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Sparrow-based Differential Evolutionary Search Algorithm for Mobility Aware Energy Efficient Clustering in MANET Network

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Abstract: A mobile node network that self-organizes and lacks a fixed infrastructure is called a mobile ad hoc network (MANET). If not effectively managed, the dynamic topology feature of MANETs can reduce network performance, mobility awareness, and energy efficiency, especially with regard to cluster head (CH) selection. The Low Energy Adaptive Clustering Hierarchy (LEACH) protocol is frequently used in MANETs to extend network lifetime by effectively utilizing the minimal energy provided. In this research, we present the Sparrow-based Differential Evolutionary Search Algorithm (SDESA) to solve the problem of energy efficiency in the communication process by selecting cluster heads. The suggested technique enhances network lifetime by combining the dynamic ability of differential evolution with the high degree of search effectiveness of the Sparrow Search technique. By integrating differential evolution's dynamic abilities with the high degree of search effectiveness of the recommended technique, node lifetime is increased.

Keywords: *MANET, cluster head (CH), sparrow-based differential evolutionary search algorithm (SDESA), LEACH*

1. Introduction

A MANET is a decentralized network of autonomous mobile nodes that communicate with each other without the need for a pre-existing infrastructure. These networks are particularly useful in scenarios where setting up a fixed infrastructure is impractical or impossible, such as emergency situations, military operations, or temporary gatherings [1]. This networking architecture uses devices that are installed for specific applications and do not require a long-term backbone or infrastructure. In MANETs, nodes rely on each other to relay data and form dynamic connections as they move around. The dynamic nature of MANETs poses several challenges that can impact network performance, including the degradation of the network's overall efficiency, mobility awareness, and energy consumption [2].

One crucial aspect of MANETs is the selection of cluster heads (CHs), which are responsible for coordinating and managing the network. Efficient CH selection optimizes energy use to improve network performance and lifespan[3].To address the challenges of energy efficiency in CH selection, the LEACH protocol has been widely used in MANETs. LEACH aims to prolong the network's lifetime by rotating the role of CH among the nodes, thus distributing the energy consumption more evenly. However, the traditional LEACH algorithm may still face limitations in achieving optimal energy efficiency [4].

In recent years, bio-inspired algorithms have gained significant attention for solving optimization problems in various domains. These algorithms mimic the behavior of natural phenomena or biological systems to find optimal solutions [5]. In the context of CH selection in MANETs, bio-inspired algorithms can be utilized to enhance the energy efficiency and performance of the network.

In this paper, we propose a novel approach called the SDESA for addressing the energy efficiency challenge in CH selection for MANETs. The SDESA algorithm combines the strengths of two powerful bio-inspired algorithms: the SSA and DE. The SSA is known for its high-level search efficiency and the ability to explore complex search spaces effectively. On the other hand, DE is a dynamic optimization technique that harnesses the power of genetic operators such as mutation, crossover, and selection to improve the search process. By integrating these two algorithms, we aim to leverage their complementary strengths and achieve better performance in terms of network lifetime and energy efficiency. The proposed SDESA algorithm selects cluster heads based on their energy levels, connectivity, and performance metrics. It aims to optimize the selection process by efficiently utilizing the limited energy resources and ensuring a

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balanced distribution of CHs throughout the network.

The rest of this paper is structured as follows: A review of related research in the area of selecting a CH in MANETs is presented in Section 2. The methodology and specifics of the suggested SDESA algorithm are presented in Section 3. The results and performance analysis are presented in Section 4. The work is finally concluded in Section 5, which also highlights potential future research areas.

2. Related Works

Article [6] presented the low-power routing protocol Adapted Gear and Steering-based Rider Optimization Technique (AGS-ROA). In order to reduce route failure and data load-induced dead nodes, AGS-ROA-AOMDV seeks paths from the fittest node with sufficient energy for broadcasting. After every cycle of transmission, the AGS-ROA update operators adjust the nodes' energy-based classifications. EC was high because the gateway was chosen based on the number of nodes. It was proposed to use Fuzzy Clustering Algorithms (FCAs). They accomplish FCA with the help of the Weighted Clustering Algorithm (WCA) for the approach.

A novel “energy-efficient CH selection technique, emperor penguin optimization fuzzy genetic algorithm (EPO-FGA)," was developed for intrusion detection in the study [7]. The fuzzy genetic algorithm with emperor penguin optimization increases the mobile node's lifetime. Based on the mobile node's speed, mobility direction, and position, the emperor penguin algorithm initially builds effective clusters. Next, a fuzzy genetic algorithm was utilized to choose the optimum CH using node energy, mobility, and degrees.

The Hybrid PSO-GA method was used to introduce the study [8] for the Energy-Efficient CH Selection method. The Soft k-means technique was used for clustering, which optimizes cluster formation by taking into account node distance, position, and speed. The Hybrid PSO-GA approach was used to choose the CH from the nodes following cluster formation. Node mobility, node degree, and node energy are utilized in CH selection.

Study [9] introduces the graph theory-based Energy Efficient Minimum Spanning Tree (EEMST) algorithm in the research for choosing the best CH and data routing in a multi-hop IoT context. The approach finds the lowest spanning tree using the Euclidean distance on a weighted graph. Therefore, they determine the shortest path for information to flow between individual nodes and the cluster leader after selecting the most effective cluster leader utilizing a weighted minimum spanning tree. Both multi-hop and single-hop routing within a cluster, as well as among clusters, are supported by the suggested EEMST algorithm. When contrasted with baselines in simulated testing findings, the suggested algorithm was demonstrated to dramatically prolong the lifespan of IoT equipment.

Article [10] developed the "modified k-means Philippine eagle (MKMPE) approach," an efficient high-yielding carry-out method. In order to find the best CH from the cluster group, the “modified k-means method (MKM)” was first utilized for transmitting data to the desired node without any kind of packet loss.

Research [11] has suggested an efficient procedure for “cluster formation and the selection of stable cluster heads (E-CFSA)” with a high energy level. The distance with centroids serves as the primary parameter in the k-means method used by E-CFSA to generate node clusters. The next step was to apply an “artificial neural network (ANN)” in each cluster to choose an effective CH.

Study [12] determines the shortest MANET data transmission path. The study provides an “Energy Efficient-Modified African Vulture and Modified Mayfly (E-MAVMMF)” technique for CH selection and optimal route selection. In the initial phase, the CH has been chosen using the “Modified African Vulture optimization algorithm (AVOA) with Brownian motion” to enhance its effectiveness. In order to identify the overall best solution, the optimal path was selected in the subsequent step utilizing the "modified Mayfly algorithm (MMF)" and the "modified mutation stage of Symbiotic Organism Search (SOS)."

In article [13], the unique Eagle Based Density Clustering (EBDC) technique forecasts link failure and increases node lifetime. EBDC creates star-topology nodes for MANET cluster and route management. The method initially selects the CH and sends the communication through the path. EBDC detects connection failure and provides a reference layer to replace the depleted layer. Thus, EBDC extends network life and reduces the consumption of energy.

2.1. Problem statement

The problem addressed in this research is the lack of mobility awareness and energy efficiency in existing clustering algorithms for MANET. Traditional clustering algorithms do not consider the dynamic nature of node mobility, leading to suboptimal cluster formations and inefficient CH selections. This results in increased energy consumption and reduced network lifetime. To tackle these issues, we present an SDESA to achieve better energy efficiency and network performance in MANETs

3. Method

This research proposes a new approach that combines mobility awareness and energy efficiency by utilizing the SDESA. The SDESA algorithm aims to enhance the selection of CHs in cluster-based MANETs, resulting in improved network mobility, energy efficiency, and overall performance

3.1. Mobility concept

The mobility of nodes in MANET has a direct impact on the performance of routing algorithms and the stability of clusters. Increased mobility leads to frequent CH re-elections and frequent updates in cluster connections, resulting in poor cluster stability. To reduce control overhead and improve stability, our approach utilizes mobility data to establish a stable path between less mobile entities. By leveraging this path, we aim to minimize the impact of node mobility on the network, enhance cluster stability, and reduce unnecessary control messages in MANETs.

3.2. Model for Energy

One important goal of a routing protocol is to maintain a network operational for as long as it is feasible rather than just determining correct and efficient paths between groups of nodes. The ME routing selects the path with the lowest overall energy consumption for packet transmission, and the max-min routing selects the path with the highest constraint residual node energy. This energy node is provided at a certain time interval by

$$E_{energy}(t_j, \Delta t) = E_{residual}(t_j, l_0) - E_{residual}(t_j, l_1) \quad (1)$$

The energy node here is represented by $E_{residual}$ at times 0 and 1, respectively.

3.3. MANET clustering model

By transmitting a packet describing their relative weight, the node was able to obtain information about other nodes. The value of significance includes the node's degree and the amount of data being transmitted from the node. Cluster and CH are initially determined based on the system's mobility and energy. Mobility leads to increased CH selection and interface refreshing, which negatively affects cluster stability.

If a group of sensor nodes is within radio range of the CHs, the CHs will send out a broadcast demanding a packet, which will then be used for developing a cluster. The transmission to the CH is unambiguous in the single-node mode, whereas in the multibounce mode, each sensor node repeats its data through its neighbors.

3.4. LEACH protocol

The LEACH protocol is a dynamic clustering algorithm used in WSN. To collect information from their nearby nodes and transfer it to the base station, LEACH network nodes alternatively take on the role of CH. The CH is responsible for aggregating and forwarding data, thereby reducing the overall energy consumption of the network.

The operation of the LEACH protocol is divided into multiple rounds, each consisting of two stages: the “set-up phase and the steady phase ."In the set-up phase, CHs are selected for each round based on a randomized rotation scheme. This allows the CH role to be evenly distributed among nodes, ensuring a balanced energy consumption across the network. Once the CHs are selected, they advertise their role to the neighboring nodes, who then choose their respective CHs to intersection. This clustering process improves network scalability and reduces communication overhead.

In the steady phase, data transmission occurs from the sensor nodes to their corresponding CHs, which in turn forward the aggregated data to the base station. The CHs employ data aggregation techniques to minimize the amount of data transmitted, thereby conserving energy. This process continues for the duration of the round, with CHs changing in each subsequent round to distribute the energy load and prolong the network lifetime.

Overall, the LEACH protocol optimizes energy efficiency by dynamically selecting CHs and employing data aggregation techniques. By rotating the CH role and reducing communication overhead, LEACH enhances the scalability and longevity of wireless sensor networks.

3.5. CH selection

A CH has been implemented to provide the participants with radio transmitters and to route communications for nodes belonging to different clusters. Each node makes the decision to be a CH at the beginning of the round with the probability $qs_j(t)$ chosen so that D is CHs are anticipated. Therefore, if the network contains nodes,

$$D = \sum_{j=1}^{N} qs_j(t)^* 1 \quad (2)$$

Here, N is the total amount of network nodes, while $N - l$ denotes ordinary nodes.

$$qs_j(t) = \frac{Anticipated\ number\ of\ cluster\ heads}{Expected\ number\ of\ nodes\ are\ not\ cluster\ heads\ in\ most\ recent\ rounds} \quad (3)$$

Every node in N-k will be CH once. Every node in a cluster has an equal probability of becoming a CH. This makes sure that after each round, the energy at each node is roughly equal. Compared to anodes with lower energy, nodes with a greater amount of energy are more inclined to form clusters. The anticipated number of cluster nodes is

$$Energy[CH] = D \Longrightarrow (N - D^*(rmod\ N/D))^*\ N/D - D^*(rmod\ N/D) \quad (4)$$

Key administration techniques assist in distributing keys to nodes in a cluster, but if keys need to be generated for all of the nodes in the cluster, the process becomes inefficient and causes key overhead. The nodes are displayed in an array of colors to represent the many distinct groups that make the whole framework. The least-weighted node in each cluster is the CH.

3.6. Optimum CH selection models

Our SDESA-based clustering method aims to strengthen CHs. This is a necessary condition to achieve cluster stability in MANET. It should be noted that in networks where data is transmitted from source to target by CHs, simply selecting the most qualified nodes to serve as CHs does not ensure clustering effectiveness.

3.6.1. SDESA

SSA's search capabilities necessitate employing a hybrid Sparrow search method built on Differential evolution. A hybrid optimization method uses elements from multiple algorithms to maximize the benefits of each. SSA is a time-consuming, lengthy process that lacks a powerful global search (GS) capability, but the DE algorithm has the latent ability to simplify the GS process and is appropriate for search space exploitation due to its delayed convergence. SSA actively seeks an ideal d dimensional solution with DE's higher convergence rate, stability, and search efficiency. The most effective solution to clustering difficulties has been found with the help of DE.

Its primary function has been as a standalone or complementary tool for solving clustering issues. “Exploitation and exploration” quality in CH selection are maintained by the dynamic properties of SSA and DE algorithms. SDESA is a novel model that uses DE to complement the results of SSA, maintaining optimal performance. This model is designed to solve the problem of CH selection in WSN. Fig. 1 depicts the SDESA flowchart.

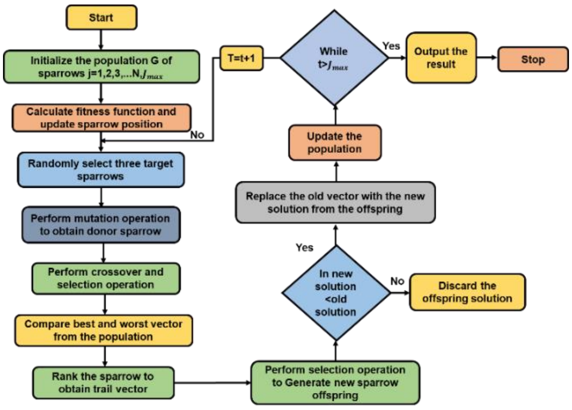

Fig.1. SDESA flowchart

The population is assumed to be equal to the overall quantity of nodes. As a consequence, the vector dimension would need to be re-clustering whenever any nodes were added or removed. Finding the optimal answer for a given individual as quickly as possible while maintaining relevant data is the primary goal of the fitness function. In SSA, the fitness value of a sparrow is proportional to the energy level. Nodes are selected in the WSN scenario based on their proximity to the optimal global positions and the nodes that communicate with them. The producers in SSA are most capable of acquiring prey. By providing the best sources of food to increase predatory value, the scavengers monitor and obey the producer. The forging approach to scroungers depends on their level of energy, which could be either high or low. The next part contains information on vector initialization of the “sparrow population, mutation, crossover, and selection operations."

For vector representation, our suggested model employs SSA. The sparrow's spots are determined at random within the bounds and are displayed in matrix form as in equation (5). Rand [0, 1], a distribution number produced at random, comprises the starting point vector. Each row is a solution to the optimization problem using the fitness function.

$$f(y) = \begin{bmatrix} f(|S_{1,1} & S_{1,2} & \cdots & S_{1,d} \\ f(|S_{2,1} & S_{2,2} & \cdots & S_{2,d} \\ \vdots & \vdots & \vdots & \vdots \\ f(|S_{n,1} & f(|S_{2,2} & \cdots & S_{n(l),d} \end{bmatrix} \begin{bmatrix} f_{obj_1} \\ f_{obj_2} \\ \vdots \\ f_{obj_n} \end{bmatrix} \quad (5)$$

Using the Mutation Rate (MR), the mutation operator chooses the best-targeted vector TV from the population: Equation (6) illustrates the newly formed offspring $S_{(h+1)}$. Furthermore, it is modified according to three arbitrary numbers, $s_1, s_2, .. s_n$ to increase the probability of producing two unique vectors. The difference between the vectors $\in [0,1]$ during the mutation procedure may be a contributing factor to the resultant's undesirable outcome. Therefore, the procedure has to generate variations in vector components in a manner that satisfies the range of values. Each sparrow experiences the evolution of every population procedure until the ideal outcome is reached.

$$S_{h+1} = s_{r_1} + MR * (s_{r_2} - s_{r_3}) \quad (6)$$

Equation (7) calculates the “Euclidean distance” among a sparrow and the best sparrow selected$Sbest_{j,k}$.

$$dist = \sqrt{\sum_{j=1}^{N} (S_{j,k} - Sbest_{j,k})^2} \quad (7)$$

According to equation (8), a kind of recombination process is carried out between DV and TaV to create a new generation of offspring known as a trial vector. An established Crossover Probability Rate (CPR) is used in this instance of binomial crossover. In $r \le CPR$, the most effective donor vector ($BestDV$) is selected; otherwise, the best target vector ($BestTV$) is. Since the DE algorithm, practically all solutions have SF and CPR set with predefined values.

$$S_{jk,h+1} = \begin{Bmatrix} BestDV_k \ if \ (r \leq CPR) \\ BestTV_k \ if \ (r > CPR) \end{Bmatrix} \quad (8)$$

Both TV offspring and newly generated TV offspring can be selected to continue on to the next generation through the selection operation. The generated fitness function evaluates both vectors. If the fitness value of the target vector is higher than the fitness value of the TV, the TV will replace the TV in the population. The producers will leave the region if they acquire the best food. Here $k = 1,2,\dots,d$, $\alpha \in [0,1]$, $S_{j,k}^{t}$ is the degree of the $k^{th}\ dimension$ of the k^{th}sparrow at the t^{th} repetition, and t is the number of iterations. R is an arbitrary number with a simple distribution, ARV is the alarm value, SFT is the safety threshold, and L is a $1\ x\ d$ matrix with all elements less than 1.

Each solution has unique characteristics that can change with each iteration, but only a select number will eventually prevail. Everyone participates in the search and shares a location. When $ARV < SFT$, the producer changes into a wider search mode, indicating that there are no predators. When$ARV \geq SFT$, few sparrows have discovered the predator, making it crucial to defend them by escaping to safer areas. Only a few scavengers then visibly follow the producer. A progeny is created using natural selection based on the objective function $SBest$The novel hybrid approach has been effective if the objective function results for the most detrimental sparrow is less than the objective function result for it. They can get the food from a producer, and a better option replaces the previous worst one.

$$S_{j,k}^{(t+1)} = \begin{cases} S_{j,k}^{t}.\,exp\left(\frac{-j}{\alpha.J\,max}\right) \ if \ ARV < SFT \\ STV_{j,k}^{t} + R.L \ if \ ARV \geq SFT \end{cases} \quad (9)$$

Equation (10) provides the position of a scrounger within the bounds of the maximum number of repetitions J_{max} using the stage size controlling parameter b with an average of zero and a variance of one.

$$S_{j,k}^{(t+1)} = S_{GBest}^{t} + \beta.\left|S_{j,k}^{t} - S_{GBest}^{t}\right|^{(t+1)} \quad (10)$$

Each repetition, up to the maximum number of iterationsJ_{max}, determines and updates the positions of all nodes. By using equation (10), the problem's resolution is an index of the CH's "l" numbers. Every repetition, the CH sends data to all the CM in the cluster to gather information, which it subsequently transfers to the BS. The neighboring nodes that are close to the node have more energy than the CH. Each individual sparrow's lifespan is determined by its fitness value, which is determined using the fitness function mentioned above and includes factors such as “residual energy, the number of CH, intra-cluster communication distance (ICCD), and distance between CH and BS." In this case, RE and CH influence the distance parameter. ICCD among the CH and BS is greater if the CH is limited in number. Similar to the previous example, if the CH count is large, the ICCD will also be low, but the distance between CH and BS will increase

4. Result And Discussion

NS2 is used to examine our proposed model. Existing important clustering methods are used in the implementation of the proposed study. Table 1 lists the NS2 simulation parameters. In this section, we evaluate the performance of the suggested and current methods. The existing methods such as GWO, CRO, and CFO. The parameters are Energy consumption, throughput, network lifetime, packet delivery ratio, and cluster lifetime.

Table 1. Simulation parameters

Parameter	No. of Nodes	Area	Mac	Simulation time	Packet size	Rate
Value	150	1000×1000	802.15	100 Seconds	550	60 kbps

The quantity of energy used by the nodes in a wireless sensor network while they are functioning is referred to as energy consumption. The outcome of energy usage is shown in Fig. 2. Our suggested method, SDESA combined with LEACH protocol, outperforms the currently used methods (GWO, CRO, and CFO) for mobility-aware, energy-efficient clustering in MANET networks.

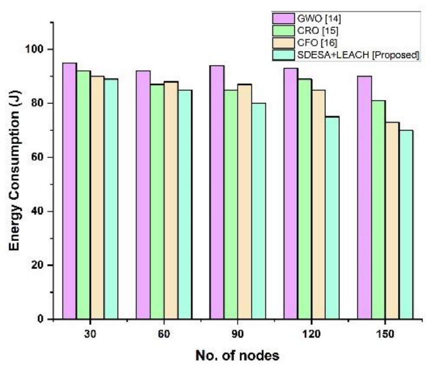

Fig. 2. Result for energy consumption

Fig. 3 presents the results for throughput, which quantifies the network's ability to efficiently handle data traffic by measuring the amount of data transmitted per unit of time. Our method SDESA + LEACH demonstrates superior performance compared to the currently utilized methods (GWO, CRO, and CFO) for mobility-aware, energy-efficient clustering in MANET networks. The specific throughput values obtained for each method affirming the superiority of SDESA in terms of data transmission capacity.

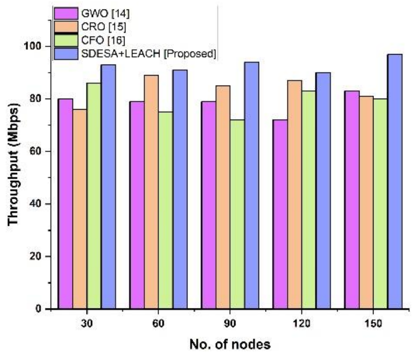

Fig.3. Result for throughput

The period of time during which a network may carry out the specified functionality is known as the network lifetime. The results for network lifetime are depicted in Fig. 4. For network lifetime, our SDESA + LEACH achieves a higher value as it indicates a longer duration for which the network can operate before node energy depletion. A higher network lifetime implies better energy efficiency and sustainability of the network. Therefore, in the context of network lifetime, a higher value is considered favourable and signifies improved performance.

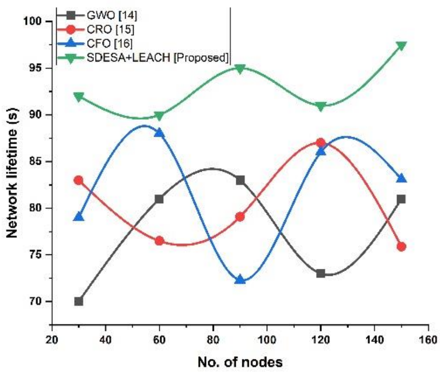

Fig. 4. Result for Network Lifetime

The percentage of properly delivered packets to all packets sent in a network is known as the packet delivery ratio, or PDR. It assesses the network's ability to reliably transmit data. Figure 5 shows the outcome of PDR. In terms of effectively delivered packets, our SDESA + LEACH receives higher scores, which indicates superior performance and reliability. A high PDR indicates a more dependable and effective data transmission because a higher percentage of the delivered packets successfully reached their intended destinations.

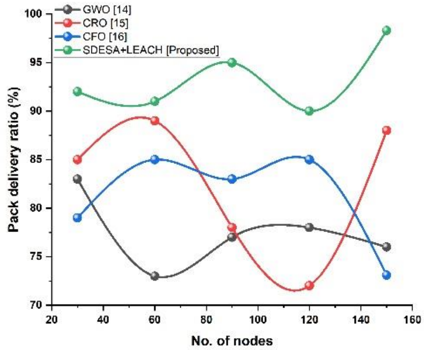

Fig. 5. Result for PDR

In a clustered wireless sensor network, cluster lifetime refers to the duration for which the formed clusters remain operational. Clustering is an energy-efficient technique that involves grouping sensor nodes into clusters with specific roles and responsibilities. Fig. 6 shows the outcome of the cluster lifetime. Our SDESA + LEACH model obtains a higher value and typically indicates a longer duration for which the formed clusters remain operational. Therefore, in the context of cluster lifetime, a higher value is generally desirable as it signifies increased stability and longevity of the clusters.

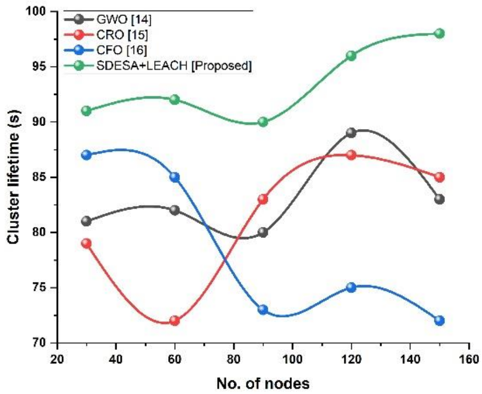

Fig.6. Result for cluster lifetime

5. Conclusion

This research focuses on addressing the challenges associated with energy efficiency, network performance, and mobility awareness in MANET, which are self-organizing networks without a fixed infrastructure. The dynamic topology of MANETs can impact these factors, particularly in terms of CH selection. The LEACH protocol is commonly employed in MANETs to prolong network lifetime by efficiently utilizing the limited energy resources available. To address this, the research proposes the SDESA as a solution for enhancing energy efficiency in the communication process through improved CH selection. SDESA combines the dynamic capabilities of DE with the effective search efficiency of the Sparrow Search technique. By integrating the dynamic abilities of DE with the highly effective search mechanism of the suggested technique, the proposed approach significantly increases the network lifetime, throughput, cluster lifetime, and PDR, and it decreases energy consumption. Future work should focus on implementing SDESA in real-world scenarios and conducting practical evaluations.

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