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Optimizing Energy Efficiency in Wireless Sensor Networks via Cluster-Based Routing and a Hybrid Optimization Approach

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ABSTRACT

Wireless Sensor Networks (WSNs) are increasingly deployed to survey various environmental conditions, finding applications across domains such as agriculture, healthcare, and environmental monitoring. The sensors within these networks are tasked with collecting data and transmitting it to a central sink node through wireless means. Given that the sensor nodes operate on battery power and are often situated in remote locations where maintenance poses logistical challenges, energy conservation emerges as a critical issue. This study introduces an Energy-based Multiobjective Hybrid Optimization Algorithm (E-MHOA), designed to optimize cluster-based routing protocols to enhance energy efficiency in WSNs. The proposed E-MHOA integrates the Cuckoo Search Algorithm (CSA) with the Whale Optimization Algorithm (WOA) to judiciously select Cluster Heads based on their residual energy levels. The primary focus of the E-MHOA is to facilitate improved energy efficiency and data delivery within the context of agricultural monitoring applications. An array of performance metrics, including energy efficiency, End-to-End Delay (EED), packet drop, and network throughput, were employed to evaluate the efficacy of the E-MHOA. Comparative analyses were conducted against existing methodologies, such as MWCSGA, PAwCOR, and CEELBRP. The results of the simulation show that the E-MHOA approach performs noticeably better than the MWCSGA in terms of energy efficiency, achieving a notable efficiency rate of 98.09% in networks comprising 100 nodes.

1. INTRODUCTION

Wireless Sensor Networks (WSNs) have garnered substantial interest due to their versatility in deployment and myriad applications [1]. These networks comprise an array of intelligent, multifunctional, low-power sensor nodes that interface with Base Stations (BS) to monitor and interact with the external environment [2, 3]. Sensor nodes are endowed with the capability to self-organize and collaborate, thus facilitating the establishment and maintenance of the network's infrastructure [4]. Each sensor, equipped with storage memory, a processor, and communication channels, undertakes the critical functions of data collection, processing, and transmission [5, 6]. The integration of embedded computing, distributed information processing, sensor technology, and communication technology has accelerated the use of WSNs in a variety of industries, including disaster relief, environmental monitoring, industrial manufacturing, armed forces, traffic management, and healthcare. [7, 8].

The longevity of sensor nodes is constrained by their reliance on non-rechargeable batteries. Despite the extensive utility of WSNs, they are impeded by limitations such as finite storage, battery life, and transmission range [9]. Consequently, energy efficiency is identified as the paramount objective within the WSN paradigm [10]. The current research focuses on developing a cluster-based routing protocol tailored for agricultural applications, where sensor technology underpins production optimization, cost management, and crop growth monitoring. These sensors measure critical agricultural parameters, including pressure, wind speed, temperature, and humidity, and are instrumental in predicting natural disasters and weather conditions [11, 12].

Energy-efficient routing protocols are essential for judicious energy utilization during packet transmission. Clustering-based routing protocols have been observed to outperform their non-clustering counterparts by mitigating energy losses due to idle listening, collisions, and over-hearing [13]. Within clusters, sensors, designated as Cluster Members (CMs), record environmental data and transmit it to their respective Cluster Heads (CHs). The CHs then aggregate and filter the data to reduce redundancy before forwarding it to the Base Station (BS) [14].

Previous methodologies have exhibited shortcomings, including suboptimal selection of fitness function parameters and reliance on single-hop data transfers. The suggested approach includes a fitness function that makes the choice of residual energy, proximity to the BS, and distance to neighboring nodes, thereby facilitating the selection of an optimal CH. This optimal CH selection is critical in reducing node energy consumption and achieving energy-efficient balance within the network [15].

The contributions of this research are as follows:

- Minimization of energy consumption in WSNs is achieved through K-means clustering and optimal CH selection, utilizing the Energy-based Multiobjective Hybrid Optimization Algorithm (E-MHOA). The E-MHOA amalgamates the Cuckoo Search Algorithm (CSA), with its superior global search capability through levy flight, and the Whale Optimization Algorithm (WOA), recognized for its efficiency with fewer parameters required for analysis.
- The E-MHOA is used to create an energy-efficient routing protocol that maximises multi-objective fitness functions, including energy, communication cost, node degree, and coverage.
- The development of an energy-efficient WSN enhances data delivery across the network.

The structure of this document is as follows: The relevant work on cluster-based routing in WSNs is reviewed in Section 2. Section 3 provides further details on the E-MHOA technique. Section 4 presents the E-MHOA approach's findings. The paper is finally concluded in Section 5.

2. RELATED WORK

Numerous research projects have been reported in the effort to advance cluster-based routing protocols in Wireless Sensor Networks (WSN). Zhao et al. [16] introduced a modified cluster head (CH) selection process inside the Low-Energy Adaptive Clustering Hierarchy (LEACH-M) architecture, which used the node's network address and residual energy to reduce energy usage. However, the crucial parameter of nodal distance was not factored into the CH selection process, representing a potential oversight for optimization.

Deepa and Suguna [17] proposed a Quality of Service (QoS)-oriented clustering and multipath routing protocol, leveraging a modified particle swarm optimization algorithm for cluster formation. A Single Sink-All Destination routing methodology was employed to identify optimal multihop paths to minimize transmission delay. Notwithstanding these advancements, the approach resulted in excessive energy burdens on CHs due to data broadcasting, thus raising concerns over energy sustainability.

In the specific context of precision agriculture, Pandiyaraju et al. [18] developed a Terrain based Routing using Fuzzy logic (TRF) to facilitate intelligent energy conservation. The TRF method determined terrain heads and relay nodes via fuzzy rules, extending network lifetime and preserving energy. Nonetheless, the analysis did not extend to data delivery metrics to the base station, leaving a gap in the assessment of routing efficacy.

The Grey Wolf Optimizer (GWO) was harnessed by Daneshvar et al. [19] for CH selection, ranking candidate solutions by the metrics of residual energy and energy expenditure. The protocol astutely circumvented superfluous clustering operations to conserve energy, with network lifetime emerging as a pivotal CH selection criterion.

Gateway Clustering Energy Efficient Centroid (GCEEC), routing strategy was introduced by Qureshi et al. [20], where CHs were chosen based on their centroid location, complemented by gateway nodes from each cluster. This method mitigated data load from CHs and streamlined broadcast to the base station, though it necessitated a refined selection of fitness measures for effective data packet transmission.

Ajmi et al. [21] released a Multi Weight Chicken Swarm-based Genetic Algorithm (MWCSGA) that gives clustering energy efficiency first priority. In order to reduce the amount of energy used during data transmission, the MWCSGA took into account both distance and energy as fitness functions.

However, the approach observed increased latency with network scaling, highlighting a limitation in the method's scalability.

Agarkhed et al. [22] presented the Precision Agriculture with Cluster Based Optimal Routing (PAwCOR), enhancing WSN performance by selecting CHs based on congestion, delay, and energy metrics. While this selection methodology reduced energy consumption, there was a necessity to minimize the communication range of cluster members to augment packet delivery rates.

Finally, Alghamdi [23] designed the Cuckoo Energy-efficient Load-Balancing On-Demand Multipath Routing Protocol (CEELBRP), which took nodes' residual energy into account to balance routing overhead. The goal of this protocol was to strike a balance between routing efficiency and energy saving.

Firdous et al. [24] created the PECR (Power-Efficient Cluster-based Routing) method to efficiently use limited energy sources. The network was clustered using the K-Means technique. Only the location and remaining energy were taken into account when choosing the CH, major CH, and route. Energy balancing between the nodes was not taken into consideration throughout the data transmission process, as the designed PECR was primarily focused on lowering the traffic to the CH.

Robinson et al. [25] Fuzzy logic (MLSEEP) was proposed by Robinson et al. [25] as a probability-based method for CH selection. Based on the probability values of the network's sensor nodes, CH are chosen. The nodes with the highest likelihood therefore stand a better chance of forming CH. Fuzzy Logic is used to transmit the data via multiple hop transmission.

It is observed that existing techniques grapple with challenges such as suboptimal selection of fitness function parameters and a reliance on single-hop data transfers. In order to overcome these constraints, a more advanced clustering strategy is required, one that includes a carefully customised fitness function that takes residual energy, base station distance, and node-to-node distances into account.

This comprehensive approach facilitates the selection of an optimal CH, instrumental in reducing nodal energy consumption. Moreover, the development of a multi-hop broadcasting mechanism within the WSN is proposed to identify the most efficient paths from source nodes to the base station via CHs, thereby circumventing the energy-intensive single-hop transmission models prevalent in previous methods. The proposed Energy-based Multiobjective Hybrid Optimization Algorithm (E-MHOA) is poised to optimize CH selection and facilitate a performance enhancement in WSNs through its strategic multi-hop routing methodology.

3. E-MHOA METHOD

An energy-efficient WSN is created using the E-MHOA technique in order to achieve dependable communication. Three crucial stages make up the E-MHOA method: routing path development, CH selection, and clustering. Here, E-MHOA is used to choose the best CH and route to raise the WSN's energy efficiency. By enhancing the E-MHOA approach with different fitness measures, including energy, communication cost, node degree, and node coverage, the WSN's data delivery is enhanced. The E-MHOA method's architecture is depicted in Figure 1.

3.1 K-means based clustering approach

The nodes are first randomly placed throughout the region of interest. After that, they are grouped using the K-means method, which divides the sensors into an arbitrary number of clusters. Given that the main factor influencing this K-means clustering is the Euclidean distance between the nodes.

One of the main goals of system design in WSN is energy optimisation.

The energy-model uses multipath fading (d^4 powerloss) or free space (d^2 powerloss) according to the distance between the transmitter and receiver. Eq. (1) expresses the energy used to transfer a data (qq) over a distance (dd):

$$E_{RX}\,(q,d) = \begin{cases} q \times E_{elec} + q \times E_{fs} \times d^2\,, d \leq d_0 \\ q \times E_{elec} + q \times E_{mp} \times d^4, d > d_0 \end{cases} \quad (1)$$

where the distance threshold is represented by the symbol d0, and E_{TX} is the amount of energy needed to transmit in free space and multipath, respectively, and is abbreviated as E_{elec} and E_{fs} and E_{mp} accordingly i.e., $d_{0=}\sqrt{\frac{E_{fs}}{E_{mp}}}$ Eq. (2) expresses the energy consumed by each node while receiving the data, is computed based on Eq. (3).

$$E_{RX}(q,d) = q \times E_{elec} \quad (2)$$

$$E_{consumed} = q \times E_{TX} + E_{RX} \quad (3)$$

where, $E_{consumed}$ defines the amount of energy that each network sensor uses. The network is first clustered, and then each cluster's optimal CH is chosen using E-MHOA.

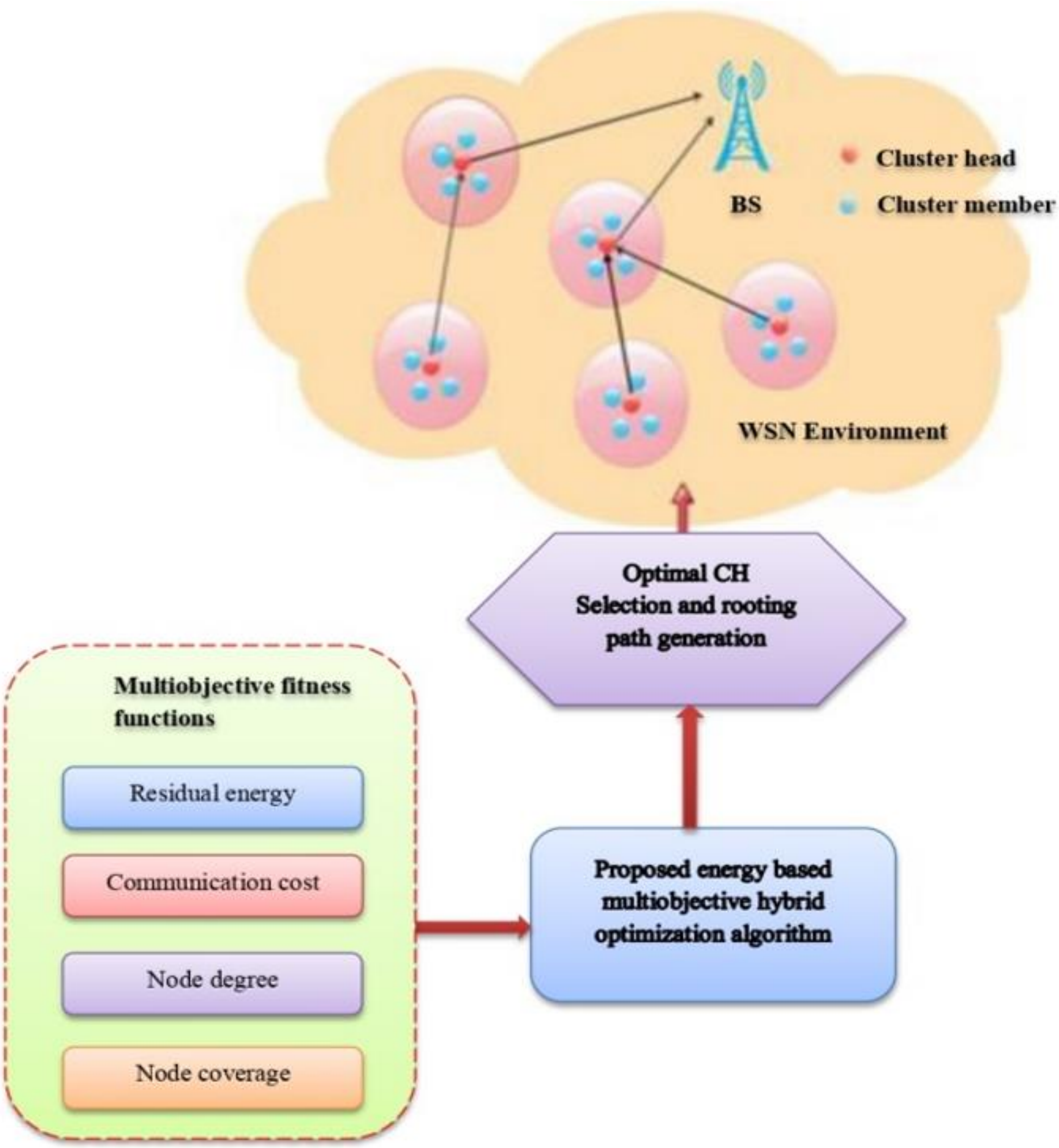

Figure 1. The architecture of the E-MHOA method

3.2 Multi-objective hybrid optimization technique based on energy

To increase energy efficiency, the best CHs from the clusters are chosen in this phase. Here, the E-MHOA with the best number of fitness functions are used to identify the optimal CHs. This hybrid algorithm, which combines WOA and CSA, is utilized for both routing and CH selection. CSA is typically an algorithm inspired by nature that replicates the cuckoo bird's reproductive cycle [26]. Furthermore, WOA imitates the humpback whales' intelligence-seeking behaviours, whereas the bubble-net feeding approach is used to describe the aging behaviour [27].

3.2.1 Multi-objective fitness function definition for E-MHOA

To improve the energy efficiency of the WSN, the best mix of distinct fitness functions, such as residual energy (ff_1), communication cost (ff_2), degree of node (ff_3) and node coverage (ff_4) in the E-MHOA are employed. E-MHOA's multi-objective fitness function is expressed as in Eq. (4):

$$Fitness=\beta_1\times ff_1+\beta_2\times ff_2+\beta_3\times ff_3+\beta_4\times ff_4 \tag{4}$$

where the weighted parameters $\beta 1$, $\beta 2$, $\beta 3$, and $\beta 4$ are employed to convert fitness scores from many targets into a single goal. The definition and formulation of these parameters are given as follows:

The proposed CH selection process utilizes a high er energy node as an optimal candidate while selecting the CH. The CH is required to have a better energy budget to balance the energy consumption because the CH has the responsibilities of cluster management and data aggregation from the CM. The residual energy of the CH is derived in Eq. (5):

$$ff_1=\sum_{i=1}^{m}\frac{1}{E_{CH_i}} \tag{5}$$

where m represents the total number of CHs in the WSN and E_{CH_i} represents the residual energy of the cluster head i.

Eq. (6) demonstrates the price needed to talk to nearby nodes:

$$ff_2=\frac{d_{avg}^2}{d_0^2} \tag{6}$$

where, d_{avg}^2 indicates the average separation between the node and its neighbor. and the d_0^2 denotes the radius of the node.

Node degree is the number of sensors that are accessible from the CH. This is utilized for balancing the load in the CH which is expressed in Eq. (7):

$$ff_3=\sum_{i=1}^{m}CM_i \tag{7}$$

where, an amount of cluster members in each cluster is denoted as CM_i.

Furthermore, network coverage is thought to increase the scalability of the network. The network coverage derived using the radius of the node is expressed in Eq. (8):

$$ff_4=\frac{1}{N}\sum_{i=1}^{N}r(N) \tag{8}$$

where, number of sensors in the WSN is N and radius of the sensors is defined as(N).

3.2.2 Working of E-MHOA based CH selection

E-MHOA combines the Cuckoo Search Algorithm and the Whale Optimization Algorithm to find the best CH. Using the fitness function, the CSA Algorithm finds the best solutions (i.e., the location of the CH). These best solutions are fed into WOA to identify the best CH. The working process of CH section is mainly comprised of two steps such as initialization and iterative process.

3.2.3 Initialization

Every solution in E-MHOA stands for a set of potential sensors that must be chosen to be CHs. Every solution has a dimension equal to the number of CHs. Here, a random node between 1 and N is used to initialize each solution location. Eq. (9) expresses the i^{th} solution of the proposed E-MHOA:

$$X_i=(X_{i,1}(t),X_{i,2}(t),\dots,X_{i,m}(t)) \tag{9}$$

where, each solution location $X_{i,l}$, $1\leq l\leq m$ denotes the node among the 1 and Nin the network.

3.2.4 Iterative process of E-MHOA

The iterative procedure for choosing the best CHs from the clusters uses the initial solutions as input. The following are the key guidelines taken into consideration by the CSA: 1) Every cuckoo lay single egg simultaneously and deposits it in a randomly chosen nest; 2). The best nests with better-quality eggs (i.e., ideal solutions) are passed down to subsequent generations; and 3) there is always a constant supply of host nests that can be accessed, and a host found the alien egg with a probability $P_a\in[0, 1]$. In that case, the host either throws the egg or leave the nest to construct the new nest in a new location. According to the aforementioned steps, the processes of the CSA is derived and given as follows:

A i-th cuckoo performs the Levy flight to create an updated location(t+1), which is expressed in Eq. (10):

$$X_i(t+1)=X_i(t)+\alpha\oplus Le\acute{v}y(\lambda) \tag{10}$$

where, the step size is denoted as$\alpha>0$; $X_i(t)$and $X_i(t+1)$ refers to the current and next position of the population; $\oplus$ denotes the entry wise multiplications. Moreover, the $Le\acute{v}y$ used in this E-MHOA is used for effective searching over the search space. An explorative random walk obtained using$Le\acute{v}y$flights is expressed in Eq. (11):

$$Le\acute{v}y\sim u=t-\lambda, 1<\lambda\leq 3 \tag{11}$$

where, λ is the parameter, which represents the average or expected occurrence of the event over the given time period. The best solutions from the CSA (i.e., locations of CH) derived using formulated fitness function are given as an input to the WOA to obtain optimal CHs. The best candidate solution from the CSA is considered as the target prey and the other solutions are tried to move towards the best solutions based on the Eqs. (12)-(13):

$$\vec{D}=\left|\vec{C}\cdot\vec{X}_b-\vec{X}(t)\right| \tag{12}$$

$$\vec{X}(t+1)=\vec{X}_b(t)-\vec{A}\cdot\vec{D} \tag{13}$$

where, the current iteration i-st; the location vector of optimal and another population are represented as $\vec{X}b$ and $\vec{X}$ respectively. Moreover, the $\vec{A}$ and $\vec{C}$ are the coefficient vectors which are expressed in Eqs (14)-(15):

$$\vec{A}=2\vec{a}\cdot\vec{r}_{(1-a)} \tag{14}$$

$$\vec{C}=2\cdot\vec{r}_2 \tag{15}$$

where, the random vectors among 0 and 1 are denoted as $\vec{r}_1$ and $\vec{r}_2$; the vector a is reduced from 2 to 0 according to the iterations. Next, the shrinking encircling, and spiral updating are done in the exploitation phase. Eq. (14) is responsible for the shrinking encircling approach. In spiral location updating, and updating approach is obtained by formulating the spiral expression as shown in Eq. (16) among the optimal solution and remaining solutions:

$$\vec{X}(\text{t+1})=\left|\vec{X}_b(t)-\vec{X}(t)\right|\text{ecr.cos}(2\pi r)+\vec{X}_b(t) \tag{16}$$

where, the distance between the best solution and the remaining solution is denoted as $\left|\vec{X}_b(t)-\vec{X}(t)\right|$; $c$denotes the constant value and the random number generated among $[-1,1]$ is denoted as r. The position updating process of WOA depends mainly on the random number generated during the searching process.

Further, the value of $\vec{A}$ decides whether the remaining solutions are going to process under the exploitation or exploration phase. The search agents accomplished the exploration in E-MHOA, when $\vec{A}\geq 1$; otherwise, it chooses the exploitation phase. The exploration of E-MHOA is shown in the Eqs. (17)-(18):

$$\vec{D}=\left|\vec{C}\cdot\vec{X}_{rand}(t)-\vec{X}(t)\right| \tag{17}$$

$$\vec{X}(t+1)=\vec{X}_{rand}(t)-\vec{A}\cdot\vec{D} \tag{18}$$

where, the randomly selected location vector from the current population is denoted as $\vec{X}$. The previously mentioned E-MHOA iterative procedure is carried out up to the point where it achieves the maximum number of iterations 100. The best way to handle E-MHOA is to employ CH, which collects data from regular nodes. Remaining energy, which is taken into account in the E-MHOA fitness function, is employed to prevent failure nodes, improving data delivery. By utilizing the communication cost, the data broadcasting distance is reduced, hence reducing energy consumption and delay. Energy balance between the nodes is accomplished by using the node degree. Moreover, the network's scalability is enhanced by the node coverage.

3.3 Working on E-MHOA based route discovery

Route discovery phase is started and carry out the routing after the CH selection. The control messages of AODV's, including route request (RREQ), hello (HELLO), route error (RERR), route reply (RREP), and are used in this route discovery process using E-MHOA. First, the source CH broadcasts the RREQ to its neighbouring CH nodes. The same fitness function that was employed in the CH section is now used to assess the routing path's fitness function. Subsequently, an ideal relay node, also known as the next-hop CH, transmits the RREP back via the reverse route. When the source sensor receives the RREP from the nearby nodes, the route discovery process is completed. During this route discovery phase, the RERR and HELLO messages are used to finish route maintenance. Once an ideal path has been found in the WSN, the data message packets are sent throughout the network. Agricultural applications can benefit from the dependable data transfer based on E-MHOA technology.

4. RESULTS AND DISCUSSION

This section displays the results of the E-MHOA method. Using the Network Simulator - 2.34 (NS-2.34), which runs on an i5 processor with 6GB of RAM, the E-MHOA method is implemented and simulated. Generally speaking, NS-2.34 uses two distinct programming languages, example C++ for the backend and TCL for the frontend. And the Network Animator displays the results of WSN node deployment (NAM). Additionally, trace files are used in the performance review process. Twenty, forty, sixty, eighty, and one hundred node simulations are used to study the E-MHOA technique. The network type is WirelessPhy, and the traffic source is CBR. The simulation time for E-MHOA is 100s. The simulation specifications of the E-MHOA method are provided in Table1.

Table1. Simulation specifications

Parameter	Value
Simulator	NS-2.34
Area	$1000m\times1000m$
Number of nodes	20,40,60,80and100
Initial energy	0.5J
Mac	IEEE802.11
Traffic source	CBR
Antenna pattern	Omni Antenna
Network interface type	WirlessPhy
Simulation time	100s

4.1 Performance analysis

The E-MHOA method's performance is examined using energy efficiency, EED, packet loss, and network throughput metrics. Here, MWCSGA is used to assess the E-MHOA method's performance analysis [21].

4.1.1 Energy efficiency

Energy efficiency is defined as the WSN's ratio of energy used to total energy intake, and it is represented in Eq. (19):

$$\text{Energy efficiency}=\frac{Consumed\ Energy}{Total\ Input\ Energy}\times 100\ \% \tag{19}$$

Figure 2 shows the comparison graph for the energy efficiency for MWCSGA [21] and E-MHOA method. From Figure 2, it is known that the energy efficiency of the E-MHOA is high when compared to the MWCSGA [21]. For example, the energy efficiency of the E-MHOA ranges from 90.52% to 98.09% whereas energy efficiency of the MWCSGA [21] ranges from 20% to 80%. To determine the quickest way and disperse load across the network, the E-MHOA takes into account both distance and node degree. Thus, the E-MHOA with the best possible collection of fitness functions increases the network's overall energy efficiency.

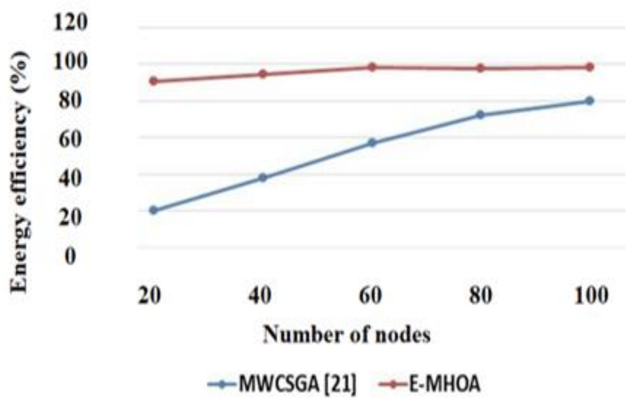

Figure 2. Graph for energy efficiency

4.1.2 End to end delay

EED, or the average data packet transmission duration over the network, is defined and represented in Eq. (20

$$EED = \frac{Sum\ of\ time\ taken\ to\ broadcast\ packet\ in\ BS}{Amount\ of\ packet\ received\ by\ BS} \quad (20$$

Figure 3 shows the EED comparison for the MWCSGA [21] and E-MHOA method. This EED analysis shows that the E-MHOA obtains a small delay than the MWCSGA [21]. For the instance, the delay of the E-MHOA ranges from 7.65ms to 16.25ms whereas the delay of the MWCSGA [21] ranges from 19ms to 100ms. The E-MHOA method achieves less delay because it uses only less amount of control messages during the route discovery phase due to its optimal set of fitness functions. Additionally, the shortest path identified using the E-MHOA method is also used to minimize the delay.

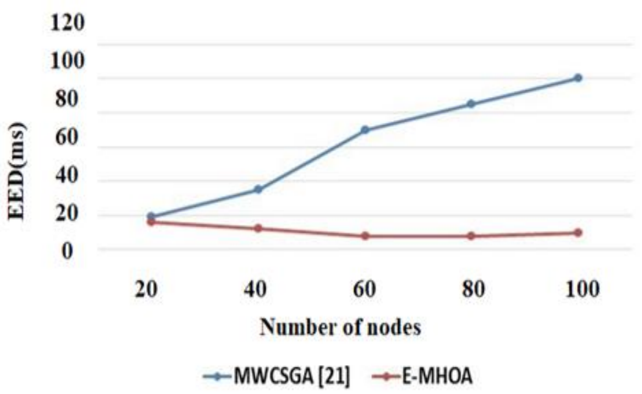

Figure 3. Graph for EED

4.1.3 Packet drop

Packet drop defines the amount of packet loss during the transmission. It is evident from Figure 4 that the E-MHOA has less packet drops than the MWCSGA [21]. For example, the packet drop of the E-MHOA ranges from 1 to 6 packets whereas the packet drop of the MWCSGA [21] ranges from 25 to 150 packets. The residual energy and node coverage considered in the E-MHOA are used to eliminate the node/link failure and improve the scalability of the WSN. Therefore, this helps to improve the data delivery of the E-MHO A which resulted in less packet drops.

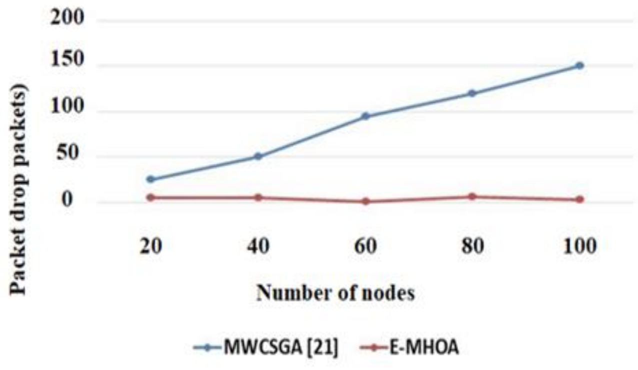

Figure 4. Graph for packet drop

4.1.4 Network throughput

The ratio of successful packets received by the BS to the packet transmission delay is known as network throughput, and it is represented as in Eq. (21):

$$Network\ throuahout = \frac{number\ of\ packets\ received}{Delay} \quad (21)$$

Figure 5 shows the network throughput comparison for the MWCSGA [21] and E-MHOA method. This network throughput analysis shows that the E-MHOA method achieves high throughput than the MWCSGA [21]. For example, the throughput of the E-MHOA ranges from 1359.11Kbps to 1373.15Kbps whereas the throughput of the MWCSGA [21] ranges from 35Kbps to190Kbps. The E-MHOA approach makes the network more energy efficient, it gets better throughput. The goal of the route discovery phase is to increase the successful data transfer to the base station (BS) by avoiding node and link failure.

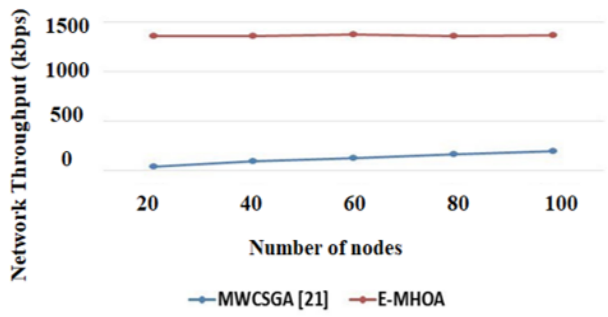

Figure 5. Graph for network throughput

4.2 Comparative analysis

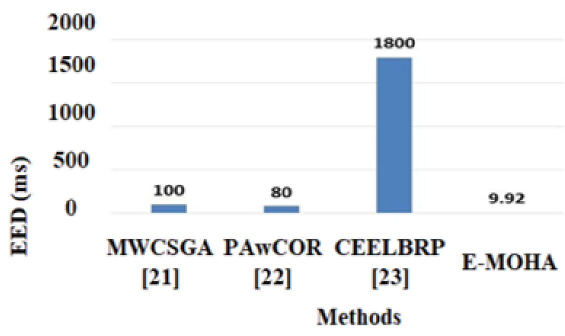

Figure 6. Comparison of EED

The effectiveness of the E-MHOA approach is shown by combining with modern methods like MWCSGA [21], PAwCOR [22], and CEELBRP [23]. Table 2 contrasts the MWCSGA and E-MHOA approaches. [21], PAwCOR [22], and CEELBRP [23], where values that were not available in those investigations are denoted by the term NA. Additionally, Figure 6 shows the EED graphically for the E-MHOA approach using CEELBRP [23], PAwCOR [22], and MWCSGA [21]. The E-MHOA approach performs better than the MWCSGA [21], PAwCOR [22], and CEELBRP [23], according to Table 2. The current body of research, including MWCSGA [21], PAwCOR [22], and CEELBRP [23], performs worse because it ignores the best set of fitness functions. But in order to create an energy-efficient WSN, the E-MHOA approach takes into account the residual energy, communication cost, node degree, and node coverage—the multi-objective fitness functions. Agricultural applications can make advantage of the developed E-MHOA based clustering and routing.

Table 2. Comparative analysis

Performances	**Methods**	**Number of Nodes**				
		20	**40**	**60**	**80**	**100**
Energyefficiency (%)	MWCSGA [21]	20	38	57	72	80
	E-MHOA	90.52	94.17	98.01	97.35	98.09
EED (ms)	MWCSGA [21]	19	35	70	85	100
	PAwCOR [22]	NA	NA	NA	NA	80
	CEELBRP [23]	NA	NA	NA	NA	1800
	E-MHOA	16.25	12.00	8.05	7.65	9.92
Packetdrop (packets)	MWCSGA [21]	25	50	95	120	150
	E-MHOA	5	5	1	6	3
Networkthroughput (Kbps)	MWCSGA [21]	35	90	120	160	190
	PAwCOR [22]	NA	NA	NA	NA	14
	E-MHOA	1361.92	1361.92	1373.15	1359.11	1367.54

5. CONCLUSIONS

To achieve dependable communication, an energy-efficient WSN is created in this study. Three crucial stages comprise this E-MHOA method: routing path development, CH selection, and clustering. Here, E-MHOA is used to choose the best CH and route in order to increase the WSN's energy efficiency. The WSN's data delivery is improved by honing the E-MHOA technique using particular fitness criteria, such as residual energy, communication cost, node degree, and node coverage. The E-MHOA takes into account communication costs for determining load distribution over the network and the quickest way. As a result, the E–MHOA with the best possible combination of fitness functions raises the network's total energy efficiency. In comparison to the MWCSGA, the E-MHOA method has a high energy efficiency of 98.09% for 100 nodes. The new optimization algorithm may be applied in the future to raise WSN performance.

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