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Original Article

Energy Aware Dung Beetle Optimization-Based Clustering Scheme for Wireless Sensor Networks

K. Nirmal[1], S. Murugan[2]

[1]Krishnasamy College of Engineering and Technology, Cuddalore, Tamilnadu, India.
[2]Dr. M.G.R. Govt. Arts and Science College for Women, Villupuram, Tamilnadu, India.

[1]Corresponding author : nirmalphd21@gmail.com

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Abstract - *Wireless Sensor Networks (WSNs) have acquired considerable interest owing to their widespread applications in habitat tracking, healthcare, agriculture, disaster prevention, fire tracking, monitoring areas, etc. Extending the WSN lifespan is significant for diverse applications, and the most effective model is optimizing Cluster Heads (CHs) through clustering. The dynamic CH formation and energy-aware clustering scheme help to improve the WSN lifetime. This study introduces an Energy-Aware Dung Beetle Optimization-based Clustering Scheme (EADBO-CS) for WSNs. The EADBO-CS technique intends to achieve energy efficiency by grouping the nodes into clusters and electing CHs. The EADBO-CS technique mainly follows the behavior of Dung Beetle (DB) populaces. To achieve this, the EADBO-CS technique designs a Fitness Function (FF) comprising various parameters, namely Residual Energy (RE), Distance to Neighbors (DTN), Distance to Base Station (DBS), Node Degree (ND), and Node Centrality (NC). The design of multiple parameters helps in achieving improved energy efficiency and maximum longevity in the WSN. An investigational analysis is performed to validate the improved achievement of the EADBO-CS technique. The simulation values signify the supremacy of the EADBO-CS method over other present approaches with minimal Energy Consumption (ECON) of 0.150mJ and maximum Throughput (THRO) of 98.22Mbps.*

Keywords - *Energy efficiency, Cluster Head Selection, Metaheuristics, Wireless Sensor Network, Dung beetle optimization.*

1. Introduction

A WSN is developed by a large number of individual Sensor Nodes (SNs) [1]. These sensors are lower-cost and employed for various purposes, but still essentially have confined resources. The sensors can have the capability to control, sense, and communicate with the other nodes, which builds the network. For collecting and monitoring data about the ambient condition, these sensors must be connected in a position to be inaccessible to human beings [2]. Real-time applications are evolved by employing sensors in various fields namely remote healthcare, surroundings monitoring, and other surveillance systems. Sensors are useful to society in all of the applications above without any trouble [3]. The limited resources are still the major feature taken into account. Sensors can satisfy their function while resource restrictions must be well handled that denote battery backup or energy [4]. Energy is the sensors' lifespan support then, it can fulfil function wherein the network has been developed. It is important to efficiently control the network's ECON due to it is not always applied to change the batteries in a sensor network [5]. Improvement of energy efficiency covers an approach for encompassing the Network Lifetime (NLT), but it can be extremely challenging. Clustering is a preeminent technique for attaining energy-efficacy in WSNs. Cluster-based model in WSN decreases the quantity of data transmission employing inter- and intra-cluster transmission [6]. However, the effectiveness of clustering is dependent upon the method of CH Selection (CHS) and the development of a great cluster amount. In this framework, an arbitrary CHs choice leads to inferior connectivity and unpredicted node failures and minimizes network lifespan [7]. Alternatively, optimum CHS improves the lifespan and productivity of WSNs. An enhanced routing method with the help of an effective CHS procedure has been crucial for large-scale WSNs. Cluster-based routing helps load balance, dependable transmission, and error tolerance to extend the lifespan of a WSN [8]. CHS is dependent upon NC, node location, RE, node rank (rank can be allocated according to the count of links and link rate), and the count of neighbors that addresses the problems of the LEACH algorithm. Dynamic and demand-based CHS depends upon the computational overhead, and the existence of activity decreases the information, and makes sure energy balancing amongst CHs [9]. Optimum clustering modification One-Hop Transmission (HT) among the sink nodes and CHs through ideal multi-hop distance for mitigating ECON as well as increases the network lifespan by around 35% in WSNs [10]. Modified CHS in heterogeneous WSNs, depending upon node position and RE, confirms that the node that can be superior to RE and near the base station develops the CH with the maximum possibility.

This study introduces an Energy-Aware Dung Beetle Optimization-based Clustering Scheme (EADBO-CS) for WSNs. The objective of the EADBO-CS method is to achieve energy efficiency by grouping the nodes into clusters and electing CHs. The EADBO-CS method mainly follows the behavior of Dung Beetle (DB) populaces. To achieve this, the EADBO-CS technique designs a Fitness Function (FF) comprising various parameters, namely Residual Energy (RE), Distance to Neighbors (DTN), Distance to Base Station (DBS), Node Degree (ND), and Node Centrality (NC). The design of multiple parameters helps in achieving improved energy efficiency and maximum longevity in the WSN. An investigational evaluation is performed to validate the improved achievement of the EADBO-CS technique.

2. Related Works

Sharmin et al. [11] developed an interpretation where Hybrid-Particle Swarm Optimization (H-PSO) was combined with Enhanced Lower-Energy Adaptive Clustering Hierarchy (HPSO-ILEACH) for CHS. The HPSO identifies the CH. Next, ILEACH was employed to decrease energy efficiency in the clustering method by modifying the CH. In [12], a new notion of EIec was introduced. Interrelated theorems to form the candidate set of CHs are developed. Afterward, a new energy-efficacy adaptive cluster data technique depending on the economic (ECFE) method was projected and accomplished. Besides, wide-ranging analyses have been performed to measure their network effectiveness and energy efficiency compared to the present standard and new intelligent clustering methods.

In [13], two classes of methods have been introduced and analyzed to improve energy efficiency at WSNs. This study field might be split into clusters at 30-m2 intervals. Furthermore, a mobile sink was implemented to decrease the power utilization of CHs. Initially, CHS was done and the mobile sink route was evaluated through a greedy model. Then, CHS could be executed by utilizing ANN, and the greedy model measured mobile sink routes. Zachariah and Kuppusamy [14] projected HOCK and HECK models, which are developed by applying the Cuckoo search and Krill herd algorithms, which are used to choose the optimum CHs.

Kumar et al. [15] present an innovative energy-effectual clustering model for CHS and cluster development. The CHS was formed dependent upon the threshold-assisted Advanced LEACH (ADV-LEACH2) algorithm. The cluster configuration (SN allocation) amongst the CHs was achieved with Modified Fuzzy c-Mean (MFCM) techniques. The cluster has been constituted with the help of the MFCM method and CHs could be chosen to employ ADV-LEACH2. In [16], an adapted clonal selection algorithm (CLONALG-M) technique was developed to increase the efficacy of rule-assisted fuzzy methods.

This method depends on the clonal selection principle that has been implemented for interpreting the simple rules of an adaptable immune system. This analysis is applied in such an algorithm for determining the rough utilization of membership based on output purposes to boost the effectiveness.

In [17], an improved Orphan-LEACH (O-LEACH) was presented. This developed study's main new contribution is the O-LEACH method, which provides network coverage with a tremendously higher rate of connectivity as well as a minimum count of orphaned nodes. A hybrid optimizer employing SA and Lightning Search Algorithm (SA-LSA), as well as the PSO-LSA method, was designed. Srinivasan et al. [18] presented a framework that incorporates bi-directional LSTM and an adaptive synthetic auto-encoder attention (ADSY-AEAMBi-LSTM) model. The DB optimizer and the ADSY-AEAMBi-LSTM are employed for classification.

3. The Proposed Model

In this study, an EADBO-CS model for energy efficacy in the WSN is proposed. The purpose of the EADBO-CS model is to achieve energy efficiency by categorizing the nodes into clusters and electing CHs. The EADBO-CS technique mainly follows the behavior of DB populaces. Figure 1 demonstrates the entire flow of the EADBO-CS model.

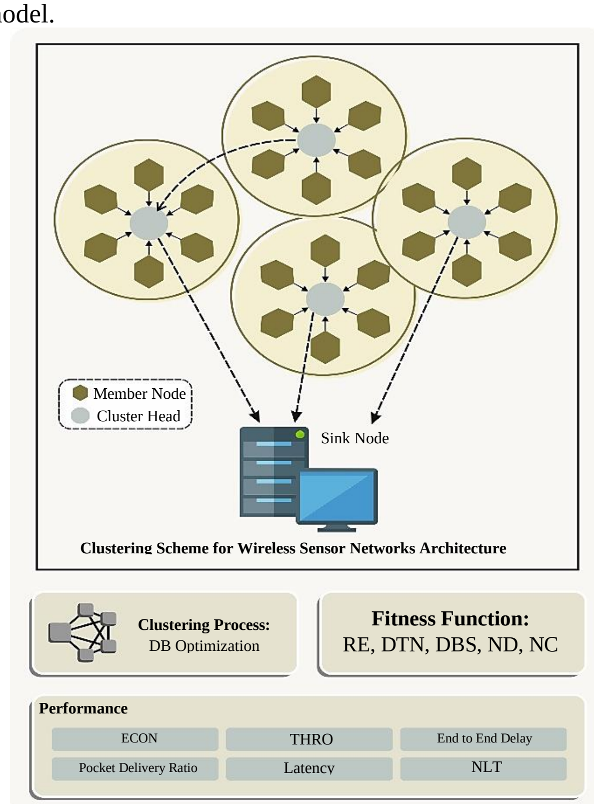

Fig. 1 Complete procedure of EADBO-CS model

3.1. System Model

Some of the assumptions in the networking approach are given below [19].

- The BS is located at the network center, and there exists a multi-HT from CH to BS.
- The SN is deployed arbitrarily in a 2D terrestrial region.
- The SN is similar inside the group, and their mobility is constrained to 0.2 m/s.
- The SN is segmented into almost identical groups, and they are disseminated at random in the group.
- BS implements the task for selecting CH and it collects the data gathered from each CH.
- BS and the nodes that contribute to multi-HT have continuous energy sources.

The multi-path propagation fading (d^4) model for the multi-HT and path loss of free space (d^2) for the single-HT are the two different radio energy models of SNs.

Thus, the power supply for sending n-bit packet over distance 'd' can be analysed as follows:

$$E_{TX}(n,d) = \begin{cases} nE_{elec} + ne_{fs}d^2 & d < d_0 \\ nE_{elec} + ne_{mp}d^4 & d \geq d_0 \end{cases} \quad (1)$$

Where

d →Distance between sender and receiver nodes

e_{mp} →Energy dissipation co-efficient of multi-path attenuation module

$d_0 = \sqrt{e_{fs}/e_{mp}}$ →Threshold distance

e_{fs} →Energy dissipation co-efficient of free-space attenuation mechanism

n →Packet Length

$Elec$ →energy pursued to send/receive 1-bit information.

At RX, the quantity of power supplied for sending an n-bit data packet is analyzed by

$$E_{RX}(n) = n \times E_{elec} \quad (2)$$

The amount of data packets acquired from SNs, viz., member of a specific cluster, aggregation of data employed by CH, and amount of integrated packets sent from CHs to BSs are the three parameters that participate in the power supply at CH and are depicted as

$$E_{CH} = E_{RX}(n,d) \times SN_{num} + E_{DF} \times n \times (SN_{num} + 1) + E_{TX}(n,d) \quad (3)$$

$SN_{num} \rightarrow SN's$ amount in a specific cluster E_{DF} →data fusion energy/bit.

For every SN except CH, the power supply is $E_{TX}(n,d)$. The overall RE at the k^{th} iteration is evaluated by:

$$E_R(k) = E_R(k-1) - \left(\sum_{l=1}^{CH_{num}(l)} E_{CH}(l) + \sum_{m=1}^{SN_{alive}(k)-CH_{num}(k)} E_{SN}(m) \right) \quad (4)$$

$\mathrm{CH_{num}}(k)$ → amount of CHs at k^{th} iteration

$E_R(k-1)$ →Overall, RE at $(k—1)$th iteration

$E_{CH}(m)$ →Power expended by m^{th} SN

$SN_{alive}(k)$ →overall amount of alive nodes at k^{th} iteration

$E_{CH}(1)$ →Power expended by 1th CH

3.2. Algorithmic Design of DBO Technique

DBO is a new swarm intelligence optimization technique that is stimulated by the behavior of DB populaces [20]. These insects compress dung into balls and roll them to a secure place. They can able to roll considerably greater dung balls and employ celestial signals to roll them directly when the source of light is obtainable. But, in the absence of a light source, their ways will become bent as well as inclined due to natural disorders. The endurance of DB is complicatedly associated with obtaining dung balls, where few are employed for the development and reproduction of offspring, whereas the rest function as food.

The DBO method pretends five main behaviors shown by DBs, such as dancing, ball rolling, stealing, reproduction, and foraging, inspired by this performance. The DB population is separated into four sub-groups, namely minor, reproducer, roller, and stealer, with dissimilar search plans used for every sub-group.

3.2.1. Roller Beetle

At the time of the rolling procedure, DB needs to directly utilize celestial signs, mainly the moon, sun, and opposed light, to preserve the straight-line rolling path of the dung ball. It is perceived that DB applies the sun for direction, with an arrow representing the rolling way.

Assume that the strength of the light source also affects the rolling path of DB, then the location of the roller beetle is upgraded as well as signified as below:

$$X_i(t+1) = X_i(t) + \alpha \times k \times X_i(t+1) + b \times \Delta x \quad (5)$$

$$\Delta x = |X_i(t) - X^w| \quad (6)$$

Whereas t signifies the present iteration count, $X(t)$ denotes the location information of i-th DB in t^{th} iteration; $k \in (0,0.2]$ is a fixed value signifying the deviation constant; b is a value of the constant that belongs to the interval $(0\ and\ 1)$; α means the natural number allocated as 1 or -1,· X^w Embodies the worst location, and Δx pretends the variant of light strength. The parameter pretends natural features like uneven terrain and wind will cause DB to differ from its novel direction.

Whereas $a = 1$ indicates no deviation, and $a = -1$ specifies deviation from the initial direction. A higher Δx suggests a weak light source that transports dual advantages. The first one is thoroughly discovering the complete issue space at the time of the optimization procedure and the second is improving search abilities and decreasing the possibility of receiving stuck in local optima.

3.2.2. Dancing Behavior

Numerous natural factors have a major effect on the path of DB. In such circumstances, DB naturally climbs to the peak of dung balls and is involved in the behavior of dancing, which includes a sequence of spins and breaks. Then, they define their actions way by varying their location, thus attaining a novel track.

To represent the behavior of dancing, a tangent function has been used to get a novel rolling way. Note that only the value definite on the [0 and 1] interval of the tangent function is required to be measured.

Once an accurate direction is effectively established, the beetles must endure rolling the ball forward. In this stage, the location upgrade of beetles is mentioned below:

$$X_i(t+1) = X_i(t) + \tan\beta |X_i(t) - X_i(t-1)| \qquad (7)$$

Whereas the deviation angle $\beta \in [0, \tau c]$. From the equation mentioned above, t signifies the current iteration count; $X_i(t)$ represents the location data of the i^{th} roller beetle at t^{th} iteration; $|X_i(t) - X_i(t-1)|$ means complete alteration among positions of the i^{th} beetles at t^{th} iteration and its position at the prior $(t-1)^{th}$ iteration.

The beetle's location upgrade is carefully linked to its prior and present position data. It is crucial to remember that if the deviation angle is equal to 0, $\pi/2$, or π, then the beetle location will not be upgraded.

3.2.3. DB Reproduction

To deliver a secure situation for their offspring, choosing the correct oviposition place is vital for DB. Stimulated by the discussion mentioned above, a boundary selection plan projected to pretend an area where female DB lay their eggs. It can be definite below:

$$Lh^* = \max(X^* \times (1-R), Lh) \qquad (8)$$

$$Uh^* = \min(X^* \times (1-R), Uh) \qquad (9)$$

Here, X^* signifies the present local finest location; Lh^* represents the upper bound; Uh^* signifies lower limits of search area; In $R = 1 - t/T_{\max}$, $T_{\max}$ signifies the extreme iteration sum; Lh said to be upper, and Uh refers to lower limits of search space, correspondingly.

Furthermore, the red dots signify the upper and lower bounds. In the DBO technique, it is expected that every female DB puts a single egg in every iteration. Owing to dynamic variations in border range at the time of iteration, this aids in stopping the technique from receiving stuck-in local goals, mainly defined by the R inertia weight value. Therefore, the egg ball position is dynamic during the iteration procedure and described by below mentioned expression:

$$Y_i(t+1) = X^* + b_1(Y_i(t) - Lh^*) + b_2(Y_i(t) - Uh^*) \; (10)$$

where $Y(t)$ signifies the location details of i^{th} egg balls at t-th iteration, X^* means the present local optimum position, Uh^* and Lh^* denotes the upper and lower boundaries of the search region correspondingly. $(Y_i(t) - Lh^*), (Y_j(t) - Uh^*)$ represents the alteration among the present egg ball location and upper and lower boundaries of the search area, b_1 denotes the random number, b_2 means arbitrary vector in (0 and 1), and D signifies the problem space dimension.

3.2.4. Minor DB

Some mature DB holes into the ground for food foraging and these beetles are mentioned as minor DB.It is essential to define an optimum foraging region to pretend the foraging procedure of minor DB. The expression has been measured as below:

$$Lm = \max(X^h \times (1-R), Lh) \qquad (11)$$

$$Um = \min(X^h \times (1-R), Uh) \qquad (12)$$

Here, X^h epitomizes the optimum location; Um Lm, Lh, and Uh are the higher and lower boundaries of the search area, correspondingly. So, the location upgrade for minor DB is mentioned below:

$$X_i(t+1) = X_i(t) + C_1 \times (X_i(t) - Lm) + C_2(X_i(t) - Um) \qquad (13)$$

Where $X(t)$ signifies the location of i^{th} DB at t^{th} iteration; $X_i(t) - Lm$ and $X_i(t) - Um$ means the differences among the current DB location and upper and lower boundaries of the search range, correspondingly. C_1 denotes a uniformly distributed random integer and C_2 refers to a random value in $(0,1)$.

3.2.5. Thieving DB

The thief's location information is upgraded at the time of the iteration procedure, considering that few DB, denoted as steals, take dung balls from other beetles. X^h signifies the optimum food source.

X^h denotes the main place for reasonable food, the location upgrade for the thief is assumed as:

$$X_i(t+1) = X^h + W \times g \times |X_i(t) - X^*| + |X_i(t) - X^h| \quad (14)$$

where $X(t)$ signifies the location information of i^{th} thief at t^{th} iteration, X^h and X^* are the global and local optimal locations, $|X_i(t) - X^*|$ and $|X_i(t) - X^h|$ characterize the complete changes among current position, local best, and global best locations, individually; g refers to the arbitrarily produced vector of size $1 \times D$ follows a standard dispersion, and W means constant. Figure 2 illustrates the DBO steps.

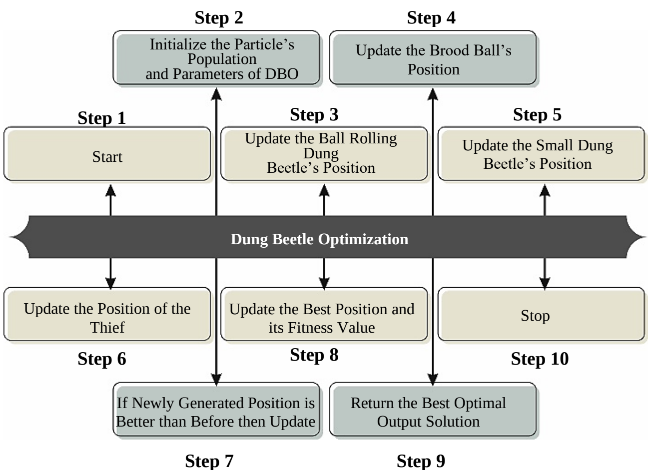

Fig. 2 Steps involved in DBO

3.3. Process Employed in the Clustering Technique

The EADBO-CS method designs an FF including various parameters such as RE, DTN, DBS, ND, and NC. The FF of the EADBO-CS technique is used to choose the optimal CH from the SNs collection in the network [21]. During the clustering procedure, the RE in the FF is implemented to evade the dead node as a CH. Then, the distance from the candidate CH to BS and the nodes are utilized to select the optimum CH to minimize the power supply of the node. The ND is assumed to select the CH with a lesser amount of standard nodes to retain the node for high rounds. Furthermore, the high importance to its Cluster Members (CMs) results in minimizing the communication distance between the CMs to CH. The FF utilized is defined below:

3.3.1. RE of CH

CH is used to gather information from typical SNs and information transmitted to BS in the networking. The CH requires greater energy to obtain the above-mentioned task. Thus, nodes with high RE are chosen as a CH. The RE (f_1) is portrayed below:

$$f_1 = \sum_{i=1}^{m} \frac{1}{E_{CHi}} \quad (15)$$

Where E_{CHi} denotes the RE of i^{Th} CHs.

3.3.2. Distance between the SNs

It describes the distance between its own CH and the typical SNs. The node's power consumption relies largely on the distance of the communication path. When the preferred node has a lower communicating distance to BS, later the energy dissipation of nodes can be smaller. The distance from the typical SNs to CH (f_2) is shown below:

$$f_2 = \sum_{j=1}^{m} \left(\sum_{i=1}^{I_j} d\,is(s_i, CH_j)/I_j \right) \quad (16)$$

In Equation (16), I_j indicates the number of SNs belonging to CH and $dis(s_i, and\ CH_j)$ denotes the distance from sensor i and CH j.

3.3.3. The Distance between the CH and BS

The power utilization of nodes depends on the distance through the communication path. If the BS is placed farther from CH, then it necessitates further energy for transmitting data. Hence, the sudden fall of CH might take place due to high power utilization. Hence, the node with a lesser distance from BS is chosen while transmitting data:

$$f_3 = \sum_{i=1}^{m} dis(CH_j, BS) \quad (17)$$

In Equation (17), $dis(CH_j, BS)$ denote the distance between j^{th} CHs and BSs.

3.3.4. ND

It represents the SN amount belonging to the CH. The CH with a lesser amount of SNs is preferred since the CH with high CM loses energy during less duration can be given as follows:

$$f_4 = \sum_{i=1}^{m} I_i \quad (18)$$

Where I_i represents the amount of SNS belonging to CH_i.

3.3.5. NC

NC (f_S) describes the node number located centrally from the neighboring nodes is represented as.

$$f_5 = \sum_{i=1}^{m} \frac{\sqrt{\left(\Sigma_{j\in n} dist^2(ij)\right)/n(i)}}{Network\ dimension} \quad (19)$$

In Equation (19), $n(i)$ denotes the amount of neighbor nodes of CH_i.The weight values are assigned for the overall objective values. In such cases, the multiple objective function is transformed into a single objective function.

$$f = \delta_1 f_1 + \delta_2 f_2 + \delta_3 f_3 + \delta_4 f_4 + \delta_S f_S$$

Where,

$$\sum_{i=1}^{5} \delta_i = 1, \qquad \delta_i \in (0,1) \tag{20}$$

In Equation (20), the weighted values are $\delta_1, \delta_2, \delta_3, \delta_4$, and δ_S, and its values are 0.35, 0.25, 0.2, 0.1 and 0.1 subsequently. The δ_1 takes RE significantly to avoid the node failure as a CH. Consequently, δ_2 and δ_3 are taken for seco[nd] and thi[rd] priority to detect CH from the BS with a lesser distance that gives an output in minimizing the ECON. The four[th] priority (δ_4) is provided to the ND for selecting CH with lesser ND. Also, the NC is taken as the fifth priority δ_5 which improves the nearness between the CMs and CH.

4. Performance Validation

Here, the investigational evaluation of the EADBO-CS method can be determined under varying nodes. In Table 1 and Figure 3, the comparative ECON outputs of the EADBO-CS method with other models [22]. The attained findings display that the EADBO-CS method gets reduced ECON values.

Additionally, the LEACH method gets poorer performance, while the SSO and fuzzy PSO systems declined moderately ECON values. Then, the MFO and WSN-MCOBA techniques gain attainable ECON values. But, the EADBO-CS approach accomplishes better performance with minimized ECON of 0.150mJ, 0.220mJ, 0.297mJ, 0.327mJ, and 0.391mJ, subsequently.

Table 1. ECON outcomes of the EADBO-CS model with other techniques under varying nodes

ECON (mJ)						
Number of Nodes	**EADBO-CS**	**WSN-MCOBA**	**MFO Protocol**	**SSO Protocol**	**Fuzzy-PSO Protocol**	**LEACH Protocol**
100	0.150	0.187	0.264	0.525	0.612	0.882
200	0.220	0.258	0.333	0.575	0.780	1.011
300	0.297	0.334	0.425	0.601	0.787	1.004
400	0.327	0.363	0.440	0.627	0.840	1.159
500	0.391	0.426	0.494	0.704	0.858	1.063

Table 2. THRO outcome of the EADBO-CS models with other techniques under varying nodes

THRO (Mbps)						
Number of Nodes	**EADBO-CS**	**WSN-MCOBA**	**MFO Protocol**	**SSO Protocol**	**Fuzzy-PSO Protocol**	**LEACH Protocol**
100	98.22	97.59	96.20	92.73	90.15	87.97
200	97.52	96.78	94.72	90.65	87.91	85.99
300	96.79	96.12	93.13	89.16	86.78	83.91
400	96.27	95.51	92.75	87.18	84.59	82.61
500	95.07	94.52	91.64	85.69	83.39	81.92

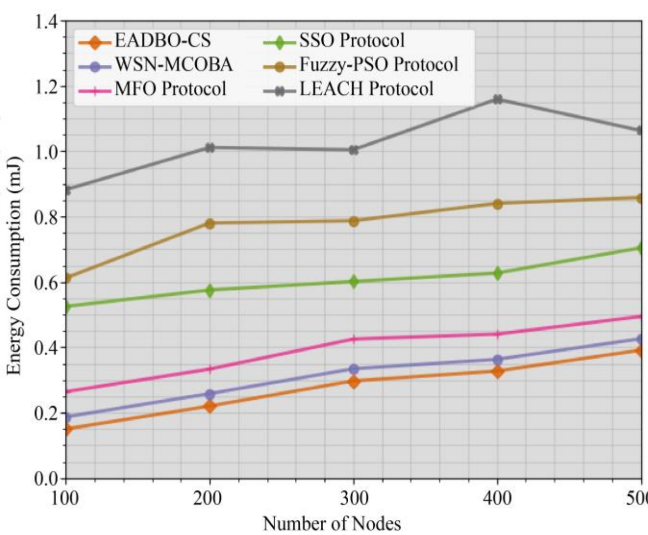

Fig. 3 ECON analysis of the EADBO-CS model under varying nodes

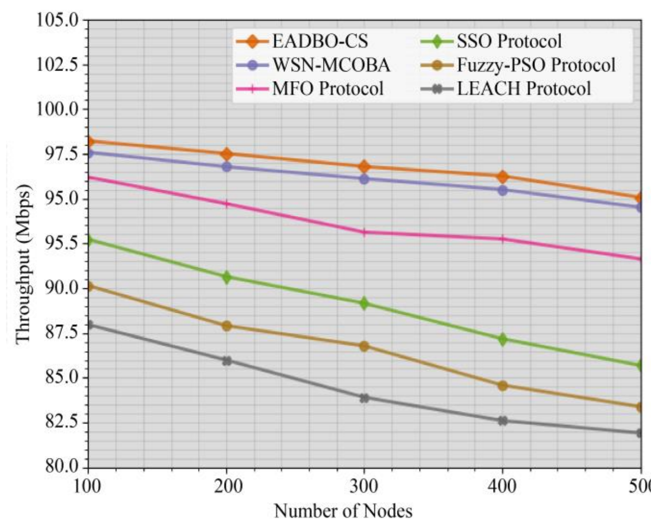

Fig. 4 THRO result of the EADBO-CS model under varying nodes

The comparison analysis of THRO outcomes of the EADBO-CS methodology under various nodes in Table 2 and Figure 4. According to 100 nodes, the EADBO-CS system gets boosted THRO of 98.22Mbps; then, the WSN-MCOBA, MFO, SSO, Fuzzy-PSO, and LEACH methods provide diminished THRO of 97.59Mbps, 96.20Mbps, 92.73Mbps, 90.15Mbps, and 87.97Mbps, correspondingly.

Furthermore, with 500 nodes, the EADBO-CS algorithm achieves an improved THRO of 95.07Mbps, but the WSN-MCOBA, MFO, SSO, Fuzzy-PSO, and LEACH systems offer minimalized THRO of 94.52Mbps, 91.64Mbps, 85.69Mbps, 83.39Mbps, and 81.92Mbps, correspondingly. The comparative analysis for the End-to-End Delay (EED) outcome of the EADBO-CS method with recent existing algorithms in Table 3 and Figure 5.

The attained findings display that the EADBO-CS method acquires decreased EED values. Next, the LEACH technique gets lower performance, but the fuzzy PSO and SSO approaches gain reasonably lessened EED values. At that time, the MFO and WSN-MCOBA techniques accomplished boosted EED values. The EADBO-CS algorithm gains excellent performance with the least EED of 2.37s, 4.64s, 5.66s, 5.78s, and 7.86s, respectively.

Table 3. EED outcomes of the EADBO-CS approach with other existing systems under varying nodes

EED (sec)						
Number of Nodes	**EADBO-CS**	**WSN-MCOBA**	**MFO Protocol**	**SSO Protocol**	**Fuzzy-PSO Protocol**	**LEACH Protocol**
100	2.37	3.12	4.38	6.13	8.59	8.96
200	4.64	5.76	6.15	7.04	7.75	9.34
300	5.66	6.39	6.62	7.22	9.41	10.17
400	5.78	6.84	7.06	7.00	8.04	9.55
500	7.86	8.64	9.18	10.14	13.11	14.02

Table 4. LAT outcome of the EADBO-CS approach with other systems under varying nodes

LAT (sec)						
Number of Nodes	**EADBO-CS**	**WSN-MCOBA**	**MFO Protocol**	**SSO Protocol**	**Fuzzy-PSO Protocol**	**LEACH Protocol**
100	2.493	3.133	3.838	5.361	7.044	8.346
200	2.158	2.838	4.740	6.546	8.038	9.153
300	2.991	3.331	5.079	7.039	8.947	10.138
400	3.835	4.135	6.217	8.046	9.731	10.116
500	4.679	5.089	7.108	8.339	10.041	12.115

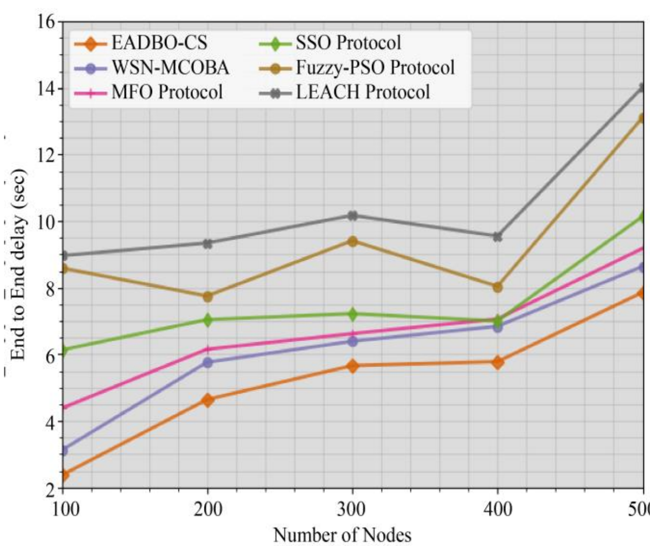

Fig. 5 EED analysis of the EADBO-CS model under varying nodes

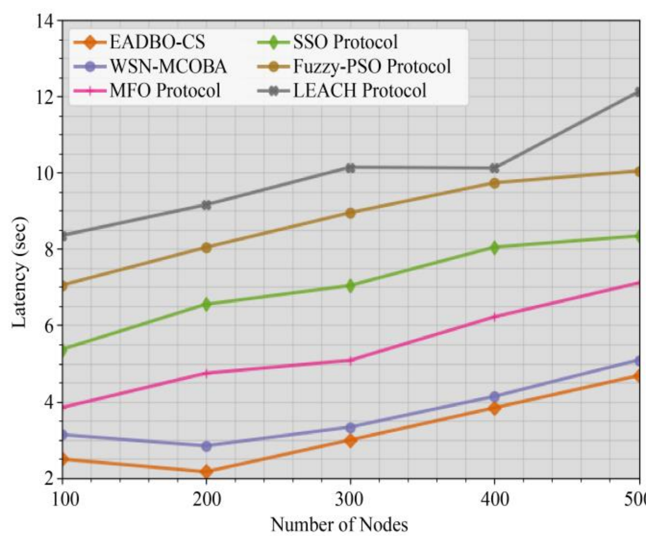

Fig. 6 LAT analysis of the EADBO-CS model under varying nodes

In Table 4 and Figure 6, the comparison Latency (LAT) analysis of the EADBO-CS methodology with other systems. The accomplished findings show that the EADBO-CS technique gets minimalized LAT values. In the meantime, the LEACH method provides lesser performance; nevertheless, the fuzzy PSO and SSO systems achieve relatively decreased LAT values. Whereas the MFO and WSN-MCOBA approach gain increased LAT values, the EADBO-CS method accomplishes superior performance with reduced LAT of 2.493s, 2.158s, 2.991s, 3.835s, and 4.679s, appropriately. The comparative Packet Delivery Ratio (PDR) result of the EADBO-CS method can be compared with other algorithms in Table 5 and Figure 7. Based on 100 nodes, the EADBO-CS system obtains an improving PDR of 98.39%, whereas the WS-MCOBA, MFO, SSO, Fuzzy-PSO, and LEACH systems provide lessening PDR of 97.81%, 96.65%, 93.49%, 90.19%, and 88.17%. Also, on 500 nodes, the EADBO-CS method gets raised PDR of 96.88%, but the WSN-MCOBA, MFO, SSO, Fuzzy-PSO, and LEACH systems give decreased PDR of 96.29%, 93.46%, 88.01%, 84.80%, and 82.57%, respectively.

Table 5. PDR evaluation of the EADBO-CS method with other models under varying nodes.

PDR (%)						
Number of Nodes	**EADBO-CS**	**WSN-MCOBA**	**MFO Protocol**	**SSO Protocol**	**Fuzzy-PSO Protocol**	**LEACH Protocol**
100	98.39	97.81	96.65	93.49	90.19	88.17
200	97.77	97.13	95.18	91.51	88.13	86.17
300	97.37	96.65	96.39	89.53	87.18	85.23
400	96.85	96.26	93.25	87.68	84.70	82.57
500	96.88	96.29	93.46	88.01	84.80	82.57

Table 6. NLT evaluation of the EADBO-CS method with other models under varying nodes.

NLT (rounds)						
Number of Nodes	**EADBO-CS**	**WSN-MCOBA**	**MFO Protocol**	**SSO Protocol**	**Fuzzy-PSO Protocol**	**LEACH Protocol**
100	1607	1570	1346	1327	1350	1150
200	1818	1747	1423	1463	1414	1396
300	2098	2012	1720	1725	1659	1292
400	2423	2331	1826	1801	1929	1571
500	2517	2429	2201	2035	2152	1958

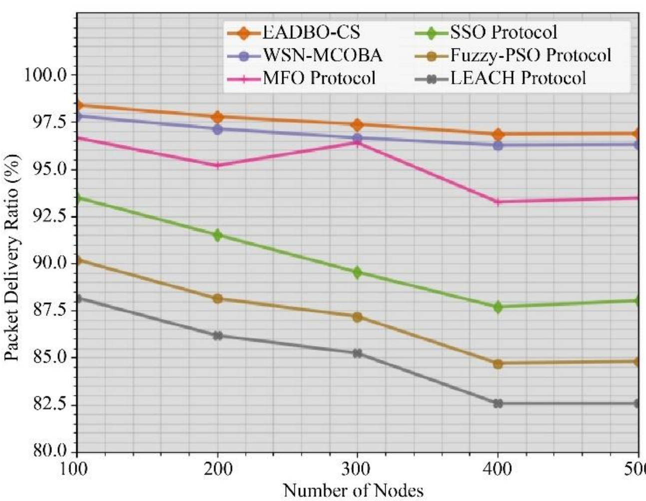

Fig. 7 PDR analysis of the EADBO-CS method under varying nodes

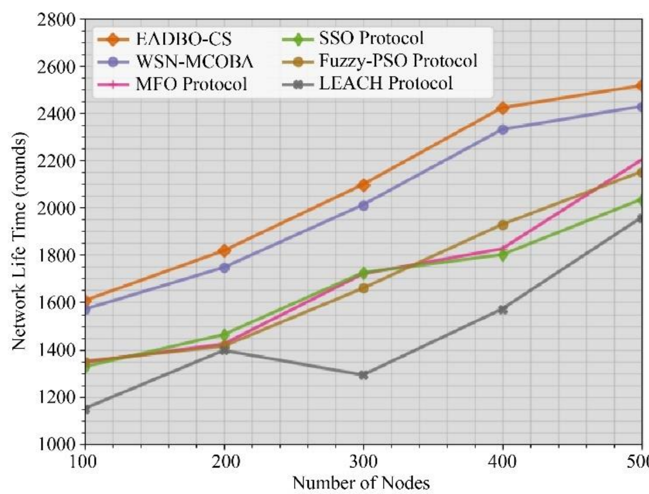

Fig. 8 NLT outcome of the EADBO-CS method under varying nodes

The comparative NLT analysis of the EADBO-CS system can be examined in Table 6 and Figure 8. According to 100 nodes, the EADBO-CS method gets raised NLT of 1607 rounds. Then, the WSN-MCOBA, MFO, SSO, Fuzzy-PSO, and LEACH algorithms provide decreasing NLT of 1570, 1346, 1327, 1350, and 1150 rounds. Similarly, with 500 nodes, the EADBO-CS algorithm gains increased NLT of 2517 rounds whereas the WSN-MCOBA, MFO, SSO, Fuzzy-PSO, and LEACH methodology offer minimized NLT of 2429, 2201, 2035, 2152, and 1958 rounds, correspondingly.

5. Conclusion

In this study, an EADBO-CS technique for energy effectualness in the WSN is proposed. The EADBO-CS technique aims to achieve energy efficacy by grouping the nodes into clusters and electing CHs. The EADBO-CS technique mainly follows the behavior of DB populaces. To accomplish this, the EADBO-CS model designs an FF comprising various parameters such as RE, DTN, DBS, ND, and NC.

The design of multiple parameters helps in achieving improved energy efficiency and maximum longevity in the WSN.

An investigational evaluation is achieved to validate the improved achievement of the EADBO-CS method. The investigational analysis signifies the dominance of the EADBO-CS method over other present approaches by means of diverse measures.

References

[1] Shukun He et al., “The Optimization of Node Clustering and Multi-Hop Routing Protocol Using Hierarchical Chimp Optimization for Sustainable Energy Efficient Underwater Wireless Sensor Networks,” *Wireless Networks*, vol. 30, pp. 233-252, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[2] R. Anandkumar, P.V. Venkateswara Rao, and Nagendra Babu Rajaboina, “Hybrid Red Fox and Improved Whale Optimization Algorithm-Based Clustering Scheme for Improving Network Longevity in Wireless Sensor Networks,” *Research Square*, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[3] Venkatesh Sivaprakasam et al., “An Improved Coyote Optimization Algorithm-Based Clustering for Extending Network Lifetime in Wireless Sensor Networks,” *KSII Transactions on Internet & Information Systems*, vol. 17, no. 7, pp. 1873-1893, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[4] Richa Sharma, Vasudha Vashisht, and Umang Singh, “eeFFA/DE - A Fuzzy-Based Clustering Algorithm Using Hybrid Technique for Wireless Sensor Networks,” *International Journal of Advanced Intelligence Paradigms*, vol. 21, no. 1-2, pp. 129-157, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[5] Kavita Jaiswal, and Veena Anand, “A Grey-Wolf Based Optimized Clustering Approach to Improve QoS in Wireless Sensor Networks for IoT Applications,” *Peer-to-Peer Networking and Applications*, vol. 14, pp. 1943-1962, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[6] J. Samuel Manoharan, “A Metaheuristic Approach towards Enhancement of Network Lifetime in Wireless Sensor Networks,” *KSII Transactions on Internet & Information Systems*, vol. 17, no. 4, pp. 1276-1295, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[7] Zhigang Wang et al., “A Metaheuristic Algorithm for Coverage Enhancement of Wireless Sensor Networks,” *Wireless Communications and Mobile Computing*, pp. 1-23, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[8] Al-Ammari, and Ali Haider Mohammed, “*Efficient Routing Scheme for Optimal Energy Consumptation in Wireless Sensor Network Using Metaheuristic Algorithm*,” Master's Thesis, Altınbaş University/Graduate Education Institute, 2022. [Google Scholar] [Publisher Link]

[9] Seema Swamy Gowda, and Ambika Ramalingappa, “Multi Objective Energy Based Improved Jellyfish Swarm Optimization for Effective Cluster Head Discovery in UWSN,” *International Journal of Intelligent Engineering & Systems*, vol. 16, no. 3, pp. 509-518, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[10] Narayanasamy Tamilarasan et al., “Hybrid Shuffled Frog Leaping and Improved Biogeography-Based Optimization Algorithm for Energy Stability and Network Lifetime Maximization in Wireless Sensor Networks,” *International Journal of Communication Systems*, vol. 34, no. 4, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[11] Sharmin Sharmin, Ismail Ahmedy, and Rafidah Md Noor, “An Energy-Efficient Data Aggregation Clustering Algorithm for Wireless Sensor Networks Using Hybrid PSO,” *Energies*, vol. 16, no. 5, pp. 1-24, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[12] Deyu Lin et al., “An Energy-Efficiency-Adaptive Clustering Formation Mechanism for the Wireless Sensor Networks,” *IET Communications*, vol. 16, no. 3, pp. 255-265, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[13] Baybars Karabekir, Muhammed Ali Aydın, and Abdül Halim Zaim, “Energy-Efficient Clustering-Based Mobile Routing Algorithm for Wireless Sensor Networks,” *Electrica*, vol. 21, no. 1, pp. 41-49, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[14] Ushus Elizebeth Zachariah, and Lakshmanan Kuppusamy, “A Hybrid Approach to Energy Efficient Clustering and Routing in Wireless Sensor Networks,” *Evolutionary Intelligence*, vol. 15, pp. 593-605, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[15] Nitin Kumar et al., “TEEECH: Three-Tier Extended Energy Efficient Clustering Hierarchy Protocol for Heterogeneous Wireless Sensor Network,” *Expert Systems with Applications*, vol. 216, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[16] Seyyit Alper Sert, and Adnan Yazici, “Increasing Energy Efficiency of Rule-Based Fuzzy Clustering Algorithms Using CLONALG-M for Wireless Sensor Networks,” *Applied Soft Computing*, vol. 109, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[17] G.A. Senthil, Arun Raaza, and N. Kumar, “Internet of Things Energy-Efficient Cluster-Based Routing using Hybrid Particle Swarm Optimization for Wireless Sensor Network,” *Wireless Personal Communications*, vol. 122, no. 3, pp. 2603-2619, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[18] Venkatasubramanian Srinivasan et al., "Detection of Data Imbalance in MANET Network Based on ADSY-AEAMBI-LSTM with DBO Feature Selection," *Journal of Autonomous Intelligence*, vol. 7, no. 4, pp. 1-15, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[19] Mandli Rami Reddy et al., "Energy-Efficient Cluster Head Selection in Wireless Sensor Networks Using an Improved Grey Wolf Optimization Algorithm," *Computers*, vol. 12, no. 2, pp. 1-17, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[20] Zijian Cai, Guolin Feng, and Qiguang Wang, "Based on the Improved PSO-TPA-LSTM Model Chaotic Time Series Prediction," *Atmosphere*, vol. 14, no. 11, pp. 1-17, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[21] Prachi Maheshwari, Ajay K. Sharma, and Karan Verma, "Energy Efficient Cluster Based Routing Protocol for WSN Using Butterfly Optimization Algorithm and Ant Colony Optimization," *Ad Hoc Networks*, vol. 110, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[22] Jeevanantham Vellaichamy et al., "Wireless Sensor Networks Based on Multi-Criteria Clustering and Optimal Bio-Inspired Algorithm for Energy-Efficient Routing," *Applied Sciences*, vol. 13, no. 5, pp. 1-14, 2023. [CrossRef] [Google Scholar] [Publisher Link]