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MOJO-BASED FUZZY AGGLOMERATIVE CLUSTERING ALGORITHM WITH ED^2MT STRATEGY FOR LARGE-SCALE WIRELESS SENSORS NETWORKS

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The wireless sensor network (WSN) is a distributed sensor network that monitors and stores environmental data wirelessly by connecting dispersed sensor nodes. Since wireless sensor nodes rely on batteries for energy, energy consumption, and limitations are considered fundamental problems. A novel multi-objective jellyfish optimization based on energy, degree, distance, mobility, and time parameters (MOJO-ED^2MT) technique has been proposed to overcome these challenges. Three phases are involved in the proposed method: selection of cluster heads, compression of data, and routing of the data. In this first phase, a fuzzy agglomerative clustering algorithm is employed to choose an optimal dual cluster head from inter-cluster and intra-cluster. In the second phase, a neighborhood indexing sequence (NIS) algorithm can compress the number of bits in the data before it is transmitted. In the third phase, jellyfish optimization selects the shortest path based on multi-objective parameters. The simulation analysis and result statistics show that the suggested MOJO-ED^2MT approach performs better than the state-of-the-art algorithms across various performance measures. The proposed MOJO-ED^2MT framework achieves 11.5, 15.4 %, and 17.99 % more network lifetime than EOR-iABC, C3HA, and ML-AEFA algorithms.

1. INTRODUCTION

WSN is a grouping of sensor nodes that is comprised of transceivers and sensors [1]. There are numerous practical uses of WSNs, such as those in traffic, the environment, and surveillance [2,3]. These sensor nodes gather data about their surroundings by monitoring mechanical, thermal, biological, chemical, and magnetic phenomena [4]. In many applications, wireless communication systems have completely transformed machine-to-machine and human-to-human contact [5]. Among these uses is the tracking and monitoring of WSNs.

To facilitate further communication, the recorded data is sent from the sensor node to the CH node and then to the BS [6]. Clustering is the most used technique for preserving WSN topology. By organizing the nodes into groups known as clusters, a clustering technique lengthens the network's lifespan [7]. In addition to clustering operations, routing data transmissions have a major impact on reducing energy consumption and thereby enhancing network lifetime. As a result, routing protocol design in WSNs is challenging since it limits the network's energy efficiency [8].

Several route optimization techniques have recently been developed for WSN [9–12]. However, the intrinsic energy limitations of the sensor nodes make it difficult to build energy-aware routing protocols [13]. To provide a solution to the energy conservation issue, researchers are now looking into and creating clustered routing algorithms [14,15]. A novel multi-objective technique based on energy, degree, distance, mobility, and time (ED^2MT) has been presented to address these issues in chicken swarm optimization [21–23]. The following are the primary contributions of the proposed method:

- The primary goal of the proposed method is to develop a multi-objective jellyfish optimization-based fuzzy Agglomerative clustering algorithm with ED^2MT strategy for large-scale WSN.
- Due to its high stability, the FAC algorithm is utilized in the WSN to pick the CH. ED^2MT is among the several objective metrics FAC uses to select the CH in this study.
- The neighborhood indexing sequence (NIS) algorithm can compress the number of bits in the data before it is transmitted.
- Jellyfish optimization is used to select the shortest path based on multi-objective parameters.

The remaining sections of this paper are arranged as follows: In section 2, the literature survey is briefly outlined. Section 3 describes the proposed algorithm technique. Section 4 provides the outcomes and analysis of the proposed model. Section 5 explains the conclusion and the future scope.

2. LITERATURE SURVEY

Energy consumption, network longevity, throughput, transmission delay or packet delay, percentage of packet loss, and other aspects of WSN performance have all been the subject of several research. This section looked at many of these strategies.

[16] suggested energy optimization routing utilizing enhanced artificial bee colonies (EOR-iABC) for cluster-based wireless sensor networks (WSNs). Based on simulation data, EOR-iABC performs 27 % better in energy efficiency than the OCABC scheme and 16 % better than the IABCOCT plan.

[17] suggested hybrid SA-LSA and PSO-LSA techniques for isolated node minimization. Experimental analysis validates the suggested technique's better performance compared to alternative approaches.

[18] introduced a cluster cantered cluster head selection algorithm (C3HA), which is meant to lower energy consumption and increase the lifespan of WSNs. Analysis and comparison were done on the clustering methods' performances. As per the findings, the suggested algorithm maintains an average of 14.68 % more nodes in the network.

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The novel customized grey wolf optimization (CGWO) method is used to transmit data, and [19] presented the Moth Levy-adapted artificial electric field method (ML-AEFA). Finally, the efficacy of the proposed methodology is evaluated with that of existing approaches using a range of metrics.

[20] introduced a chicken swarm optimization-based clustering algorithm (CSOCA) to increase the lifetime of WSN. Using a sigmoid function on everyone, the optimization of the chicken swarm is discretized. Findings indicate that, in comparison to current algorithms, the suggested CSOCA approach extends network longevity.

According to the literature study, various cluster-based routing techniques have been proposed. However, they face challenges like consuming a large amount of time for clustering, cluster head selection, data compression, minimum storage, and high energy consumption. A novel multi-objective Jellyfish optimization based on ED^2MT approach has been proposed to overcome these challenges.

3. **PROPOSED SYSTEM**

This section proposes a multi-objective jellyfish optimization based on ED^2MT parameters (MOJF ED^2MT) technique. Figure 1 depicts the general flow of the proposed strategy. Cluster head selection, data compression, and routing are the three stages of the proposed approach. in this first phase, a fuzzy agglomerative clustering algorithm is utilized to select an optimal dual cluster head from inter-cluster and intra-cluster. In the second phase, a neighborhood indexing sequence (NIS) algorithm can compress the number of bits in the data before it is transmitted. Jellyfish optimization is employed in the third phase using multi-objective parameters to determine the shortest path.

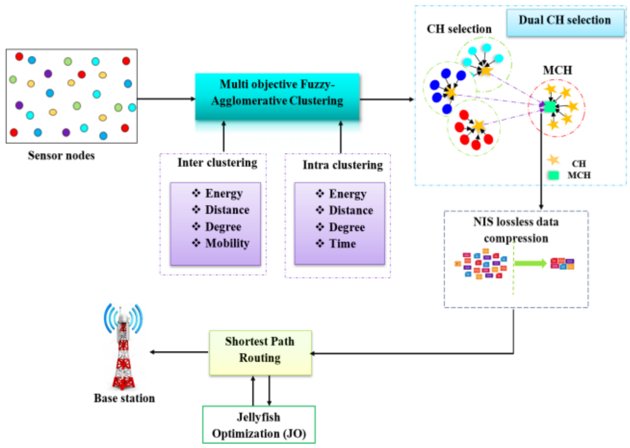

Fig. 1 – Proposed architecture of the ED^2MT Framework.

3.1. FIRST PHASE: CLUSTERING AND DUAL CH SELECTION

Clustering divides the incoming data into a predefined number of groups based on parallel data vectors. Looking through a list of clusters and details about each cluster will lead you to the cluster center.

3.1.1. Agglomerative clustering algorithm

The ACA clustering protocol is a centralized clustering method in which the BS uses the SNs' location data to compute and assign clusters to them. The proper cluster head was generated by the six-step clustering process to apply the ACA algorithm in WSNs.

Step 1. An attribute-component data matrix is an input data set for ACA. We intend to organize nodes according to commonalities, which are called components.

Step 2. The likeness coefficient between two nodes indicates how similar or unlike they are from one another. Using the position data, equation (1) is utilized to calculate the Euclidean distance;

$$E_D = [(p_i - q_k)^2 + (p_j - q_j)^2]^{1/2}. \tag{1}$$

Step 3. Following constructing the similarity matrix, the clustering algorithm is applied to assign the nodes into a "tree" using the ACA method, which repeatedly finds the smallest coefficient in the resemblance matrix. Alternatively known as the nearest neighbor method, single LINKage (SLINK). The minimal resemblance coefficient between each pair of things in two clusters is the similarity measure between them.

$$D_{Sl} = \mathrm{Min}(S_{(1,1)}, S_{(1,1)}, \dots, S_{(x,y)}, \dots, S_{(a,b)}). \tag{2}$$

The furthest neighbor technique is another name for complete LINKage (CLINK). The greatest resemblance coefficient between each pair of things in two clusters is the similarity measure between them.

$$D_{Cl} = \mathrm{Max}(S_{(1,1)}, S_{(1,1)}, \dots, S_{(x,y)}, \dots, S_{(a,b)}). \tag{3}$$

Step 4. To avoid clusters from becoming too large or from merging, they build a cut using a pre-configured threshold value, which might be the propagation distance, the total number of clusters, or the cluster density.

Step 5. A cluster merges with its nearest neighboring cluster if its size falls below the minimum cluster size, which is a predetermined threshold.

Step 6. Once clustering is complete, various procedures can be used to calculate CHs initially. The nodes that meet both requirements listed in this research having the lower ID and being in the bottom level after merging into the cluster in the first step, are referred to as CHs.

3.1.2. Fuzzy-based dual CH selection

Determining the probability value of the CH is a critical step in large-scale WSNs. To determine the chance value of the CH in the intra-cluster, the fuzzy chance prediction model includes four goals: node degree (ND), residual energy (Res), time (TM), distance (Dis), and one output chance value (CH). To determine the chance value of the MCH in an inter-cluster environment, the fuzzy chance prediction model includes four goals: neighbor distance (Dis), residual energy (Res), node degree (ND), mobility (MB), and one output chance value (CH). Mobility is the main goal when inter-clustering. The necessary input objectives for CH and MCH selection are displayed in Table 1.

Table 1

(a) Input objectives with range for CH selection

Input objectives	Range		
Residual Energy (Res)	Minimum (Min)	Average (A)	Maximum (Max)
Distance (Dis)	Far (F)	Medium (MD)	Near (N)
Node degree (ND)	Low (L)	Medium (M)	High (H)
Time (TM)	Less (LS)	Average (AG)	Heavy (HV)

(b) Input objectives with range for MCH selection

Input objectives	Range		
Residual Energy (Res)	Minimum (Min)	Average (A)	Maximum (Max)
Distance (DT)	Far (F)	Medium (MD)	Near (N)
Node degree (ND)	Low (L)	Medium (M)	High (H)
Mobility (MB)	Low (LW)	Moderate (Med)	Frequent (FQ)

3.1.3. Fuzzy inference system

A fuzzy inference engine simulates the SN inference system with inputs and IF-THEN rules. The fuzzy inference system framework is shown in Fig. 2.

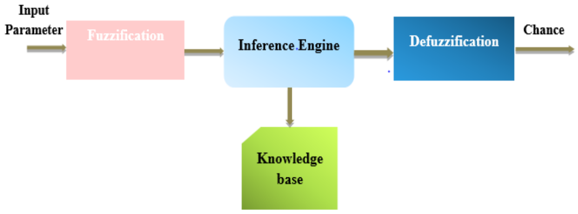

Fig. 2 – Fuzzy inference system.

Fuzzification is implemented using eq. (4) by combining the Sugeno inference rules with Gaussian membership functions. In the equation, CH denotes the chance value.

$$f(p,q,r,s,\beta)=\begin{cases}0 \text{ when } CH<p \text{ and } CH>s\\ \frac{(p-CH)\beta}{p-q} \text{ when } p\le CH\le q\\ \beta \text{ when } q\le CH\le r\\ \frac{(s-CH)\beta}{s-r} \text{ when } r\le CH\le s\end{cases}. \quad (4)$$

Figure 3 displays the input membership function. The output objective is the chance value of becoming the CH, which is displayed in Fig. 4. Small (S), very small (VS), rather high (RH), rather small (RS), high (H), medium (M), very large (VL) and very high (VH) are the linguistic ranges for the fuzzy output objective (chance).

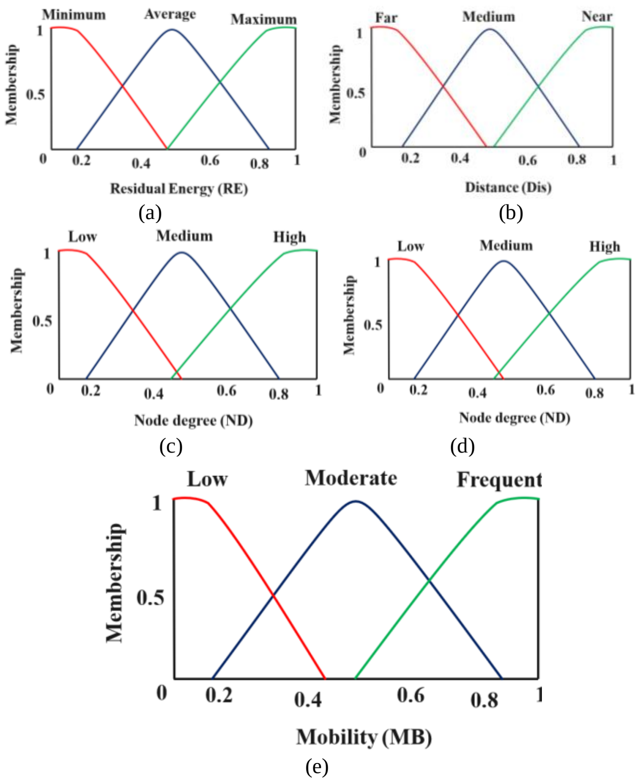

Fig. 3 – Membership function for: a) residual energy (RE); b) distance (Dis); c) node degree (ND); d) time (TM); e) mobility (MB).

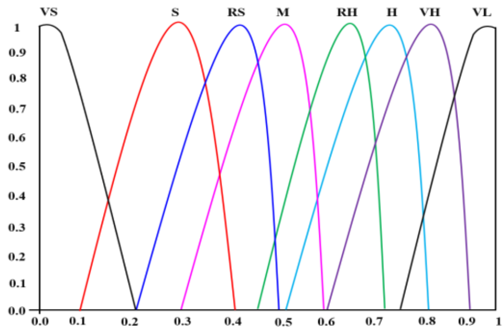

Fig. 4 – Output chance value (CV).

3.1.4. Fuzzy rule estimation

There are 241 fuzzy rules produced when three fuzzy sets are used with four inputs. All conceivable input combos are taken into account. The Sugeno fuzzy method eliminates many of these rules, making this a sizable list.

Table 2

Fuzzy rule base for Inter CH selection

1	(Res = = Min) & (Dis= = F) & (ND = = L) & (TM = = LS)→(CH = = NC)
2	(RE = = A) & (Dis = = N) & (ND = = M) & (TM = = HV) →(CH = = HC)
3	(Res = = Max) & (Dis = = MD) & (ND = = H) & (TM = = AG)→(CH = = HV)
4	(Res = = min) & (Dis = = F) & (ND = = L) & (TM = = AG) → (CH = = NC)
5	(Res = = min) & (Dis = = F) & (ND = = M) & (TM = = HV)→ (CH = = LC)
6	(Res = = A) & (Dis = = N) & (ND = = M) & (TM = = LS)→ (CH = = NC)
7	(Res = = A) & (Dis = = N) & (ND = = H) & (TM = = AG)→ (CH = = LC)
8	(Res = = max) & (Dis = = MD) & (ND = = H) & (TM = = HV)→ (CH = = HC)
9	(Res = = max) & (Dis = = MD) & (ND = = L) & (TM = = LS)→ (CH = = NC)
10	(Res = = min) & (Dis = = F) & (ND = = M) & (TM = = LS)→ (CH = = NC)

(b) Fuzzy rule base for MCH selection

1	(Res = = min) & (DT = = F) & (ND = = L) & (MB = = LW)→ (CH = = NC)
2	(Res = = A) & (DT = = N) & (ND = = M) & (MB = = FQ)→ (CH = = HC)
3	(Res = = max) & (DT = = MD) & (ND = = H) & (MB = = Med)→ (CH = = HC)
4	(Res = = min) & (DT = = F) & (ND = = L) & (MB = = Med)→ (CH = = NC)
5	(Res = = min) & (DT = = F) & (ND = = M) & (MB = = FQ) → (CH = = LC)
6	(Res = = A) & (DT = = N) & (ND = = M) & (MB = = LW)→ (CH = = NC)
7	(Res = = A) & (DT = = N) & (ND = = H) & (MB = = Med)→ (CH = = LC)
8	(Res = = max) & (DT = = MD) & (ND = = H) & (MB = = FQ)→ (CH = = HC)
9	(Res = = max) & (DT = = MD) & (ND = = L) & (MB = = LW)→ (CH = = NC)
10	(Res = = min) & (DT = = F) & (ND = = M) & (MB = = LW) → (CH = = NC)

Table 2 displays the output's assigned numbers and the sample's fuzzy rules for the input factors. Based on Table 2, the node with the highest chance value will become CH /MCH. The fuzzy logic system uses the area centroid to extract the output objective chance from the SNs' input objectives. Using eq. (5), the output acute value of CV has been selected.

$$\text{Chance} = \frac{\sum_i p_i * \beta_{n\cdot}(p_i)}{\sum_i \beta_{n\cdot}(p_i)}. \quad (5)$$

Conversely, the aggregated output's Membership function is represented by $\beta_n(z)$. When a node in a group has the greatest chance value, it becomes a CH/MCH and eventually notifies all of its member nodes about the dual CH.

3.2. LOSSLESS DATA COMPRESSION

Data compression was done before it was sent to the BS to reduce the number of bits in the data. The NIS algorithm has been proposed for lossless data compression. The proposed NIS method uses a single character for encoding and is predicated on "traversing data based on 1s and 0s." It gives each character in the input sequence a shorter-length codeword by utilizing the helpful information found in the nearby bits of each input character. Depending on how few bits are required to hold the codeword of a specific character, the best codeword will be chosen among the two shorter codewords generated by traversing 1s and 0s.

To store the compressed data for an input sequence of length L, the NIS algorithm needs D_{bits}, which is equated as:

$$D_{bits} = \sum_{j=1}^{L} N_{bits}(j) + \text{control bits}, \quad (6)$$

where the number of bits in a code is indicated by N_{bits}. The algorithm specifies not only the minimum number of bits for the compressed data but also an additional 8 control bits. The NIS technique is then used in eq. (7) to get the average amount of bits required to hold a single character.

$$N_c = \frac{D_{bits}}{L}, 1 \le N_c \le 4. \quad (7)$$

Lower the value of D_{bits} and N_c, higher the performance of the compression. Equation (7) indicates that the method requires a maximum of four bits to store a character. The capacity to store a character in a single bit can help with compression in some circumstances.

Normally, the compression ratio (C_{ratio}) is used to calculate the performance of compression methods and is equated as

$$C_{ratio} = 100\left(1 - \frac{\text{No.of bits in compressed data}}{\text{No.of bits in uncompressed data}}\right). \quad (8)$$

Data compression can speed up information transfers, minimize the amount of network bandwidth used, and free up storage space.

3.3. SHORTEST PATH ROUTING

Following compression, the data is routed via Jellyfish optimization and sent to the BS. The multi-objective shortest path algorithm, which considers several factors like energy, node degree, distance, time, and mobility, has been utilized to choose the route. Here, the route is optimized using MO, which includes energy, node degree, distance, mobility, and time. An algorithm called the JO is inspired by the survival tactics used by jellyfish in the water. The exploration and movement patterns of jellyfish in the ocean serve as the inspiration for this technique. This algorithm provides a better balance between exploration and exploitation approaches and quickly arrives at the best answers. The active and passive movements of water currents within a jellyfish swarm must be understood to imitate jellyfish search behavior.

Ocean current. The ocean current attracts jellyfish because it offers a lot of food. By averaging the vectors from each jellyfish in the water, the current ocean direction, $\overrightarrow{C_o}$ is determined,

$$\vec{e} = \frac{1}{x}\sum \vec{e}_a = \frac{1}{x}\sum (P_{best} - Y_f P_a) = P_{best} - Y_f \frac{\sum P_a}{x} =$$
$$= P_{best} - Y_f \vartheta = P_{best} - l_k, \quad (9)$$

where n denotes population number, P_{best} denotes the best position acquired, Y_f denotes a convergence factor, denotes the average position of the jellyfish, and l_k is the discrepancy between the best position and the average location of the jellyfish. Therefore, the following is how the new position can be obtained,

$$P_a(t+1) = P_a(t) + rand(0,1)(P_{best} - \beta s)\vartheta, \quad (10)$$

where s is a random (0,1) and β denotes a positive distribution coefficient (=3).

Jellyfish swarm. The jellyfish swims passively (type A) and vigorously (type B) during this phase. The first movement of the swarm is type A. Later, they gradually begin to exhibit type B motions. The next list is a description of type A movement,

$$P_a(t+1) = P_a(t) + \omega\, \text{rand}(0,1)(Up_b - Lo_b), \quad (11)$$

whereas Up_b and Lo_b stand for the top and lower boundaries of search spaces, respectively, ω represents a movement factor that is proportional to the circumference of the jellyfish's movement. The movement of type A can be described as the following.

$$P_a(t+1) = P_a(t) + \text{rand}(0,1)\,\vec{G}, \quad (12)$$

$$\vec{G} = \begin{cases} P_b(t) - P_a(t) & \text{if} \quad \text{fit}(P_a) \ge \text{fit}(P_b) \\ P_a(t) - P_b(t) & \text{if} \quad \text{fit}(P_a) < \text{fit}(P_b) \end{cases}, \quad (13)$$

where b is selected randomly, and "fit" stands in for the goal function.

The time control mechanism. The jellyfish swarm movement and ocean current types are switched using the time control mechanism T_c. Its value can be determined as shown below

$$P_a(t+1) = P_a(t) + \text{rand}(0,1) \cdot \text{Direction}, \quad (14)$$

$$T_c(t) = \left|\left(1 - \frac{t}{I_{max}}\right) \cdot (2\,\text{rand}(0,1) - 1)\right|. \quad (15)$$

The most significant number of iterations is indicated here by I_{max}.

4. SIMULATION RESULTS AND DISCUSSIONS

In this section, several computer simulations have been evaluating the efficiency of the proposed MOJO-ED^2MT. MATLAB 2020b was used to execute all the simulations. It was configured with an Intel i5 processor operating at 2.60 GHz, 4 GB of RAM, and a 1 TB hard drive under Windows 10. Table 3 is a list of the parameters used in this simulation.

Table 3

Simulation parameter

Parameters	Value
Area of the network	300 m × 300 m
Size of the packet	5600 bits
Packet length	700 bytes
Nodes	500
Initial Energy	0.4 mJ
Simulation time	850 s
Transmission Power	1.6 W
State-of-the-art methods	EOR-iABC [16], C3HA [18] and ML-AEFA [19]

4.1. PERFORMANCE METRICS

In WSNs, different routing algorithms are compared using various performance criteria.

- **Throughput.** The quantity of bits sent to BS via WSN is known as the throughput. We express throughput in bits per second.
- **Energy consumption.** This parameter estimates the average energy in the simulated networks for each round.
- **Network lifetime.** This measure indicates the first node to run out of energy.
- **Packet Delivery Ratio.** It calculates the percentage of all packets transmitted from the starting node to all packets delivered.
- **Alive nodes.** The network's performance capacity is determined by its active nodes, and the network's performance improves with more active nodes.

4.2. COMPARATIVE ANALYSIS

To verify its promising performance, the proposed MOJO-ED^2MT is tested against cutting-edge techniques like the ML-AEFA [19], C3HA [18], and EOR-iABC [16] protocols.

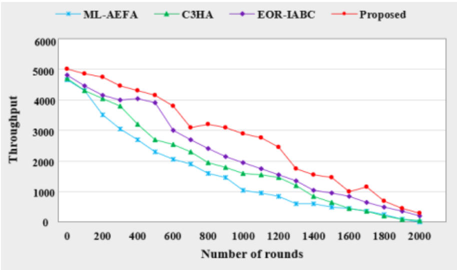

Fig. 4 – Comparative analysis of throughput.

Figure 4 compares the suggested throughput analysis with alternative methods. Regarding throughput, the MOJO-ED^2MT technique outperforms the current approaches. The suggested method outperforms the ML-AEFA [19], C3HA [18], and EOR-iABC [16] methods in terms of average throughput, with differences of 19.5 %, 12.3 %, and 9.35 %, respectively.

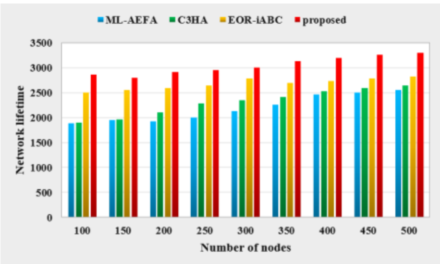

Fig. 5 – Performance analysis of Network lifetime with different nodes.

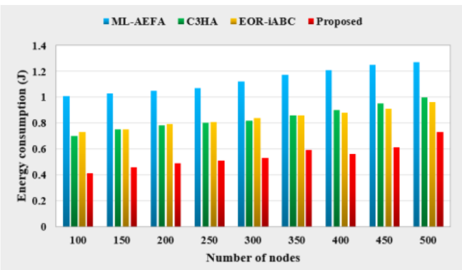

Fig. 6 – Comparison of energy consumption analysis.

Figure 5 shows the network's lifetime for different node numbers. The analysis uses a range of fitness coefficient values. Compared with the current methodology, the proposed MOJO-ED^2MT technique has a lower lifetime up to 1 200 rounds and a higher lifetime up to 3 300 rounds. Figure 6 compares the suggested MOJO-ED^2MT method with prior methods based on total energy usage by expanding the nodes from 100 to 500. The energy consumption of the existing EOR-iABC [16], C3HA [18], and ML-AEFA [19] yields 0.82 mJ, 0.8 mJ, and 1.2 mJ, respectively, while the proposed approaches consume 0.45 J when a node is 300. The total amount of energy consumed increases with the number of nodes.

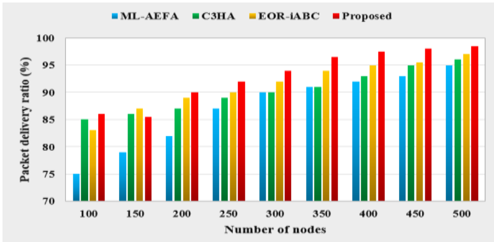

Fig. 7 – Comparative analysis of packet delivery ratio.

Figure 7 displays the PDR comparison between various techniques and the proposed MOJO-ED^2MT approach. The recommended approach outperforms the other methods for 100 nodes, yielding the greatest PDR value (86 %). When the node is 100, the existing approaches' packet delivery rates are ML-AEFA (75 %), C3HA (85 %), and EOR-iABC (84 %), respectively.

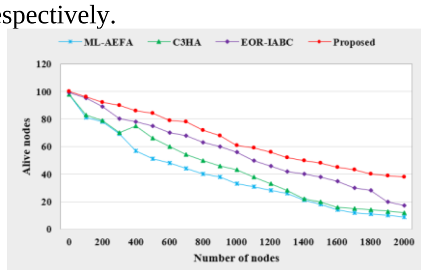

Fig. 8 – Alive nodes comparison.

Figure 8 illustrates that the proposed MOJO-ED^2MT technique provides many living nodes compared to other methods such as ML-AEFA [19], C3HA [18], and EOR-iABC [16]. The MOJ-ED^2MT scheme increases the percentage of active nodes in the network compared with earlier methods.

5. CONCLUSION

In this paper, a multi-objective jellyfish optimization based on energy, degree, distance, mobility, and time parameters (MOJO-ED^2MT) technique has been proposed. Cluster head selection, data compression, and routing are the three stages of the proposed approach. The best dual cluster head from the intra- and inter-cluster groups is selected using the fuzzy agglomerative clustering algorithm in the first phase. The number of bits in the data can be reduced in the second stage before transmission by using a neighborhood indexing sequence (NIS) method. Using multi-objective parameters, the Jellyfish optimization is employed in the third phase to determine the shortest path. Through the use of simulation analysis and statistical data, it is found that the proposed MOJO-ED^2MT approach performs better than the existing algorithms across a range of performance criteria. The proposed MOJO-ED^2MT framework achieves 11.5 %, 15.4 %, and 17.99 % more network lifetime than EOR-iABC, C3HA, and ML-AEFA algorithms. The effectiveness of a cluster head with a cluster density in a mobile environment needs to be examined for future work, and an algorithmic evaluation may also consider the energy consumption resulting from this intentional motion.

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