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Original Article

Leveraging Chaotic Wind-Driven Optimization with Equilibrium Optimization Algorithm for Cluster-Based Routing in WSN

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Abstract *- Wireless Sensor Networks (WSNs) contain many spatially spread sensor nodes linked over the wireless standard to observe and trace the physical data from the location. Generally, the WSN nodes are battery-driven; therefore, they will lose whole energy after a definite time. This kind of energy restriction leads to the lifetime of the system. The objective is to diminish the complete energy utilization and boost the networking lifespan. Routing and clustering techniques are commonly employed in WSNs to improve the lifespan. The aim is to mitigate the energy utilization of the sensor nodes throughout data transmission. This upsurges the total packet spread to BS by lowering the sensor nodes' energy utilization. This study generally employs swarm intelligence due to its searching capability, self-adaptability, and robustness. This article proposes the Chaotic Wind Driven with Equilibrium Optimization Algorithm for Efficient Cluster-based Routing (CWDEO-ECBR) technique in WSN. The CWDEO-ECBR technique utilizes the concept of clustering with a route selection process to enhance the network efficiency. The CWDEO-ECBR technique comprises two significant phases of operations. Initially, the CWDEO-ECBR technique uses a chaotic wind-driven optimization (CWDO) technique for selecting the cluster heads (CHs) and organizing clusters. In the second stage, the CWDEO-ECBR technique employs an equilibrium optimizer (EO) method for the routing process. A comprehensive simulation analysis is conducted to evaluate the performance of the CWDEO-ECBR approach. The CWDEO-ECBR model achieved a superior accuracy of 99.54% in NOAN, highlighting its efficiency in improving WSN network performance compared to existing methods.*

Keywords *- Wireless Sensor Network, Equilibrium Optimizer, Clustering, Routing, Cluster Head, Chaotic Wind-Driven Optimization.*

1. Introduction

A WSN is described as a small-scale reunion for sensor hubs, particularly for monitoring, capturing, sensing, and processing the data about an application. So, these hubs fully trust storage, data size, bandwidth, battery backup, and computation [1]. Presently, WSN has become essential in everyday life; therefore, numerous studies concentrate on the exact properties of its application. Real applications have invited more attention from analysts and technocrats because of the current innovations in the field of sensors [2]. To overcome the problems in the sensor field, technologists and scientists have found a solution in real-time WSN applications. Generally, the sensors can identify, send, and record feedback instantly to the end client for future processing of all the collected data [3]. Notably, a real-time application presents simple uses that want restricted delay latency [4]. The deficient power sources of the sensor node have been measured as a primary concern in WSNs [5]. So, because of node failure, the fault occurs in the network. So, the main dissimilarity between WSNs and other standard wireless systems is that WSNs are generally vulnerable and hypersensitive to energy [6]. The sensor nodes use their energy rapidly because of straight data spread from every sensor to BS. Furthermore, the optimal energy used in WSNs is needed to attain the highest lifespan and improve the WSN performance [7]. Thus, grouping sensors into groups has been applied to reduce network energy utilization and upsurge the system's scalability. Every group of a system has one header named CH, which links with other CHs in the network [8]. A more significant amount of energy is essential to hand over the detected data to the BS directly; a routing protocol is employed in the grouped WSN to recognize the finest direction among the BS and CHs to decrease energy utilization [9]. The routing protocol features contain scalability, fault tolerance, data accumulation, and reliability. The requirement for efficient data transmission and energy conservation in

WSNs drives the use of advanced optimization techniques like chaotic wind-driven and equilibrium optimization algorithms [10]. This article proposes the Chaotic Wind Driven with Equilibrium Optimization Algorithm for Efficient Cluster-based Routing (CWDEO-ECBR) technique in WSN. The CWDEO-ECBR technique utilizes the concept of clustering with a route selection process to enhance the network efficiency. The CWDEO-ECBR technique comprises two significant phases of operations. Initially, the CWDEO-ECBR technique uses a chaotic wind-driven optimization (CWDO) technique for selecting the cluster heads (CHs) and organizing clusters. In the second stage, the CWDEO-ECBR technique employs an equilibrium optimizer (EO) method for the routing process. A comprehensive simulation analysis is conducted to evaluate the performance of the CWDEO-ECBR approach.

- The CWDEO-ECBR technique efficiently chooses and organizes CHs using CWDO. This methodology enhances the network's performance by optimizing energy consumption (EC) and improving data communication. Furthermore, CWDO ensures effective resource distribution, maximizing the overall network efficiency.
- The CWDEO-ECBR method integrates an EO model to select optimal routes for data transmission. This improves the network's efficiency by minimizing congestion and enhancing communication. EO optimizes routing paths and enhances network performance by ensuring smoother data flow.
- A detailed simulation study is conducted to assess the performance of the CWDEO-ECBR approach over recent techniques. The results show its superior efficiency in various network conditions. The analysis highlights the capability of the CWDEO-ECBR approach to attain better network performance and optimize resource utilization.
- The CWDEO-ECBR technique introduces a novel dual optimization strategy by integrating CWDEO for clustering and EO for routing. This unique approach effectively improves WSN's performance. Integrating these two techniques ensures improved efficiency in network organization and data transmission.

The article is structured as follows: Section 2 presents the literature review, Section 3 outlines the proposed method, Section 4 details the results evaluation, and Section 5 concludes the study.

2. Literature Works

In [11], a Red Kite Optimization Algorithm (OA) was introduced with an Average Ensemble Module for the ID (RKOA-AEID) method. By applying min-max normalization, this technique performs pre-processing. Furthermore, the algorithm performs the RKOA-based FS technique. An AEI approach is utilized. Lastly, the Lévy-fight chaotic whale OA (LCWOA) is performed to select hyperparameters optimally. In [12], an Evolutionary Gravitational Neocognitron Neural Networking-assisted Blockchain Technology for Secure Dynamic Optimum Routing in WSN (BT-SDOR-WSN-EGNNN) was proposed. The EGNNN is considered for selecting relevant nodes. Next, Trust-assisted Secure Intelligent Opportunistic Routing Protocol (TBSIOP) is applied. Nayak and Kumar [13] present an energy management system (EMS) model using a hybrid mechanism based on an IoT network. The presented technique is a shared implementation of multi-fidelity meta-optimization (M2FWO) and turbulent flow of water-driven optimizing (TFWO) models. The proposed architecture gathers DR from devices and transfers the information to the central server. The M2FWO technique can empower data transmission. In [14], an energy-effectual dispersed node clustering mobility pattern routing protocol (DNC-MPRP) is developed. The rectangle mobility pattern is employed. Then, the CH formation is used to initialize the cluster region in the standard and large area. Finally, the transmitting data is adopted.

Thangaraj et al. [15] provide the HMML, a hybrid approach combining ML and hybrid metaheuristics. This HMML approach utilizes an automatic tuning metaheuristic (evolutionary approach) to finetune the heuristic method for specific configurations. This is done for different combinations. A network simulation is performed, implementing the altered heuristic technique to reach an outcome. Aqeel et al. [16] present a new, energy-aware AI-assisted load-balance algorithm that exploits the big data analytics (BDA) and Chaotic Horse Ride OA (CHROA) for a cloud-assisted IoT. This improves the ability of HROA to optimize using the chaotic principle. The CHROA technique is used for load balancing, which enhances energy resources using the AI technique. Sagu et al. [17] propose a deep fusion attack recognition method. The input dataset is subject to normalization and pre-processing. The higher order and statistical factors are extracted from the pre-processed dataset. Lastly, the feature extracted is subject to a hybrid DL approach to identify the presence of an attack. The presented models integrate DBN and CNN methods. Sureshkumar, Joseph, and Priya [18] present a modified snake swarm OA (MSSOA) for routing and an adaptive binary bird swarm OA (ABBSOA) for CH formation and selection.

Selvi et al. [19] introduce a WSN cluster-based routing model with optimal CH Selection (CHS) and routing using a Remora Customized Shark Optimization (RCSO) approach. The method considers risk, delay, energy, and distance for CHS and optimizes routing based on link quality, trust, and distance. Sangeetha et al. [20] propose an energy-efficient routing, incorporating Voronoi-based node deployment, game theory for CH selection, and Improved Pelican Optimization (ImPe) for segment routing. Vissapragada, Abarna, and Sree [21] present an Energy-based Multiobjective Hybrid OA (E-MHOA) methodology. By incorporating the Cuckoo Search

Algorithm (CSA) with the Whale OA (WOA), E-MHOA selects CHs based on residual energy. Melkamu et al. [22] propose a modified cluster-based routing protocol (MCBRP) technique for MANETs to improve stability and network longevity. It optimizes CH selection using nodes with high residual energy or degree centrality, mitigating re-clustering and ensuring continuous cluster maintenance. Yang, Liu, and Cao [23] introduce a discrete particle swarm optimization (PSO)-based routing protocol with energy-aware fitness functions and a greedy discrete PSO (GMDPSO) to optimize routing. GMDPSO redefines particle dynamics and uses a greedy strategy for faster optimization. Alsuwat et al. [24] propose an Improved Q-learning-based Artificial Bee Colony Algorithm (IQ-ABC) technique for optimal CH selection in WSNs, improving energy efficiency, latency, and trust using a multiobjective fitness function and Fuzzy Logic. Rekha and Garg [25] present the K-LionER scheme integrating K-means clustering and Ant Lion Optimization (ALO) for energy-effectual routing in WSNs.

Despite the advancements in energy-efficient routing protocols, many existing methods suffer from high re-clustering frequency, inefficient energy management, and insufficient trust and latency optimization. Several algorithms overlook dynamic environmental changes, leading to suboptimal performance in real-world scenarios. Moreover, most existing models lack comprehensive strategies for balancing energy efficiency, security, and reliability in large-scale networks. Therefore, there is a requirement for more robust, adaptive, and hybrid optimization techniques that can effectively address these challenges and improve overall network longevity and stability.

3. The Proposed Method

This article presents the CWDEO-ECBR model in WSN. The CWDEO-ECBR technique exploits the concept of clustering with a route selection process to enhance network efficiency. It involves two major phases of operations. Figure 1 depicts the entire flow of the CWDEO-ECBR model.

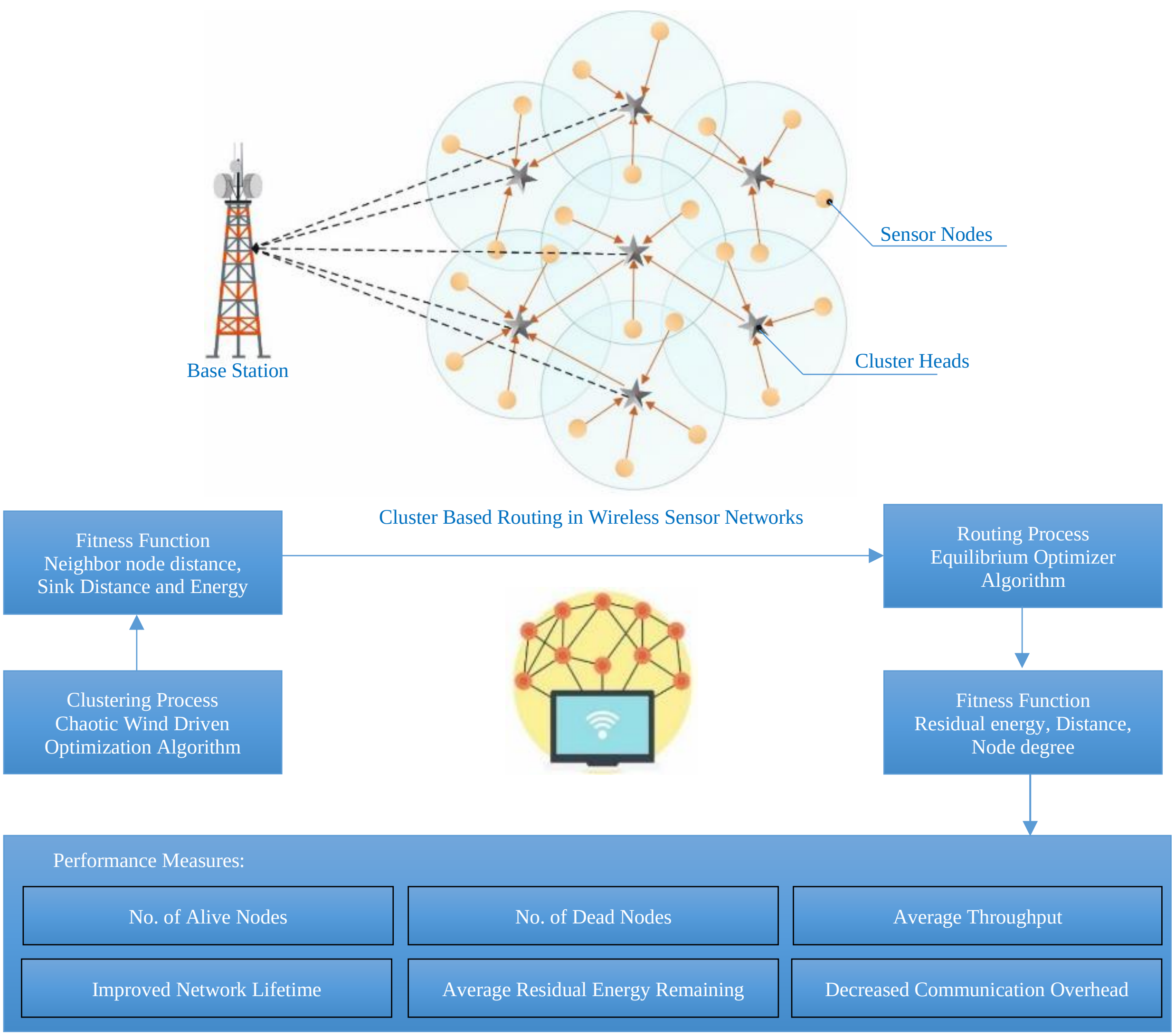

Fig. 1 Structure of the CWDEO-ECBR model

3.1. Algorithmic Design of CWDO Model

The air in the atmosphere is clarified into particles to contract with, known as air particles [26]. This model is chosen because it can balance exploration and exploitation, averting premature convergence in complex optimization tasks. Its robust performance and flexibility make it ideal for enhancing energy efficiency and network stability in large-scale systems, outperforming conventional optimization methods. The WDO approach is attained, and the model is simplified based on the perfect gas equation of state and Newton's second law in the non-inertial coordinate method.

$$\rho\omega = \sum F_i, \tag{1}$$

In Equation (1), ω is acceleration; ρ represents air density; F_i is the force used on the air particle. The four significant forces exerted on air according to aerodynamics are:

$$F_G = \rho\delta V g, \tag{2}$$

$$F_{PG} = -\nabla p \delta V, \tag{3}$$

$$F_C = -2\Omega \times u, \tag{4}$$

$$F_F = -\rho a u, \tag{5}$$

F_G is gravity; g denotes the acceleration vector; F_{PG} indicates the pressure gradient force; Ω indicates the earth rotation angle vector; F_C indicates the Coriolis force; ∇p shows the pressure gradient. F_F shows the friction force; δV represents the air particle's volume; a shows the friction coefficient. u represents the wind velocity vector. By replacing Eqs. (2)-(5) and $\omega = \frac{\Delta u}{\Delta t}$ into Equation (1), thus:

$$p\frac{\Delta u}{\Delta t} = \rho\delta V g - \nabla p \delta V - 2\Omega \times u - \rho a u. \tag{6}$$

Consider $= 1$, $\delta V = 1$, then Equation (6) is written as:

$$\rho\Delta u = \rho\delta V g - \nabla p - 2\Omega \times u - \rho a u. \tag{7}$$

The pressure formula for a perfect gas is given below:

$$P = \frac{RT}{P}, \tag{8}$$

In Equation (8), R indicates the ideal gas coefficient; P is pressure, and T is the temperature. Substitute Equation (8) into Equation (7) produces:

$$\Delta u = g - \frac{\nabla p}{\frac{RT}{P_{cur}}} - \frac{2\Omega \times uRT}{P_{cur}} - au. \tag{9}$$

The velocity and position of air particles will be changed to explore new space.

$$\Delta u = u_{new} - u_{cur}. \tag{10}$$

$$g = |g|(0 - x_{cur}), \tag{11}$$

$$-\nabla p = |p_{opt} - p_{cur}|(x_{opt} - x_{cur}), \tag{12}$$

Now p_{opt} denotes the optimum pressure value; p_{cur} indicates the existing pressure value of the particle point; x_{opt} shows the optimum location; x_{cur} represents the existing location:

$$u_{new} = (1 - a)u_{cur} - gx_{cur} + \left(\frac{RT}{p_{cur}}|p_{opt} - p_{cur}|(x_{opt} - x_{cur})\right) + \left(\frac{-2\Omega \times uRT}{p_{cur}}\right) \tag{13}$$

$u_{cur}^{other\dim}$ denotes the air particle velocity, set the constant to $c = -2|\Omega|R$. Rather than p_{opt} and p_{cur}, i denotes the decreasing order of air particles. The pressure value is minimal, and p_{opt} is 1 when x_{opt} is in position. Then the formula for updating velocity and position is given below:

$$u_{new} = (1 - a)u_{cur} - gx_{cur} + \left(RT\left|1 - \frac{1}{i}\right|(x_{opt} - x_{cur})\right) + \left(\frac{cu_{cur}^{other\dim}}{i}\right) \tag{14}$$

$$x_{new} = x_{cur} + (u_{new} \times \Delta t). \tag{15}$$

For the air quality point in every dimension, the time interval is one and, based on the specific problem, the position of the search range is set, and the update speed has a particular scope, concluding velocity value size:

$$u_{new}^{*} = \begin{cases} u_{\max}\ if\ u_{new} > u_{\max} \\ -u_{\max}\ if\ u_{new} < -u_{\max} \end{cases} \tag{16}$$

In Equation (16), $u_{\max}$ denotes the speed boundary value.

Chaotic mapping produces a chaotic sequence that could change a deterministic system into a random sequence. In this OA, the chaotic map replaces the pseudorandom number generator for making a batch of chaotic numbers within [0,1].

Studies have shown that initializing populations with chaotic sequences can improve optimization performance compared to pseudorandom numbers. This study uses chaotic maps, specifically tent mapping, to enhance wind particle initialization. Tent mapping is chosen for its iterative, ergodic, and uniform speed advantages. This is mathematically formulated as follows:

$$x_{t+1}^{i} = \begin{cases} 2x_t^i & 0 \le x_t^i \le 0.5 \\ 2\left(1 - x_t^i\right) & 0.5 < x_t^i \le 1 \end{cases} \tag{17}$$

Where $t = 1,2 \dots M$ indicates space dimension; $i = 1,2 \dots N$ denotes the number of populations. Based on Equation (17), N initial value is chosen, n chaotic series x_t^i, and later substituted in Equation (18) reverse to the search range, an even initialization of random air proton is attained.

$$y_t^i = lb_i\{(ub_i - lb_i)x_t^i, \tag{18}$$

Where lb_i and ub_i show the lower and upper limitations of the search range of x_t^i.

3.2. Design of Clustering Technique using CWDO Model

During the cluster formation phase, this selection procedure of CH favours irregular clustering development. Minimize f_1 (neighbor distance), f_2 (sink distance), and f_3 (energy reduction from CHs to RE) for optimal CH selection. Regularize the objective within [0, 1] to minimize the combined functions efficiently.

Note: The f_1, f_2, and f_3 are employed to originate the fitness function (FF) for the HHO-based model. Minimize f_1, f_2 and f_3 functions of objective and linear integration. Thus, the Linear Programming (LP) for the optimal CHS issues is set below:

$$Minimize\ F = \alpha_1 f_1 + \alpha_2 f_2 + \alpha_3 f_3 \tag{19}$$

Subjected to,

$$dis(s_i, CH_j) \leq d_{\max}, \forall s_i \in S, CH_j \in C \tag{20}$$

$$E_{CH_J} > T_H,\ 1 \leq j \leq m \tag{21}$$

$$\alpha_1 + \alpha_2 + \alpha_3 = 1, (\alpha_1, \alpha_2, \&\ \alpha_3)\ \varepsilon\ (0,1) \tag{22}$$

$$\alpha_2 \geq (\alpha_1 + \alpha_3) \tag{23}$$

The limitation (20) certifies that the sensor s_i is in the range of CH_j. The limitation (21) warrants that the energy of CH_j nodes must be greater than TH. The restriction (22), α_1, α_2, and $\alpha 3$ are the weights of the f_1, f_2 and f_3 functions, respectively, and it also safeguards that these values must not be 0% weight or 100.

Constraint (23) confirms that α_2 must be equivalent to or larger than the number of remaining weights, which aids in picking more CHs closer to the sink. The derivation of FF trusts on the subsequent parameters:

a) Neighbor node distance: It is the least distance from the neighbour, viz., $dis(CH_j,s_i)$. Throughout the communication procedure, every sensor uses a small amount of energy to transport data to the related CH. Reduce the distance from its neighbours to mitigate EC.

Objective 1:

$$Minimize\ f_1 = \sum_{j=1}^{m} dis(CH_j, s_i) \tag{24}$$

b) Sink distance: It signifies distance among CH_j and BS, i.e., $dis(CH_j, BS)$. Sink distance is central to the CHS, which is nearer to BS. This process aids in the cluster creation of smaller sizes closer to the sink.

Objective 2:

$$Minimize\ f_2 = \sum_{j=1}^{m} dis(CH_j, BS) \tag{25}$$

c) Energy ratio states the ratio of used-up energy through the CH_j to the RE of CH_j. If CH_j consumes less computation, detection, and transmission energy, the RE will be enlarged and have a lower energy ratio.

Objective 3:

$$Minimize\ f_3 = \sum_{j=1}^{m} \frac{E_C(CH_j)}{E_R(CH_j)} \tag{26}$$

A weighted aggregation model reduces each objective, as they are not strongly incompatible with each other. So, the FF is utilized:

$$Fitness\ = \alpha_1 f_1 + \alpha_2 f_2 + \alpha_3 f_3 \tag{27}$$

The purpose is to reduce fitness; smaller values result in better particle positions and more CHs.

3.3. Overview of the EO Approach

EO is a new OA that stimulates laws of physics to attain optimal solutions [27]. This technique is chosen due to its robust capacity to balance exploration and exploitation, which is crucial for finding optimal routing paths in dynamic WSNs.

Unlike conventional algorithms, EO adapts efficiently to network changes and optimizes multiple energy efficiency and latency objectives. Its fast convergence and capability to handle complex, nonlinear routing problems make it a superior choice for ensuring robust and efficient data transmission in WSNs. Figure 2 exemplifies the steps implemented in EO. It is used to deal with problems with various complexity levels. The search unit of EO is named particles that receive an initial concentration value as follows:

$$C_j = LB + r \times (UB - LB), \tag{28}$$

In Equation (28), r shows the random integer within $[0\ and\ 1]$. UB and LB are the upper and lower restrictions of the search range. Like other optimizer algorithms, the particle quality is portrayed by the fitness value. Then, they are arranged to hire four of them, each differentiated by the maximum fitness value. Also, the fifth particle denotes the fourth particle' mean. The exponential term (F) is represented as follows:

$$F = CP_1 \cdot sign(r - 0.5)\left(e^{-\beta t} - 1\right), \quad (29)$$

$$t = (1 - R_{iter})^{(CP_2 \times R_{iter})}, \quad (30)$$

$$R_{iter} = \frac{iter}{T}, \quad (31)$$

Where β denotes the turnover rate, CP_1 and CP_2 are controlling parameters for the exploration and exploitation stages. G_{CP} and GP are the generation probability mathematically expressed as follows:

$$R_G = G_0 \cdot G_{CP} \cdot \left(C_{eq} - \beta C\right) \cdot F, \quad (32)$$

$$G_{CP} = \begin{cases} 0.5 r_1 & if\ r_2 \geq GP \\ 0 & otherwise \end{cases} \quad (33)$$

In Equation (33), C_{eq} represents the equilibrium pool and r_1 and r_2 are random integers within [0,1].

The solution is updated by Equation (34) based on the above calculation:

$$C_j = C_{eq} + \left(C_j - C_{eq}\right) \times F + (1 - F)\frac{R_G}{\beta V} \quad (34)$$

Where y refers to the considered unit.

Fig. 2 Steps utilized in EO

3.4. Process Involved in EO-based Routing

The EO-based routing model aims to reduce EC and extend the NLT of each SN. The objective function h_1 maximizes the selection of Next-hop CHs with high RE to extend NLT. h_2 minimizes the shortest distance between CHs, Next-hop CHs, and the BS to reduce energy usage. h_3 minimizes the selection of Next-hop CHs with high ND to extend NLT. b_{ij} is the Boolean variable given as follows.

$$b_{ij} = \begin{cases} 1\ if\ next - hop(CH_i) = CH_j, \\ 0, Otherwise \end{cases} \forall (i,j) 1 \leq i,j \leq m \quad (35)$$

$$Minimize\ F = \frac{1}{h_1} \times \beta_1 + h_2 \times \beta_2 + h_2 \times \beta_3 \qquad (36)$$

Subjected to,

$$dis(CH_i, CH_j) \times \leq d_{\max} CH_j \epsilon \{C + BS\} \qquad (37)$$

$$\sum_{j=1}^{m} b_{ij} = 1\ and\ 1 \neq j \qquad (38)$$

$$0 < \beta_1, \beta_2, \beta_3 < 1 \qquad (39)$$

Constraint (37) ensures the Next-hop node of CH_i is within range and is CH_j. Limitation (38) specifies the Next-hop node of CH_i is uniquely CH_j, and (39) ensures weights are neither 100% nor 0%.

The derivation of FF depends on the following parameters.

a) RE of Next-Hop nodes: The BS maps to the Next-hop node based on RE, selecting a node with higher RE from the middle of the Next-hop nodes.

Objective 1:

$$Maximize: h_1 = \sum_{j=1}^{m} E_{CH_j} \qquad (40)$$

b) Next-Hop node and BS distance: The c mapping to the Next-hop node depends on the distance to the Next-hop node and the BS. A CH selects the Next-hop node with the shortest distance to the BS.

Objective 2:

$$Minimize: h_2 = \sum_{j=1}^{m} d\,is(CH_j, NH(CH_j)) + dis(NH(CH_j) + BS) \qquad (41)$$

c) Node degree ND of Next-Hop node: The CH mapping to the Next-hop node depends on the ND of the Next-hop node, which is allotted with CH and assessed with minimal ND.

Objective 3:

$$Minimize: h_3 = \sum_{j=1}^{m} N_d\,(NH(CH_j)) \qquad (42)$$

Here, a weighted aggregation method reduces the entire objective because they do not conflict. Thus, the following FF is used:

$$Minimize\ Fitness\ = \beta_1 \times \frac{1}{h_1} + \beta_2 \times h_2 + \beta_3 \times h_3 \qquad (43)$$

Where,

$$0 < \beta_1, \beta_2, \beta_3 < 1 \qquad (44)$$

4. Result Analysis and Discussion

This section investigates the distinct aspects of the performance of the CWDEO-ECBR technique. Table 1 and Figure 3 represent a comparative number of alive node (NOAN) outcomes of the CWDEO-ECBR methodology with existing approaches [28]. The outputs indicate that the HAS-PSO and FFOCR methodology have reported ineffectual performance with the lowest values of NOAN.

Additionally, the FFC-GWO methodology and HABC-MBOA technique have slightly increased NOAN values. However, the CWDEO-ECBR methodology has obtained effectual performance with maximum values of NOAN.

Table 1. NOAN assessment of the CWDEO-ECBR methodology with existing models under various rounds

NOAN (in %)					
No. of Rounds	**HAS-PSO**	**FFOCR**	**FFC-GWO**	**HABC-MBOA**	**CWDEO-ECBR**
0	97.20	98.23	99.51	99.00	99.54
100	96.69	96.95	99.00	99.76	99.55
200	93.62	96.44	98.48	98.23	99.29
300	89.53	94.39	96.18	97.46	98.78
400	80.32	82.11	90.04	97.72	99.29
500	59.08	64.71	79.30	97.20	98.01
600	43.48	51.41	65.48	96.95	98.52
700	31.97	45.78	53.46	83.90	97.49
800	23.52	30.69	41.94	69.32	95.19
900	12.01	23.01	34.78	67.53	83.18
1000	9.96	16.87	20.71	45.52	72.43
1200	0.75	5.10	15.08	30.94	58.61
1400	0.24	0.24	6.64	22.24	47.88
1600	0.00	0.00	0.24	13.80	29.95
1800	0.00	0.00	0.00	0.50	11.54
2000	0.00	0.00	0.00	0.00	8.73

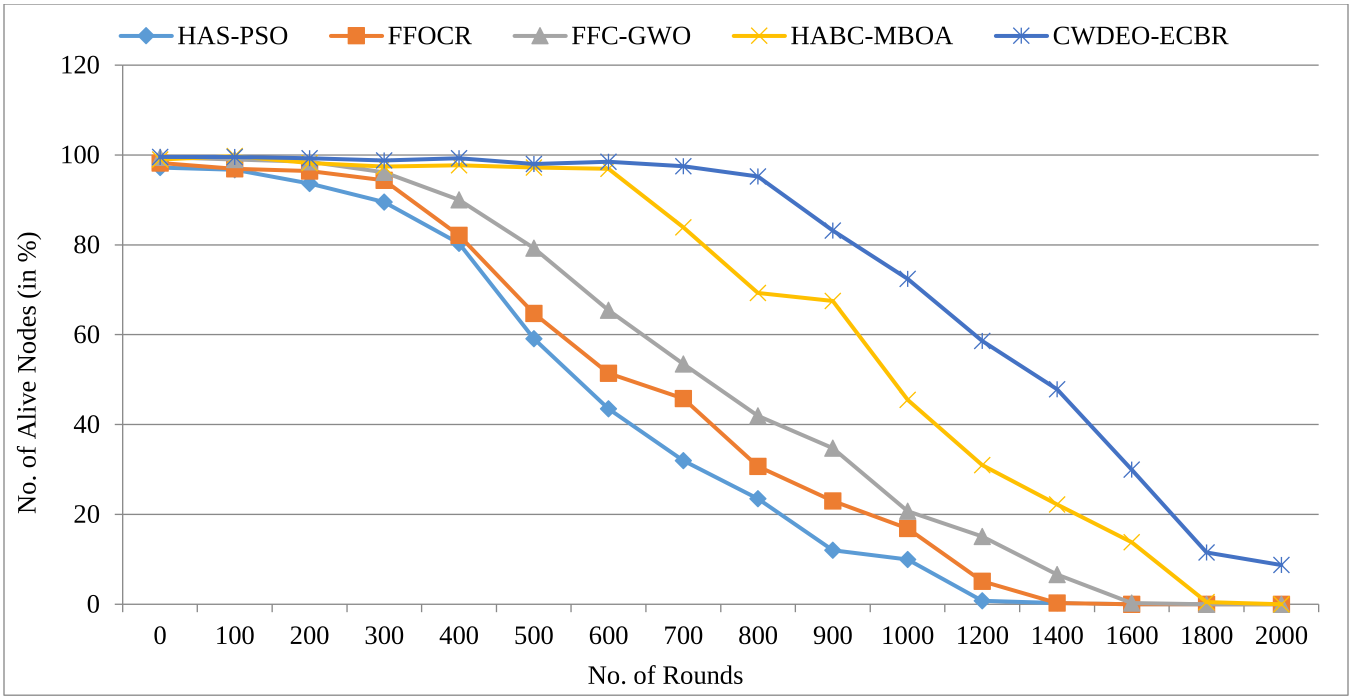

Fig. 3 NOAN analysis of the CWDEO-ECBR approach under various rounds

Table 2 and Figure 4 clearly illustrate the NODN results of the CWDEO-ECBR method with recent models. The obtained outcomes demonstrated the poor accomplishment of the FFOCR and HAS-PSO methodologies with increased NODN values. At the same time, the FFC-GWO and HABC-MBOA methodologies resulted in moderated NODN model values. Nevertheless, the CWDEO-ECBR methodology depicted superior performance with minimal NODN values.

Table 2. NODN assessment of CWDEO-ECBR approach with existing methods under various rounds

NODN (in %)					
No. of Rounds	**HAS-PSO**	**FFOCR**	**FFC-GWO**	**HABC-MBOA**	**CWDEO-ECBR**
0	2.80	1.77	0.49	1.00	0.46
100	3.31	3.05	1.00	0.24	0.45
200	6.38	3.56	1.52	1.77	0.71
300	10.47	5.61	3.82	2.54	1.22
400	19.68	17.89	9.96	2.28	0.71
500	40.92	35.29	20.70	2.80	1.99
600	56.52	48.59	34.52	3.05	1.48
700	68.03	54.22	46.54	16.10	2.51
800	76.48	69.31	58.06	30.68	4.81
900	87.99	76.99	65.22	32.47	16.82
1000	90.04	83.13	79.29	54.48	27.57
1200	99.25	94.90	84.92	69.06	41.39
1400	99.76	99.76	93.36	77.76	52.12
1600	100.00	100.00	99.76	86.20	70.05
1800	100.00	100.00	100.00	99.50	88.46
2000	100.00	100.00	100.00	100.00	91.27

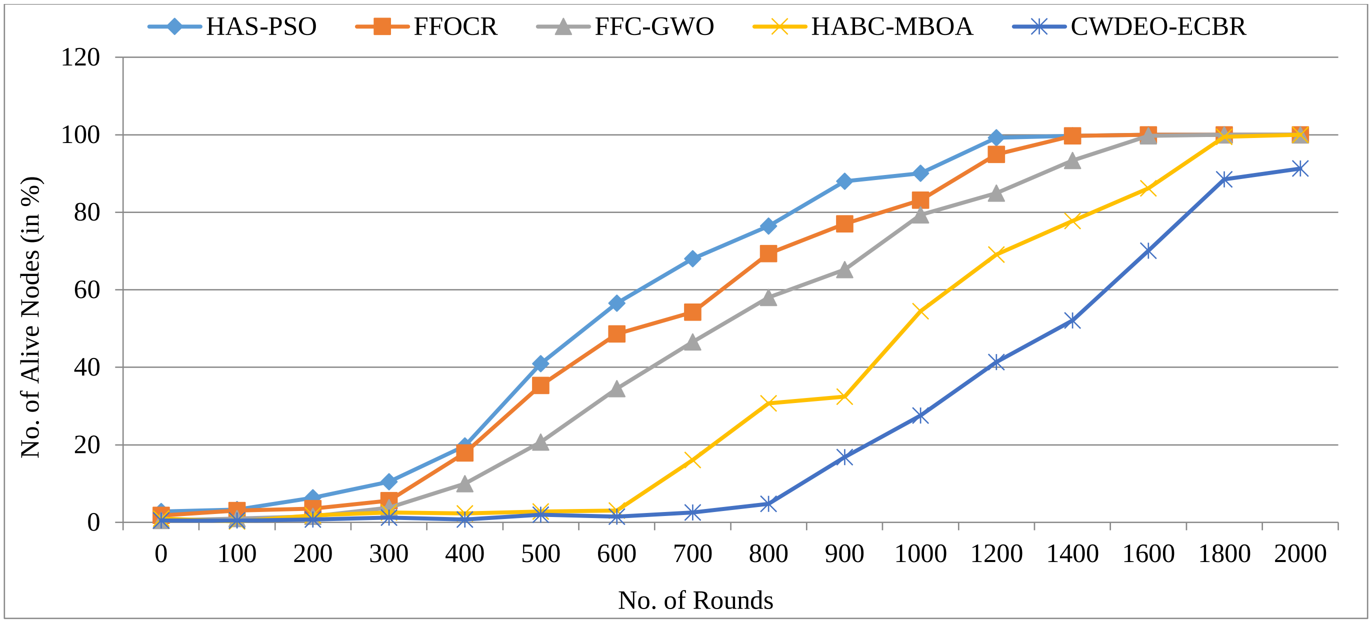

Fig. 4 NODN assessment of the CWDEO-ECBR method under various rounds

Table 3. ATHRO analysis of the CWDEO-ECBR approach with recent methods under various SNs

	ATHRO (Mbps)				
No. of Sensor Nodes	**HAS-PSO**	**FFOCR**	**FFC-GWO**	**HABC-MBOA**	**CWDEO-ECBR**
100	1.88	3.34	3.97	6.28	8.84
200	3.55	5.02	7.12	9.01	11.94
300	5.44	6.49	9.22	13.00	18.44
400	7.54	8.17	10.48	16.56	22.29
500	8.59	10.69	13.84	20.76	26.41
600	9.64	13.63	16.98	26.22	30.07
700	13.21	15.93	20.97	30.83	35.53
800	15.51	16.77	24.96	34.61	42.87
900	18.03	19.92	28.52	40.06	51.31
1000	19.50	24.54	31.67	51.40	57.61

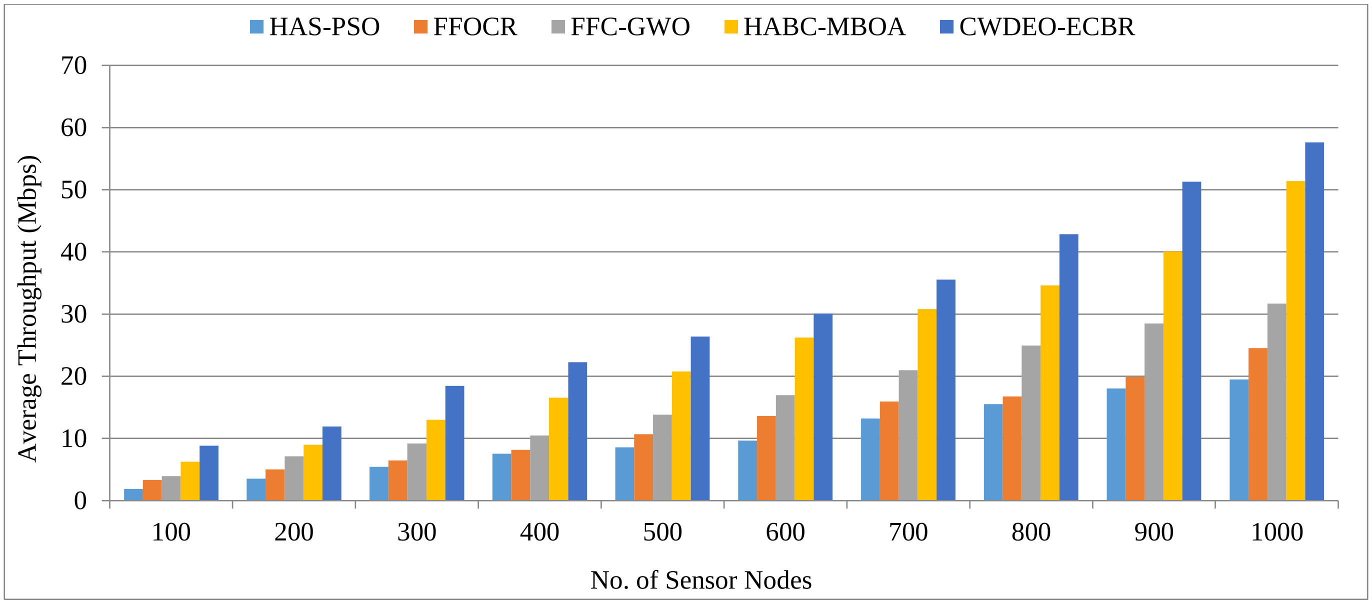

Fig. 5 ATHRO assessment of the CWDEO-ECBR approach under various SNs

Table 4. ARER analysis of the CWDEO-ECBR approach with recent methods under various SNs

ARER (in %)					
No. of Sensor Nodes	**HAS-PSO**	**FFOCR**	**FFC-GWO**	**HABC-MBOA**	**CWDEO-ECBR**
100	9.79	13.43	16.91	22.18	24.97
200	8.50	11.81	15.05	19.50	22.87
300	7.77	9.87	12.62	18.05	21.14
400	7.04	7.61	10.52	16.27	20.22
500	5.74	6.80	10.03	14.32	18.66
600	4.77	5.58	8.33	12.22	16.83
700	3.80	5.02	7.44	10.76	14.57
800	2.75	3.96	6.88	9.79	14.66
900	1.86	2.99	5.10	8.82	13.69
1000	0.73	2.02	4.61	7.61	11.98

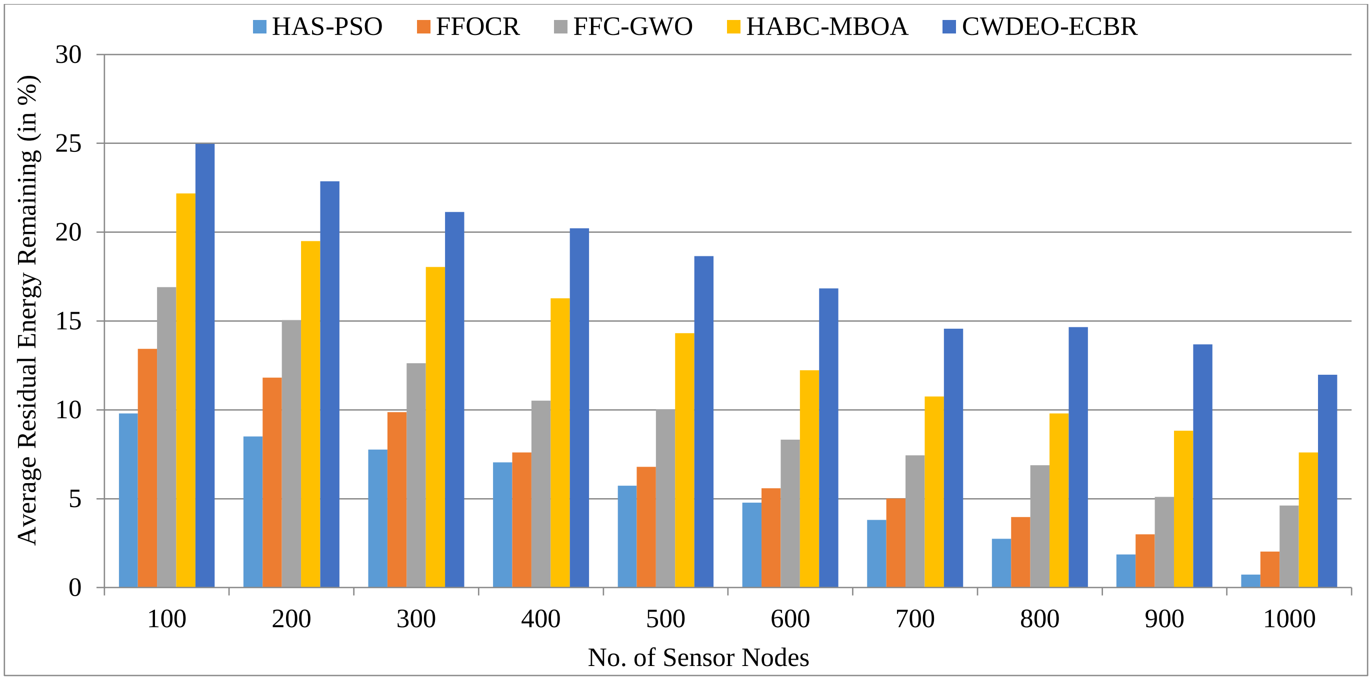

Fig. 6 ARER analysis of the CWDEO-ECBR approach under various SN

Table 3 and Figure 5 demonstrated a comparative average throughput (ATHRO) outcome of the CWDEO-ECBR approach with existing techniques. The outputs implied that the HAS-PSO approach and FFOCR methodology have reported ineffectual performance with minimal ATHRO values. Besides, the FFC-GWO performance and HABC-MBOA methodology have reached somewhat increased ATHRO values.

However, the CWDEO-ECBR method has attained effective performance with superior ATHRO values. Table 4 and Figure 6 depict the average residual energy remaining (ARER) assessment of the CWDEO-ECBR methodology with other models. The acquired outputs exposed the worse outcome of the FFOCR and HAS-PSO approaches with increased ARER values. Simultaneously, the FFC-GWO and HABC-MBOA approaches led to moderate ARER values. However, the CWDEO-ECBR approach depicted a higher solution with minimal ARER values. Table 5 and Figure 7 define a relatively improved NLT (INLT) output of the CWDEO-ECBR method with recent models. The simulation outputs showed that the HAS-PSO and FFOCR models reported ineffectual solutions with lesser INLT values. Besides, the FFC-GWO and HABC-MBOA techniques have reached maximum INLT values. However, the CWDEO-ECBR technique has attained effective performance with higher INLT values.

Table 6 and Figure 8 depict the decreased communication overhead (DCOH) investigation of the CWDEO-ECBR method with existing approaches. The acquired outputs illustrated the lowest outcome of the FFOCR and HAS-PSO approaches with increased DCOH values. In addition, the FFC-GWO and HABC-MBOA approaches lead to moderate DCOH values. However, the CWDEO-ECBR methodology exposed maximal performance with lesser DCOH values.

Table 5. INLT analysis of the CWDEO-ECBR approach with existing methods under various SNs

INLT (in %)					
No. of Sensor Nodes	**HAS-PSO**	**FFOCR**	**FFC-GWO**	**HABC-MBOA**	**CWDEO-ECBR**
100	21.47	26.63	29.68	37.89	39.60
200	19.74	21.47	27.56	34.98	37.36
300	17.36	19.74	26.10	31.80	34.85
400	15.24	18.68	23.45	29.55	33.12
500	12.85	16.30	21.86	29.41	32.42
600	12.19	14.44	21.33	26.76	30.86
700	9.81	12.59	20.14	24.91	28.76
800	8.22	11.13	19.08	22.79	24.93
900	6.36	10.07	16.70	21.60	25.01
1000	5.70	9.68	14.97	20.54	23.91

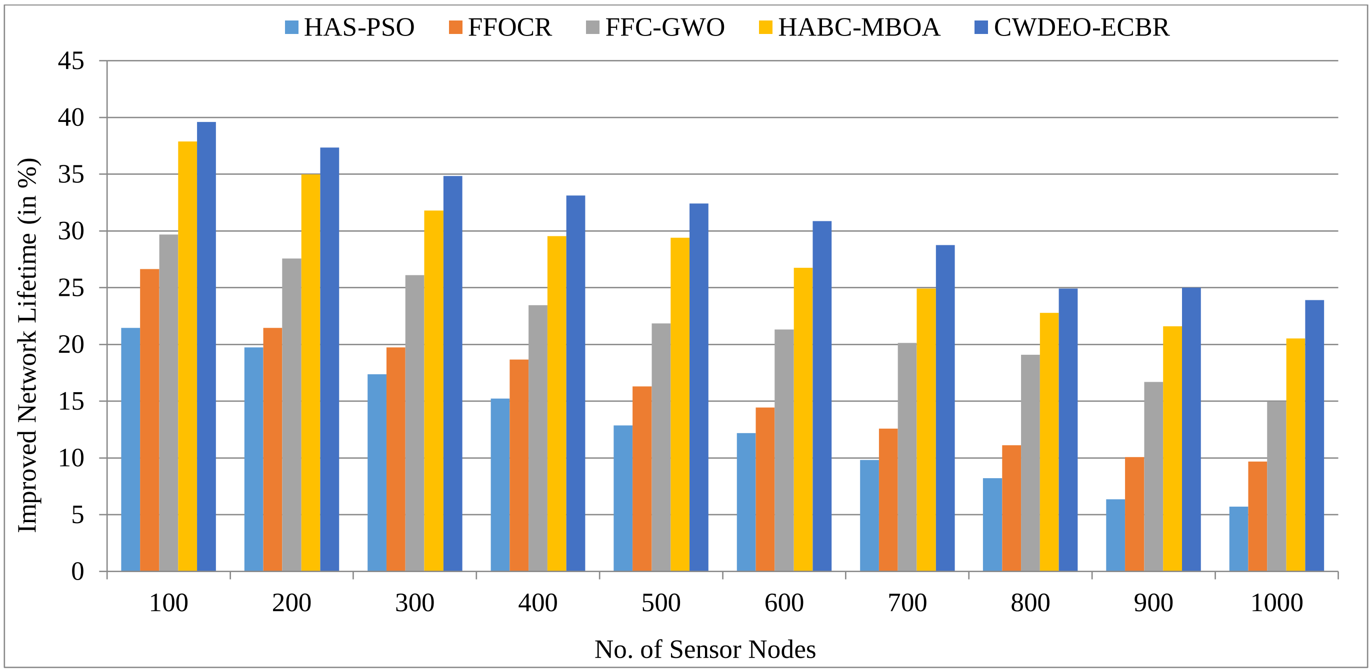

Fig. 7 INLT evaluation of CWDEO-ECBR method under various SNs

Table 6. DCOH analysis of the CWDEO-ECBR approach with recent methods under various SNs

DCOH (in %)					
No. of Sensor Nodes	**HAS-PSO**	**FFOCR**	**FFC-GWO**	**HABC-MBOA**	**CWDEO-ECBR**
100	15.82	19.87	25.23	33.86	37.48
200	14.64	17.91	22.49	31.64	34.75
300	12.42	17.52	21.83	29.68	33.35
400	10.72	16.08	21.18	25.36	30.84
500	9.94	15.82	19.87	23.79	27.71
600	9.15	13.21	18.96	21.83	25.27
700	6.54	9.94	13.34	19.22	22.61
800	6.02	8.76	10.98	16.60	19.37
900	3.27	6.93	10.33	14.90	18.48
1000	2.49	5.88	9.15	13.07	16.08

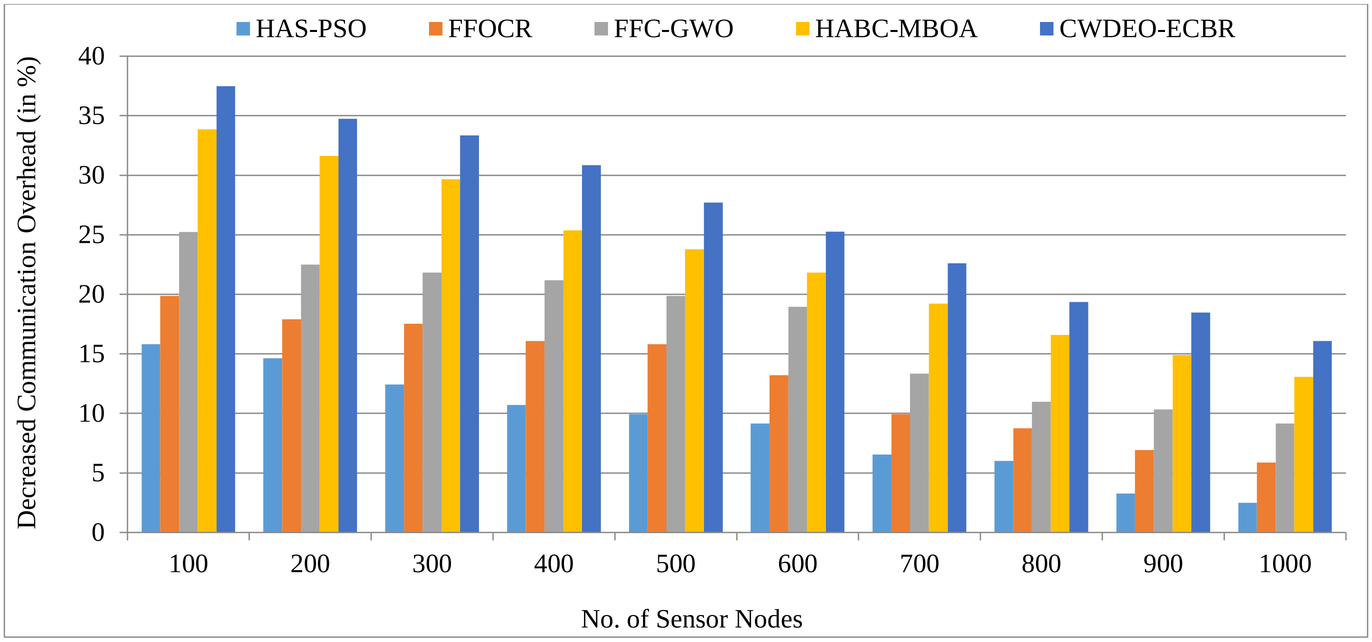

Fig. 8 DCOH analysis of CWDEO-ECBR approach under various SNs

Thus, the CWDEO-ECBR technique is applied to enhance network performance in the WSN.

5. Conclusion

This paper focuses on the designs and growth of the CWDEO-ECBR technique in WSN. The CWDEO-ECBR technique exploits the concept of clustering with a route selection process to enhance network efficiency. The CWDEO-ECBR technique comprises two significant phases of operations. Initially, the CWDEO-ECBR technique uses the CWDO method to select the CHs and organize clusters. Next, the CWDEO-ECBR technique utilizes the EO method for the routing process. A comprehensive simulation analysis is conducted to compute the performance of the CWDEO-ECBR approach. The CWDEO-ECBR model achieved a superior accuracy of 99.54% in NOAN, highlighting its efficiency in improving WSN network performance compared to existing methods.

The limitations of the CWDEO-ECBR model comprise the assumption of ideal network conditions and limited consideration of factors beyond energy efficiency, such as security and scalability. The impact of node mobility on routing performance is also not addressed. Future work should concentrate on adapting the model for dynamic topologies, incorporating security features, and exploring scalability in more extensive networks. Additionally, integrating ML for real-time optimization could improve system performance.

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