, the Python platform has been chosen for implementation.

5.1. Evaluation parameters and criteria

The proposed protocol was implemented on a network of 50 to 200 nodes in steps. On the other hand, several metrics are used to assess an effectiveness of suggested technique, including throughput, power consumption (PC), error estimate, EC, packet delivery rate (PDR), packet loss rate (PLR), and end-to-end latency:

- MSR: it defines the successful completion of whole message transfer process from source node to CH.
- PDR: it is the percentage of packets that are delivered successfully out of all packets that are transmitted across network.
- PLR: the proportion of data packets in communication system or computer network that are not successful in reaching their intended destination.
- EC: a typical sensor node gathers data and sends it to CH which uses energy among other two unique responsibilities. In a similar vein, energy is used by CH when receiving, combining, and transmitting data.

- End-end-delay: the total of all the delays brought on by each participating node in a particular transmission is known as the end-to-end delay. The calculation of node delay is based on the time taken for communication to begin and end.
- Throughput: throughput measures the rate of successful message delivery within the network over a specific period.
- PC: it is the total amount of electrical energy used by each sensor node or by network as a whole when it is in use.
- Network lifetime: network lifetime in the context of WSNs refers to the duration over which the network can effectively operate before a significant number of sensor nodes become depleted of their energy resources or fail.
- Error estimation: it refers to the process of assessing or quantifying the accuracy or correctness of a measurement, calculation, prediction, or any other output in comparison to a known or expected value.

5.2. Evaluation of proposed method with existing techniques

The proposed system is evaluated for effectiveness by comparing it with current methods such as GIFM, stator flux-oriented (SFO), dual cluster head k-means (DCK-LEACH), and monte carlo gradient sign attack (MGSA). A simulation is used to assess each protocol's performance, and several factors related to number of nodes are compared. The evaluation results with 100 nodes are shown in Table 3.

Table 3. Evaluation of Proposed and existing method for 100 nodes

Model	ARanEOR (proposed)	GIFM	SFO	DCK-LEACH	MGSA
Message success rate	230	185	215	220	195
Packet delivery ratio	93	87	85	90	89
PLR	42	57	50	47	45
EC	150	167	180	161	157
End-to-end delay	62	70	65	74	71
Throughput	215	190	195	205	210
PC	120	127	134	135	141
Network lifetime	220	205	198	200	215
Error estimation	125	132	140	131	135

From the aforementioned results, the proposed algorithm demonstrates magnetic shielding room (MSR) ranging 240 bits/s for 50 nodes, 230 bits/s for 100 nodes, 225 bits/s for 150 nodes, and 220 bits/s for 200 nodes. The MSR range of proposed method is better than all other existing methods. This result shows that the proposed protocol is more efficient in cross layer routing for WSN. The graphical representation of performance analysis of MSR for various number of nodes is displayed in Figure 3.

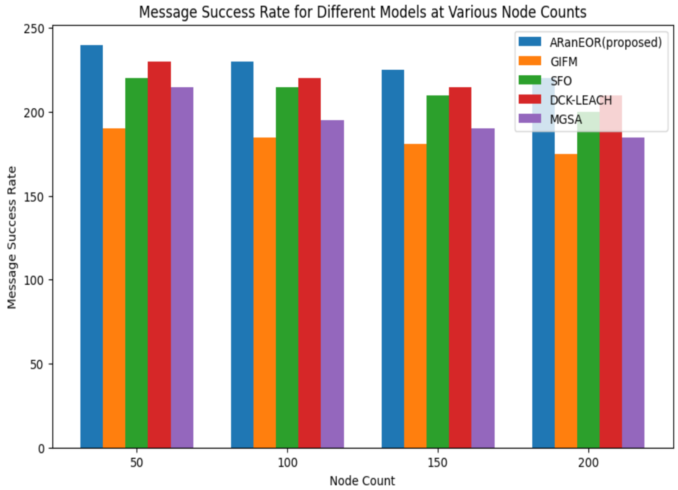


Figure 3. Proposed routing protocol performance variation by means of MSR compared with other protocols

The proposed protocol has recorded the PDR for 95% for 50 nodes, 93% for 100 nodes, 90% for 150 nodes, and 88% for 200 nodes. Out of all the methods currently in use, the suggested approach has the highest percentage of PDR. This outcome demonstrates how much more effective the suggested technique is at cross-layer routing for WSN. Figure 4 shows the graphical depiction of the PDR performance analysis for different numbers of nodes.

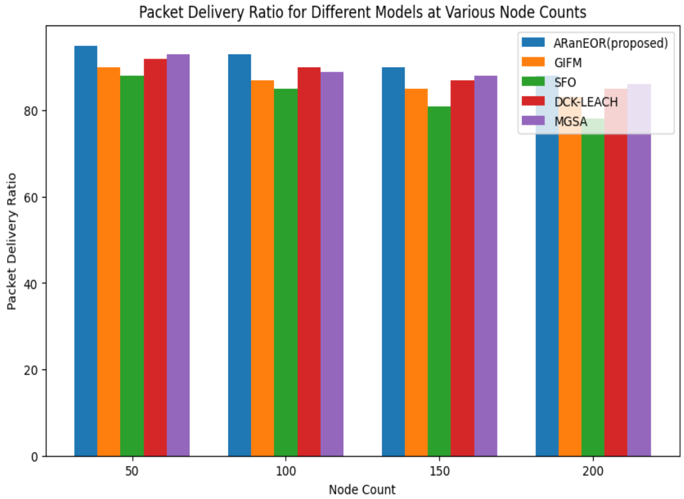
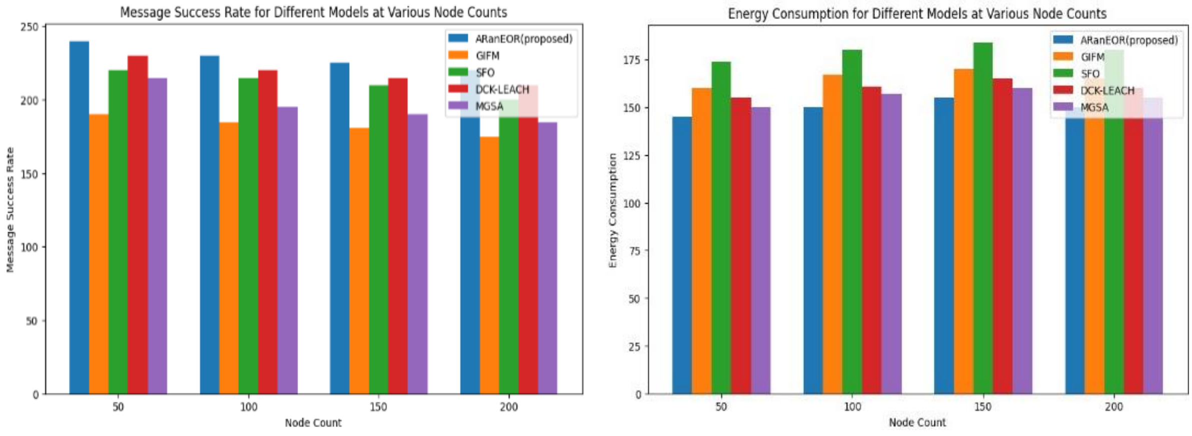


Figure 4. Comparison of suggested routing protocol's performance variation using MSR against other protocols

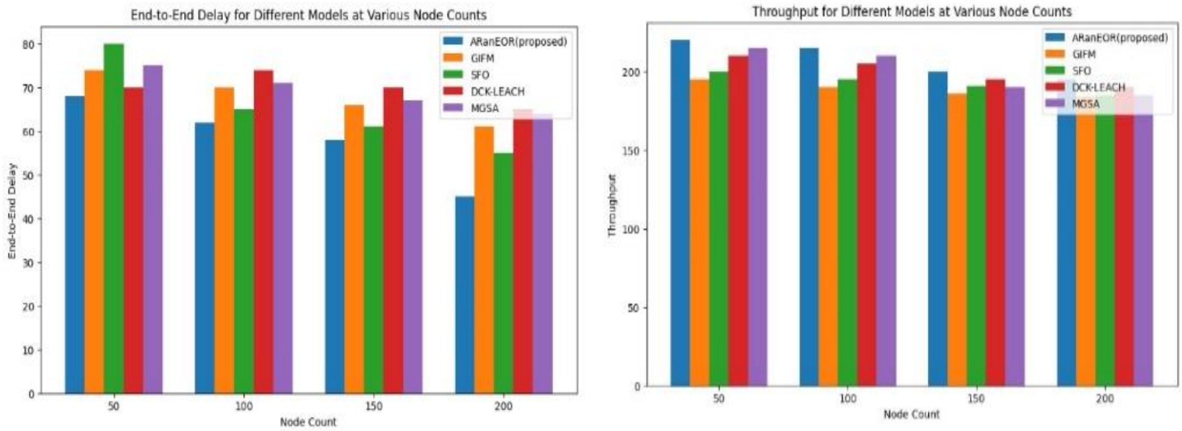
The suggested approach has recorded the PLR values of 35, 42, 45, and 40 for the number of nodes 50, 100, 150, and 200 respectively. This achieved is less than other existing approaches. This least PLR value of proposed technique proves that, the method having less loss rate and it is well suited for cross layer routing for WSN when compared to existing methods. The analysis of PLR and EC are shown in Figure 5, where Figure 5(a) shows the PLR and Figure 5(b) shows the EC.



(a) (b)

Figure 5. Analysis of proposed protocol with other protocols over (a) PLR and (b) EC

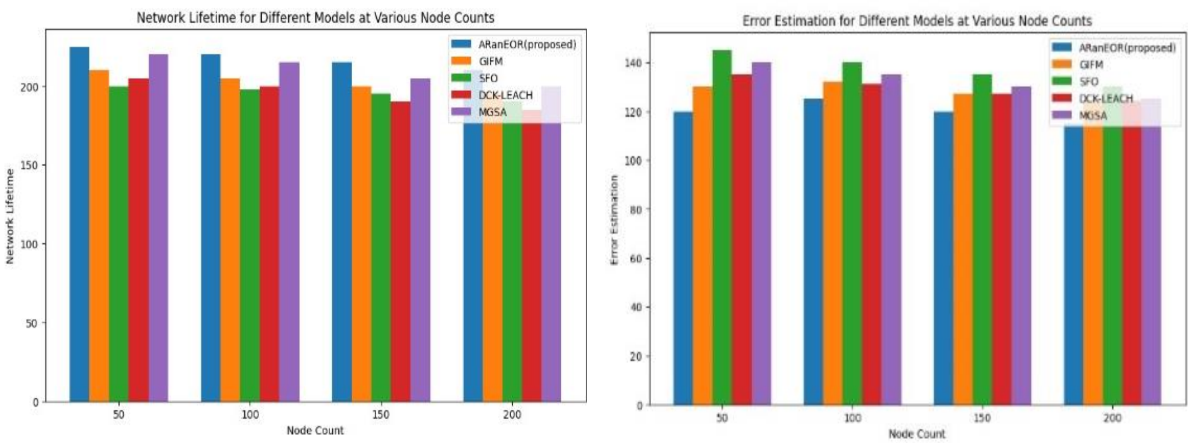
The energy consumed for 50, 100, 150, and 200 nodes of proposed method are recorded as 145 mJ, 150 mJ, 155 mJ, and 150 mJ respectively. The recorded EC of developed approach is less when compared to other techniques. A model with less EC will well suited for WSN routing. Therefore, the proposed routing protocol is suitable for cross layer routing. For the numbers of nodes 50, 100, 150, and 200, respectively, the recommended method has recorded delay values of 68, 62, 58, and 45 seconds. This is less than other methods now in use. When the suggested strategy is compared to the current techniques, its lowest end-end-delay value indicates that it has a lowest delay and is a good fit for cross-layer routing in WSN. This analysis is displayed in Figure 6. Figure 6(a) shows the graphical analysis of end-to-end analysis and Figure 6(b) shows the throughput of proposed and current protocols



(a) (b)

Figure 6. Various node counts at model (a) end-end-delay analysis and (b) throughput of proposed and current protocols

The proposed approach recorded network lifetime of 225 seconds with 50 nodes, 220 seconds with 100 nodes, 215 seconds with 150 nodes, and 210 seconds with 200 nodes. The lifetime of network serves as one of the important metrics for evaluating the overall performance of the model. These recorded values surpass those of all other existing methods, affirming the efficiency of the suggested protocol for WSN routing. Refer to Figure 7 for graphical analysis of lifetime of network. Figure 7(a) shows the graphical analysis of lifetime of network and Figure 7(b) shows the error estimation of different models.



(a) (b)

Figure 7. Analysis of proposed and other techniques over in (a) network life time and (b) error estimation.

6. CONCLUSION

This study presents a novel method for energy-efficient clustering and routing in WSNs. We achieve this by using the following techniques: FKMeds clustering, HIGWAC optimization for CH, and ARanEOR protocol for data transmission. This work has mainly focused on improving energy efficiency, ensuring QoS factors in WSNs, and extending the network lifetime. By using FKMeds clustering, this study able to cut network traffic, enhance scalability, and improve robustness, all of which improved operational efficiency. The adoption of HIGWAC optimization for CH selection emphasized energy stability, distance reduction, and latency minimization among network nodes, adding greatly to energy efficiency and network stability. Furthermore, by enabling data to be sent along the most energy-efficient paths, the ARanEOR protocol dynamically decreased network overhead and guaranteed effective energy use. The suggested approach was assessed using a range of performance measures, including message success rate, error estimation, throughput, PDR, PC, EC, PLR, and end-to-end latency. The proposed approach to WSN optimization is successful, as evidenced by the higher performance it showed in comparison to existing approaches in terms of EC, throughput, PC, network lifespan, and error prediction.

REFERENCES

[1] A. M. Khedr, P. P. Raj, and A. Al Ali, "An energy-efficient data acquisition technique for hierarchical cluster-based wireless sensor networks," *Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications (JoWUA)*, vol. 11, no. 3, pp. 70–86, Sep. 2020, doi: 10.22667/JOWUA.2020.09.30.070.

[2] V. T. Vu, T. V Quyen, L. H. Truong, A. M. Le, C. V Nguyen, and M. T. Nguyen, "Energy efficient approaches in wireless sensor networks," *ICSES Transactions on Computer Networks and Communications*, vol. 6, no. 1, pp. 1–10, Mar. 2020.

[3] S. Bharany *et al.*, "Energy-efficient clustering scheme for flying ad-hoc networks using an optimized LEACH protocol," *Energies*, vol. 14, no. 19, p. 6016, Sep. 2021, doi: 10.3390/en14196016.

[4] S. El Khediri, R. U. Khan, N. Nasri, and A. Kachouri, "Energy efficient adaptive clustering hierarchy approach for wireless sensor networks," *International Journal of Electronics*, vol. 108, no. 1, pp. 67–86, Jan. 2021, doi: 10.1080/00207217.2020.1756454.

[5] A. M. Jubair *et al.*, "Optimization of clustering in wireless sensor networks: techniques and protocols," *Applied Sciences*, vol. 11, no. 23, p. 11448, Dec. 2021, doi: 10.3390/app112311448.

[6] S. Sharmin, I. Ahmedy, and R. Md Noor, "An energy-efficient data aggregation clustering algorithm for wireless sensor networks using hybrid PSO," *Energies*, vol. 16, no. 5, p. 2487, Mar. 2023, doi: 10.3390/en16052487.

[7] M. R. Reddy, M. L. R. Chandra, P. Venkatramana, and R. Dilli, "Energy-efficient cluster head selection in wireless sensor networks using an improved grey wolf optimization algorithm," *Computers*, vol. 12, no. 2, p. 35, Feb. 2023, doi: 10.3390/computers12020035.

[8] R. Bharathi, S. Kannadhasan, B. Padminidevi, M. S. Maharajan, R. Nagarajan, and M. M. Tonmoy, "Predictive model techniques with energy efficiency for IoT-based data transmission in wireless sensor networks," *Journal of Sensors*, vol. 2022, pp. 1–18, Dec. 2022, doi: 10.1155/2022/3434646.

[9] S. R. Lahane and K. N. Jariwala, "Secured cross-layer cross-domain routing in dense wireless sensor network: a new hybrid based clustering approach," *International Journal of Intelligent Systems*, vol. 36, no. 8, pp. 3789–3812, Aug. 2021, doi: 10.1002/int.22438.

[10] O. Deepa and J. Suguna, "An optimized QoS-based clustering with multipath routing protocol for wireless sensor networks," *Journal of King Saud University - Computer and Information Sciences*, vol. 32, no. 7, pp. 763–774, Sep. 2020, doi: 10.1016/j.jksuci.2017.11.007.

[11] S. Uppalapati, "Energy-efficient heterogeneous optimization routing protocol for wireless sensor network," *Instrumentation, Mesures, Métrologies*, vol. 19, no. 5, pp. 391-397, Oct. 2020, doi: 10.18280/i2m.190510.

[12] P. Maheshwari, A. K. Sharma, and K. Verma, "Energy efficient cluster based routing protocol for WSN using butterfly optimization algorithm and ant colony optimization," *Ad Hoc Networks*, vol. 110, p. 102317, Jan. 2021, doi: 10.1016/j.adhoc.2020.102317.

[13] S. Doostali and S. M. Babamir, "An energy efficient cluster head selection approach for performance improvement in network-coding-based wireless sensor networks with multiple sinks," *Computer Communications*, vol. 164, pp. 188–200, Dec. 2020, doi: 10.1016/j.comcom.2020.10.014.

[14] A. Mehbodniya, S. Bhatia, A. Mashat, M. Elangovan, and S. Sengan, "Proportional fairness based energy efficient routing in wireless sensor network," *Computer Systems Science and Engineering*, vol. 41, no. 3, pp. 1071–1082, Nov. 2022, doi: 10.32604/csse.2022.021529.

[15] S. R. Lahane and K. N. Jariwala, "Secured cross-layer cross-domain routing in dense wireless sensor network: a new hybrid-based clustering approach," *International Journal of Intelligent Systems*, vol. 36, no. 8, pp. 3789-3812, 2021, doi: 10.1002/int.22438.

[16] L. Bharathi, N. Sangeethapriya, R. Sasikala, and A. Srinivasan, "Quality aware heterogeneous energy efficient clustering protocol for wireless sensor network," *International Journal of Conceptions on Electronics and Communication Engineering*, vol. 5, no. 1, May 2022.

[17] P. Durgadevi, T. Veeramakali, and M. S. Glory, "Energy efficient distributed cooperative cluster based communication protocol in wireless sensor networks," *International Journal of Innovative Technology and Exploring Engineering (IJITEE)*, vol. 9, no. 6, pp. 754-758, Apr. 2020, doi:10.35940/ijitee.F3889.049620

[18] N. Malisetti and V. K. Pamula, "Energy aware cluster-based routing in WSN using hybrid pelican-blue monkey optimization algorithm," *Evolutionary Intelligence*, Feb. 2024, doi: 10.1007/s12065-023-00903-6.

[19] N. D. Tan, D.-N. Nguyen, H.-N. Hoang, and T.-T.-H. Le, "EEGT: energy efficient grid-based routing protocol in wireless sensor networks for IoT applications," *Computers*, vol. 12, no. 5, p. 103, May 2023, doi: 10.3390/computers12050103.

[20] A. Ali and M. Vadivel, "Pegasis double cluster head hybrid congestion control in wireless sensor networks," *Journal of Communications Software and Systems*, vol. 17, no. 3, pp. 221-231, Sep. 2021, doi: 10.24138/jcomss-2021-0032.

[21] S. Gopinath, E. V. Boopathy, S. Pragadeswaran, S. Madhumitha, and N. Sureshkumar, "Location based energy efficient routing protocol for improving network lifetime in WSN," *SSRG International Journal of Electrical and Electronics Engineering*, vol. 10, no. 2, pp. 84-91, Feb. 2023, doi: 10.14445/23488379/IJEEE-V10I2P108.

[22] M. Gurupriya and A. Sumathi, "Dynamic clustering in wireless sensor networks using hybrid jellyfish optimization-leach protocol," *Dynamic Systems and Applications*, vol. 30, no. 11, pp. 1698-1718, Nov. 2021.

[23] R. Dogra, S. Rani, Kavita, J. Shafi, S. Kim, and M. F. Ijaz, "ESEERP: enhanced smart energy efficient routing protocol for internet of things in wireless sensor nodes," *Sensors*, vol. 22, no. 16, p. 6109, 2022, doi: 10.3390/s22166109.

[24] M. Wu, Z. Li, J. Chen, Q. Min, and T. Lu, “A dual cluster-head energy-efficient routing algorithm based on canopy optimization and K-means for WSN,” *Sensors*, vol. 22, no. 24, p. 9731, 2022, doi: 10.3390/s22249731.
[25] S. Pradeep, Y. K. Sharma, C. Verma, S. Dalal, andC. Prasad, “Energy efficient routing protocol in novel schemes for performance evaluation,” *Applied System Innovation*, vol. 5, no. 5, p.101, 2022, doi: 10.3390/asi5050101.

BIOGRAPHIES OF AUTHORS

Haritha K. Sivaraman is an assistant professor, in Department of Electronics and Communication Engineering, RajaRajeswari College of Engineering, Bangalore, India. Her major interests are wireless sensor networks, energy efficient designs in sensor networks, internet of things, and wireless communication. She can be contacted at email: harithareseachscholar@gmail.com.

Rangaiah Leburu is a professor in Department of Electronics and Communication Engineering, RajaRajeswari College of Engineering, Bangalore, India. His major interests are VLSI, wireless communications, sensor networks, Ad-Hoc networks, and Routing protocols in wireless networks. He can be contacted at email: rleburu@gmail.com.