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Multi Objective Energy based Hybrid Optimization Algorithm for Clustering and Routing in WSN

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Abstract. Wireless Sensor Network (WSN) typically consists of thousands of relatively small nodes, each equipped with a sensing device. The sensor node which contains higher energy constraints is considered insignificant where the energy does not substitute and cooperate. Consequently, data transmission is the main cause of energy consumption in WSN. Clustering is an efficient procedure to gain energy efficiency through data transmission in WSN. So, this research proposed a Multi Objective Energy-based Hybrid Optimization Algorithm – (MOEHOA) attain the energy-efficient process. The hybrid optimization is composed of Improved Moth Flame Algorithm (IMFO) along with Firefly algorithm. Also, this proposed method eliminates excessive retransmissions and delay to improve the performance metrics. The simulation model displayed that proposed MOEHOA achieved better results in terms of residual energy (12.7725 J), end-to-end delay (12.65ms), packet delivery ratio (0.994), normalized routing overhead (0.118949) and throughput (1.097 Mbps) when compared with Cluster-Based Data Aggregation (CBDA) which attains less performance in all the performance parameters.

Keywords: Data Aggregation, Firefly Algorithm, IMFO, Multi Objective Energy-based Hybrid Optimization Algorithm WSN

1. Introduction

In recent trends, most of the sensor networks utilizes remote communication and the nodes which are regularly battery controlled and applied for checking the environment by utilizing various sensor nodes (Tyagi and Kumar, 2013), (Kuila and Jana, 2014). Routing strategy assumes an indispensable part in the remote sensor organization, therefore, ordinary protocols may not be substantial for WSN (Azharuddin et al, 2015). Compared to an ordinary remote communication network, WSN has essential qualities such as heterogeneity, mobility of nodes and limited power consumption (John et al, 2018). These qualities make it an extremely provoking responsibility to substitute a routing protocol for various applications (Liu, 2012). Consequently, the lifespan of the network gets decreased, because the primary features of the sensor hub contain higher energy depletions (Wang et al, 2019), (Yarinezhad and Hashemi, 2019). Sending repetitive information consumes the additional energy present in sensor nodes, so, WSN has not contained any decent background which has been intensely dominant (Elhabyan et al, 2018).

Clustering is a technique by which sensor nodes are progressively coordinated based on their relative vicinity to one another (Srinivasa and Banka, 2017). The progressive energy utilization makes a successful and solid method for directing gathered information from the actual climate, through the sensor hubs to the BS (Jannu and Jana, 2016). Clustering of sensor hubs supports the routing process to some extent so that the exposure mode between sensor hubs is accomplished effectively (Wang et al, 2018). The clustering process protects the data transfer capacity since it restricts the group connections to CHs and maintains a strategic distance between the sensor hubs (Johny and Meenakshi, 2018). Every sensor hub plays out a course table search up for the CH in its district and afterwards courses its gathered information to the CH. Similarly, CH plays out a course disclosure assessment dependent on the briefest distance to a beneficiary CH nearer to the BS or straightforwardly to the BS (Asha, 2018). To regulate the routing process, network data is swapped amongst sensor nodes in a particular time period. To familiarize the modification in energy constraint for data communication through each and every node present in the network, the CH selection process is required.

The major contribution of this research is as follows:

- In this research, Multi Objective Energy-based Hybrid Optimization Algorithm (MOEHOA) is proposed to accomplish the energy efficient process under various node counts.
- The proposed MOEHOA is used to provide low energy consumption and better link superiority amongst the various sensor nodes to increase the reliability of data transfer.
- To examine the performance of the proposed method with existing methods

in an energy network model, residual energy, delay, PDR, routing overhead and throughput are calculated.

The organization of this research paper is given as follows: The review of the current techniques associated with the clustering/routing process in WSN are described in Section 2. The description of the proposed MOEHOA process with a flowchart is given in Section 3. The simulation results and their comparative analysis of the MOEHOA method are given in Section 4. The conclusion of this research paper is given in Section 5.

There are many existing techniques related to the energy-efficient clustering and routing in WSN that were developed for various applications. A brief evaluation of some contributions to the existing literatures are given as follows:

(Deepa and Suguna, 2017) projected an Optimized QoS-based Clustering with Multipath Routing Protocol (OQoS-CMRP) for lessening the energy utilization in WSN. The Modified Particle Swarm Optimization (MPSO) based clustering calculation was utilized to shape groups for choosing bunch heads in the inclusion region and to confront the energy opening problem. The created OQoS-CMRP for WSN accomplishes conspicuous information correspondence with sensible energy protection. It additionally diminishes transmission deferral and correspondence overhead based on guaranteeing the result of the whole organization. In some cases, cluster heads gain more energy because of the extra load for receiving and communicating the data packets.

(Mahdi et al, 2019) exhibited another packet calculation that chooses CHs utilizing the Gray Wolf Optimizer (GWO). To choose CHs, the arrangements were appraised dependent on the anticipated energy utilization and current lingering energy of every hub. To further develop energy effectiveness, the proposed protocol utilizes similar clustering in different sequential rounds. The set-up protocol expects loss because of superfluous execution of the cluster arrangement stage in adjusts where the existing cluster process is still adequate. Here, the set-up protocol doesn't consider QoS metric separated from lifetime. In some of the applications, there was a variation in an internal component which creates problems to the routing protocol.

(Zhang and Yan, 2019) introduced a Centralized Energy-Efficient Clustering Routing protocol for versatile hubs (CEECR) that was created to limit energy dissipation. Also, it was utilized to deliver ideal clusters using hub portability and the hub energy property. The CEECR protocol uses a focal control calculation which was utilized to make a superior arrangement of Cluster Heads (CHs) with not so much portability but rather more energy. Moreover, the ideal CH was chosen for a withdrawn hub relying upon the consolidated loads. Thus, that CEECR was more energy proficient and beats its comparatives. The expanded number of Mobile Nodes (MN) will prompt more Detached Nodes (DNs) which are confined from their CHs and hence cause more data packet loss.

(Mittal et al, 2018) exhibited the CH determination and route generation among the node were done by utilizing the GA calculation. Then, at that point, Threshold-delicate Energy-proficient Routing Protocol (TERP) based between bunch information transmission calculation was utilized for communicating the information in the organization. The multi-bounce correspondence was refined by GA and it was utilized for further developing the heap adjusting and to diminish the energy utilization of the far off CHs. In some cases, CH selection portion mainly depends upon the residual energy of the nodes.

(Lalwani et al, 2018) the Biogeography Based Optimization (BBO) was utilized for clustering by considering different target capacities like residual energy, the intra-group distance among CHs and BS for better CH choice. Then, at that point, the leftover energy, Euclidean distance and hub degree were considered in the course age of BBO. The information bundles got by the BS was boosted by saving the leftover energy of the hubs. The residual energy of the network slightly degrades when the BS was situated outside of the system.

(Morsy et al, 2018) introduced the ideal CH was chosen by thinking about the remaining energy of every hub. The target capacities considered in the CH selection were Energy Efficiency and distance between the BS. The information transmission was finished by the one expectation approach. The target of progressive grouping was to expand the organization lifetime and delay network dependability. The immediate information transmission among the CH to BS glows through more energy. Along these lines, multipath routing was needed to improve energy utilization.

(Seedha Devi et al, 2020) suggested Cluster Based Data Aggregation Scheme (CDAS) for Packet Loss Decrease and Latency in WSN. The projected structure contains dual stages: Structure of Aggregation Tree and Slot planning procedure. In stage one, every CH exploits compressive accumulation for data acknowledged from the participants. Formerly the accumulation tree was created through the sink by means of the Spanning Tree procedure. While in the second stage, latency and packet loss are reserved for analysis whereas highlighting and allocating intervals to nodes with the collected information.

(Pattnaik and Sahu, 2020) demonstrated a fuzzy based clustering method and Elephant Herding Optimization (EHO)-Greedy method for routing process in WSN. EHO-Greedy deliberates both the stable and portable sink to minimize energy consumption. A stable node is positioned indiscriminately diagonally through the setup and a portable node changes into various positions through the setup for data gathering. A proper group of CH can enormously decrease energy consumption and similarly increase the lifetime. On the other hand, in some other applications, the expansion of additional energy-efficient procedures result in enlarged zones of WSNs.

2. MOEHOA method

In this research, clustering and routing are developed using MOEHOA. The searching ability of the algorithm was integrated with the fitness function values. Therefore, an effective CH and routing path are selected in this network. In the clustering process, four different fitness function parameters are considered such as residual energy, distance and degree of nodes. The energy consumption of the network is greatly minimized by considering two different distance functions. Additionally, node failure is avoided in the transmission path by considering the residual energy of the nodes. The packet loss occurred in the data transmission is minimized by avoiding node failure. The main objective of this research is to diminish energy depletion for improving the lifespan of the network. The general flowchart of clustering and routing is shown in Figure 1.

The flowchart for the MOEHOA is shown in figure 1. The steps for the flowchart are mentioned as follows:

- Initially, the nodes are arbitrarily positioned in the concerned zone, then mobile nodes are denoted as a dynamic that is completely reliant on the position of the node.
- A clustering procedure is established to distribute the system into groups. Here, MOEHOA is executed for network clustering. At that time, CH is established on neighbour’s distance, residual energy, distance to base station location, etc.
- The ideal path between CH to BS is attained through routing procedures that are established via the proposed MOEHOA.
- Commencing from the routing process, an ideal node is designated to produce the specified path from CH to BS.
- Once the path is established from source to destination, the source node communicates the information in the direction of the destination.
- This MOEHOA calculates the ideal route to consider multiple objective functions like residual energy, distance amongst the CH to BS and the number of hops.
- Frequently, the nodes residual energy is observed through BS. The re-clustering/rerouting is achieved frequently to eliminate network packet loss.

2.1. Moth Flame Optimization

Moths consistently attempt to make steady points with the close light sources, for example, fire while drawing nearer to them in a winding way nearby the source. MFO calculation is in light of similar assets of fly. In calculation, the moths address the arrangement whereas their situation in the space addresses the flexibility of an issue in which it has been employed. At first, MFO randomly creates the moths inside the solution space and fitness values are generated for each moth. Next, an optimal location is tagged by the flame. The function of spiral movement is used to define the location update of the moths. This location update is used to obtain the optimal location labelled by the flame and a new best individual location is updated in the MFO. The same processes such as location update of the moth and new location generation are performed in the MFO.

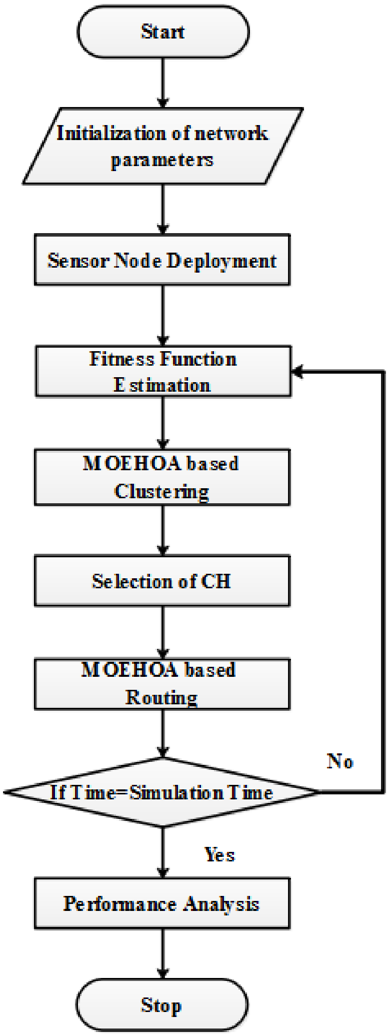

Fig. 1: Flowchart of Clustering and Routing using MOEHOA

The fitness function of every moths is saved in an array which is arranged in matrix form and supposed for storage of equivalent standards that are similarly characterized through an array. Formerly moth position is designed using a subsequent function (1).

$$M_i = S(M_i, F_j) \tag{1}$$

If M_i characterizes the ith Moth, jth a flame is designated by F_j and function of a spiral path is stated as S. Deliberating the aforementioned state, the moth route is described as subsequent equation (2),

$$S(M_i, F_j) = D_i . e^{bt} . \cos(2\pi t) + F_j \quad (2)$$

Where distance amongst the ith moth and jth flame of problematics are signified as D_i. Constant values are stated as b that support the outline of the curved route and t diverge in the range of -1 and 1 indiscriminately. Supplementary D_i is designed as in equation 3,

$$D_i = |F_j - M_i| \quad (3)$$

In equation (3), M_i represents ith Moth, F_j represents jth flame and D_i signifies distance amongst the nodes. Through the usage aforementioned equivalence, the moth location is restructured all over the flame. Using flame, the population gets diminished through the repetition count. Those formulations are mentioned in equation 4,

$$Flame\ no = round\ \left(N - 1 * \frac{N-1}{T}\right) \quad (4)$$

Where N denotes the maximum flame count and T represents the maximum iterations count.

2.2. Firefly Algorithm

MFO algorithm is used to minimize the magnitude interferences. Through this strategy, convergence accuracy and process performance are enhanced considerably. At that time, a firefly mechanism is calculated for updating the positions of moths that can efficiently support the procedure to preserve the population diversity and increase the global search capability. The hybrid MFO and Firefly can efficiently synchronize the global search and local search to increase the convergence speed.

To keep away from the distance between individual fireflies from being excessively far, the fascination between them might be right around nothing. The firefly should be improved to accomplish better advancement execution. By investigating the boundaries of the FA, light retention coefficient γ is excessively enormous and works as decent worth. Every firefly contains bright influence $I\ (r)$ which is written as

$$I\ (r) = I_0 e^{-\gamma r^m}\ m \geq 1 \quad (5)$$

So, firefly attraction β can be diverged conferring to the calculation assumed through (6),

$$\beta(r) = \beta_0 e^{-\gamma r^m}\ m \geq 1 \quad (6)$$

where β_0 signifies the greatest engaging quality (at r = 0) and γ is the light assimilation constant, which regulates the diminishing of the light power. The expanse amongst dual fireflies i and j at p_i and p_j locations are considered as given in equation (7)

$$r_{ij} = |p_i - p_j| = \sqrt{\sum_{k=1}^{l} p_{i,k} - p_{j,k}^{\ 2}} \tag{7}$$

where $p_{i,k}$ is three-dimensional harmonize p_i. The effort is defined in equation (8)

$$p_i = p_i + \beta_0 e^{-\gamma_{ij}^{\ 2}}(p_i - p_j) + \alpha(rand\ \tfrac{1}{2}) \tag{8}$$

where the initial term is the current situation of a firefly i (p_i is the arrangement of a firefly). At every iterative, the splendor and the engaging quality of every firefly are registered. The brilliance of every firefly is contrasted and any remaining fireflies and the places of the fireflies are refreshed utilizing condition (8).

2.3. Process of MOEHOA

The main purpose of MOEHOA is to discover the path from respective CH to BS. To accomplish this determination, MOEHOA is implemented through different fitness function that contains residual energy, distance and node degree.

2.3.1. Initialization of MOEHOA

In clustering, every MOEHOA characterizes the probable results of issues. At this time, the firefly measurement is equivalent to m + 1, where m characterizes the CH count in the setup and 1 represe nts BS. The pseudocode for the proposed MOEHOA is described as follows:

Pseudocode

```
Initialize the parameters for Moth Flame
Generate initial moth using locations of candidate CH node
for i = 1 to n do
    Calculate the fitness function (residual energy, distance and degree of nodes)
using eq. 5, 6 &7.
end
for iterations ≤ max_iterations do
    Update the position using equation 1.
    Calculate the number of flames using eq. 4.
    Evaluate the fitness function using equation 10.
    if iteration == 1, then
    F=Sort (M), and OF=Sort (OM)
    else
    F=Sort (M_{t-1}, M_t) and OF=Sort (M_{t-1}, M_t)
    end
    for i = 1 to n do
    for j = 1 to d do
    Update the random values of t (1 to -1) and r (-1 to -2)
    Calculate the value of D_i with respect to its corresponding moth eq. 3
    Update M(i,j) respect to its corresponding moth eq.2
    end
    end
end
Report the best CH nodes
Initialize the best CH nodes from IMFO
Evaluate the fitness calculation of each firefly (residual energy, distance and degree
of nodes)
 for iterations ≤ max_iterations do
   for i = 1 to n do (all fireflies)
      for j = 1 to n do (all fireflies)
         if fitness (p_i) ≥ fitness (p_j), then p_i is brighter than p_j
             Move p_j firefly towards the p_i firefly
         end
       Vary attractiveness with distance between the fireflies
     end
    end
    Sort the fireflies and find the Optimal CH position
end
```

2.3.2. MOEHOA based Clustering

2.3.2.1. Fitness function Derivation

The main function of MOEHOA based clustering process is to choose the nearby finest number of nodes such as CHs. The objective is to accomplish, proper fitness by formulating residual energy, distance and degree of nodes.

You might notice that the first paragraph after a header is not indented. Use the "Body text 1" style for the first paragraph after a header. Subsequent paragraphs are indented (Use "Body Text" style). The following is an example of the "Bullet" style, which you may want to use for lists.

a) Residual energy

The first objective of the residual energy is f_1 that is reduced and represented in Equation 9.

$$Minimize\ f_1 = \sum_{i=1}^{m} \frac{1}{E_{CHi}} \tag{9}$$

b) Distance

The distance between each CH to BS is described in this section. As declared previously, the sensor node is completely influenced by the distance of transmission while considering energy consumption. If the base station has more distance from the mobile node, at that time it needs higher energy to complete the process. As a result, cluster head with the smallest Euclidean distance commencing from BS is most favoured in the network. So, the following objective is f_2 which can be minimized and expressed in equation (10).

$$Minimize\ f_2 = \sum_{i=1}^{m} (dis\ (CH_j, BS)) \tag{10}$$

c) Degree of Nodes

Node degree is defined as the quantity of non-CH participants who goes to the particular mobile node. If cluster head has reduced participants, formerly it sustains for an extensive period which preferred the less degree of the node. Hence, the final objective f_3 is decreased in equation (11).

$$Minimize\ f_3 = \sum_{i=1}^{m} I_i \tag{11}$$

The above-declared objectives are an inconsistent environment that converts that multi objective function into a single objective. Consequently, the normalization process ($F(x)$) is exploited to every objective $\alpha_1, \alpha_2, \alpha_3$ which is shown in (12).

$$F(x) = \frac{f_i - f_{min}}{f_{max} - f_{min}} \tag{12}$$

where function value is signified as f_i , f_{min} and f_{max} are specified as a minimum and maximum fitness value is given in equation (13).

$$Minimum\ fitness = \alpha_1 f1 + \alpha_2 f2 + \alpha_3 f3 \quad (13)$$

$$Where \sum_{i=1}^{4} \alpha_i = 1; and\ \alpha_i \in (0,1)$$

In the process of routing, every population dimension is identical to the quantity of cluster head(m*). Let* $P_i = P_i^1, P_i^2, \dots P_i^m$*) be* i^{th} population, where each dimension of a population $P_i^1 = (0,1)$, are randomly initialized. Further, a new plotting is employed to determine the following node in the direction of BS.

2.3.3. MOEHOA based Routing

The main objective of this research is to choose a neighboring ideal route from every cluster head to the respective BS. In MOEHOA, the routing path is generated between the source CH to the BS using the same fitness function considered for the CH selection.

2.3.3.1. Initialization

In routing, each MOEHOA represents the data forwarding path from each CH to the BS. The dimension of each MOEHOA is the same as equal to the total number of CH'S in the network and one extra position added for the BS. Every moth in the routing process is modified through the potential transmission route amongst the source node to BS. The measurement of each moth is equal to the quantity of CHs occur in the corresponding transmission route.

2.3.3.2. Route selection

MOEHOA applies the equivalent fitness function (residual energy, distance and degree of nodes) which is previously expressed in section 3.3.1 to identify the route for data transmission. The source node communicates the Route Request (RREQ) message which is transmitted to neighbor nodes for modifying the route identification process. At that time, the subsequent node that has a superior fitness value sends the message to source CH by means of the reverse route. Once the routing path is produced, source CH collects the message from the neighboring nodes. After generating the routing path, the data transmission is originated through the network.

3. Result and Discussion

NS - 2 has been utilized as the test system for carrying out and validating the proposed calculation. This exploration objective is to limit the energy utilization of every node wisely as directed through routing strategy. The contribution to the proposed calculation to perform advancement is made out of four performances in particular {distance, overhead, delay, packet size}.

Table 1: Simulation specification

Parameter	Value
Packet size	512 bytes
Receiving power	0.4 W
Transmission power	0.660 W
MAC protocol	IEEE 802.11
Number of nodes	200
Initial energy	14.0 J
Transmission rate	50 to 250 kb/s
Network size	1000 × 1000 m
Antenna model	Omni antenna

Table 1 represents the simulation settlings parameters for the proposed model. The number of nodes is fixed as 200. The proposed system is effectively executed and tried with customary cluster based methodologies, for example, proposed calculations and its prevalent execution such as PDR, throughput, energy consumption, normal energy utilization of different node counts. Tables 2, 3, 4 and 5 show the results for the 50, 100, 150 and 200 node counts.

3.1. Performance of Residual energy

The outcome of residual energy for proposed and conventional CDAS [20] methods are illustrated shown in figure 2. When the node count is getting a rise, the dimension of the routing path also rises which leads to intensification in delay. Table 2 shows the performance comparison for residual energy. From table 2, clearly shows that the performance of the proposed MOEHOA varies from 12.7725 to 13.3439 whereas CDAS [20] varies from 6.4 to 8.

Table 2: Performance of Residual Energy

Number of nodes	Residual Energy (J)	
	Existing CDAS	Proposed MOEHOA
50	8	12.9416
100	7.5	13.3439
150	7	13.4044
200	6.4	12.7725

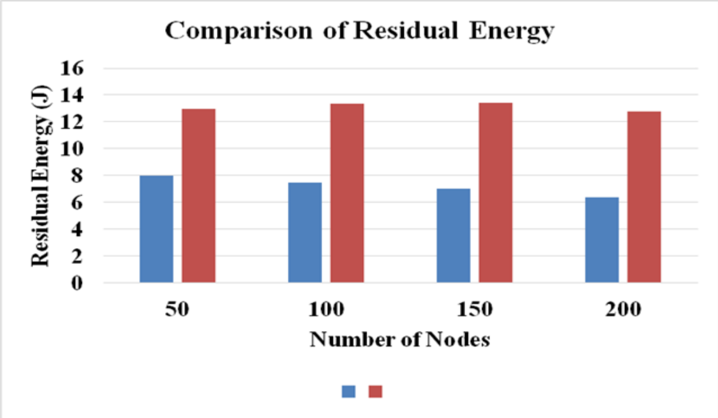

Fig. 2: Performance of Residual Energy

3.2. Performance of End-to-End Delay

To examine the result of ode density and network size, the node count is diverse from 50 to 200. The outcome of end-to-end delay for proposed and existing methods are illustrated shown in figure 3. when the node count is getting a rise, the dimension of the routing path also rises which leads to intensification in delay. Table 3 shows the performance comparison for the end-to-end delay. Table 3, clearly shows that the delay of the proposed MOEHOA increases from 7.5 ms to 12.6 ms whereas CDAS (Seedha et al, 2020) varies from 9.6 ms to 14.5 ms.

Table 3: Performances of End-to-End Delay

Number of nodes	End-to-End Delay (ms)	
	Existing CDAS [20]	Proposed MOEHOA
50	9.6	7.5
100	11.4	8.0
150	13.1	8.3
200	14.8	12.6

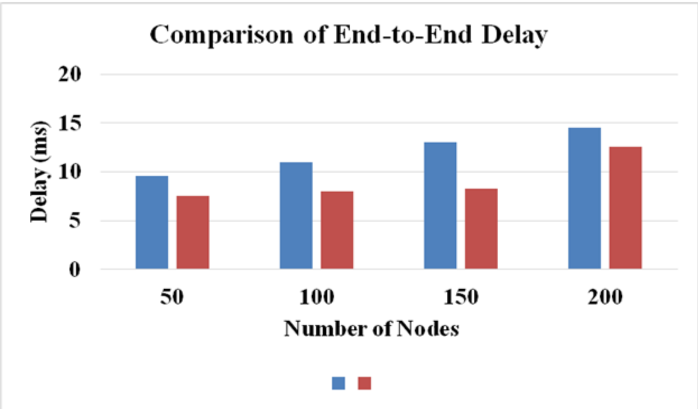

Fig. 3: Performance of End-to-End- delay

3.3. Performance of Packet Delivery Ratio

The outcome of Packet Delivery Ratio for proposed and existing methods are illustrated in figure 4. When the node count is getting a rise, the dimension of the routing path also rises which leads to intensification in delay. Table 4 shows the performance comparison for the Packet Delivery Ratio (PDR). Table 4, clearly shows that the PDR of the proposed MOEHOA varies from 0.992 to 0.997 where CDAS [20] varies from 0.38 to 0.6 and EHO-Greedy [21] achieves the PDR between 0.941 to 0.982.

Table 4: Performances of Packet Delivery Ratio

Number of nodes	Packet Delivery Ratio		
	Existing CDAS	Existing EHO-Greedy	Proposed MOEHOA
50	0.6	0.941	0.992
100	0.42	0.982	0.997
150	0.4	-	0.992
200	0.38	-	0.994

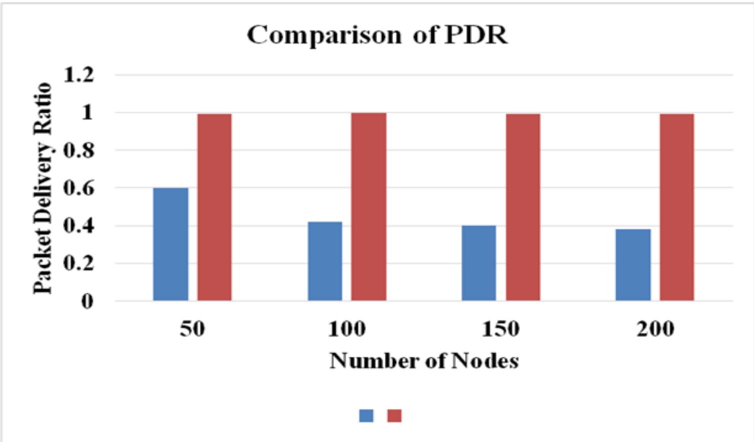

Fig. 4: Performance of PDR

3.4. Performance of Normalized routing overhead

The outcome of Normalized routing overhead for proposed and existing methods are illustrated as shown in figure 5. when the node count is getting a rise, the dimension of the routing path also rises which leads to intensification in delay. Table 5 shows the performance comparison for Normalized routing overhead. From Table 5, clearly shows that the Normalized routing overhead of the proposed MOEHOA varies from 0.118949 to 0.0469409 where CDAS [20] decreased from 0.2 to 0.4.

Table 5: Performances of Normalized routing overhead

Number of nodes	Normalized routing overhead	
	Existing CDAS	Proposed MOEHOA
50	0.2	0.0119023

100	0.26	0.0338107
150	0.31	0.0469409
200	0.4	0.118949

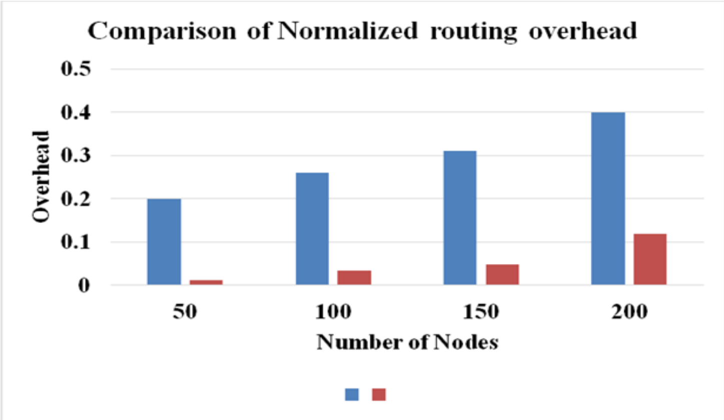

Fig. 5: Performance Analysis of Normalized routing overhead

3.5. Performance of Throughput

The outcome of the throughout performance for proposed and existing methods are shown in figure 6. The major justifications behind the proposed MOEHOA accomplish improved results over EHO Greedy (Pattnaik and Sahu, 2020) in terms of throughput. The primary cause is that MOEHOA has an extensive network lifespan, consequently, the base station obtains additional data packets. Table 6 shows the performance comparison for Throughput. Table 6, clearly shows that the throughput of the proposed MOEHOA attains the maximum throughput of 1.097 Mbps where EHO-Greedy (Pattnaik and Sahu, 2020) achieved 0.999 Mbps only.

Table 6: Performances of Throughput

Number of nodes	Throughput (Mbps)	
	Existing EHO-Greedy	Proposed MOEHOA
50	0.452	1.092
100	0.999	1.097
150	-	1.092
200	-	1.095

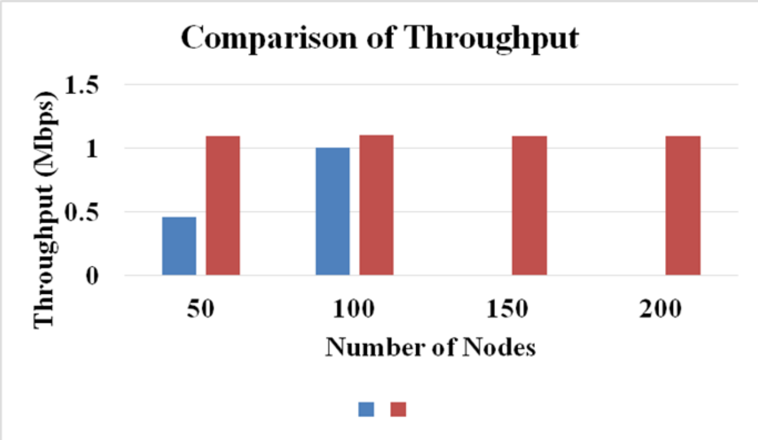

Fig. 6: Performance Analysis of Throughput

The overall simulation results indicates that the proposed MOEHOA provides better results in all the node count (50-200) when compared with the existing CDAS method.

4. Conclusion

In this research, MOEHOA is introduced for examination and a well-organized routing process is recognized on an optimization development. Here, the MFO is proposed with FF to attain the base station through less energy consumption. The suggested combination of MOEHOA is executed for a system dimension that extends the node counts from 50 to 200, where the energy efficiency would be revealed through the network that is examined through PDR, delay, residual energy, throughput and routing overhead. The simulated outcomes of MOEHOA are associated in contrast to traditional and cluster-dependent routing systems named CDAS. From this simulation outcomes, it designates that proposed MOEHOA overcomes the existing protocol systems in all characteristics by controlling the delay and normalized routing overhead up to7.5ms & 0.118949, similarly, achieves the residual energy as 13.4044 J, maximum PDR up to 0.997, and attains the maximum throughput of 1.097 Mbps respectively. In future, the proposed methodology can be analyzed with different specification parameters and a number of node counts also changed to a routing procedure that can attain better results in terms of energy consumption.

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