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Original Article

Improved ACO Oriented Efficient Cluster Head Selection Mechanism for Energy Aware Routing Scheme in WSN

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Abstract *- WSNs introduce a modern model of an enhanced computing paradigm which has a significant impact on real-time embedded systems with minimal computing, connectivity, storage, and energy capacity that are being used for a wide variety of applications where conventional networks are largely infeasible. Sensor nodes are compactly installed in a hostile atmosphere to observe, track, and interpret physical phenomena, using significant energy. Replacing the battery and extending the network's life span is difficult, if not impossible. As a result, the battery's lifespan is limited, and energy saving is a difficult problem to solve. Befitting Cluster Head (CH) selection is one such problem that can significantly minimize energy consumption. In this manuscript, we bestow a novel approach to performing the cluster head selection to improve the network performance. This approach adopts an improved ant colony optimization strategy, which helps update nodes' residual energy for cluster head selection. Finally, we compare the proposed approach's outcomes with state-of-art techniques. This comparative study has validated the significance of the proposed approach.*

Keywords *- Ant colony optimization*, *Cluster head selection, Energy-aware routing, Network lifespan enhancement, Wireless sensor network.*

1. Introduction

Currently, the demand for wireless communication systems has increased drastically. In this field, wireless sensor networks (WSN) have attracted research, industry and education due to their use in various applications. These sensor networks are constructed with the help of numerous tiny devices known as sensors. These sensing devices perform several tasks related to sensing for the desired location [1]. The WSN-based communication standards are broadly embraced in various real-time wireless communication scenarios, including agricultural fields, military applications, security systems, medical domain and weather forecasting for disaster management [2]. Each sensor node comprises a battery, transceiver, and microcontroller [3]. Despite their wide use in various applications, they still suffer from random deployment, limited battery capacity, and the huge number of sensor nodes [4].

Additionally, these networks are installed in a harsh and unpatentable environment, i.e., unsuitable to maintain manually; substituting the battery to sustain the power supply is challenging. Due to the random deployment of these networks in harsh environments, the network life span is a challenging task. Thus, improving the performance and minimizing these networks' energy consumption and efficiency is challenging [26].

Generally, most energy is dissipated during data exchange, which depends on the distance between the source and sink or two communicating nodes. The current research community has focused on developing routing protocols to deal with these issues [6]. Generally, the routing schemes are classified into two classes flat and hierarchal routing [7–8]. As mentioned above, random deployment, limited energy resources, and variations in network topology can be addressed efficiently by using hierarchal routing compared to flat routing [9]. The clustering algorithm aims to partition the sensor network nodes into groups. A cluster has a head node, which receives information from the other member nodes and proceeds to fuse and forward the data. Choosing a cluster head is an integral part of the clustering algorithm. Research on how to reduce node energy usage by choosing the cluster head and then forming a high-quality cluster is important.

During the last decade, several clustering schemes have been developed, such as LEACH, Hybrid Energy-Efficient Distributed clustering (HEED) and many more [10]. The performance of these schemes is restricted due to different types of conditions, i.e. lack of resources, poor link connectivity, etc., which leads to deteriorating communication performance.

Generally, the sensor node clustering and efficient cluster head selection algorithm is considered a type of optimization problem that can be solved with the help of optimization strategies. Several optimization techniques are widely adopted in different applications of wireless sensor networks, such as genetic algorithm [11], ant colony optimization [12] and particle swarm optimization [29]. However, these strategies have many difficulties, such as computational complexities and poor convergence. To overcome these issues, authors have presented new approaches, such as in [14], authors presented a new approach which uses a new variant of the bat algorithm which adopts the two-stage cluster formation strategy. The outcome of this technique shows that this approach minimizes energy consumption compared with the LEACH protocol. In [15], the authors proposed a new approach known as enhanced multi-hop LEACH (EM-LEACH). This approach improves the network efficiency by improving the energy distribution.

Similarly, in [27], the authors developed a multi-hop routing approach combined with the LEACH protocol. Several optimization techniques such as particle swarm optimization where inaccurate local search is a performance degrading issue, and local minima trapping problem, genetic algorithm (GA), simulated annealing (SA), Honey Bee optimization (HBO) (suffers from sluggishness toward solution convergence), and ant colony optimization (ACO) reported their significance in finding the best optimal path between nodes. These optimization techniques follow different strategies according to their process, such as the genetic algorithm using crossover and mutation techniques to obtain the optimal solution based on the fitness function.

According to the genetic algorithm, the fitness functions are applied to each node, and the node with a higher fitness value has a higher chance of survival. Similarly, the ant colony optimization algorithms are based on the ant foraging behaviour used in various applications to find the shortest path. According to ACO, two ants, including forwarding and backward ants, are considered. Forward ants collect the required information that can be used for possible paths between source-sink or installed nodes. This information is accumulated, and an information tree is constructed to support the other nodes in finding the optimal path for their corresponding destination.

On the other hand, the backward travelling ants update the node data by travelling in the reverse direction, i.e., backward and travel from the destination to the source node. However, these techniques are suitable for small search spaces and suffer from complexity issues for large search spaces. Hence, improving the working of ACO is a promising solution to augment the performance of WSN. In this work, we focused on the optimization strategy. We developed a novel approach for cluster formation, cluster head selection and ant colony-based optimization strategy to select the next optimal hop for energy-aware routing.

The remainder of this article is systematized into the following subsections: Section II describes the literature review about the clustering techniques, including optimization-based strategies. Section III describes the proposed solution for energy-aware cluster head selection and optimal node selection. Section IV presents the comparative experimental analysis by considering various simulation parameters. Finally, section V illustrates this research's concluding remarks and future scope.

2. Literature Survey

In the previous section, we briefly presented an overview of sensor networks and identified the well-known problems in this field. We also discussed the traditional problems and their solutions in WSN. In this section, we expand the study of existing schemes and study the most recent techniques to handle the performance-related issues of WSN. This section mainly includes studying routing and data aggregation methods in WSN.

Thi et al. [12] discussed the coverage-related issues of WSN and developed an evolutionary computation-based optimisation scheme using a genetic algorithm to increase the network coverage in WSN. Generally, the heterogeneous sensor nodes suffer from the issue of limited sensing range, leading to coverage problems in WSNs. This problem is known as an NP-hard problem. The NP-hard problem can be solved with the help of optimization schemes which use metaheuristic fitness functions. Thus, a genetic algorithm s adopted, and a new fitness function is defined based on Laplace and arithmetic crossover operators.

Cui et al. [29] considered the scenario of big data sensing using IoT systems and focused on minimizing energy consumption. LEACH is considered a promising state-of-art technique to increase energy consumption performance. To overcome the issues of the existing LEACH protocol, the authors developed a new bat algorithm combined with a centroid strategy. Moreover, a new scheme is presented to update the inertia-free velocity. Similarly, [14] also authors developed a multi-hop clustering approach using LEACH protocol where new rules are designed for cluster head formation.

Nigam et al. [15] reported that the LEACH algorithm doesn’t focus on the remaining power of the sensors. Thus, the CH selection using LEACH is unsuitable for increasing the network's efficiency. To overcome these issues, the authors developed an enhanced clustering approach called ESO-LEACH, which focuses on improving the performance of LEACH. This approach uses a meta-heuristic particle swarm optimization scheme to perform the clustering.

Logambigai et al. [17] established a routing methodology to increase energy utilization and network life span. According to the clustering approach, the node closer to the base station consumes excessive energy due to more congestion on this node. However, to resolve this issue, unequal clustering is considered a promising solution; however, these techniques suffer from load issue which affects network performance. To overcome this issue, a load balancing approach using fuzzy logic based on unequal clustering. This fuzzy logic scheme considers three parameters for fuzzy rule formation: distance between node and base station, residual energy and node degree. Bagci et al. [18] also discussed the faster energy depletion of nodes closer to the base station. This problem is known as a hot-spot problem. Similar to [17], the authors also presented an unequal clustering mechanism using fuzzy logic in this work.

In [19], the authors developed a new routing scheme known as Energy-aware Grid-based Routing. The foremost goal of this methodology is to deliver the data packets to multiple mobile sink nodes and improve the network life span. For this type of dynamic topology, this approach adopts the rerouting scheme to minimize the frequency of rerouting. Moreover, a time-scheduling method is also adopted to minimize energy consumption. Nayak et al. [20] also developed FL (Fuzzy logic) enabled approach and significant rules for WSN clustering. According to this approach, a supercluster head selection is performed to exchange the data with BS. The fuzzy logic module considers different fuzzy descriptors, including residual energy, BS portability, and cluster supremacy. The Mamdani fuzzy function is used for fuzzification to perform the cluster head selection. Selvi et al. [21] focused on the issues of existing techniques and presented a combination of two heuristic strategies: fuzzy logic and gravitational search algorithm. The fuzzy logic used for cluster head selection and optimization approach helps to optimize the selection process dynamically.

Yuan et al. [28] reported that searching for optimal cluster head selection in dynamic WSNs is challenging. To resolve this issue, the authors proposed a GA-dependent self-organizing network clustering (GASONeC) approach, which offers a continuous process to optimize the performance of WSN nodes. The remaining energy, projected energy consumption, distance to BS, and the number of nodes in the surrounding area are all used in GASONeC to find the best, most complex network configuration.

Osamy et al. [23] considered optimisation strategies a promising solution to increase the efficiency of sensor networks. The CSOCA is based on the chicken swarm optimization strategy proposed in this paper to increase energy competence in WSN. Individuals in the chicken swarm optimization are discretized using a sigmoid function. In addition, we suggested CSOCA with a Genetic Algorithm, which is an update to CSOCA by incorporating the processes of the Genetic Algorithm into CSOCA.

El Khediri et al. [24] developed a novel clustering technique described as the MW-LEACH, which considers minimum weight to formulate the cluster. The Cluster Heads (CHs) in MW-LEACH are chosen based on the surplus energy and distance criteria between them. The suggested methodology compiles the primary group of CH candidates by selecting nodes from the initial set based on excess energy around the density's centre. These candidates continue to collect information from their people in various methods and give it to the BS.

Improving the performance of WSNs has been considered an important research area. Thus, several techniques have been developed. Recent techniques are discussed in this section, including cluster formation, cluster head selection, optimization scheme for node clustering, and improving the overall performance. To achieve this, optimization-based strategies are widely adopted to accomplish these tasks. However, the optimization strategies suffer from the issue of poor convergence, local & global optimum, computational complexity, and time requirement. Moreover, most of the schemes are single objectives which are not efficient, and multi-objective problems pose the tradeoff between computation complexity and performance. These issues must be addressed; thus, an innovative method is obligatory to increase the system's overall performance.

3. Results and Discussion

This section presents the proposed routing approach to increase the overall network life span. This proposed model consists of the following phases: network radio modelling, problem statement, cluster formation, cluster head selection and improved ACO-based routing. The proposed ACO-based routing transmits the data from cluster head to cluster head with the help of relaying mechanism. To increase the path selection process, we incorporate a dynamic threshold strategy for residual energy and a new approach to update the pheromones. This approach considers convergence speed, routing reliability, energy efficiency and load balancing with low maintenance cost because of its simple structure.

3.1. Network Model

A wireless sensor network comprises numerous sensor nodes and wireless links to communicate with other sensor nodes in the communication range. A WSN is characterized as an undirected graph which is symbolized as $G(V, E, W)$

where V denotes the group of sensor nodes $V = \{v_1, v_2, \dots, v_n\}$ Where each node has a communication range with a radius R. E represents the bidirectional communication link as $(i,j)(i,j \in V)$. A communication link (i,j) is denoted as $e(i,j) \in E$, which exists between node v_i and v_j if it is in the range as $d(v_i, v_j) < R$ where $d(v_i, v_j)$ represents the distance between node v_i and v_j. W is the weight matrix for each for directed link. For this network, we have following assumptions:

- N signifies the count of sensor nodes is distributed uniformly within the squared region. Each sensor is assigned a unique ID
- All sensor nodes remain static after deployment.
- These sensor nodes have power constraint devices installed in a harsh environment; thus, the battery cannot be replaced and recharged.

The location of each sensor node is already known to the communicating node, which is stored along with their IDs.

3.2. Radio Model

To transmit the data and establish the link for data exchange from node i to j, the communication system dissipates energy which can be estimated by the radio model. The sensor nodes consume more energy in communication when com0pared with other tasks such as sensing collection and processing. Thus, we mainly focus on minimizing energy consumption while performing communication. To transmit the l bit data packet from source to destination at a distance d, the energy dissipation can be symbolized as:

$$E_T(l,d) = E_{Tx-elec}(l) + E_{Tx-amp}(l,d) = \begin{cases} l\, E_{elec} + l\, \epsilon_{fs}\, d^2 \; for\; d < d_0 \\ l\, E_{elec} + l\, \epsilon_{mp}\, d^4 \; for\; d \geq d_0 \end{cases} \tag{1}$$

$E_{Tx-elec}$ denotes the energy dissipated by electronics which rely on several elements such as modulation, digital coding, signal spreading, and filtering. E_{Tx-amp} denotes the energy dissipation by amplifiers, ϵ_{fs} and ϵ_{mp} denote the energy constant for the free space model and multipath models.

Similarly, energy dissipated by the node to accept the l bit data is expressed as:

$$E_R(l) = lE_{elec} \tag{2}$$

3.3. Problem Statement

To obtain the energy-efficient outcome proposed, we focus on obtaining the optimal number of clusters, selection of cluster head and optimal path to the sink node. Here, our key objective is to augment the network life span and curtail energy depletion. This problem can be expressed as follows:

$$\max T_{net}, \min \sum_{[i,j \in V, (i,j) \in E]} e_{ij} \tag{3}$$

Let us consider that we have discovered N number of paths between the cluster head and the sink node. The energy dissipation of route p where $p \in N$ is the energy consumption by CPU, data transmission and receiving the data. The sequence of nodes along path p is denoted as $(n_1, n_2, \dots, n_m)$. The total energy dissipation can be characterized as:

$$E(p) = \sum_{k=1}^{m-1} (E_r + E_{cpu} + E_t) = (E_r + E_{cpu} + E_t) \times (m-1) \tag{4}$$

where E_r and E_t denotes the energy dissipated to receive and transmit the data, and E_{cpu} is the energy dissipated by the data's sensing, collecting and processing. As discussed before, the energy dissipated in transmission and receiving the data is a more energy-consuming process; thus, the energy consumption can be expressed as:

$$E(p) = (E_t + E_r) \times (m-1) \tag{5}$$

Here, the value of $(m-1)$ same as the number of available nodes count between CH and sink; then the energy dissipation can be updated as:

$$E(p) = (E_t + E_r) \times h_{CH}(p) \tag{6}$$

Where h_{CH} represents the hops between the cluster head and the sink node. The network life span is based on the remaining energy after dissipation and energy dissipation in the path. The network life span is expressed as:

$$T_{net} = \min_{p \in N} T(p) = \min_{p \in N} E_{min}(p) \times h_{CH}(p) / E(p) \tag{7}$$

With the help of this, the network life span maximization problem can be formulated as:

$$maximize \min_{p \in N} T(p) \tag{8}$$

3.4. Optimal Number of Cluster Formation

To increase the network life span, cluster head selection and optimal cluster formation play an important role. In this approach, we adopted the LEACH protocol and modified its process to develop a novel approach for the clustering process. In this process, the cluster formation and selection of CH are determined based on the threshold values $T(n)$. This threshold can be expressed as:

$$T(n) = \begin{cases} \dfrac{p}{1 - p * \left(r * mod \left(\dfrac{1}{p}\right)\right)}, n \in G \\ 0, otherwise \end{cases} \quad (9)$$

Where p is the probability of cluster, i.e., the ratio of cluster heads to sensor nodes in each round, r denotes the current round count, and G is a group of nodes selected as cluster head. Here, we assume that N amount of sensor nodes are installed in the $L \times L$ 2D terrestrial region where free space and multipath models are used. In this scenario, when the distance between the base station is much less, we adopt the free space model. In this case, the energy consumption of CH in each round can be expressed as:

$$E_{CH} = \left(\frac{N}{k} - 1\right) \times E_{elec} \times m + \frac{N}{k} \times E_{DA} \times m + m \times E_{elec} + m \times \epsilon_{fs} \times d_{BS}^2 \quad (10)$$

Where k denotes the total count of clusters in each round, $\frac{N}{k}$ is the average number of cluster members in each cluster, E_{DA} is the energy dissipated by the cluster head to aggregate the 1-bit data and d_{BS}^2 represents the squared distance between the current CH node and BS. We assume that the nodes are distributed in an arbitrary region as $\rho(x, y)$ and the base station is located at (a, b). The distance between CH and the base station can be calculated as:

$$E[d_{BS}^2] = \int\int ((a - x)^2 + (b - y)^2)\rho(x, y)dxdy \quad (11)$$
$$\int\int \frac{(a - x)^2 + (b - y)^2}{A} dxdy$$

Where A represents the node distribution, thus, the energy dissipated by each cluster member is computed as:

$$E_{nonCH} = m \times E_{elec} + m \times \epsilon_{fs} \times d_{CH}^2 \quad (12)$$

In general, the distance between cluster head and cluster member is computed as:

$$E[d_{CH}^2] = \int\int (x^2 + y^2)\rho(x, y)dxdy = \frac{L^2}{2\pi k} \quad (13)$$

With the help of this energy and distance computation. The overall energy consumption by each cluster is expressed as:

$$E_{cluster} = E_{nonCH} \times \left(\frac{N}{k} - 1\right) + E_{CH} \quad (14)$$

Further, the energy dissipated in each round can be denoted as:

$$E_{round} = kE_{cluster}$$
$$= m(2NE_{elec} + NE_{DA} + k\,\epsilon_{fs} d_{BS}^2 + N\epsilon_{fs} d_{toCH}^2 \quad (15)$$

With the help of this, the optimal number of clusters for the free space model can be represented as:

$$k_{opt} = \frac{\sqrt{N}}{\sqrt{2\pi}} \frac{L}{d_{toBS}} \quad (16)$$

Similarly, the optimal number of cluster heads for the multipath energy consumption model can be expressed as:

$$k_{opt} = \frac{\sqrt{N}}{\sqrt{2\pi}} \sqrt{\frac{\epsilon_{fs}}{\epsilon_{mp}}} \frac{L}{d_{toBS}^2} \quad (17)$$

The conventional LEACH approach uses a threshold for cluster head selection which doesn't consider the residual energy parameter of the nodes. To mitigate this issue, a new threshold criterion for CH selection is presented, which is given as:

$$T(s_i) = \begin{cases} \dfrac{p_i}{1 - p_i\left(r\ mod \left(\dfrac{1}{p_i}\right)\right)}, s_i \in G \\ 0,\ otherwise \end{cases} \quad (18)$$

Where s_i represents the i^{th} the node in the network. We introduced a parameter to adjust the energy values dynamically, which is called an energy regulating factor p_i. This can be expressed as:

$$p_i = \frac{p * s_i * E_r^i * E_i}{E_a * E_t} \quad (19)$$

Where p represents the proportion of CH selection, s_i is the node, E_r^i denote the residual energy, E_i is the initial energy of the node, E_a denotes the average energy of all nodes present in the considered sensor network. The average energy can be computed as:

$$E_a = \frac{E_t\left(1 - \dfrac{r}{r_{max}}\right)}{s_i} \quad (20)$$

Generally, the nodes with higher residual energy are considered the most eligible for cluster head selection; however, a cluster selection also depends on several other parameters.

3.5. Improved ACO-Based Routing

This section presents the proposed ant colony optimization-based strategy for optimal next hop selection to minimize energy consumption. Ant colony optimization is a widely adopted probabilistic technique for computational problems. This optimization approach solves these problems by finding the optimal paths. Artificial agents are used in this approach which adopts the behaviour of real ants where a pheromone-based communication strategy is used for communication. Below, figure 1 depicts a basic process of ant colony optimization.

According to this figure, the conventional ant colony optimization scheme uses an objective function to find ants' positions and achieve the optimal solution. However, this scheme fails to obtain the desired performance for huge network scenarios. To overcome this issue, we introduced a new objective function that handles the cluster head selection and minimises energy consumption problems.

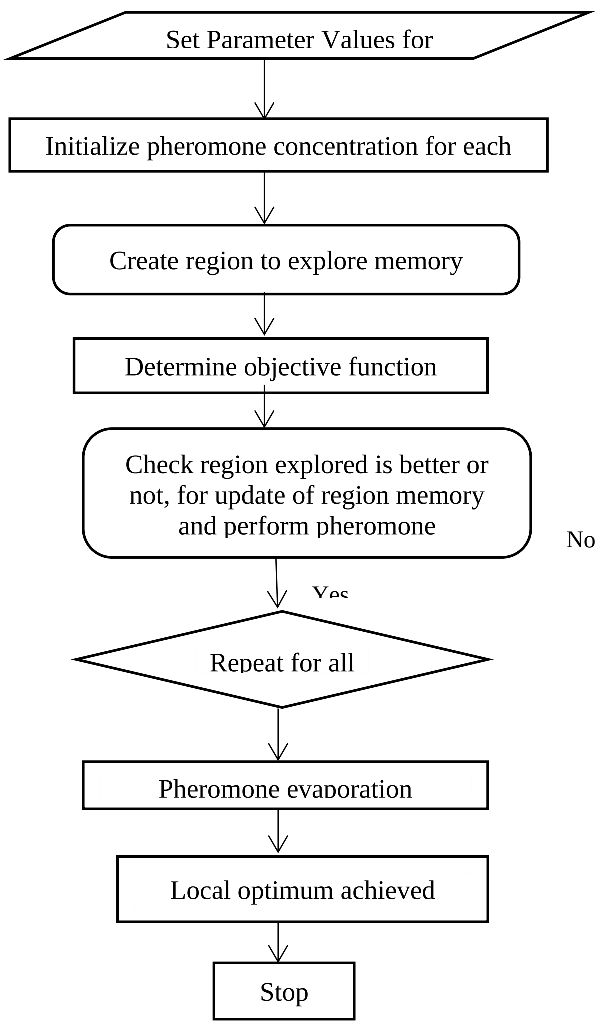

Fig. 1 Basic process of ACO optimization

Let us consider that the initial energy of each node is assigned as $\mathbb{E}$ where the energy threshold and lower bound of the energy threshold are considered as θ and θ_{min}. According to the concept of ACO, the ant initializes the search for food, which is considered the next hop in this work. This search operation contains the θ_c which is a copy of the energy threshold θ. In the search operation, it finds the nodes which are having the higher energy when compared to the θ_c. The nodes with less energy than the threshold are used for data sensing and collection. Moreover, these nodes are not responsible for data transmission. For these types of nodes, the energy is updated dynamically, which is updated as:

$$\theta_c = \begin{cases} \lambda \times \theta_c, \lambda \times \theta_c > \theta_{min} \\ \theta_{min}, \lambda \times \theta_c \leq \theta_{min} \end{cases} \tag{21}$$

Where λ denotes a decrease in the threshold value, during this data transmission process from one cluster to another, multi-hop communication plays an important role. It helps to minimize energy consumption while facilitating reliable packet delivery. Generally, the CH with a minimum distance to the base station consumes more energy due to higher data traffic rates. In this scenario, the conventional schemes adopted equal clustering where all clusters are treated with the same type of configuration. Thus, we focus on presenting unequal clustering for sensor networks. Moreover, the cluster which is near BS have smaller size of clusters; thus, the cluster radius can be defined as:

$$\mathcal{R} = \mathrm{r}_0 \times \sqrt{\frac{E_{res}}{E_0}} \times \left(1 - \tau \times \frac{d_{max} - d(i, BS)}{d_{max} - d_{min}}\right) \tag{22}$$

Where r_0 denotes the predefined maximum radius, $d(i, BS)$ is the distance between node and base station, d_{min} is the minimum distance between node and base station and $d_{max}$is the maximum distance between the node and base station.

To optimize the CH, a cost function $\mathbb{C}$ is signified as:

$$\mathbb{C}(*) = \lambda_1 \times \eta_1 + \lambda_2 \times \eta_2 + \lambda_3 \times \eta_3 \tag{23}$$

Where $\eta_1 = \frac{d(i,j)}{\sqrt{E(d_i)}}$, $\eta_2 = \frac{|E_0 - E_{res}(j)|}{\sqrt{E(E_{res}(G_i))}}$ and $\eta_3 = \frac{T}{r^2}$ in such a way that $\lambda_1 + \lambda_2 + \lambda_3 = 1$. Here, i is the current node, G_i is the group of a neighbouring node for node i,$E(d_i)$ is the expected distance, $E_{res}(j)$ Characterize the energy which is left in the cluster head. The minimum cost value helps to obtain the most stable clusters. Further, we incorporate weighted values of these parameters obtained with the help of standard and average deviation. The standard deviation can be defined as:

$$\sigma_i = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\left\|w_i\eta_{ij} - \frac{1}{n}\sum_{k=1}^{n} w_i\eta_{ij}\right\|\right)^2} + N(0,1) \quad (24)$$

And average deviation can be obtained as:

$$M = \frac{1}{n}\sum_{i=1}^{n}\left(\left\|w_i\eta_{ij} - \frac{1}{n}\sum_{k=1}^{n} w_i\eta_{ij}\right\|\right)^2 + N(0,1) \quad (25)$$

$N(0,1)$ is the normal distribution. This normal distribution process helps maintain cluster stability, minimising switching between cluster heads. It improves in minimizing packet collision. ACO uses a pheromone strategy to increase the search operation and domain knowledge to proliferate the search speed. The pheromone values illustrate the learning of good paths based on the ants' actions and domain or node. For this scheme, we consider the residual energy of the node and the distance between node i and j. Moreover, we incorporate a weighting factor γ_1 and γ_2 to obtain the importance of the energy and distance parameters. This factor is expressed as:

$$\eta_{ij} = \frac{E_j}{C}\gamma_1 + \frac{d_{sum}}{d_{ij}}\gamma_2 \quad (26)$$

η_{ij} helps to identify the sensor node whose distance is short and residual energy levels are high for cluster head selection to balance the energy consumption. Here E_j represents the residual energy. At this stage, we find the probabilistic node where ant k indicates the data exchange between node i and j, which can be expressed as:

$$P_{ij}^{k} = \begin{cases} \dfrac{\tau_{ij}^{\alpha}\left(\frac{E_j}{C}\gamma_1 + \frac{d_{sum}}{d_{ij}}\gamma_2\right)^{\beta}}{\sum_{\mu\in success}\tau_{i\mu}^{\alpha}\left(\frac{E_j}{C}\gamma_1 + \frac{d_{sum}}{d_{ij}}\gamma_2\right)^{\beta}}, \\ j \in Success_k \\ 0, otherwise \end{cases} \quad (27)$$

Where τ_{ij} denotes the pheromone value, α is the influence on the pheromone value on the considered path, β is the influence value on the heuristic factor of an ant for path selection.

4. Results and Discussion

Here, we demonstrate the experimental analysis of the proposed combined method and compare the obtained performance with various existing schemes. To validate the outcome of the proposed approach, we measure the performance in terms of network life span for varied nodes, energy depletion performance for different node configurations, residual energy for communication rounds, and throughput. Below, table 1 shows the simulation parameters used to obtain these performance matrices.

Table 1. Experimental parameters used for WSN

Parameter Name	Value
Size/dimension of deployment region	100mx100m
Node Count	Min.100 and max 300 nodes
Initial energy	1J
Radio energy E_{elec}	50nJ/bit
Type of propagation	Free space Model
ϵ_{fs}	10 pJ/bit/m
ϵ_{mp}	0.0015 pJ/bit/m^4
Packet size	512 Bytes
Data aggregation energy	0.0015 nJ/bit/signal

To measure the performance of the proposed approach, we have considered a 2d geographical region as 100mx100m where 100 to 300 nodes are installed. The initial energy of each sensor node is assigned as 1J, and the packet size is 512 Bytes. In this model, we select IEEE802.11 as the MAC protocol. First, we measure the performance of the network life span for varied nodes, as depicted in figure 2. The obtained performance is compared with the existing techniques described in [25].

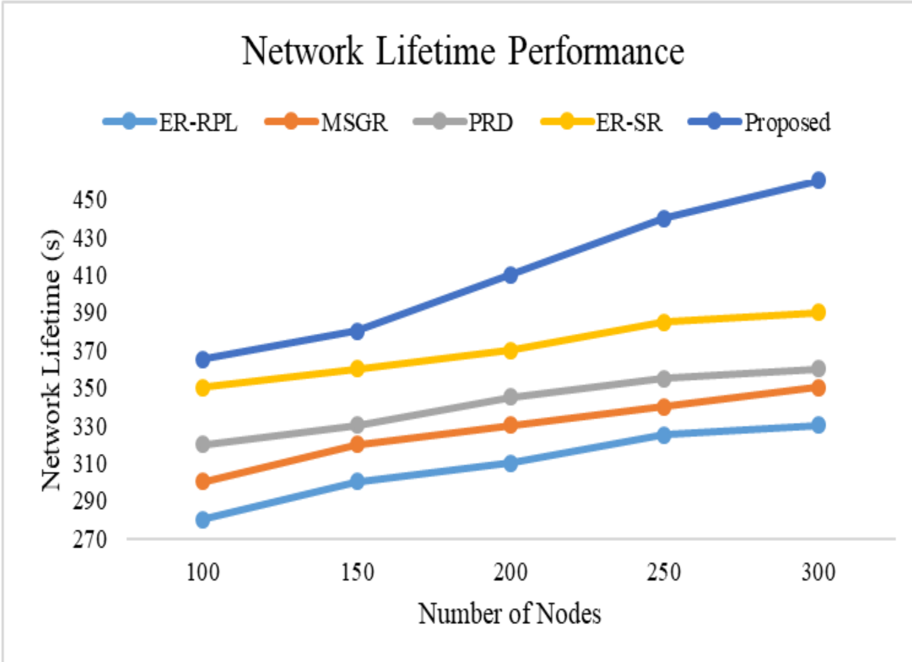

Fig. 2 Network lifespan performance

The average network life span performance is obtained as 309s, 328s, 342s, 371s, and 411s by using ER-RPL, which is a region-based approach for routing, MSGR, which is a grid-based routing, PRD, which is based on link-delay statistics, ER-SR which is region-source based scheme, and Proposed approach, respectively. Further, we considered the same simulation setup and measured the energy consumption for varied nodes. The obtained performance is compared with existing schemes. The comparative analysis is depicted in figure 3.

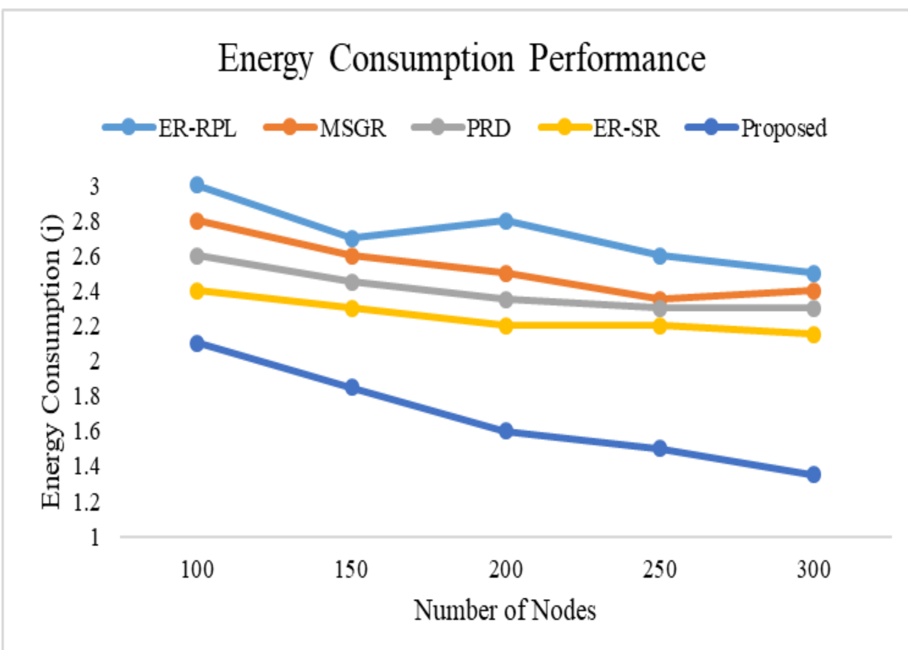

Fig. 3 Energy consumption performance for the varied number of nodes

The average energy consumption is obtained as 2.72J, 2.53J, 2.4J, 2.25J, and 1.68J using a region-based approach for routing, grid-based routing, link-delay statistics-based routing, region-source-based scheme, and Proposed approach, respectively. Furthermore, we compared the performance with other existing techniques such as PSO

[21], GA-based routing [21], fuzzy logic unequal clustering (FBUC) [17], Fuzzy energy-aware unequal clustering (EAUCF) [18], energy-efficient grid-based routing (EEGBR) [19], Fuzzy Leach [20] and fuzzy based cluster formation protocol (FBCFP) [21]. First, we measure the performance in terms of residual energy for 1000 rounds. Below, figure 4 depicts the comparative analysis of residual energy.

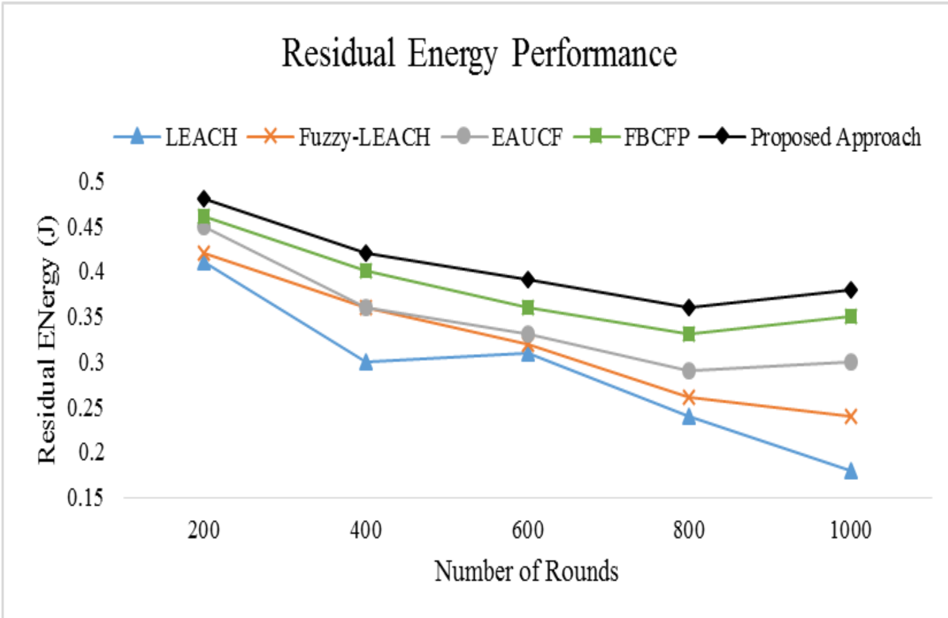

Fig. 4. Residual energy performance for the varied number of rounds

The average residual energy is obtained as 0.288, 0.32, 0.346, 0.38, and 0.406 using LEACH, Fuzzy-LEACH, EAUCF, FBCFP, and the proposed approach, respectively. The increasing number of rounds increases energy consumption. Thus, residual energy decreases. The proposed approach achieves better performance because of its cluster stability. Similarly, energy consumption performance also can be obtained with the help of residual energy. Below given figure 5 depicts the energy consumption performance for 1000 rounds.

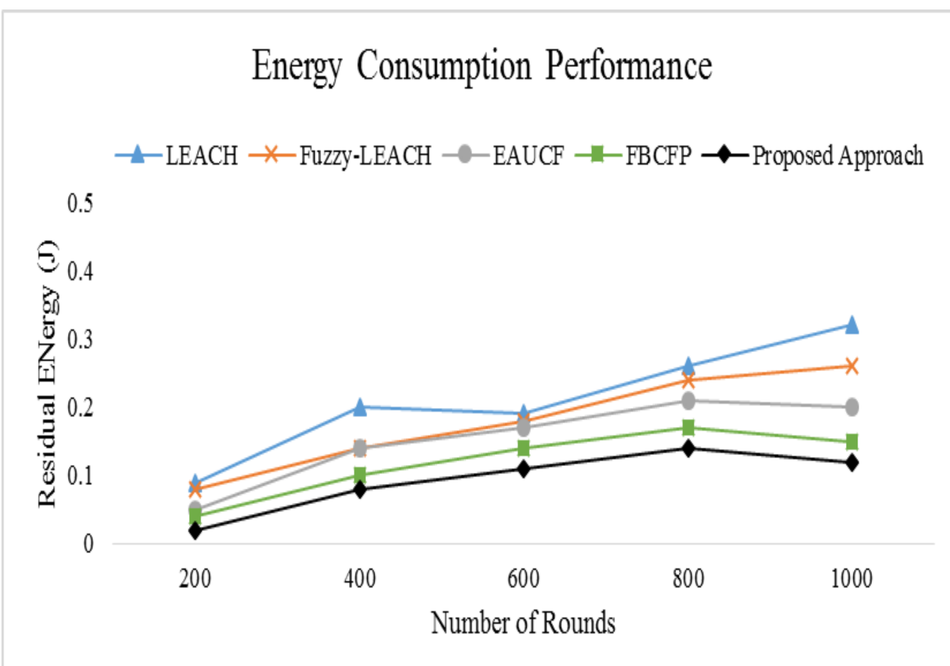

Fig. 5. Energy consumption performance for the varied number of rounds

The average energy consumption performance is obtained as 0.212, 0.18, 0.154, 0.12, and 0.094 using LEACH, Fuzzy-LEACH, EAUCF, FBCFP, and Proposed Approach, respectively.

In next experiment, we measure the throughput performance for varied network sizes which are considered as 200x200, 400x400, 600x600, 800x800 and 1000x1000. For this setup, the obtained outcome and its comparison are depicted in figure 6, which shows the consistency in the proposed approach's performance.

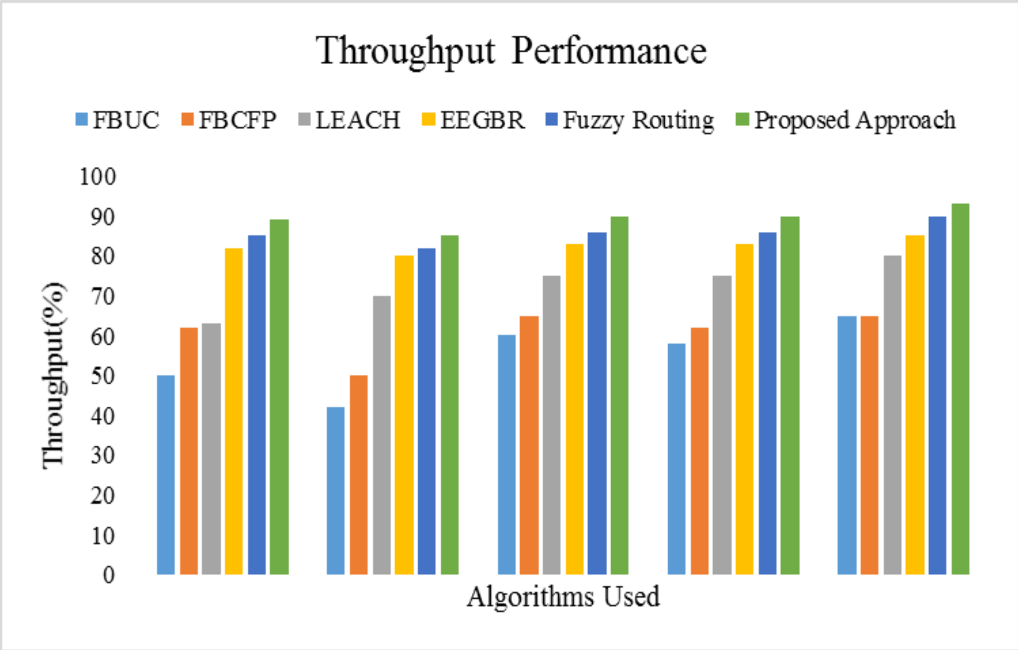

Fig. 6 Throughput performance for the varied number of rounds

In this experiment, we obtain the average performance as 55, 60.8, 72.6, 82.6, 85.8, and 89.4 Mbps using FBUC, FBCFP, LEACH, EEGBR, Fuzzy Routing, and Proposed Approach.

In this work, our main aim is to increase the overall performance of WSNs by adopting optimizing strategies. However, conventional optimization strategies suffer from various issues. Thus, we introduce a new approach which improves the overall network performance in terms of network life span, energy consumption, residual energy, and overall throughput.

5. Conclusion

Since each sensor has a limited battery, one of the most critical issues for routing in wireless sensor networks is reducing the energy usage of network nodes. Several approaches have been presented to increase network performance, but these techniques suffer from various issues. Moreover, the current research community have suggested that optimization techniques can increase performance. Thus, we have presented an improved ACO-based optimization strategy where a new threshold model is developed and incorporated with the LEACH protocol. The proposed approach is simulated by using various parameters, and a comparative analysis is presented to validate the enhanced performance using the proposed approach.

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