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Energy Efficient Clustering and Routing using Energy Centric MJSO and MACO for Wireless Sensor Networks

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Abstract. Wireless Sensor Networks (WSNs) are a multihop self-organizing network that generates wireless communication by using numerous tiny sensor nodes. The energy efficiency of the WSN is a key issue, because of the restricted, irreplaceable, and non-rechargeable energy resources of the sensors. Clustering over sensors is an adequate approach in developing the routing approach for WSN that helps to improve energy efficiency and life expectancy. Therefore, Energy Centric optimization such as Multiobjective Jellyfish Search Optimizer and Multiobjective Ant Colony Optimization (EC-MJSO-MACO) is proposed to enhance the energy efficiency of WSN. The optimal Cluster Heads (CHs) in the network are selected by using EC-MJSO, whereas the path via the CHs is discovered using EC-MACO. The developed EC-MJSO-MACO minimizes the energy expenditure of the nodes while improving the data delivery. The performances of EC-MJSO-MACO are analyzed based on alive & dead nodes, normalized energy, packets to BS, throughput, and life expectancy. The EC-MJSO-MACO is compared with other approaches such as Low Energy Adaptive Clustering Hierarchy (LEACH), Butterfly Optimization Algorithm (BOA) and Grasshopper Optimization Algorithm (GOA), Cuckoo Insisted-Rider Optimization Algorithm (CI-ROA), Rider-Cat Swarm Optimization (RCSO). Alive nodes of the EC-MJSO-MACO for 2000 rounds are 100, which are greater than other methods.

***Keywords**: Energy Centric Optimization, Energy Efficiency, Life Expectancy, Multiobjective Ant Colony Optimization, Multiobjective Jellyfish Search Optimizer.*

1. Introduction

Wireless Sensor Networks (WSNs) is a self-managed network architecture that has numerous distributed sensors. The WSN is either used to observe changes in the environment such as humidity and temperature or discover the motion of the mobile target such as wildlife or fire spread (Li, X., Keegan et al., 2019; Moshref et al., 2021). The WSN combines embedded computing, sensor, modern network & wireless communication, and distributed information processing & other fields of technology (Wang et al., 2020). The sensor of the WSN is a tiny hardware device that has the processing, sensing, communication, and power unit for processing the data. The collected data is transmitted to Base Station (BS) either directly or through the remaining sensors (Naeem et al., 2021). The sensors of the WSN are characterized by their lesser range of transmission, storage, and processing capability, and mostly inadequate irreplaceable and or non-rechargeable batteries. Therefore, the sensors are required to broadcast the gathered information to BS. From the abovementioned drawbacks, the node's energy consumption is considered as a primary issue of the WSN (Rezaeipanah et al., 2021; Ma et al., 2021). The sensor's lifetime is mainly based on the energy used while observing, processing, and communicating operations (Singh et al., 2021).

Clustering is a well-known approach used to ensure the WSN operation with high energy efficiency. In this cluster-based approach, the sensor nodes are organized into various groups namely clusters (Mehra, P.S et al., 2020). Each cluster has its leader node referred to as Cluster Head (CH) and the other nodes are represented as Cluster Members (CMs). The CH collects the information from its CMs and broadcasts that information to the Base Station (BS) (Nagarajan et al., 2022; Mohanadevi and Selvakumar, 2021; Trinh et al., 2022). The selection of CHs is an important task in the hierarchical clustering approach to improving the throughput, lifetime, and energy consumption (Mohamed et al., 2020) .Generally, the CHs gather the information from their CMs, and also from the remaining CHs and broadcast the gathered data to the BS using the routing approach (Rao et al.,2021;Hung et al.,2020). Routing is also an important issue in the WSN. The conventional routing approach cannot be used in sensors, because the WSN is varied from other ad hoc networks in the following views such as

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battery-operated sensors and adaptive communication design. Since, the WSNs have ad hoc topology and there is no organization, discovering the route and broadcasting the information to the BS is a challenging task (Deepa and Suguna, 2020).

The contributions are concise as follows:

- The energy-efficient CH selection and routing are developed to improve the life expectancy of the WSN. The EC-MJSO is developed for choosing appropriate CHs that help to minimize the energy consumed by the nodes.
- Next, the path via the CHs is efficiently discovered by using the EC-MACO. The shortest path discovery and mitigation of node failure help to reduce energy utilization and improve packet delivery.

The remaining of the paper is organized as follows: A detailed explanation of the proposed Method EC-MJSO-MACO is given in Section2. Section3 presents the results and discussions of the EC-MJSO-MACO whereas the conclusion is presented in Section 4.

2. EC-MJSO-MACO Method

In this EC-MJSO-MACO method, energy-aware cluster-based routing is proposed for improving the life expectancy of the WSN. The optimal CHs in the network are determined by using the EC-MJSO followed by routing via CHs to the BS which is accomplished by using the EC-ACO. Therefore, the energy-centric optimization approaches helps to minimize the energy consumption of the nodes. The flowchart of the EC-MJSO-MACO as shown in Figure 1.

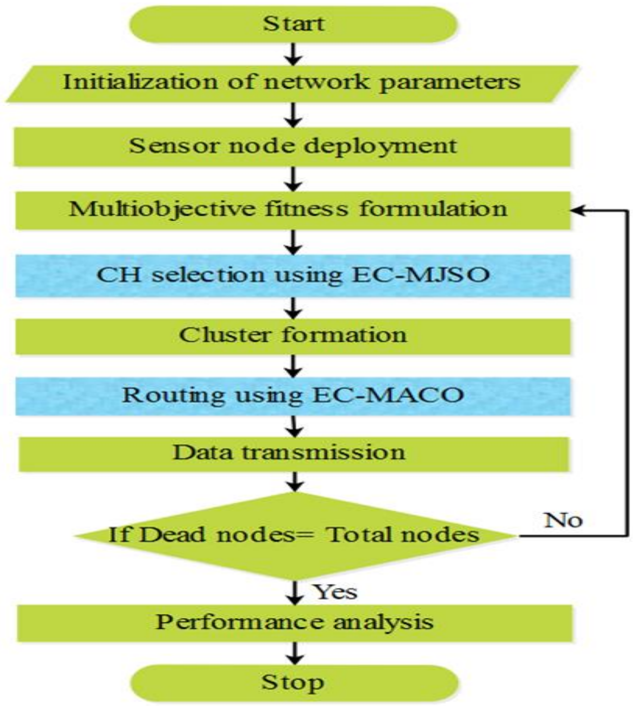

Fig. 1 Flowchart of the EC-MJSO-MACO

3.1. sensors Initialization

Initially, sensors are randomly dispersed in the network followed by the CHs chosen by using the EC-MJSO. After choosing the CHs, the clusters are generated in the WSN. Next, the route from the transmitter CH to the BS is discovered by using the EC-MACO. The selection of CHS and routes are detailed in the next sections.

3.2. EC-MJSO based Cluster head selection

Here, the CHs from the wireless sensors are discovered by using the EC-MJSO. The typical artificial JSO is one of the metaheuristic approaches that imitate the food searching behavior of jellyfish in the ocean. The Jellyfish follows either the ocean current or moves inside the swarm, whereas the time control mechanism is used to switch between these motions. Next, the jellyfish is attracted to positions where the food quantity is high. Since the position and objective function is used to discover the food. Here, the typical JSO is converted into EC-MJSO for minimizing the energy consumption of the WSN.

3.2.1. Representation and initialization

In EC-MJSO, the initial solutions, namely, jellyfish comprise the set of candidate sensors that are required to be selected as CH. Each jellyfish solution is initialized with the ID of the random node between 1 to N, where the total number of nodes in the WSN are denoted as N. Consider, the ith jellyfish of EC-MJSO as X_i=(X_(i,1), X_(i,2),…,X_(i, dim)), where the dimension of each solution is denoted as dim i.e., the number of CHs. The position of jellyfish is X_ (i, p), 1≤p≤dim defines the random node location of the sensors of WSN.

3.2.2. Iterative process

After initializing the jellyfish solutions, each solution is monitored and the one with the best fitness is selected as the position with the high quantity of food i.e., the best set of CHs(X ⃗_best). Subsequently, each jellyfish's position is updated either using the ocean current or moving in the swarm according to the time control mechanism. Equation (1) expresses the position update ocean current.

$$\vec{X}_i(t+1) = \vec{X}_i(t) + \vec{r}.* (\vec{X}_{best} - \beta \times r_1 \times \mu) \quad (1)$$

Where, the updated and current positions of the jellyfish are denoted as X ⃗_i (t+1) and X ⃗_i (t) respectively; iteration number is denoted as t; random vector generated between [0, 1] is r ⃗; the vector multiplication by an element-by-element manner is denoted as.*; distribution coefficient is denoted as β i.e., β>0; mean of the population is denoted as μ and random value generated between [0,1] is r_1.

The motions in the swarm are separated into two types such as passive and active. The jellyfish travels around its position during passive movement, where the passive movement-based position update is expressed in equation (2).

$$\vec{X}_i(t+1) = \vec{X}_i(t) + r_3 \times \gamma \times (UB - LB) \quad (2)$$

Where, random value generated between [0, 1] is r_3; motion length around the current position is denoted as γ i.e., γ>0; the lower and upper bound of foraging space are denoted as LB and UB respectively. Equation (3) expresses the active movement of jellyfish.

$$\vec{X}_i(t+1) = \vec{X}_i(t) + \vec{r} \times \vec{D} \quad (3)$$

Where, the movement direction of current jellyfish within the following generation is denoted as D ⃗ and this movement is always towards the position of best food which is expressed in equation (4).

$$\vec{D} = \begin{cases} \vec{X}_i(t) - \vec{X}_j(t), & if\ f(\vec{X}_i) < f(\vec{X}_j) \\ \vec{X}_j(t) - \vec{X}_i(t), & otherwise \end{cases} \quad (4)$$

Where j is the jellyfish which is randomly chosen from the population and fitness function is denoted as f. Equation (5) derives the time control mechanism (c) that is used to switch between ocean current, and passive and active movement.

$$c(t) = \left(1 - \frac{t}{t_{max}}\right) \times (2 \times r - 1) \quad (5)$$

Where a maximum number of iterations are denoted as t_max and random value generated between [0, 1] is r as well as the constant c_0 is used to define the motion of jellyfish. If c (t) ≥c_0, the jellyfish follows ocean current-based position update; otherwise, it moves inside the swarm either in passive or active motion. Here, the random number r_4 generated between [0, 1] to define the passive and active motion. If r_4 is greater than the1-c(t), the passive motions take place; otherwise, the jellyfish location is updated according to the active movements.

3.2.3. Multiobjective fitness formulation

The fitness metrics used to choose an optimal CH are residual energy (fm_1), neighbor node distance (fm_2), sink distance (fm_3), CH balancing factor (fm_4) and node centrality (fm_5). The multiobjective fitness of EC-MJSO is derived as shown in equation (6).

$$f = \sigma_1 \times fm_1 + \sigma_2 \times fm_2 + \sigma_3 \times fm_3 + \sigma_4 \times fm_4 + \sigma_5 \times fm_5 \quad (6)$$

Where, σ_1-σ_5 is the weight parameters allocated for each of the fitness metric. The fitness metrics of EC-MJSO are explained as follows:

Energy expenditure of the CH becomes important in WSN because the CH is required to accomplish different tasks such as data gathering, aggregation of data, and distributing over the WSN. Therefore, the sensor with higher remaining energy is chosen as CH and equation (7) expresses the remaining energy calculation.

$$fm_1 = \sum_{i=1}^{dim} \frac{1}{E_{CH_i}} \quad (7)$$

Where, the remaining energy of the i^{th} CH is E_{CH_i}

Neighbor node distance is the distance between the sensors and sink distance is the distance between the CH and BS. The sensors in the WSN utilize energy to broadcast the information to the respective destination. The energy usage of the sensor is directly proportional to the path distance; therefore, it is required to minimize the distance while transmitting the information. Accordingly, the sensor with less distance to the BS is required to be chosen as CH.

Equations (8) and (9) express the neighbor distance and sink distance, respectively.

$$fm_2 = \sum_{j=1}^{dim}\left(\sum_{i=1}^{CM_j} dis(N_i, CH_j) \Big/ CM_j\right)$$

$$fm_3 = \sum_{i=1}^{dim} dis(CH_i, BS) \tag{8}$$

Where, the CM_j represents the amount of intra CMs for the cluster j; dis (N_i, CH_j) denotes the distance among the i^th node and j^th CH and dis (CH_i, BS) denotes the distance among the ith CH and BS.

In a network, there is a probability that some big clusters are generated with some small clusters. Hence, this CH balancing factor expressed in equation (9) is considered to balance the cluster that helps to achieve the energy balancing in WSN.

$$fm_4 = \sum_{i=1}^{dim} \frac{A}{dim} - CM_j \tag{9}$$

Where A represents the total number of alive nodes in the network

Node centrality defines the value that classifies the sensor according to the distance from the neighbor sensors in proportion to the network dimension that is expressed in equation (10).

$$fm_5 = \frac{\sqrt{\left(\sum_{k \in NCR(CH_i)} dist^2(CH_i,k)\right)/NCR(CH_i)}}{Network\ dimension} \tag{10}$$

Where, the $NCR(CH_i)$ defines the number of nodes that exist in the clustering range of i^{th} CH.

The aforementioned fitness metrics are used to select appropriate CHs from the normal nodes. The energy is used to identify whether the CH has enough energy or not because the CH with inadequate energy causes data loss. The distance and CH balancing factors are used to improve the energy efficiency of the WSN, which results in a higher life expectancy of the network. Furthermore, the node centrality is used to maximize the closeness between the CH and CM.

3.3. Cluster generation

The CMs are allocated to the CHs in the EC-MJSO for cluster generation. The cluster is generated based on the distance and remained energy, where the potential function considered during the cluster generation is shown in equation (11).

$$Potential\ function\ (N_i) = \frac{E_{CH}}{dis(N_i, CH)} \tag{11}$$

Hence, the sensors are allocated to the CH which has high residual energy and less path distance based on equation (11).

3.4. Routing using EC-ACO

After forming the clusters, the route between the transmitter CH and BS is discovered by using the EC-ACO. In this phase, each node comprises artificial ants and each route is associated with its weight. The initial weight of each route is computed according to the path distance between the nodes. The node transition rule is the probability of choosing m as following relay CH from the lth CH by ant n as shown in equation (12).

$$P_{lm}^{n} = \begin{cases} \frac{[\tau_{lm}(t)]^{\alpha}[\eta_{lm}(t)]^{\beta}}{\sum_{o \epsilon \mathcal{N}_n}[\tau_{lo}(t)]^{\alpha}[\eta_{lo}(t)]^{\beta}} & if\ m \epsilon \mathcal{N}_n \\ 0 & otherwise \end{cases} \tag{12}$$

Where, the node selection probability is denoted asP_{lm}^{n}; the pheromone intensity and heuristic value are denoted as τ_{lm} and η_{lm} respectively; the relative importance of τ_{lm} and η_{lm} are controlled by using α and β. The group of CHs n which doesn't visit yet is represented as$\mathcal{N}_n$.

The artificial ants imitate the foraging process of real ants. If the transmitter CH is required to broadcast the information, the node transition rule is employed for selecting the next relay CH. If the ants i.e., relay CH reaches the BS, then the same path is retraced to the transmitter CH. Consequently, the path's pheromone value is updated based on the pheromone update rule, which includes the pheromone reinforcement and evaporation. The pheromone reinforcement and evaporation maximize or minimize the pheromone of path, respectively. Therefore, the ACO discovers the energy efficient path from transmitter CH to BS. Equation (13) shows the pheromone update rule.

$$\tau_{lm}^{new} = (1-\rho)\tau_{lm}^{old} + \sum_{n=1}^{A} \Delta\tau_{lm}^{n} \tag{13}$$

Where, A represents the number of ants and ρ defines the pheromone decay coefficient i.e., $\rho\ \epsilon\ (0,1)$. The pheromone quantity calculation is expressed in equation (14).

$$\Delta\tau_{lm}^{n} = \begin{cases} \frac{Q}{a_n} & if\ the\ ant\ n\ travelled\ route\ (l,m) \\ 0 & otherwise \end{cases} \tag{14}$$

Where, Q is the constant value and the fitness function of the route is denoted as a_n which is expressed in equation (15). The fitness function considered in the EC-MACO is the residual energy, sink distance, and node degree.

$$a_n = \varepsilon_1 \times \sum_{i=1}^{dim} \frac{1}{E_{CH_i}} + \varepsilon_2 \times \sum_{i=1}^{dim} dis(CH_i, BS) + \varepsilon_3 \times \sum_{i=1}^{dim} I_j \quad (15)$$

Where, $\varepsilon_1 - \varepsilon_3$ is the weight parameters allocated to the fitness metrics of the routing process; and node degree is denoted as $\sum_{i=1}^{dim} I_j$. The energy considered in the EC-MACO helps to eliminate node failure in the route. Furthermore, the distance and node degree helps to lessen the energy usage of the sensors. Therefore, the developed EC-MJSO-MACO method is used to increase the network life expectancy and packet delivery of the WSN.

3. Results and Discussion

3.1. Simulation environment

The implementation and simulation of the proposed EC-MJSO-MACO method are done by using MATLAB R2018a software. Here, the system is operated with an i5 processor and 6GB of RAM. The simulation environment of this EC-MJSO-MACO comprises 100 sensor nodes deployed in the area of $100m \times 100m$. The location of the base station is $(100, 100)$ whereas the sensors are initialized with the energy of 0.5J. The following table gives the simulation parameters

Table 1 Simulation parameters

Parameter	Value
Network size	$100\text{m} \times 100\text{m}$
Number of nodes	100
Location of BS	$100, 100$
Initial energy	0.5J
Transmitter energy	$50nJ/bit/m^2$
Energy of free space model	$10pJ/bit/m^2$
Energy of power amplifier	$0.0013pJ/bit/m^2$
Size of packet	4000 bits

3.2. Performance analysis

The performance of the EC-MJSO-MACO is analyzed based on alive & dead nodes, normalized energy, packets to BS, throughput, and life expectancy. The EC-MJSO-MACO is compared with one traditional approach namely, LEACH, and with some optimization methods such as BOA and GOA.

3.2.1. Analysis of Alive nodes and dead nodes

The nodes that have the energy to broadcast the information are referred as alive nodes. Dead nodes are the difference between the total number of nodes and alive nodes. More specifically, the node which exhausts its whole energy during communication is termed a dead node. Figures2 and 3 shows the performances of alive nodes and dead nodes for EC-MJSO-MACO with LEACH, BOA, and GOA. From the figures, it is known that the EC-MJSO-MACO has a high number of alive nodes than the LEACH, BOA, and GOA. The energy efficient CH and route discovery are used to minimize the energy used by the sensors resulting in higher alive nodes. However, the single hop transmission accomplished by the LEACH causes higher energy consumption that leads to an increase in the dead nodes

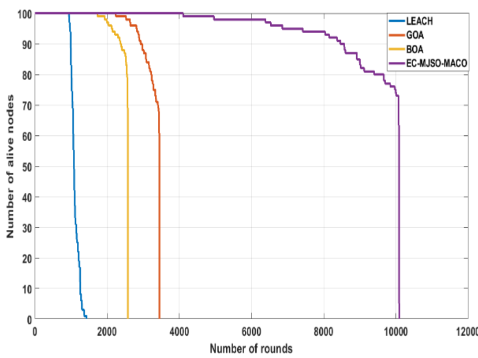

Fig. 2 Alive node Vs. round

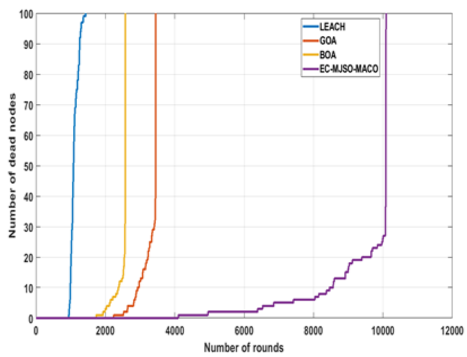

Fig. 3 Dead nodes Vs. rounds

3.2.2. Normalized energy

Normalized energy is one of the key parameters which define the amount of average residual energy that exists in the sensors of the network. The normalized energy comparison between EC-MJSO-MACO, LEACH, BOA, and GOA is shown in Figure 4. This analysis shows that the normalized energy of the EC-MJSO-MACO is increased than the LEACH, BOA, and GOA. The optimal CH selection of EC-MJSO-MACO along with the CH balancing factor is used to ensure the balance among the clusters that helps to minimize the energy consumption. Moreover, the shortest path discovery of MACO is used to minimize the node's energy usage.

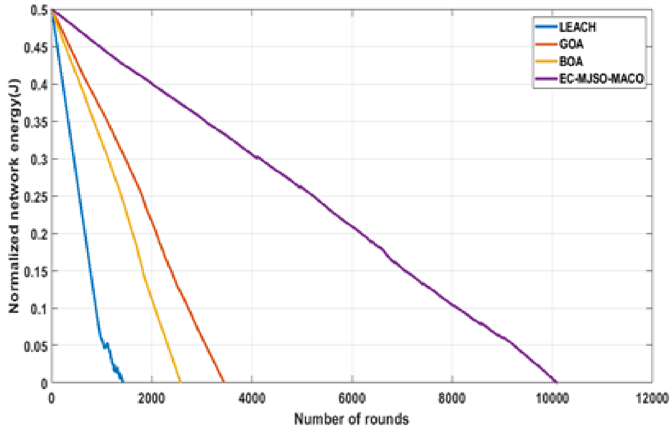

Fig. 4 Normalized energy Vs. rounds

3.2.3. Packets to BS

The packet to BS is shown in Figure 5, where the EC-MJSO-MACO is evaluated with the LEACH, BOA and GOA. From Figure 5, it is known that the packet to BS are high than the LEACH, BOA, and GOA. Generally, the number of alive nodes is directly proportional to the packets to BS. Since, the EC-MJSO-MACO has higher alive nodes; the packets to BS are high in WSN. The direct transmission of LEACH causes the packet to drop over the network.

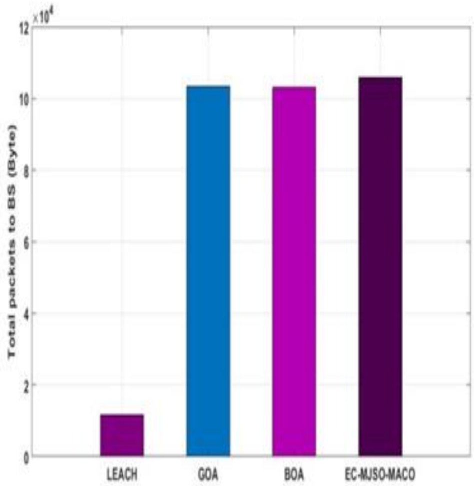

Fig. 5 Packets to BS Vs. rounds

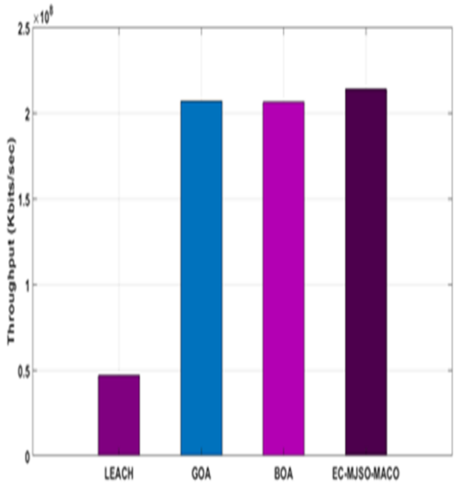

Fig. 6 Throughput Vs. rounds

3.2.4. Throughput

Throughput is the amount of packets which is collected by BS from the transmitter CH at a particular period. Since, this throughput is calculated as bits per second. The evaluation of throughput between EC-MJSO-MACO, LEACH, BOA, and GOA is shown in Figure 6. This analysis shows that the throughput of the EC-MJSO-MACO is increased than the LEACH, BOA, and GOA. The throughput of the EC-MJSO-MACO is increased by preventing node failure during routing and decreasing the energy consumption of the nodes.

3.2.5. Life expectancy

Life expectancy defines the amount of time that the nodes in active while transmitting data packets. Here, the life expectancy is analysed by using different parameters such as FND, HND, and LND. Figure 7 shows the performance of life expectancy for EC-MJSO-MACO with LEACH, BOA, and GOA. From the figure, it is known that the EC-MJSO-MACO has high life expectancy than the LEACH, BOA and GOA. The design of energy efficient CH selection and routing using EC-MJSO-MACO leads to increase in the life expectancy.

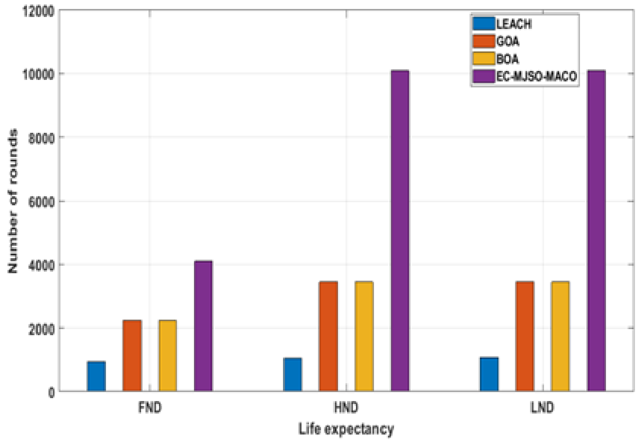

Fig. 7 Life expectancy Vs. rounds

3.3. Comparative analysis

The comparative analysis of the EC-MJSO-MACO is given in this section. Existing research such as CI-ROA (Yadav and Mahapatra, 2021) and RCSO (Shyjith et al., 2021) are used to evaluate the efficiency of the EC-MJSO-MACO. There are two different scenarios considered for evaluating the EC-MJSO-MACO. In scenario 1, the nodes are initialized with the initial energy of 0.5J, whereas the nodes in scenario 2 consider the initial energy of 0.55J. For scenario 1, the EC-MJSO-MACO is compared with the CI-ROA, which is shown in Table 2. The EC-MJSO-MACO is compared with the RCSO for scenario 2, which is shown in Table 3. From Tables 2 and 3, it is known that the EC-MJSO-MACO is delivering improved performance than the CI-ROA (Yadav and Mahapatra, 2021) and RCSO (Shyjith et al., 2021).

Table 2 Comparative analysis of scenario 1

Performance measures	Methods	Rounds			
		500	1000	1500	2000
Alive nodes	CI-ROA	100	55	36	25
	EC-MJSO-MACO	100	100	100	100
Dead nodes	CI-ROA	0	45	64	75
	EC-MJSO-MACO	0	0	0	0
Normalized energy (J)	CI-ROA	0.44	0.29	0.19	0.16
	EC-MJSO-MACO	0.4739	0.4477	0.4228	0.4002

Table 3 Comparative analysis of scenario 2

Performance measures	Methods	Rounds			
		200	500	800	1000
Alive nodes	RSCO	50	50	50	7
	EC-MJSO-MACO	50	50	50	50
Dead nodes	RSCO	0	0	0	43
	EC-MJSO-MACO	0	0	0	0
Normalized energy (J)	RSCO	0.43	0.28	0.09	0.05
	EC-MJSO-MACO	0.5359	0.5148	0.4944	0.4808

4. Conclusions

In this paper, the EC-MJSO-MACO is developed to improve the energy efficiency of the WSN. The developed EC-MJSO is used to choose the optimal CHs followed by the EC-MACO which is used to discover the route from the transmitter CH to the destination. The identification CH with less neighbor node and sink distance is used to decrease the energy consumed by the nodes. Next, the balancing between the clusters is accomplished by considering the CH balancing factor in the MJSO, which helps to reduce the energy consumed by the nodes. The shortest route with less node degree is chosen by using the MACO that is used to achieve reliable communication in WSN. From the results, it is concluded that the EC-MJSO-MACO achieves better results than the LEACH, BOA, GOA, CI-ROA, and RCSO. The alive nodes of the EC-MJSO-MACO for 2000 rounds are 100, which is high than the LEACH, BOA, GOA, and CI-ROA.

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