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Energy and Distance Aware Multi-Objective Firebug Swarm Optimization Based Clustering and Routing in Wireless Sensor Networks

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Abstract: In recent years, Wireless Sensor Networks (WSNs) have received increased international attention due to advancements in the communication, electronics, and information fields. These sensor networks integrate a huge number of sensor nodes to track rapidly changing physical events. The key improvement is that these nodes can be easily positioned in any environment due to their small size. Therefore, maintaining network connectivity is crucial in WSNs. If some nodes become unavailable, the connectivity of the routing path fails, resulting in significant packet loss in the WSN. Therefore, many types of research in WSNs have focused on energy efficiency, where energy consumption is minimized to improve the network lifetime. Here, Energy and Distance-aware Multi-Objective Firebug Swarm Optimization (ED-MOFSO) is projected to achieve an energy efficient process. Furthermore, ED-MOFSO minimizes delays to enhance performance measures. From the overall simulation, it shows that ED-MOFSO achieves improved metrics, including residual energy (14.29 J), delay (11.1 ms), packet delivery ratio (0.994), routing overhead (0.10), and throughput (1.233 Mbps) when compared to conventional Elephant Herding Optimization (EHO) greedy and Ant Colony Optimization Integrated Glow-worm Swarm Optimization (ACI-GSO).

Keywords: Distance, Energy Consumption, Multi-Objective Firebug Swarm Optimization, Wireless Sensor Networks, Network Lifetime

Introduction

Normally, sensor networks have small sensors that gather data by interacting with one another which was facilitated by wireless transmission (Elhoseny *et al*., 2020). Mobile nodes are small sensing modules that have a CPU, storage, energy, and transmitter. The size of every detector node gets changed because it depends on the specific application (Shafiq *et al*., 2020). The expense of a node is determined by factors such as system memory, computing performance, and storage capacity (Savitha *et al*., 2020). Pollution prevention, habitat measuring, medical, quality control, and intelligence gathering are just a few of the residential and commercial applications of sensor networks (Anand and Pandey, 2020). For instance, researchers could utilize a monitoring system to observe a movement in a hazardous region. If congestion has occurred in the network, then the individual sensor nodes detect it and communicate with some other nodes to transfer the data to the base station (Dhiman *et al*., 2020). The need for wireless communications is growing day by day, but it is also encountering energy limits in the form of restricted battery capacity. Since all node's activities are dependent on data packets they are becoming a serious concern in sensor networks (Janakiraman, 2020). Therefore, all the sensing is categorized under three states, operational, resting, or sleepy phases (Verma *et al*., 2020), so, the loss of one node could interrupt the entire network.

Several strategies have been designed for clustering and routing to improve energy efficiency in sensor networks. Clustering is a way of chronologically organizing sensor nodes depending on their relative connectivity to one another (Moussa *et al*., 2020; Alrashidi *et al*., 2020). In wireless communication, the process of routing mechanisms and allocating global records in sensed data is highly complex and critical (Khalaf and Abdulsahib, 2020). Transmission of data, image analysis, and equipment functioning are the 3 primary uses of energy in sensor networks (Mehta and Saxena, 2020). As a result, the data communication method must be streamlined to maximize the system's lifetime (Srivastava *et al*., 2020). Communication can be improved in a network by employing efficient clustering and routing protocols (El Assari, 2020). In the majority of instances, data from numerous sources must be sent to a cloud-based server. The nodes which are closest to the outlet consume more energy and died for a rapid duration, so, the connection is separated and the network's lifespan gets shortened (Pal *et al*., 2020; Wang *et al*., 2020). In contrast to other typical data transmission networks, WSNs have a dense deployment of sensors and nodes that are susceptible to damage from the hostile environment. In some installations, the topology occasionally changes, requiring the reconfiguration of links among the nodes leading to instability and consuming more energy. These factors make WSNs unstable in the real world. The fundamental parameters like energy consumption and lifetime of WSN are frequently used to assess the value of WSN network algorithms and procedures. Normally, the sensor devices are battery-operated systems that are challenging to control in many situations and provide low performance. On the other side, individual nodes in a WSN have a constrained range of communication and establish a network over a common wireless medium. Furthermore, because of the constrained communication range and signal propagation issues, the base station is sometimes placed distant from the sensing region and is frequently not reachable to all the nodes. Thus, the data packets must be routed utilizing a multi hop communication model for a dependable data connection. The network's energy efficiency, data transfer dependability, and scalability are significant features that have been increased by clustering the sensor nodes. Therefore, an effective clustering and routing scheme named called ED-MOFSO is proposed to update the position via element-wise Hadamard matrix arithmetic operations to improve the routing performance.

The major contributions are given as follows:

- Due to its high stability and low computing overhead, ED-MOFSO is initially exploited to select the CH
- FSO's rapid identification feature is used to find the shortest route between the source and BS
- In a conclusion, to increase the network's lifespan, efficient CH selection and optimal route architecture are dependent on ED-MOFSO

Reddy *et al*. (2021), presented a merged Glow-worm Swarm Optimization (GSO) incorporating Ant Colony Optimization (ACO) name called (ACI-GSO) in WSN. The main aim was to condense the distance among CHs which accomplishes the fitness parameters by relating several objectives. Conversely, data transfer could have been improved by choosing the optimal route and, one significant point was the total energy exploited through every connection was very high.

Daneshvar *et al*. (2019), demonstrated the Grey Wolf Optimizer (GWO) for the optimal selection of CH to enhance energy efficiency. The estimation was based on the node's current energy level and the anticipated energy consumption of the CH choice. After then, dual hop routing was used to transmit the data packets through the network. To save energy, needless clustering processes were avoided using the GWO approach. While choosing CHs from the system, the GWO approach disregards the distance factor.

Pattnaik and Sahu (2020), developed an EHO-Greedy algorithm that aimed at route discovery. EHO-Greedy incorporates all temporary and moveable sources while conserving energy. A fixed network was placed vertically across the configuration at irregular intervals, whereas a movable node migrated to different locations to transfer the data. A better clustering of CH could lead to cost savings on energy thereby further extending lifespan. Additional industries benefit from the use of higher energy-efficient approaches, which results in wider WSN zones.

To select pertinent steps along the routing procedure, (Vinitha *et al*., 2020) introduced Cat-SSA (C-SSA) method to select the CH that would minimize data traffic. The randomized CH selection feature of LEACH was to blame for the increased energy consumption.

CDAS for network congestion and performance management in WSN was developed by Devi *et al.* (2020). The aggregation decision tree and slot scheduling method are the two steps of the suggested structure. During the first phase, every CH collects information from the participants using cumulative aggregation. Traditionally, the collecting graph through into the source which was generated using the spanning tree procedure. Transmission delay and throughput were saved for study in the second phase, whereas the obtained information was exploited to emphasize and allocate durations to nodes.

Problem Statement

In WSN, the data transmission from source to target gets delayed because of collisions and changes in nodes' mobility.

The energy consumption gets increased due to the improper maintenance of the routing path.

The overall efficiency of clustering and routing gets minimized because of non-CH members in a cluster group.

Nodes became unreliable and malfunctioned during an uncontrolled and hostile environment. Due to that, WSN receives less energy which interrupts communication.

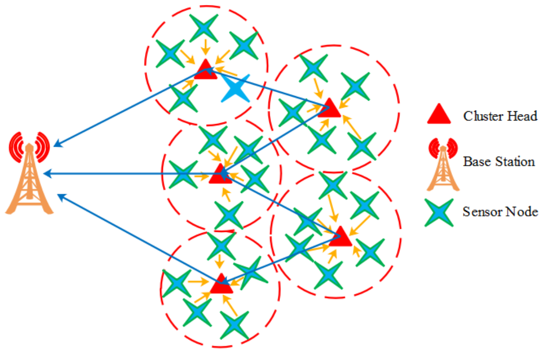

Fig. 1: Network model

Solution

To establish an efficient WSN, this study used both distance and energy fitness functions. Additionally, the WSN uses energy consideration to minimize packet loss. Throughout this instance, multi hop routing is configured to avoid routing issues. As a consequence, the defined energy efficient WSN is utilized by both large and small-scale WSNs.

Network Model

Figure 1 the organization of the cluster based WSN. The assumptions used to create the network model are stated as follows:

- The sensors in WSN are identical to each other using processing time and energy
- A Euclidean distance formula is used for measuring the distance between the sensors
- In the network area, the sensors are randomly located as well as the location of sensors is constant, after it is organized in the system
- Nodes with residual energy and distance are given to BS which chooses the CHs using a suitable CH selection technique. Additionally, the transmission route from the CH to BS is found by the routing algorithm

Materials and Methods

In this research, ED-MOFSO is used to build clustering and routing. The fitness function values were merged with the system's exploring abilities. As a consequence, an efficient CH and routing are established in this system. The four unique fitness functions are considered throughout the clustering. Additionally, node failure is minimized by considering the nodes' residual power throughout the transmission process. To avoid node failure, the data packet is minimized during communication. The article's main goal is to prevent energy consumption of the network to prolong the network's lifetime. The comprehensive structure of the proposed ED-MOFSO is shown in Fig. 2.

The major steps in the schematic block diagram are stated as follows: Primarily, the clusters are indiscriminately placed in a particular area; afterward network elements are established as a phenomenon that is completely reliant on node location. A clustering procedure is used to partition the network into groups. In this situation, ED-MOFSO is utilized to cluster systems. CH is calculated at that time depending on several criteria. The routing algorithms were developed using the proposed ED-MOFSO to determine the best route among CH and BS. To establish the desired position from CH to BS, the routing procedure begins by selecting an optimum node. The source node transmits the packet in the path of the target when the route from the transmitter to the receiver was being created. The suggested ED-MOFSO algorithm regulates the ideal path by deliberating numerous objectives. BS is extensively applied to evaluate node energy Re-rerouting is performed to alleviate data loss.

Firebug Swarm Optimization (FSO)

This study describes the biological motivation for the FSO method. Firebugs can behave in one of two ways: They can travel and investigate as solitary creatures or they might behave gregariously and form groupings. The firebugs benefit from these groupings because they help them avoid predators and identify suitable mates for reproduction. The FSO algorithm starts with N_M and N_F male and female bugs arbitrarily scattered in the solution space. Let $m(m)$. F be the D by N_F matrix, whose sections correlate to female bug places, which is denoted by F. The problem formulation update Eq. (1) and (2) are presented:

$$M_x \leftarrow repmat\left(m\left(m\right).x, 1, N_F\right) \tag{1}$$

$$M_y \leftarrow repmat(m(a).x, 1, N_F) \tag{2}$$

where, a is a random number among 1 and N_F. The function $repmat(a, m, N)$ proceeds a medium that comprises m duplicates of a laterally the row measurement and n duplicates laterally the column measurement. Thus, if a is a p by q indexes at that time $repmat(a, m, N)$ provides mp by nq matrix that is formulated in Eq. (3):

$$m(m).F \leftarrow m(m).F + C_1 \odot \left(M_x - m(m).F\right) + C_2 \odot (M_y - m(m).F) \tag{3}$$

Since these numbers C_1 are chosen to be much bigger than C_2. The FSO algorithm performed much better when C_2 is less than C_1. The research is aided by female bugs' receptivity to unexpected males. The subsequent Eq. (4) shows the conceptual update rule for male bugs moving towards the strongest female bug:

$$m(m).x \leftarrow m(m).x + C_3 \odot \left(g - m(m).x\right) \tag{4}$$

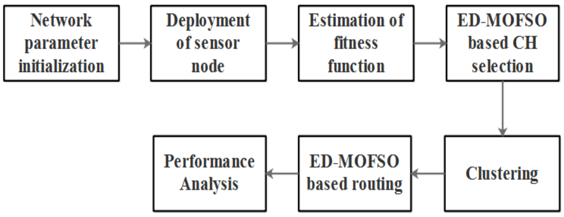

Fig. 2: Schematic block diagram of proposed ED-MOFSO

Here, the FSO differs significantly from methods such as the PSO, where every particle strives for a unique global optimal solution which is stated in Eq. (5):

$$m(m).x \leftarrow m(m).x + C_4 \odot \left(g - m(b).x\right) \tag{5}$$

This investigation for the finest reproductive mates can examine potential results in the exploration area. The vector x is articulated in terms of x^1 and x^2 via the triangular law of vector calculation which is mentioned in Eq. (6):

$$x = x^1 + a(x^2 - x^1) = (1-a)x^1 + ax^2 \tag{6}$$

From the above points, it is evident that the migration of male bugs through location $m(m).x$) to appropriate female bugs is attained through Eq. (7):

$$m(m).x \leftarrow m(m).x + a(g - m(m).x) \tag{7}$$

Equation (7) is simple and restricts $m(m).x$ $m(m).x$ and g limits the number of potential results explored. The researchers suggested the vector be substituted through the scalar matrix a which is substituted by Hadamard manipulation to increase investigation and independent search in numerous dimensions, resulting in the updated equation given in Eq. (8):

$$m(m).x \leftarrow m.(m).x + C_4 \odot (g - m(b).x) \tag{8}$$

Equation (9) is used to explain the powerful movement and weak motion of female bugs toward a different male insect:

$$m(m).F \leftarrow m.(m).F + C_1 \odot (M_x - m(m).F + C_2 \odot (M_Y - m(m).F) \tag{9}$$

The following relations, $C_1 \odot (M_x - m(m).F)$ and $C_2 \odot (M_Y - m(m).F)$ characterizes the movement in the direction of the dominant and indiscriminate male bug correspondingly. The level of attraction is determined by matrices C_1 *and* C_2.

ED-MOFSO Based CH Selection

To select and route the CHs, the ED-MOFSO is utilized. This recommended ED-MOFSO is most effective for creating congestion-aware routing in crises because it has a congestion mitigation feature by source.

Fitness Function

The suggested ED-MOFSO chooses from the clusters the best optimum CHs for reliable data transfer. The clustering optimization was done using the parameters listed below.

Congestion Metric (CM)

By looking at reserve utilization, one may determine the node traffic. The amount of data stored in each node's memory is referred to as the available bandwidth. As the number of data messages that enter or exit the architecture fluctuates, so does the queue's length. Queue length is utilized to measure whether the network node is congested or not. Equation (10) determines the total number of network connections arriving at the node at a particular frequency (λ) over the specified period t:

$$CM = \lambda t \tag{10}$$

Load (L_j)

Data is often transferred to a different location and certain bits have remained buffers for prospective analysis. Equation (11) generates the load factor terms:

$$L_j = a_i + a_{quej} + (l * a_{dr_i}) \tag{11}$$

Now a_i, a_{quej}, a_{dr_i} and l denotes bits in the string of the i^{th} and j^{th} node.

Residual Energy (RE)

RE is categorized in Eq. (12):

$$Minimize\, RE = \sum_{i=1}^{m} \frac{1}{ECHi} \tag{12}$$

Inter and Intra Cluster Distance (D)

Each *CH* and *BS*'s position from one is thoroughly examined. As previously said, communication range completely controls how much energy is used by a system. As the network device gets further away from the network nodes, it consumes more power to complete the process. In conclusion, *CH* through the minimum Euclidean distance beginning from *BS* which are favored even more in the system. So, *D*1 and *D*2 are inter and intra cluster objectives, that can be minimized and stated in Eq. (13) and (14):

$$MinimizeD1 = \sum_{j=1}^{m} \left(dis(CH_j, BS)\right) \tag{13}$$

$$MinimiseD2 = \sum_{j=1}^{q} \left(\sum_{i=1}^{cm_j} dis\left(s_i, CH_j\right) / cm_j\right) \tag{14}$$

The nodes count in the cluster cm_j; the distance between the sensor i and j^{th} *CH* is stated as $dis(s_i, CH_j)$.

Therefore, the process of normalization ($F(x)$) is subjugated to each function a_1, a_2, a_3, a_4, a_5 which is expressed in (15):

$$F(x) = \frac{f_i - f_{\min}}{f_{\max} - f_{\min}} \tag{15}$$

Minimum fitness is expressed in Eq. (16):

$$Minimumfitness = \alpha_1 CM + \alpha_2 L_j + \alpha_3 RE + \alpha_4 D1 + \alpha_5 D2 \tag{16}$$

where, $\sum_{i=1}^{s} \alpha_i = 1; and\ \alpha_i \in (0,1)$

The defined weighted factor (a_i) is the one that is assigned to each fitness function. By choosing the network with the greatest amount of leftover energy, the channel capacity across the WSN is reduced and deliberates the fitness evaluation *RE*, *D*1, and *D*2. As a result, those fitness functions are used to identify the ideal data communication route. Once *CH* is selected, clustering based on distance and energy occurs.

Routing using ED-MOFSO

The primary objective is to find the closest best route from *CH* to a suitable *BS*. The network starts to transmit data when the routing path has been established. Below are thorough explanations of how the fitness function works.

Link Life Time (LLT)

LLT regulates the lifespan of the network that connects various strategies except for the information that exists in it. To lessen the effects of failure, the routing method computes the lifetime of the communication gateway. Additionally, the mobility direction, node coordination, and node mobility parameters are used to determine the lifetime. Two nodes G_1 and G_2 are placed at U_{G0}, V_{G1}, and U_{G2}, V_{G2} for that *LLT* is calculated as (17-19):

$$LLT = \frac{-(fk + xz) + \sqrt{\left(f^2 + z^2\right)w^2 - \left(fz - xk\right)^2}}{\left(f^2 + z^2\right)} \tag{17}$$

$$\begin{cases} f = J_{G1}\cos\theta_{G1} - J_{G2}\cos\theta_{G2} \\ k = U_{G1} - U_{G2} \\ x = J_{G1}\sin\theta_{G1} - J_{G2}\sin\theta_{G2} \end{cases} \tag{18}$$

$$z = V_{G1} - V_{G2} \tag{19}$$

Transmission range is declared as w, J_{G1} is the speed mobility of G_1; J_{G2} speed mobility of G_2; U_{G2} represents the node coordination of G_2, U_{G1}; V_{G1} states the node present at G_1; θ_{G1} defines the direction of motion.

Finally, multi-functions are translated into single functions which are stated in Eq. (20):

$$Routingfitness = \delta_1 \times LLT + \delta_2 \times CM + \delta_3 \times D1 + \delta_4 \times D2 + \delta_5 \times RE \tag{20}$$

Weighted parameters specified as δ_1, δ_2, δ_3, δ_4, and δ_5 are equivalent to 0.25, 0.3, 0.20, 0.15, and 0.25 correspondingly. *CM* is utilized to send information via the system and then assess the efficiency since it relies on sender-receiver data. The data transmission starts when the routing is identified by ED-MOFSO.

Results and Discussion

The outcomes of the suggested cluster-based routing algorithm are presented as follows. Effectiveness is assessed using the following metrics: The number of active nodes, energy consumption, delay, total transferred packets, throughput, and network lifetime. Utilizing MATLAB R2020 software, the recommended energy efficient routing method is tested. To evaluate the routing mechanism, a Windows 8 with an i3 desktop and 8GB RAM is used. In the ED-MOFSO, traffic is clustered and routed using an efficient fitness function. Table 1 lists the model parameters utilized in the ED-MOFSO.

Residual Energy

Figure 3 shows the RE outcomes for the suggested and traditional CDAS (Devi *et al*., 2020). As soon as the node count rises, the size of the routing path gets increases which maximizes energy consumption. The RE comparison is exposed in Table 2 which validates that recommended ED-MOFSO results vary from 12.44 to 14.29, whereas the CDAS (Devi *et al*., 2020) varies from 6.4 to 8.

Delay

Node is diverged to study the effect of the size of the network and the density of the node. Figure 4 the effects of delay for proposed and traditional procedures. The dimension of the path expands as the number of nodes increases, maximizing the delay. Table 3 shows the comparison study which reveals that CDAS (Devi *et al*., 2020) vary from 9.6 to 14.5 milliseconds and suggested ED-MOFSOs vary from 6.8 to 11.1 milliseconds.

PDR

Figure 5 displays the outcomes for the proposed and conventional methods. Once the count gets rises, the routing size gets increased which minimizes the packet transfer. The presentation for PDR is exposed in Table 4, which demonstrates that recommended ED-MOFSOs vary from 0.994 to 0.999, whereas EHO-Greedy varies between 0.941 to 0.989.

Routing Overhead

Figure 6 illustrates the outcomes of routing overhead for suggested and conventional methods. Once the node count gets rises, the routing size gets increased which maximizes the routing overhead. The presentation for routing overhead is revealed in Table 5 which demonstrates that ED-MOFSO's overhead varies from 0.10 to 0.29, whereas CDAS (Devi *et al*., 2020) fell.

Throughput

The outcomes of throughput for proposed and existing techniques are shown in Fig. 7. The main justifications for the suggested ED-MOFSO outperform EHO Greedy in regards to throughput (Pattnaik and Kumar, 2020). The main cause is that ED-MOFSO has a longer lifespan than BS, which allows BS to obtain additional data packets. Table 6 displays the throughput display. Table 6, the recommended ED-MOFSO can achieve a throughput of up to 1.233 Mbps, but EHO-Greedy (Pattnaik and Kumar, 2020) could only achieve 1.093 Mbps. While analyzed with the traditional CDAS, the entire model outcomes display that recommended ED-MOFSO provides improved outcomes in every situation.

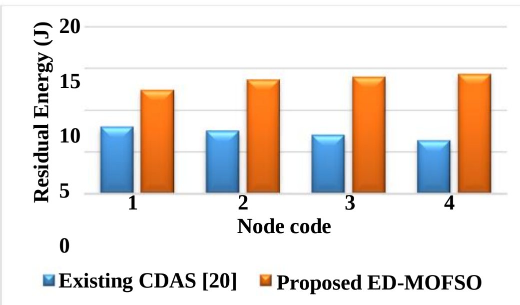

Fig. 3: Graphical representation of residual energy

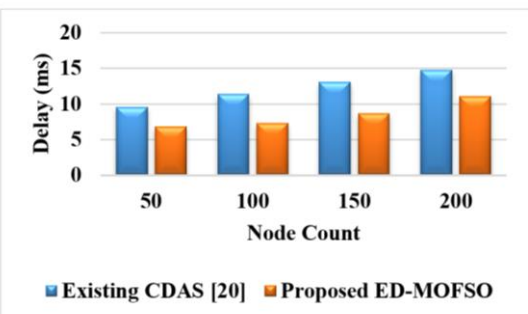

Fig. 4: Graphical representation of the delay

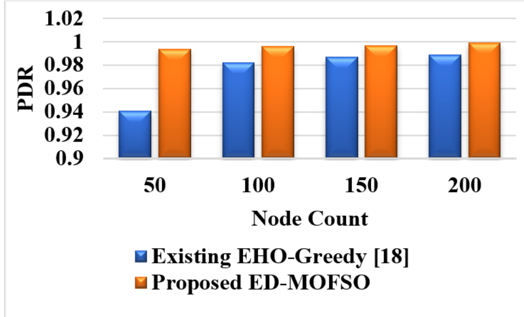

Fig. 5: Analysis of PDR

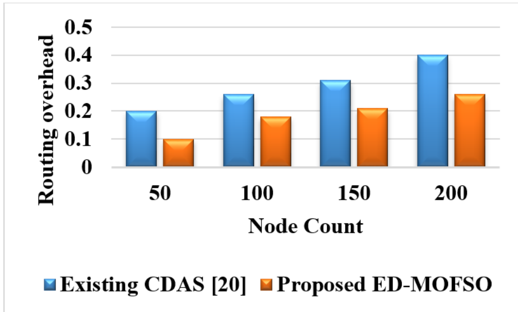

Fig. 6: Graphical illustration of routing overhead

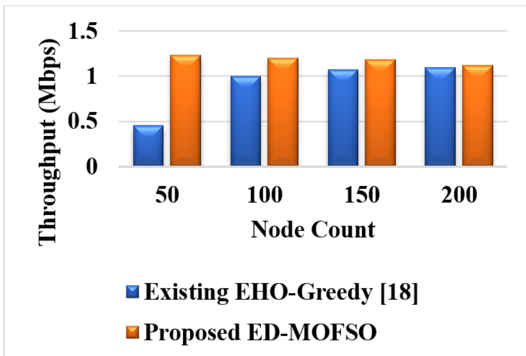

Fig. 7: Graphical illustration of throughput

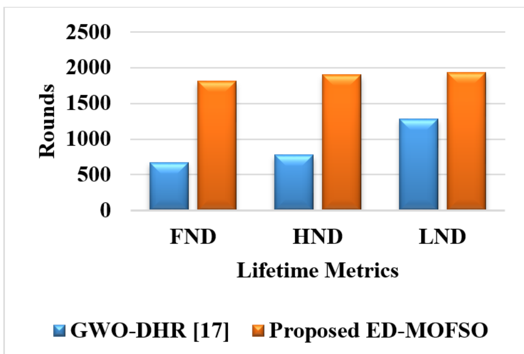

Fig. 8: Assessment of lifetime

Table 1: System specification

Parameters	Range
Sense power	0.0175 nj/bit/m^2
Initial energy	0.5j
Number of nodes	100
Length of data	4000 bits
Idle power	0.05 pj/bit/m^2
Transmission power	0.001310 pj/bit/m^4
Receiving power	50 nj/bit
Area	100 × 100 m

Table 2: Residual energy

	RE (J)	
Node count	CDAS (Devi *et al*., 2020)	ED-MOFSO
50	8.0	12.44
100	7.5	13.68
150	7.0	13.99
200	6.4	14.29

Table 3: Analysis of delay

	Delay (ms)	
Node count	CDAS (Devi *et al*., 2020)	ED-MOFSO
50	9.6	6.8
100	11.4	7.3
150	13.1	8.7
200	14.8	11.1

Table 4: Performances of PDR

	PDR	
Node count	EHO-Greedy (Pattnaik and Kumar, 2020)	ED-MOFSO
50	0.941	0.994
100	0.982	0.996
150	0.987	0.997
200	0.989	0.999

Table 5: Routing overhead

Node count	CDAS (Devi *et al*., 2020)	ED-MOFSO
50	0.20	0.10
100	0.26	0.18
150	0.31	0.21
200	0.40	0.26

Table 6: Analysis of throughput

	Throughput	
Node count	(Mbps) EHO-Greedy (Pattnaik and Kumar, 2020)	ED-MOFSO
50	0.452	1.233
100	0.999	1.201
150	1.074	1.184
200	1.093	1.119

Table 7: Comparison of alive nodes

Performance parameters	Methods	Rounds 20	40	60	80
Alive nodes	ACI-GSO (Reddy *et al*., 2021)	31	28	26	23
	ED-MOFSO	49	46	42	39

Table 8: Evaluation Assessment of various metrics

	Alive nodes			Total energy (J)		Throughput (Kbps)	
Rounds	ACI-GSO (Reddy *et al*., 2021)	C-SSA (Vinitha *et al*., 2020)	ED-MOFSO	ACI-GSO (Reddy *et al*., 2021)	ED-MOFSO	ACI-GSO (Reddy *et al*., 2021)	ED-MOFSO
20	81	47	91	12.79	27.88	49.53	79.46
40	70	40	77	12.45	24.26	54.09	92.29
60	50	34	65	12.25	21.45	84.80	99.76
80	33	24	46	11.82	18.85	105.16	110.32

Table 9: Evaluation assessment of lifetime

Performances	GWO-DHR (Daneshvar *et al*., 2019)	ED-MOFSO
FND	671	1812
HND	778	1901
LND	1286	1934

Comparative Study

Because of its acceptable fitness function, the suggested technique receives a sizable number of data packets at the BS. The presented scheme also enhances the number of alive nodes, enabling nodes to function for longer intervals of time. As a consequence, the recommended approach has several living nodes than the current ACI-GSO (Reddy *et al*., 2021). Table 7 that the suggested technique outperforms ACI-GSO in terms of effectiveness (Reddy *et al*., 2021).

The utility of ED-MOFSO is shown by comparison with the existing approaches. An area of 100 × 100 m is covered by 100 sensors for this ED-MOFSO vs. GWO-DHR (Daneshvar *et al*., 2019) evaluation. BS is therefore situated beyond the system. To acquire data from non-CH connections and transmit it to BS, 5% of the nodes at 100 sensors are classified as CHs.

The proposed ED-MOFSO is related to existing ACI-GSO (Reddy *et al*., 2021) and C-SSA (Vinitha *et al*., 2020) is displayed in Table 8. Table 9 the comparative analysis of ED-MOFSO with GWO-DHR. Figure 8 displays an illustration of a lifetime of existing GWO-DHR (Daneshvar *et al*., 2019) and suggested ED-MOFSO.

The ED-MOFSO method surpasses the GWO-DHR (Daneshvar *et al*., 2019) method, according to the outcomes of the evaluation. The GWO-DHR (Daneshvar *et al*., 2019) performed lower because of an inaccurate fitness function evaluation during cluster formation. To find an optimal CH among the sensors in ED-MOFSO clustering, multiple fitness variables are being used. After that, the ED-MOFSO is used to establish an effective path to reduce energy consumption. The simulation outcome displays that ED-MOFSO is exploited to attain an extended lifespan while evaluated with existing GWO-DHR (Daneshvar *et al*., 2019). The proposed ED-MOFSO consists of an extended lifespan because it contains a large number of data packets which is transferred to BS.

Conclusion

In recent years, WSN attains energy efficiency by identifying the optimal CH selection and route discovery. In this research, Utilizing the ED-MOFSO approach, a network's lifespan can be increased while total energy consumption is decreased. When choosing a CH using ED-MOFSO, five fitness parameters are taken into consideration. Utilizing residual energy, hop count, and distance, ED-MOFSO is again utilized to determine an energy-efficient path. The suggested ED-MOFSO overcomes the traditional methods in all the features; according to simulation results, the proposed ED-MOFSO has a lower delay (11.1 ms) and overhead (0.10). Additionally, the proposed ED-MOFSO achieved a throughput of 1.233 Mbps, residual energy of 14.29 J, and PDR of 0.999 correspondingly. In future work, this research will be further investigated through novel routing techniques to provide improved outcomes for the same network model/specifications.

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Gundeboyina Srinivasalu: Designed the research plan.

Hanumanthappa Umadevi: Coordinated with data analysis.

Ethics

This article is original and contains unpublished material. The corresponding author confirms that all of the other authors have read and approved the manuscript and no ethical issues are involved.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this study.

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