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RESEARCH ARTICLE

Energy Efficient Cluster Based Routing Using Multiobjective Improved Golden Jackal Optimization Algorithm in Wireless Sensor Networks

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Abstract – In recent decades, the Wireless Sensor Networks (WSNs) have played a prominent role in different fields because of cost efficiency and energy efficiency. However, sensor nodes deployed in WSNs are generated by batteries which may drain all their energy after a certain period. The process of clustering assists in enhancing network lifespan thereby minimizing an energy consumption. A lifetime expectancy of WSNs can be improvised by selecting the optimal Cluster Head (CH) and optimal shortest path to transmit data packets. A maintenance of energy efficiency in WSN is a challenging process due to constrained sources that cannot be operated for a longer time. So, this research focuses on energy efficiency and introduces the Multiobjective Improved Golden Jackal Optimization Algorithm (MIGJOA). The MIGJOA helps to choose CHs and optimal routing path to transmit data. A fitness objectives like the distance among neighbor node and Base Station (BS), distance between BS and CH, node degree, and mean node energy are employed as fitness functions to select optimal CHs. The efficiency of the suggested technique is assessed with Adaptive Blackhole Tuna Swarm Optimization (ABTSO), Hybrid African Vultures Cuckoo Search Optimization (HAVCSO), Butterfly Optimization Algorithm-Ant Colony Optimization (BOA-ACO) based on alive nodes, normalized energy and consumption of average energy. The alive nodes of proposed approach when a number of rounds is 2500 is 97 whereas the alive node count in the existing BOA-ACO is 89.

Index Terms – Cluster-Based Routing, Multi-Objective Improved Golden Jackal Optimization, Energy Efficiency, Life Expectancy, Wireless Sensor Network.

1. INTRODUCTION

A Wireless Sensor Network (WSN) refers to sensor group node that are grouped uniformly in space to record and monitor the factors that take place in the physical environment and organize the data in centralized sites [1,2]. The WSNs are primarily employed in different applications like weather forecasting, agriculture, and industrial applications [3]. The architecture of WSN is on the basis of parametric such as scalability, power efficiency, and stability. The sensors act like repeaters that receive data then convert it from analog to digital form and transmit it to another node and Cluster Heads (CHs). Implementing energy efficiency in the sensor nodes of WSN is a difficult task due to energy-constrained sources which are operated independently for a long time duration [4,5]. The non-rechargeable nodes can be stimulated by replacing the battery but it is cost expensive and time-consuming process [6]. The short span of battery life in WSN leads to exceeded energy consumption so maintaining energy efficiency in WSN remains a challenging issue [7]. The energy efficient algorithms help to diminish energy consumption and improves network life span.

The usage of hierarchical and routing techniques in WSN routing protocol tends to enhance network efficiency by minimal consumption of energy [8]. In a scenario related to hierarchical routing protocols, nodes of sensor are categorized

RESEARCH ARTICLE

into various clusters and all cluster selects an effective node to rely on CH whereas the remaining nodes act as cluster members [9,10]. The transmission of data packet to BS requires high amount of energy to detect the optimal route, so designing an energy-efficient routing protocol is the major factor while designing WSNs [11,12]. Load balancing and reliable data transfer support to maintain energy efficiency during the transmission of data packet from CH to BS [13]. An optimization-based clustering techniques perform one-hop communication among CH members to increase energy efficiency and lifespan [14,15]. Most of the existing research does not provide an optimal solution to minimize energy consumption. So, this research introduced an optimization-based routing protocol which is developed based on multi-objective functionalities to choose CH and optimal route for data transmission.

The primary findings of this research are explained below:

1. The Multiobjective Improved Golden Jackal Optimization Algorithm (MIGJOA) is utilized in the process of choosing optimal CH in WSN because of minimal computational complexity and higher stability. This research utilized MIGJOA to choose CHs based on the distance among a neighbor node and BS, distance among BS and CH, mean node energy, and node degree.
2. Moreover, MIGJOA was employed to choose shortest routing path among CH to BS using fitness functions such as distance between BS and CH, residual energy, and the node degree.
3. A network lifespan is enhanced due to energy-efficient CH and optimal selection routing path using MIGJOA. Moreover, data packet count at BS improves with minimal energy consumption.

This manuscript is structured as follows: Section 2 determines related works based on energy-efficient routing protocol using optimization techniques in WSNs. Section 3 presents the details related to the process involved in the proposed methodology to select the CH and optimal routing path. Section 4 determines experimental outcome and overall conclusion is presented in Section 5.

2. RELATED WORKS

Recent research is presented in this section based on energy efficient routing protocols using optimization techniques in WSNs.

R. Sheeja et al [16] have introduced Adaptive Blackhole Tuna Swarm Optimization (ABTSO) for energy-efficient routing in WSNs. ABTSO maximizing lifespan and throughput. However, CH with higher cluster members requires additional energy in shorter period. A. Asha et al [17] have introduced Hybrid African Vultures-Cuckoo Search Optimization (HAV-CSO) for multi-objective derived energy routing in WSN. HAV-CSO selects optimal CHs to improve the network life span. The integration of African vulture with cuckoo search achieved better performance by rectifying multiobjective parametric and improvising the transmission rate. Moreover, the suggested HAV-CSO enhances the efficiency of the system by choosing the best routing path to broadcast data packets. However, enlargement of node count leads to path loss which affects the overall transmission rate.

Ambareesh Srinivasa Gowda and Neela Madheswari Annamalai [18] have introduced Hybrid Salp Swarm Firefly (HSSFF) for effective routing in WSNs. HSSFF chooses the shortest route with reduced delay by considering the multi-objective approach to diminish the issues relied on in routing. The suggested approach achieved the least delay and low expected transmission count by detecting the shortest path. However, residual energy was higher at the initial rounds and the convergence issue of the HSSFF degrades the efficiency while routing. C. Jothikumar et al [19] have introduced Optimal Cluster Based Routing (O-CBR) to enhance the lifespan of WSNs. The O-CBR utilized a k-means algorithm for cluster node and multi-hop routing. An clustering stage takes place till two-thirds of nodes were dead and remaining stage will be based on data transmission. CH obtains pockets from cluster members and transmit them to BS. O-CBR performs multi-hop routing to enrich the energy efficiency and network lifespan. However, the Optimal CBR is suitable only for shorter distances and it is not scalable for large networks.

Prachi Maheshwari et al [20] developed an energy-efficient cluster based routing using Butterfly Optimization Algorithm (BOA) in WSN. An optimal route between BS and CH was detected with the help of Ant Colony Optimization (ACO) which considers residual energy, node degree, and distance. The CH selection from node group takes place by considering fitness functionalities. At the time of simulation, the position of the BS varied from inside and outside for evaluating developed method efficiency. However, BOA experiences inequality between stages of exploration and exploitation due to the computational cost of BOA. Shivaraj Sharanabasappa Kalburgi and M. Manimozhi [21] introduced a Taylor-Spotted Hyena Optimization (T-SHO) algorithm for energy efficient CH selection and routing in WSN. The optimal CH selection was performed using distance, delay, and energy. The routing is employed using modified k-Vertex Disjoint Path Routing (mod-k VDPR) by utilizing reliability of the link and throughput. Finally, route maintenance takes place for monitoring packet delivery and inform as link failure.

S. Ramalingam et al [22] have developed an effective clustering and routing in WSN using fuzzy with Adaptive Sailfish Optimizer (ASFO) and Improved Elephant Herd Optimization (IEHO) to identify clustering and routing path. The fuzzy logic was utilized in clustering and ASFO was utilized in CH to consider efficiency of energy as primary

RESEARCH ARTICLE

factor. A suggested framework detects the shortest routing path which helps in diminishing the energy consumption and delay. However, the IEHO utilized in identifying the routing path is computationally expensive. Shaha Al-Otaibi et al [23] have developed K-medoids with sunflower based energy efficient clustering and cross layer based routing in WSN. The sunflower optimization approach helps to provide opportunistic routing protocol thereby minimizing consumption of energy and balancing between a nodes. K-medoids and sunflower optimization helps to distinguish best medoids and offers optimal clustering. The suggested methodology offers energy efficiency and helps to enhance the network life span. However, lengthy convergence time was experienced due to evaluation of objective function for individual particle.

Sengathir Janakiraman [24] developed a multi-objective Hybrid Bald Eagle Search Optimization Algorithm (HBESAOA) for energy efficient clustering to enhance the network lifespan. HBESAOA was comprised of a balanced exploration and exploitation that ensured potential search process at the time of CH selection. The developed approach diminishes the probability of achieving maximal diversity. However, the suggested framework applies the sink mobility of perform single-hop communication which results in imbalance in energy consumption. Rajeswarappa Govardanagiri and Vasundra Sanjeevulu [25] have developed Hybrid Grasshopper and Improved Bat Optimization Algorithm (HGIBOA) based CH to improvise energy efficiency and life span for sustaining in WSN. An exploration ability of HGIBOA was enhanced using the Levy flight technique. The random strategy is introduced to offer high quality population with enhanced potentiality of exploitation. However, the network scalability was limited because of single hop communication among the CH and BS.

2.1. Problem Statement

The existing routing approaches faced issues related to poor selection of routing path with extended delay, higher consumption of energy and poor delivery of packets. Moreover, inappropriate path maintenance results in poor packet delivery with packet losses. By considering these drawbacks, this research proposed an effective routing protocol utilizing MIGJOA.

A summarized table of existing techniques which presents the method used, their advantage and disadvantage is listed in table 1.

Table 1 Summarization of Existing Techniques

Author	Methods	Advantages	Disadvantages
R. Sheeja et al [16]	ABTSO for energy-efficient routing in WSNs	The ABTSO’s multi-objective functions maximize the network throughput and life span	CH with higher member of cluster requires additional energy in a shorter period
A. Asha et al [17]	HAV-CSO for multi-objective derived energy routing in WSN	HAV-CSO enhances the efficiency of the system by choosing the best routing path to broadcast data packets.	Enlargement of node count leads to path loss which affects the overall transmission rate.
Ambareesh Srinivasa Gowda and Neela Madheswari Annamalai [18]	HSSFF algorithm for effective routing in WSNs	The suggested approach achieved the least delay and low expected transmission count by detecting the shortest path.	Residual energy was higher at the initial rounds and the convergence issue of the HSSFF degrades the efficiency while routing
C. Jothikumar et al [19]	O-CBR to enhance the lifespan of WSNs	O-CBR performs multi-hop routing to enrich the energy efficiency and network lifespan.	However, the Optimal CBR is suitable only for shorter distances and it is not scalable for large networks.
Prachi Maheshwari et al [20]	Energy-efficient cluster based routing using BOA in WSN	BOA considered multi-objective fitness functions while selecting optimal path in WSNs	BOA experiences inequality between stages of exploration and exploitation due to the computational cost of BOA
Shivaraj Sharanabasappa Kalburgi and M. Manimozhi [21]	T-SHO technique for energy-efficient CH selection and routing in WSN	Mod-k VDPR offers reliability of the link and throughput	The path failure occurs while evaluating the proposed method

RESEARCH ARTICLE

S. Ramalingam et al [22]	Effective clustering and routing using ASFO and IEHO in WSN	The suggested framework detects the shortest routing path which helps in diminishing the energy consumption and delay.	However, the IEHO utilized in identifying the routing path is computationally expensive
Shaha Al-Otaibi et al [23]	K-medoids with sunflower based energy efficient clustering and cross layer based routing in WSN	The suggested method offers energy efficiency and helps to increase network life span.	Lengthy convergence time was experienced due to evaluation of objective function for individual particle
Sengathir Janakiraman [24]	HBESAO for energy efficient clustering to enhance the lifespan of the network	The suggested method diminishes the probability of achieving maximal diversity with premature convergence issues.	The suggested framework applies the sink mobility of perform single-hop communication which results in unexpected imbalance in energy utilization
Govardanagiri and Vasundra Sanjeevulu [25]	HGIBOA based CH selection to improvise the energy efficiency and life span to sustain energy efficiency in WSN	An exploration ability of HGIBOA was enhanced using the Levy flight technique	The scalability of the network is limited due to single hop communication among the CH and BS

3. MIGJOA-BASED ROUTING IN WSN

This research developed MIGJOA to perform cluster-based routing for minimizing energy consumption and enhance network's life span. The parameters such as sensor position, selection of energy-efficient CHs, and generating cluster-based routing act as significant factors while implementing MIGJOA in selecting an optimal path. This MIGJOA selects optimal CHs and the shortest routing path to transmit the data packets which considers energy efficiency and lifespan as the major factors. The fitness functions such as distance between neighboring nodes, residual energy, distance between BS and CHs, node degree, and mean node energy are considered while selecting the optimal routing path. The workflow takes place in optimization-based clustering and routing using MIGJOA is presented in Figure 1 as follows:

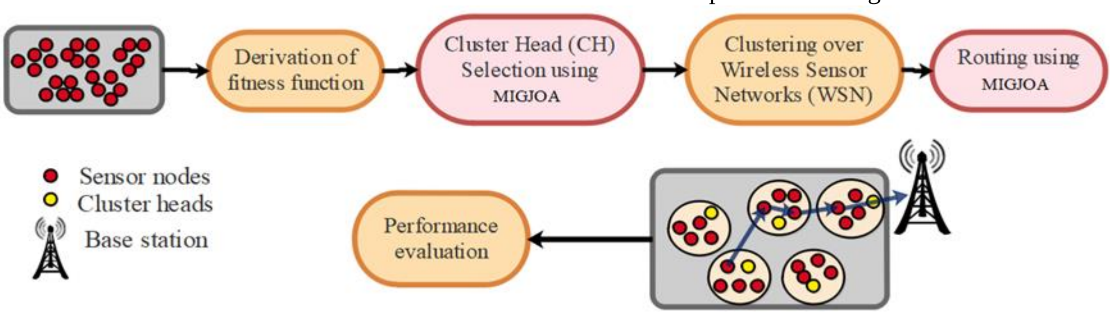

Figure 1 Workflow in Cluster-Based Routing Using MIGJOA

3.1. Energy Model

In this research, first-order radio approach is used for evaluating energy from transmitter to receiver. Energy consumption is utilized to transfer and gather data packets p over distance d is mathematically formulated in equations (1) and (2) correspondingly

$$E_T(p,d) = \begin{cases} p \times E_{elec} + l \times \varepsilon_{fs} \times p^2 \; if \; d \leq d_0 \\ p \times E_{elec} + l \times \varepsilon_{mp} \times p^4 \; if \; d > d_0 \end{cases} \quad (1)$$

$$E_R(p,d) = p \times E_{elec} \quad (2)$$

Where the energy quantity in transmitter and receiver is denoted as E_{elec} and threshold distance is represented as d_0 and the value of d_0 is represented using equation (3)

$$d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}} \quad (3)$$

Where the energy of the model in the free space and multipath denotes ε_{fs} and ε_{mp} respectively.

3.2. Initializing the Sensors

It is a foremost stage where WSN nodes are employed randomly by selecting optimal CHs using MIGJOA. When the CH is selected from the network, the formation of the cluster takes place and an optimal path from CH to BS is detected utilizing MIGJOA. The overall process takes place in selection CH and the shortest routing path is explained in the following sections.

3.3. Selection of Optimal CH Using MIGJOA

The MIGJOA introduced in this research was used in optimal CH selection from the sensor nodes. The existing Golden Jackal Optimization Algorithm (GJOA) [26] depending on search ability and hunting behavior but it faced issues related to the number of undesirable characters like poor convergence, trapped in the local solutions that tend to minimize the exploration ability. So, this research utilized MIGJOA for CH maintenance to help in replacing dead nodes by considering energy-efficient clusters as CHs.

3.3.1. Iterative Process Involved in MIGJOA

The iterative process that takes place in MIGJOA is based on exploration and exploitation along with opposition-based learning. The exploration stage is based on the search ability of the jackal and the exploitation stage is based on jackal's hunting behavior. The process involved in stages of exploration and exploitation along with opposition-based learning is described below.

- Stage of Exploration: Jackals identify and track the prey but they escape from being caught so they take time and search for their new prey. At the time of the hunting process, the male jackals perform lead, and female ones tend to follow them, this behavior is mathematically represented in equations (4) and (5).

$$Z_1(t) = Z_M(t) - E|Z_M(t) - rl \times prey(t)| \quad (4)$$

$$Z_2(t) = Z_M(t) - E|Z_F(t) - rl \times prey(t)| \quad (5)$$

Where iteration in the present state is represented as t and the position vector is represented as $prey(t)$. A male and female jackal position is denoted as $Z_M(t)$ and $Z_F(t)$ respectively. E denotes energy exhibited by the prey is represented in equation (6):

$$E = E_1 \times E_0 \quad (6)$$

Where initial energy and the decreasing phase is denoted as E_0 and E_1 which is represented in equation (7) and (8) as follows:

$$E_0 = 2 \times r - 1 \quad (7)$$

$$E_1 = c_1 \times \left(1 - \left({}^{t}/_{T}\right)\right) \quad (8)$$

Where r denotes random number lies among the range [0,1] and constant value indicates c_1. The iteration in the current state and maximum iteration are denoted as t and T correspondingly.

- Stage of Exploitation: In this stage, the capability of the prey to escape from the jackal will be diminished. The pair of jackals encircle the prey and their activity of hunting prey with male and female jackals is represented in equations (9) and (10) as follows:

$$Z_1(t) = Z_M(t) - E.|rl.Z_M(t) - prey(t)| \quad (9)$$

$$Z_2(t) = Z_F(t) - E.|rl.Z_F(t) - prey(t)| \quad (10)$$

Where the factor rl is responsible for producing random behavior during the stage of exploitation which emphasizes exploration and avoids local optima.

3.3.2. Integrating Opposition Based Learning in GJOA

In this section, a brief description of IGJOA which is the combination of GJOA with opposition-based learning is explained to improve the searching ability and enhance the accuracy in detecting the optimal solution. The IGJOA integrates the opposing value that covers search area based on probable solutions. IGJOA is based on two stages such as initialization and updating the new generation.

- Initialization: At the initial stage, the original population $Z_0 = \{z_{i1,}z_{i2}, \dots, z_{ij} \dots z_{iD}\}$ is created arbitrarily in a search region, where $i = 1,2,3, \dots NP; j = 1,2, \dots D$, the dimension is represented as D and the size of the population of represented as NP. The opposition based learning strategy is considered and the opposition jackal is produced based on the equation (11) as follows:

$$\bar{Z} = L + U - Z \quad (11)$$

Where the real and the opposite position vector is represented as Z and $\bar{Z}$. Upper and lower bound values are represented U and L. After this, original and actual position is integrated as a single group. Then, select best solution from population size NP in the range $\{Z_i, \bar{Z}_i\}$.

- Stage of update: The search for an optimal outcome using male and female jackals is identified and these two jackals are considered as the fittest one. The convergence of GJO takes place quickly but it easily falls into the local optima due to poor searching ability. So, this research utilized opposition-based learning to create new jackals with a probability of P_r and the random assessment among 0 and 1 is generated. When it is less than P_r, opposition-based learning technique is utilized to acquire new jackals based on the prevailing population. It acts as a mutation factor that prevents the technique from falling to a local optima and enhances its ability to explore. The algorithm 1 of MIGJOA is presented below:

1. Initialize position of the prey Z_0 in a randomized search space
2. Fitness value is evaluated for each prey
3. Choose the best prey (Z_1) and second best one (Z_2)
4. Initialize population based on opposition learning
5. Fitness function is evaluated for range $\{Z_{0,}\bar{Z}\}$
6. Choose an optimal fittest solution from $\{Z_i, \bar{Z}_i\}$ to create a position for prey
7. while $t <$ maximum iteration

for each prey
Update the energy
    Update arbitrary vector rl
        if $((E) < 1)$
            Update position of the prey
        else $((E) \geq 1)$
        Update position of the prey
        end
    end
end
        if $rand < P_r$
Create position of the prey
Fitness function is evaluated for range $\{Z_{0,}\bar{Z}\}$
Choose the fittest solution in the range $\{Z_{0,}\bar{Z}\}$
$t = t + 1$
end

Algorithm 1MIGJOA

3.4. Derivation of Multi-Objective Fitness Function for MIGJOA

The multi-objective functionalities like distance among neighbor node and BS (f_1), distance between BS and CH (f_2), mean node energy (f_3) and node degree (f_4) are considered as the fitness functions to select the optimal CHs. Among the considered fitness, the node energy is considered as the major fitness which helps in maintaining the energy efficiency while transmitting information among WSNs. The mathematical expression for the mentioned fitness function utilized in procedure of selecting CH using MIGJOA is represented in equation (12) as follows:

$$F_{CH} = \alpha_1 \times f_1 + \alpha_2 \times f_2 + \alpha_3 \times f_3 + \alpha_4 \times f_4 \qquad (12)$$

Where the weighted values are allotted to f_1, f_2, f_3 and f_4 is denoted as $\alpha_1, \alpha_2, \alpha_3$ and α_4. The description of the aforementioned fitness functions is represented as follows:

A distance among neighbor nodes and CHs is a primary fitness function while selecting optimal CH. Whenever the distance among the neighboring nodes is minimal, the consumption of energy will also be diminished. It is represented in equation (13):

$$f_1 = \frac{d(i,j)}{R} \qquad (13)$$

Where the distance between neighboring nodes is denoted as $d(i,j)$ and neighborhood radius is denoted as R.

Secondly, the distance between BS to CH is chosen as a fitness function and it is stated as the total distance taken for transmitting packets from source to BS. When transmission distance becomes higher, the energy consumption will also become higher. However, the proposed MIGJOA selects the optimal path and helps to reduce the transmission distance which is evaluated based on the equation (14) as follows:

$$f_2 = \sum_{i=1}^{m} dis\,(H_i, D) \qquad (14)$$

Where D represents node destination, $dis(H, D)$ indicates distance among ith node in cluster H and destination.

Thirdly, mean node energy is considered to calculate the fitness function. The mean node degree is defined as the average energy level across node in network which provides sustainability to WSN. A mean node energy is evaluated using the equation (15) as follows:

$$f_3 = \frac{1}{CM} \sum_{i=1}^{CM} E_i \qquad (15)$$

Where E_i determines energy used by the sensor and the cluster member is indicated as CM.

Node degree is considered as the final fitness function which is used to select CH. The node degree is stated as amount sensor nodes that belong to respective CHs. A CH with minimal amount of sensors is chosen because higher cluster members lose energy in a less period. A node degree is computed based on equation (16) as follows:

$$f_4 = \sum_{i=1}^{m} I_i \qquad (16)$$

Where the overall sensor nodes in CH is represented as I_i.

The fitness functions which are described above are utilized to choose optimal CHs. The remaining fitness values are utilized to detect the CH with shorter distances and less number of hops. This is utilized to minimize the consumed energy thereby enhancing the life expectancy of the network.

3.5. Stage of Clustering

When the CH selection is performed using MIGJOA, the ordinary nodes of sensor are assigned to well-suited CHs. The factors depending on energy and distance are used as potential functions (S) based on (17)

$$S = \frac{E_{C\,H}}{dis\,(S,CH)} \qquad (17)$$

Where the remaining energy present in the CH is represented as $E_{C\,H}$

3.6. Selection of Shortest Routing Path Using MIGJOA

Next to the stage of choosing optimal CHs, the optimal route is identified to transfer the data packets with minimal loss and delay. This research utilized MIGJOA to select the shortest routing path and help achieve better energy efficiency. The fitness-like distance between BS and CH(f_1), residual energy (f_2), and the node degree (f_3) are used for detecting a shortest routing path. Residual energy is known as retained energy after the accomplishment of transmitting data packets. Node with an large number of residual energy is taken and intermediate nodes are used to transfer and receive the data packets among nodes which is evaluated based on equation (18).

RESEARCH ARTICLE

$$f_2 = \frac{E_{max} - E_i}{E_{max} - E_{min}} \quad (18)$$

Where individual node's residual energy in WSN is denoted as E_i.

The steps comprised in detecting shortest routing path using MIGJOA are listed below:

1. The population of jackals is adopted with the possible route between CH and BS which is based on the amount of relay nodes.

2. Next to the exploration and exploitation of MIGJOA, the fitness value of the path gets updated which is detailed in previous sections. Evaluation of the routing path based on the aforementioned fitness functions is mathematically represented in equation (19).

$$F_R = \delta_1 \times f_1 + \delta_2 \times f_2 + \delta_3 \times f_3 \quad (19)$$

Where the weighted parameters of the fitness function f_1, f_2 and f_3 is denoted as δ_1 , δ_2 and δ_3 respectively. Thus, MIGJOA considered the aforementioned fitness functions to select the optimal routing path for data transmission.

4. RESULT AND ANALYSIS

Here, the detailed analysis of outcome achieved while evaluating MIGJOA. The efficiency of MIGJOA is simulated in MATLAB R2020b with 16 GB RAM, an i7 processor, and Windows 11 operating system. The MIGJOA helps to achieve consistent transmission of data in a network. A simulation parameters which are considered in this research are described in Table 2 as follows:

Table 2 Simulation Parameters

Parameter	Values
Size of network	200m × 200m
Number of nodes	50, 100
Location of BS	80 × 80
Initial energy	0.5 J
Packet size	4000 bits

4.1. Performance Analysis

Initially, proposed MIGJOA is estimated with conventional techniques like Low Energy Adaptive Clustering Hierarchy (LEACH), Distributed Energy-Efficient Clustering (DEEC), Threshold-Based Distributed Energy-Efficient Clustering (TDEEC) and Centralized LEACH (CLEACH). The simulation of those classical techniques is implemented in a similar simulation environment to the proposed MIGJOA. The efficacy of MIGJOA is computed using the number of alive nodes, dead nodes, packet loss ratio, energy consumption, life expectancy, and network throughput.

4.1.1. Alive Nodes

The number of alive nodes is evaluated depending on amount of nodes which can perform data transmission in WSN. An evaluation of alive nodes of MIGJOA is evaluated with different node counts of 50 and 100. The alive node evaluation for node count of 50 and 100 is evaluated with existing LEACH, DEEC, TDEEC, and CLEACH which is presented in Figure 2 and Figure 3 respectively. The efficiency of MIGJOA in retaining more alive nodes is due to the energy balancing which is achieved by optimal selection of CH and node degree. Moreover, MIGJOA helps to detect the short optimal path to transmit the data packets.

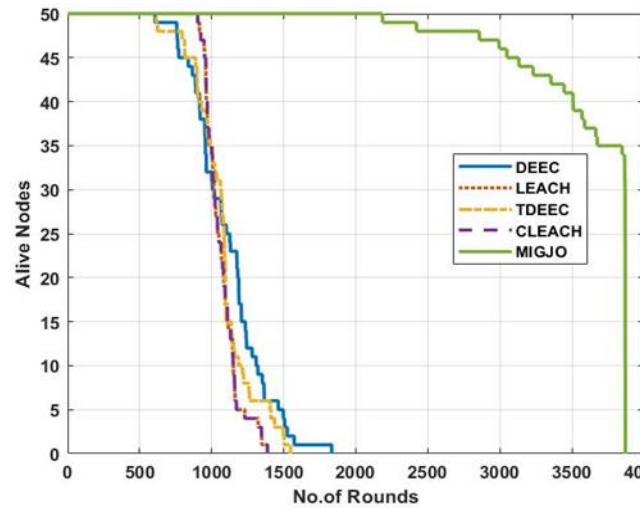

Figure 2 Alive Node for 50 Node Count

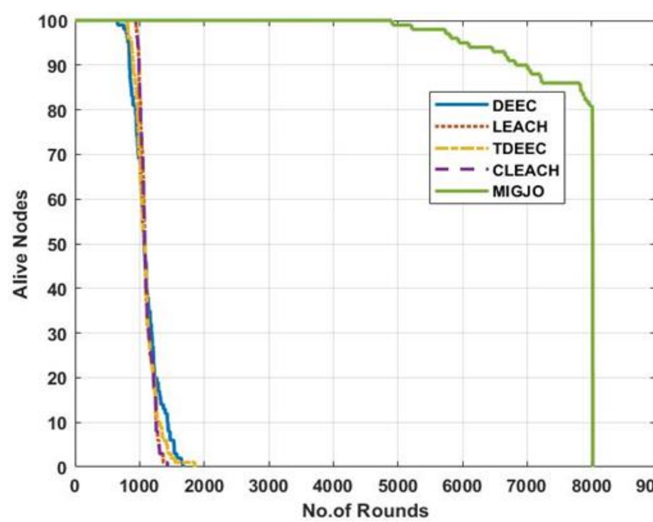

Figure 3 Alive Node for 100 Node Count

4.1.2. Dead Nodes

A total count of dead nodes are based on nodes in which the energy got depleted when transmitting a packets of data in

RESEARCH ARTICLE

WSN. An evaluation of dead node for node counts of 50 and 100 exhibited by MIGJOA while transmitting data packets is represented in Figure 4 and Figure 5 respectively. The dead node evaluation for node counts of 50 and 100 is evaluated with existing LEACH, DEEC, TDEEC, and CLEACH. The better result of MIGJOA is due to its efficiency in selecting the optimal CH and identifying an optimal routing path to transmit the data.

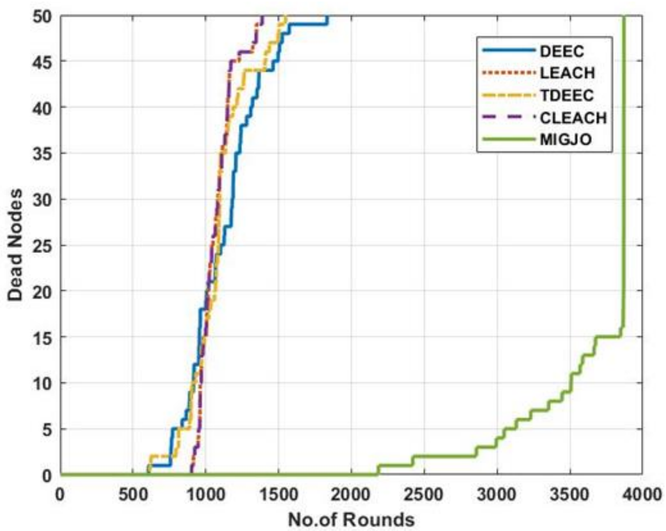

Figure 4 Dead Node for 50 Node Count

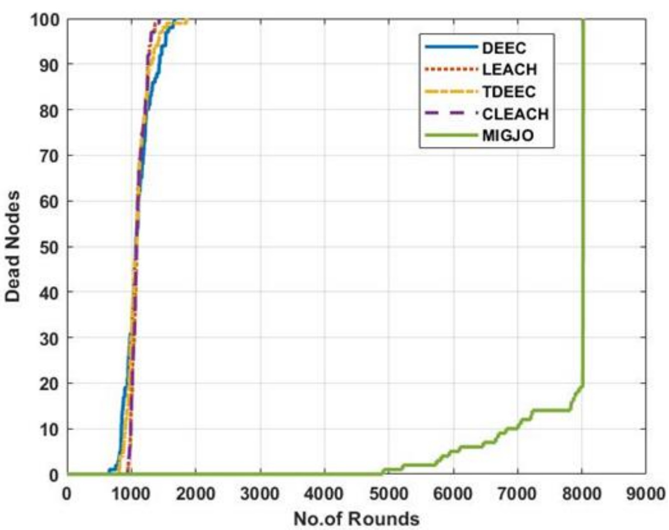

Figure 5 Dead Node for 100 Node Count

4.1.3. Energy Consumption

It is stated as total energy consumed while transmitting packets of data from CH to BS. Moreover, energy consumption is considered one of the primary metrics that is used access efficiency of framework. The energy consumption of MIGJOA for 50 and 100 node counts are evaluated with classical techniques such as LEACH, DEEC, TDEEC and CLEACH. Figure 6 and figure 7 presented below show the results obtained while evaluating the energy consumption rate of MIGJOA for 50 nodes and 100 nodes respectively.

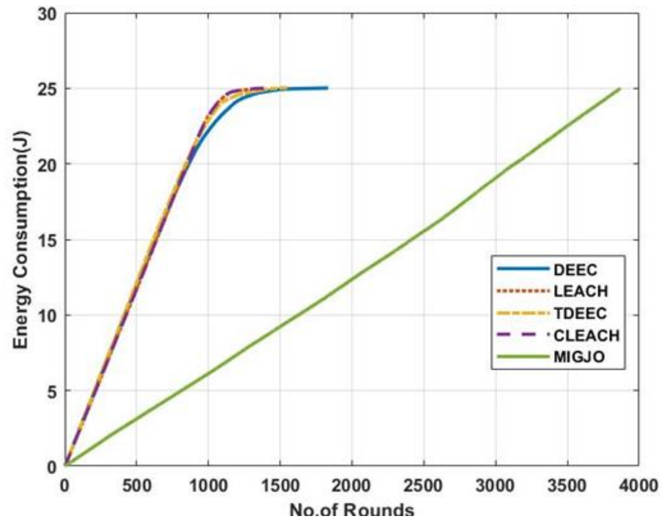

Figure 6 Energy Consumption for 50 Node Count

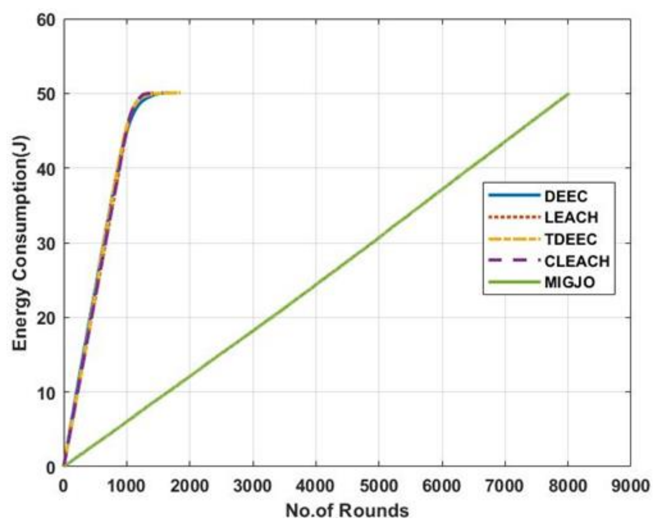

Figure 7 Energy Consumption for 100 Node Count

The results from Figures 6 and 7 indicates that MIGJOA achieved better energy consumption rather than the classical approaches and this is due to its efficiency in detecting the optimal CHs with minimal hops depending on BS position which decrease an energy usage of while transmitting data packets.

4.1.4. Life Expectancy

It is a time interval between deploying initial node and death of the last node. The life expectancy is evaluated based on three metrics such as First Node Death (FND), Last Node

RESEARCH ARTICLE

Death (LND), and Half Node Death (HND). FND is the first node that depletes the fullest energy, HND is the half of the node count which depletes the fullest energy and LND represents all nodes that exhaust an energy. A life expectancy of MIGJO is evaluated with two different node counts of 50 and 100 which are indicated in Figures 8 and 9 respectively.

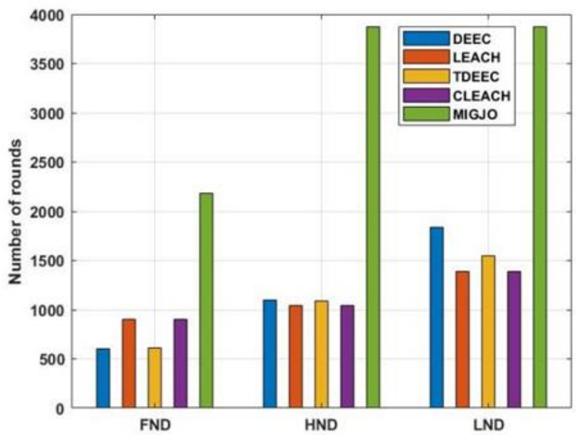

Figure 8 Life Expectancy for 50 Nodes

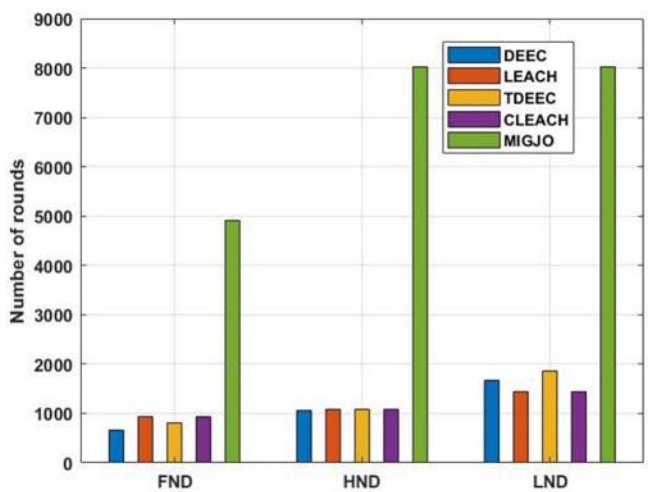

Figure 9 Life Expectancy for 100 Nodes

4.1.5. Packet Loss Ratio (PLR)

The PLR is a ratio between overall number of lost packets and total data packets which broadcasts from source node to destination node. Figure 10 shows the graphical representation of PLR for different node counts of 50 and 100. Compared to the classical approaches such as DEEC, LEACH, TDEEC and CLEACH, the proposed technique achieved better results with minimal PLR. The optimal selection of cluster head and the shortest routing path selected using the proposed MIGJOA helps to achieve better results with minimal loss of data packets.

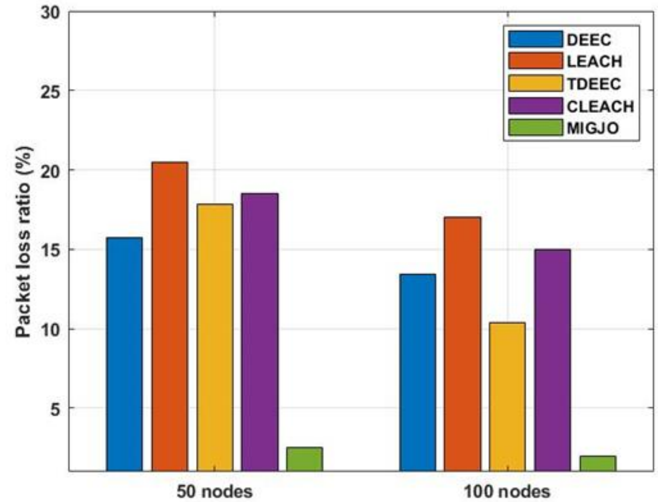

Figure 10 Evaluation of PLR for 50 Nodes and 100 Nodes

4.1.6. Throughput

It is known as total count of successfully transmitted data packets. Figure 11 depicted below shows a representation for evaluation of throughput for 50 nodes and 100 nodes. The proposed MIGJOA achieved better throughput than the classical approaches due to it can transmit the data packets with fewer loss. Moreover, shortest and optimal routing path detected using the proposed MIGJOA helps to achieve better throughput than the existing techniques.

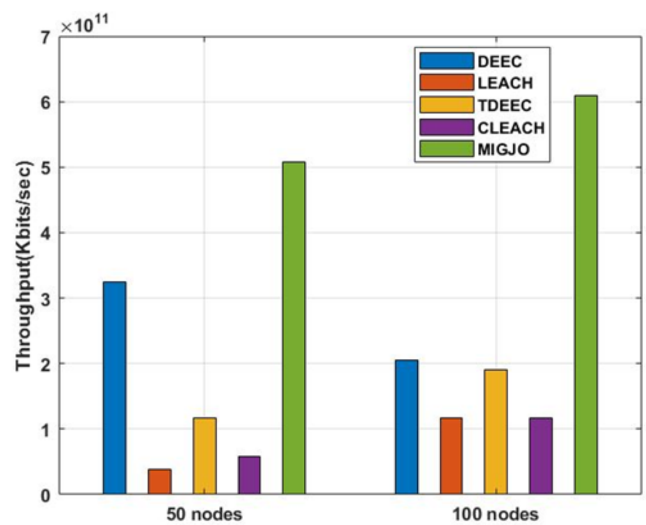

Figure 11 Evaluation of Throughput for 50 Nodes and 100 Nodes

4.1.7. Evaluation of MIGJOA for Different Node Count

Here, the efficiency of MIGJOA is evaluated with different node count of 50, 100, 150 and 200. The metrics like Packet Delivery Ratio (PDR), delay, and total number of rounds are considered for evaluation. The table 3 presents the

RESEARCH ARTICLE

experimental outcome based on evaluation of MIGJOA for different node count.

Table 3 Evaluation on Different Node Count

Method	Performance metrics	No.of. nodes			
		50	100	150	200
MIGJOA	Delay (seconds)	0.012	0.045	0.087	0.12
	Packet delivery ratio (%)	97.4	98	98.1	98.2
	Total number of rounds	3871	8020	10012	12056

The experimental outcome achieved through table 3 exhibits that the results achieved by MIGJOA for different node count ranges from 50 to 200. The delay experienced by MIGJOA for 50 nodes is 0.012 and the PDR for 50 nodes is 97.4%. When a number of nodes gets increased, time in transmitting data packets are also increased. Similarly, PDR is enhanced while a number of nodes gets increased. Thus, the proposed MIGJOA is scalable for increased number of nodes with minimal delay and maximized PDR.

4.2. Comparative Analysis

Here, a valid analysis of the outcomes achieved by the MIGJOA when it is evaluated with the existing techniques while broadcasting data packets in WSNs. The proposed MIGJOA is evaluated with state of art approaches such as ABTSO [16], HAVCSO [17], BOA-ACO [20]. A evaluation is performed by considering three different scenarios listed as follows:

Scenario 1: In this scenario, the dimension of the field is 100×100m; the node variation is analyzed for 100 nodes and the initial energy is 0.3 J [16].

Scenario 2: In this scenario, the field dimension is 100×100m; the node variation is determined for 100 nodes and the initial energy is 0.5 J [17].

Scenario 3: BS is positioned in area (100,100), the dimension of the field is 200×200m; the node variation is evaluated for 100 nodes and initial energy is 0.5 J [20].

An efficiency of MIGJOA is evaluated with existing ABTSO [16], HAVCSO [17] BOA-ACO [20] correspondingly. The comparative results of cases 1 to 3 are determined in tables 4 to 6 respectively.

Table 4 Comparative Analysis for Scenario 1

Methods	Performances	Number of rounds			
		500	1000	1500	2000
ABTSO [16]	Alive nodes	97	22	16	12
MIGJOA		100	100	100	99
ABTSO [16]	Normalized energy(J)	0.13	0.04	0.03	0.02
MIGJOA		0.292	0.256	0.201	0.154

Table 5 Comparative Analysis for Scenario 2

Methods	Performances	Number of rounds			
		500	1000	1500	2000
HAVCSO [17]	Alive nodes	100	100	10	10
MIGJOA		100	100	100	100
HAVCSO [17]	Normalized energy(J)	0.38	0.15	0.09	0.08
MIGJOA		0.47	0.445	0.401	0.362

RESEARCH ARTICLE

Table 6 Comparative Analysis for Scenario 3

Methods	Performances	Number of rounds				
		500	1000	1500	2000	2500
BOA-ACO [20]	Alive nodes	100	100	100	100	89
MIGJOA		100	100	100	100	97
BOA-ACO [20]	Average energy consumption (J)	0.41	0.32	0.23	0.12	0.04
MIGJOA		0.46	0.401	0.376	0.265	0.198

The overall outcomes from Tables 4 to 6 indicates that MIGJOA achieved better performance in overall metrics considered for evaluation. The outcomes from Tables 4 to 6 demonstrate the proposed MIGJOA achieved optimal results in all overall metrics when it is evaluated with ABTSO, HAVCSO and BOA-ACO. For example, alive nodes in proposed approach when number of rounds is 2500 is 97 whereas number of alive nodes in existing BOA-ACO is 89. An efficiency of MIGJOA in retaining more alive nodes is due to the energy balancing which is achieved by optimal selection of CH.

4.3. Discussion

The results attained by MIGJOA with their advantages are discussed. The efficiency of MIGJOA is assessed with classical techniques such as LEACH, DEEC, TDEEC and CLEACH. The efficacy of MIGJOA is evaluated based on many alive nodes, dead nodes, energy consumption, life expectancy, packet loss ratio, and network throughput. The proposed MIGJOA achieved an optimal outcome than the classical approaches. CH selection with an optimal shortest path is used to transfer packets from CH to BS. Similarly, the evaluation of results is performed with existing research such as ABTSO, HAVCSO, and BOA-ACO with respect to alive nodes, normalized energy and energy consumption. Number of alive nodes of MIGJOA when a number of rounds is 2500 is 97 whereas the alive nodes in existing BOA-ACO is 89. The suggested approach selects optimal CHs with minimal hops based on the position of the BS and diminishes the energy usage while transmitting data packets.

5. CONCLUSION

An optimal CH selection and shortest routing path plays a major role in transmitting the data packets over WSN. This research developed MIGJOA to select an optimal CH and routing path to transfer packets. The suggested MIGJOA is constructed using fitness values such as distance among the neighbor node and BS, the distance among BS to CH, mean node energy and node degree. Moreover, the optimal shortest routing path is evaluated by considering distance among BS and CH, node degree, and residual energy. MIGJOA achieved better energy consumption rather than the classical approaches. Detecting the optimal CHs with minimal hops depending on BS position and diminished energy usage of transmitting data packets helps to achieve better efficiency. The results through experimental analysis also prove the efficiency of the proposed MIGJOA when transmitting a packets of data from BS to CH by considering multi-objective functionalities. The MIGJOA's number of alive nodes for 2500 rounds is 97 whereas the alive nodes in existing BOA-ACO is 89. In the future, the proposed MIGJOA can be implemented to overcome the security concerns in WSNs which will help to retain trustworthiness when transmitting packets of data. Moreover, the efficiency of MIGJOA can be evaluated with dynamic WSN environment to validate its efficiency where sensors are either mobile themselves or deployed in changing environment.

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