SSRG International Journal of Electrical and Electronics Engineering
ISSN: 2348-8379/ https://doi.org/10.14445/23488379/IJEEE-V10I7P106

Volume 10 Issue 7, 63-75, July 2023
© 2023 Seventh Sense Research Group®

Original Article

Enhanced Flower Pollination-Based Energy Aware Clustering Scheme for Lifetime Maximization in IoT-Enabled Wireless Sensor Networks

A. Gayathri[1], S. Sasikumar[2], R. Yalini[3]

[1,2]*Department of Electrical Engineering, Faculty of Engineering and Technology, Annamalai University, Annamalai Nagar, Chidambaram.*
[3]*Department of Electrical Engineering, Faculty of Engineering and Technology, Jayam College of Engineering and Technology, Dharmapuri.*

[1]*Corresponding Author : gayathri.network@gmail.com*

Received: 27 April 2023 Revised: 26 June 2023 Accepted: 15 July 2023 Published: 31 July 2023

Abstract *- Wireless Sensor Network (WSN) based on the Internet of Things (IoT) involves the process of transmitting the data acquired by sensors mounted on the Sensors Node (SN) to the Base Station (BS). WSN Lifespan is highly dependent on the higher battery life or energy of SNs resulting in a longer lifespan. The WSN sustained operation can be attained with the efficient utilization of SN energy. Clustering stands as one popular technique for increasing the WSN's lifespan. The optimum number of Cluster Heads (CHs) and the way of organizing the clusters were the main problems that needed to be solved in the clustering approaches. This study develops an Enhanced Flower Pollination based Energy Aware Clustering Scheme for Lifetime Maximization (EFPB-EACSLM) in IoT-enabled WSN. The core aim of the EFPB-EACSLM methodology is to properly construct the clusters in WSN and effectively identify the CHs in the network. In the presented EFPB-EACSLM methodology, the first-order radio energy model was exploited. Besides, the EFPB-EACSLM model calculates a Fitness Function (FF) so that energy consumption is mitigated and the lifespan is increased. For validating the performance of the EFPB-EACSLM model, numerous simulation analyses are carried out and the experimental outcomes are compared with current methods. The gained outcomes portrayed the superior performance of the EFPB-EACSLM technique through diverse measuring.*

Keywords *- Flower Pollination Algorithm, Internet of Things, Wireless Sensor Networks, Clustering, Energy efficiency, Lifetime maximization.*

1. Introduction

WSNs consisting of several distributed SNs are among the subsections of ad-hoc networking. Such nodes are utilized in systems containing the IoT [1]. WSN can be leveraged in various applications like automobiles, traffic monitoring, health monitoring, agriculture, etc [2]. In IoT, devices transfer and process information using intellectual sensors lacking human intervention. Thus, SNs are one key factor of the IoT [3]. WSNs present a structure to manage SNs. In WSN-based IoT, several SNs work together for environment monitoring[4]. They were linked to the Internet through the SN or BS [5]. SNs utilized in WSN-related IoT networks have several limitations on processing power, energy sources, and radio range [6]. Given that attaining the most extended lifespan becomes a significant problem in such networks, the core challenge in such networks was saving SNs energy [7].

The authors are deeply indulged in devising energy-efficient solutions, but network lifespan can be prolonged by enforcing a proper plan for energy-efficient methods [8]. It is recognized that the cluster-related hierarchical method was a potential means to save energy for dispersed WSNs [9], increasing the span of the networking life by effectively utilizing the node energy and supporting the dynamic WSN atmosphere [10, 11]. In cluster-related WSN, SN was classified into many groups known as clusters with group leaders known as CHs [12].

Clustering has numerous merits over traditional methods. Initially, data aggregation can be implemented on the dataset [13, 14] from several SNs within a cluster to diminish the data that should be sent to BS; thus, energy necessities decline sharply [15]. Then, the rotation of CHs aids in ensuring a balanced power utilization in the network [16] that avoids getting particular nodes starved because of a lack of energy [17]. However, selecting suitable CH with the best abilities while balancing the network's energy-efficiency ratio was a well-distinct NP-hard optimized issue in WSNs [18]. Therefore, Computational Intelligence (CI) related techniques like Artificial Bee Colony (ABC), Evolutionary Algorithms (EAs), Artificial Immune Systems (AIS), and Reinforcement Learning (RL) were utilized widely as population-related metaheuristics for energy-efficient clustering protocols in WSN[19]. This study develops an Enhanced Flower Pollination based Energy Aware Clustering Scheme for Lifetime Maximization (EFPB-EACSLM) in WSN. The key objective of the EFPB-EACSLM method is to properly construct the clusters in WSN and effectively identify the CHs in the network. In the presented EFPB-EACSLM technique, the first-order radio energy method was employed. Besides, the EFPB-EACSLM technique computes an FF so that the utilization of the energy is reduced and the lifespan is increased. Numerous simulation analyses were carried out to validate the performance of the EFPB-EACSLM technique.

2. Literature Review

Yadav and Mahapatra [20] modelled a novel Energy-Aware CH-selection structure by the Hierarchical Routing (EACH-HR) in the WSN through a fusion-optimized method[21]. Besides, CH-selection can be done by considering the eminence of the service, delay, energy, and distance. A novel hybrid technique called Particle Distance Updated Sea Lion Optimizer (PDU-SLnO) system is presented for choosing the best CH that integrates the PSO and Sea Lion Optimization (SLnO) method. Umamaheswari and Kumar [22] present an Energy-Aware Metaheuristic-Related Path Planning with Mobile Sinks (EAM-PPMS) method for WSNs. The EAM-PPMS approach primarily executes the Chicken Swarm Optimizer (CSO) related cluster method for choosing the CH set and organising the network into a cluster set.

In [23], a Self-Adaptive Cuckoo Search-Related CH-Selection (SACS-CHS) method was devised to maximize network lifespan with sustained energy stability of SNs. The method mentioned above was modelled with adaptive parameters that attribute to a superior selection of CH without tuning the used parameters. It involved the mitigated populace proportion idea depending on the fitness assessed relies upon the current best and previous solution. Yadav and Mahapatra [24] introduced a method called an innovative EACH-HR in the WSN by an innovative hybrid optimizer technique. Additionally, choice goes with some criteria i.e., reduction of delay during data transmission, energy stabilization, and reduction of distance amongst nodes. The described non-linear objective function achieves lifespan lengthening by choosing the best CH. This technique was called Cuckoo Insisted-Rider Optimizer Algorithm (CI-ROA), hybridizing Cuckoo Search Algorithm (CSA) and ROA.

In [25], a hybrid Sparrow Search Algorithm (SSA) with Differential Evolution (DE) techniques was projected to overcome the problematic situation of energy effectiveness by the CH-selection in WSN Networking. The proposed technique implements the high-level search effectiveness of SSA and the DE's potential that enriches the node lifespan. Wang et al. [26] present a method to optimize the endurance time of WSN routing with an efficient routing technique related to an elite hybrid meta-heuristic optimizer system. The formulating system derives as an innovative approach that brings together the global searching abilities of the PSO; differential procedures can be difference operators and pheromones of ACO to evade local search and preserve the population's diversity.

3. The Proposed Model

In the present article, a novel EFPB-EACSLM model for WSN. The main target of the EFPB-EACSLM model is to correctly build the clusters in WSN and effectively classify the CHs in the network. In the presented EFPB-EACSLM model, the first-order radio energy method was leveraged. Figure 1 illustrates the comprehensive procedure of the EFPB-EACSLM approach.

3.1. Design of EFPA Short

The low search efficiency, lack of diversity agents, and optimal local trap are presented in the FPA technique as its shortcomings while handling complex optimization problems. Diverging agents, adapting hop size, and diversifying local search were the different methods designated from the SCA method used to accurately depict the presented model to avoid the drawbacks of the FPA technique [27]. Initially, adapting hop size takes place, also known as step size, to add Levy Flight (LF) as exploring pollination updating equation to accelerate convergence. Meanwhile, pollen works in FPA depend on the rule of LF for updating global pollination values; the LF equation that may affect convergence speed using $\mu \times L$ is known, whereas μ indicates the parameter given as follows:

$$\mu = h_w - (h_w - l_w) \cdot \frac{ite}{Iter\,\mathrm{Max}} \tag{1}$$

Whereas h_w and l_w denote the weighted co-efficient constant of the control step length coefficient, h_w was fixed as 0.9 and l_w is fixed as 0.2; ite denotes existing iteration; $IterMa\chi$ represents the overall iterating amount).

The global pollination's uniform mutation operator processes by step size parameter concerned results in a considerable changing hop in an earlier phase that could make the process converge to optimum value rapidly as follows:

$$S_i^{t+1} = S_i^t + \mu \times L(g_{best} - S_i^t) + rand\left(S_j^t - S_k^t\right) \tag{2}$$

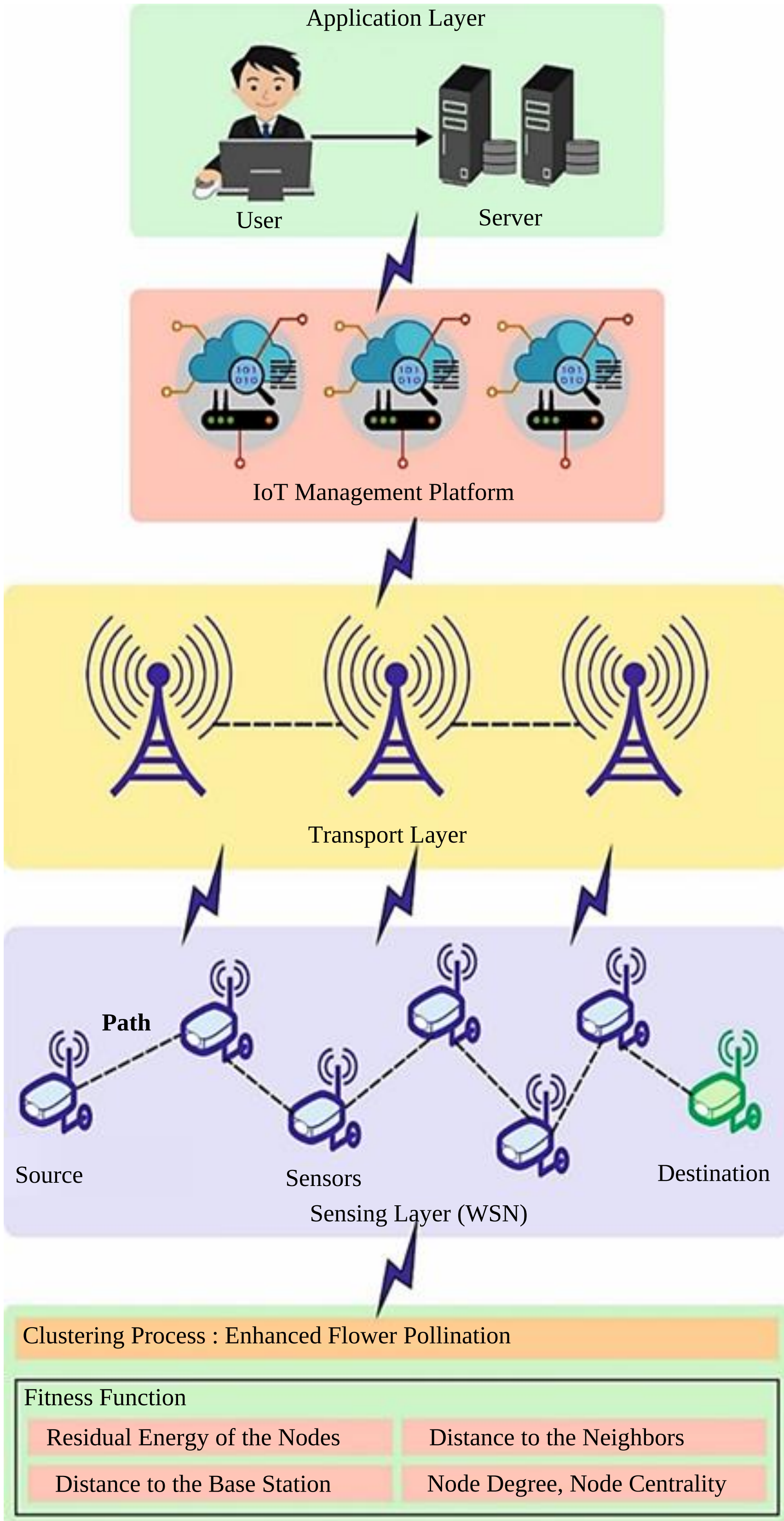

Fig. 1 Overall procedure of the EFPB-EACSLM approach

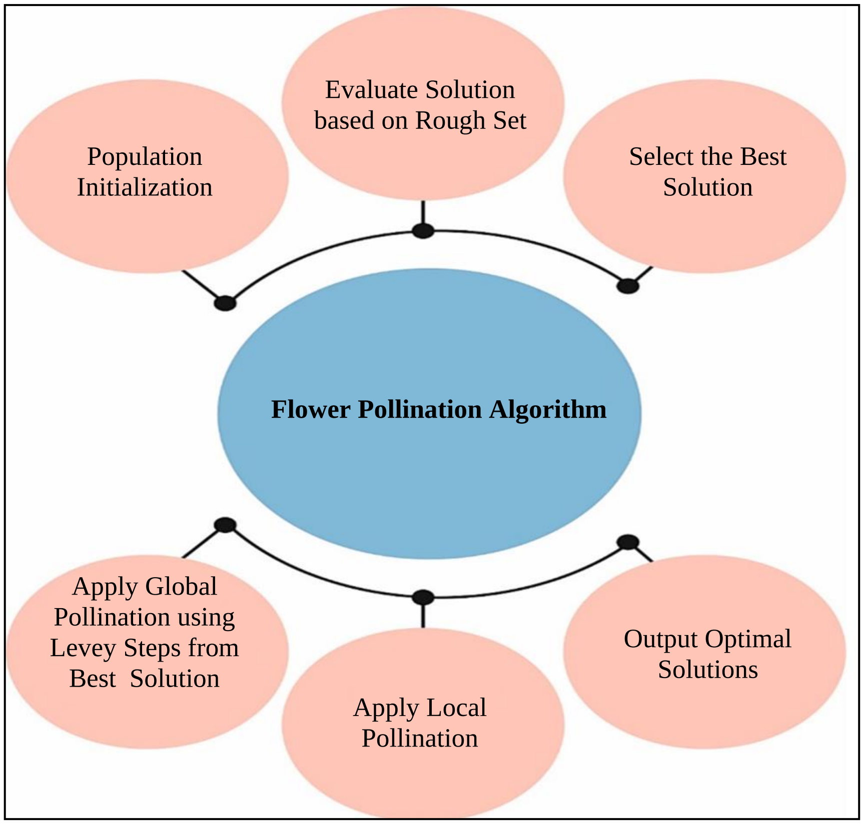

Fig. 2 Steps involved in FPA

Where S_i^{t+1} and S_i^t denote the location of pollen solution i at existing iteration t, S_j^t and S_k^t represents pollen solution at j and k randomly generated; g_{best} shows the optimum global pollen solution. The following approach is to diversify local search. It was utilized as a mutation model with a more negligible probability revised to make it easier to escape from the local optimum solution. As per the benefits of the mutation process, certain modifying and adjusting methods are performed in the local search process, and it can be stated in the equation as follows:

$$S_i^{t+1} = \left(\frac{S_i^t + g_{best}}{2}\right) rand + \varepsilon(S_a^t - S_b^t) \qquad (3)$$

Where $(S_i^t + g_{besi})/2$ retains the beneficiary data of the present optimum individual and valuable data of individual i that was directed to the best location; S_i^t shows the operator itself; $rand$ denotes the random value; S_a^t and S_b^t show the random vector. The more negligible mutation probability is utilized to check the value of the boundary to escape from the local optimum solution to the best promising region based on fitness value. If the agent is above the upper or lower boundary, then place it in a space search's radius as follows:

$$S_i^t = \begin{cases} U\ (1\text{-}rand), & \text{if iteration is } even \\ L_b \cdot (1 + rand)\ , & otherwise \end{cases} \qquad (4)$$

Where L_b and U_b denote lower and upper limitations of search space; $rand$ indicates a randomly generated value. The randomness neighbour search is employed to reduce the lower search efficacy problem caused. Figure 2 depicts the steps that take part in FPA. The third strategy, variant agent, is utilized to vary local search during the search stage. The typically used variation technique is derived out of the local differential search that considerably improves optimization technique, and it can be formulated by:

$$S_i^{t+1} = \begin{cases} S_i^t + \varepsilon \times sin(\alpha) \times |r_1 g_{besi} - S_i^t|\ if\ \omega \le 0.5 \\ S_i^t + \varepsilon \times cos(\alpha) \times |r_1 g_{best} - S_i^t|\ otherwise \end{cases} \qquad (5)$$

Where α denotes the randomly generated value is fixed as $2 \cdot \pi \cdot rand(0,1)$; ε indicates the scaling factor; r_1 shows the random number within [0,1] ω denotes the choosing coefficient quality pollination agent that is shown below:

$$\omega = 1 - \frac{fit(i) - bestfit}{worsefit - bestfit}, \qquad (6)$$

In Eq. (6), $fit(i)$ Indicates the fitness value of objective function attained corresponding to i^{th} pollination; $bestfit$ and $worsefit$ denote best and worst fitness values. The algorithm convergence was essential to find the optimum outcome, allowing for "jumping from" the local optimum point. The convergence term is regarded as an optimum measure to obtain a better solution and was possibly seen in assessment techniques for optimum solutions. The HSFPA is created depending on FPA and a few strategies upgrading from the SCA technique. Pollination diversity has improved, and an arbitrarily generated segment was utilised to produce a new solution.

3.2. Process Involved in EEPA-Based Clustering

The EFPB-EACSLM model calculates an FF so that energy utilisation is mitigated and the lifespan is increased. The FF of the EFPB-EACSLM model is performed to select an optimum CH from the collection of SNs in the networking [28].

The RE deliberated in the FF was exploited to avoid the dead nodes as a CH at the clustering method. Then, the candidate CH to the BS distancing and the distancing among nodes are exploited for choosing an optimal CH to minimalize the energy depletion of the node. Furthermore, the high centrality to the cluster member minimises communication distancing between cluster members to CH. The FF can be defined as:

3.2.1. Residual Energy (RE)

In RE, CH implements different tasks gathering the dataset from regular sensors and conveying information to BS. The CH needs higher energy to achieve the task mentioned above; hence the nodes with maximum RE are selected to be CH. The RE can be defined as follows:

$$f_1 = \sum_{i=1}^{m} 1/E_{CHi} \tag{7}$$

In Eq. (7), E_{CHi} represents the RE of i^{th} CHs.

3.2.2. Distance between the SNs

It determines the CH and the routine sensor distancing. The energy dissipation of nodes depends mainly on the communication path’s distance. The energy depletion of the nodes is more minor once selected nodes have less communication distance toward BS. The standard sensor and CH distancing can be formulated by:

$$f_2 = \sum_{j=1}^{m} (\sum_{i=1}^{I_j} dis(s_i, CH_j)/l_j) \tag{8}$$

Where is the distance between i^{th} sensors and j^{th} CHs are denoted by $dis(s_i CH_j)$ and the number of sensors that belong to CHs is represented by I_j.

3.2.3. The Distance between the CH and BS

It determines the CH to BS distancing. The node's energy depletion mainly relies on the distance over the communication channel. For example, if BS was located farther from CH, it requires additional energy for data communication. Hence, an unexpected fall of CH might happen because of maximum energy depletion. Therefore, the node with less distance from BS was selected during data transmission. The subsequent signifies the primary function of the distance between BS and CH.

$$f_3 = \sum_{i=1}^{m} d\,is(CH_j, BS) \tag{9}$$

Where, the CH_j and BS distancing is represented by $dis(CH_j, BS)$.

3.2.4. Node Degree

It determines the total counting of sensors belonging to the subsequent CH. The CH with fewer SNs is carefully chosen since the CH with maximum cluster members loses the energy in a smaller duration.

$$f_4 = \sum_{i=1}^{m} l_i \tag{10}$$

Eq. I_i denotes the number of sensors belonging to CH_i.

3.2.5. Node Centrality

Node centrality (f) determines what amount of the nodes are located centrally from the neighbouring node, and the following expression formulates it:

$$f_5 = \sum_{i=1}^{m} \frac{\sqrt{(\sum_{j\epsilon n} dist^2(i,j))/n(i)}}{Network\ dimension} \tag{11}$$

Where $n(i)$ denotes the CH_i’s adjacent node numbers.

The weight values are assigned for all the objective values. The numerous objectives were transformed into a sole objective function in such cases. The weighted value is $\delta_1, \delta_2, \delta_3, \delta_4$, and δ_5. The mathematical expression of the primary function was given as follows:

$$f = \delta_1 f_1 + \delta_2 f_2 + \delta_3 f_3 + \delta_4 f_4 + \delta_5 f_5,$$
$$\text{Where, } \sum_{i=1}^{5} 1, \delta_i \in (0,1), \tag{12}$$

Where, the $\delta_1, \delta_2, \delta_3, \delta_4$, and δ_5 values are 0.35, 0.25, 0.2, 0.1, and 0.1. The δ_1 regarded the RE as a greater priority to prevent the failure of the node as CH. Consequently, δ_2 and δ_3 are taken into account as a secondary and tertiary priority to recognize CH in BS with the lesser distancing that reduces energy dissipation. The quaternary priority (δ_4) was considered for node degree for choosing CH with a lesser degree of the node.

Furthermore, node centrality was deliberated as the final priority δ_5 that increases the nearness between cluster members and CH. Afterwards, choosing the CHs by the EFPB-EACSLM algorithm, the sensors are assigned to the CHs with promising functions deliberated. The sensors are assigned to the CH with lesser communication distance and maximum RE. Thus, the energy expended would be less in the data transmission stage.

$$SN_p = \frac{Z \times Energy(CH_j)}{Distance(s_i, CH_j)} \quad (13)$$

In Eq. (13), SNs possibly denote SN_p; proportionality constant represents Z and distance (S_i, cH_j) denotes distance amongst the CH_j and sensor s_i, $Energy(CH_j)$ signifies the RE of corresponding CH; The sensors are assigned to specific CH with maximum potential. If the distance among sensors and two dissimilar CHs were similar, then the sensors interconnect to the CH has maximum energy.

4. Results and Discussion

In this segment, the clustering achievement of the EFPB-EACSLM model is examined in detail. The suggested model is tested by the process of simulation that utilizes Python 3.6.5 tool on PC i5-8600k, 250GB SSD, GeForce 1050Ti 4GB, 16GB RAM, and 1TB HDD. The parameter setups are stated as activation: ReLU, rate of learning: 0.01, count of the epoch: 50, dropout: 0.5, and batch size: 5. In Table 1 and Figure 3, an elaborated End-To-End Delay (ETED) assessment of the EFPB-EACSLM method is studied [29]. The outputs portray that the EFPB-EACSLM approach attains mitigated ETED values.

For the sample, with 100 SNs, the EFPB-EACSLM approach gains a lower ETED of 1.08ms while the MHCRT-EEWSN, F-GWO, FRLDG, MBC, and HEED techniques accomplish higher ETED of 1.41ms, 2.18ms, 3.30ms, 4.15ms, and 5.32ms respectively. Meanwhile, with 500 SNs, the EFPB-EACSLM method gains a lower ETED of 4.38ms while the MHCRT-EEWSN, F-GWO, FRLDG, MBC, and HEED techniques accomplish higher ETED of 6.39ms, 7.89ms, 8.66ms, 9.02ms and 9.53ms correspondingly.

Table 1. ETED analysis of the EFPB-EACSLM method with other techniques under varying SNs

ETED (ms)						
Nodes Numbers	**EFPB-EACSLM**	**MHCRT-EEWSN**	**F-GWO**	**FRLDG**	**MBC**	**HEED**
100	1.08	1.41	2.18	3.30	4.15	5.32
200	1.76	2.41	3.21	4.50	4.87	6.04
300	2.46	3.56	5.01	5.39	6.14	7.35
400	3.05	4.66	6.16	7.38	7.87	8.62
500	4.38	6.39	7.89	8.66	9.02	9.53

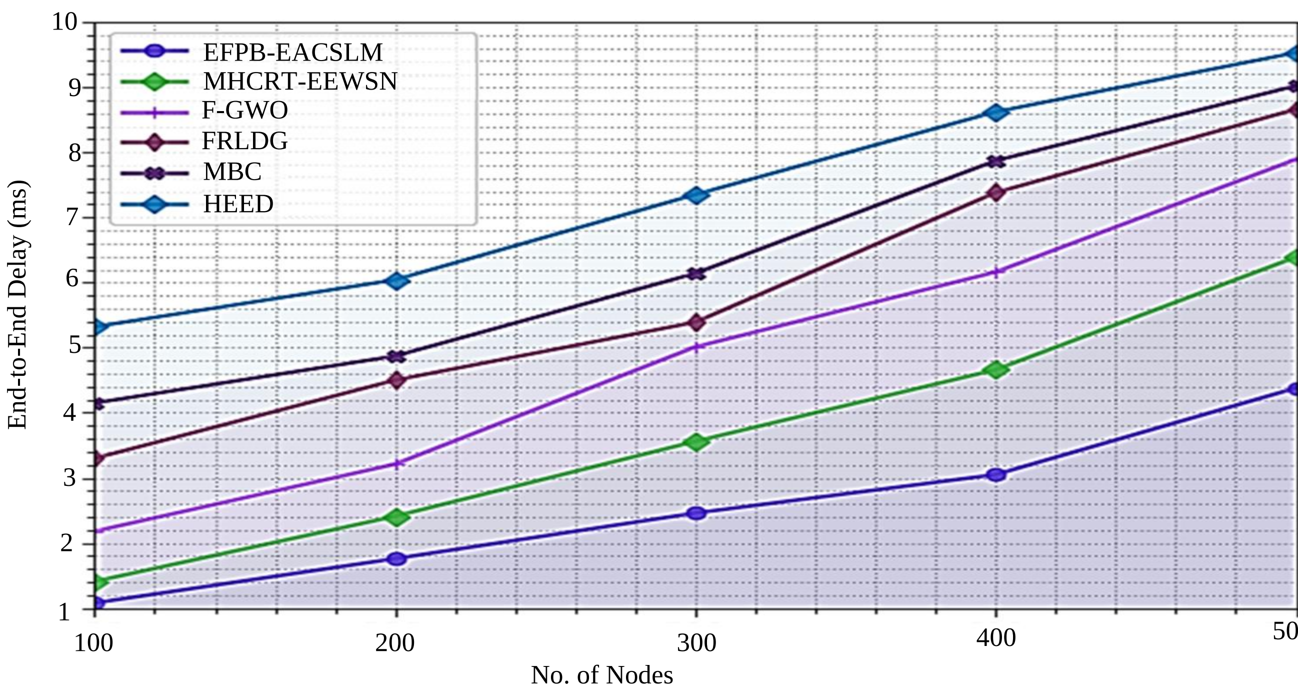

Fig. 3 ETED investigation of EFPB-EACSLM method under varying SNs

The PDR study of the EFPB-EACSLM method with current approaches under several SNs is given in Table 2 and Figure 4. The acquired values infer that the EFPB-EACSLM approaches improve PDR values. For the sample, with 100

SNs, the EFPB-EACSLM technique accomplishes a maximum PDR of 99.84% while the MHCRT-EEWSN, F-GWO, FRLDG, MBC, and HEED techniques achieve minimal PDR of 99.39%, 98.82%, 97.23%, 94.26%, and 91.86% respectively. Furthermore, with 500 SNs, the EFPB-EACSLM system accomplishes a maximal PDR of 98.13% while the MHCRT-EEWSN, F-GWO, FRLDG, MBC, and HEED techniques attain minimal PDR of 96.46%, 94.59%, 92.34%, 89.94% and 86.28% subsequently. Table 3 and Figure 5 show a brief PLR calculation of the EFPB-EACSLM method. The outcomes portray that the EFPB-EACSLM technique reaches reduced PLR values.

Table 2. PDR evaluation of the EFPB-EACSLM method with other techniques under varying SNs

Packet Delivery Ratio (%)						
No. of Nodes	**EFPB-EACSLM**	**MHCRT-EEWSN**	**F-GWO**	**FRLDG**	**MBC**	**HEED**
100	99.84	99.39	98.82	97.23	94.26	91.86
200	99.47	98.46	97.48	96.01	92.67	90.67
300	99.31	97.93	96.38	93.53	91.69	89.05
400	98.33	96.87	95.28	93.16	90.43	87.46
500	98.13	96.46	94.59	92.34	89.94	86.28

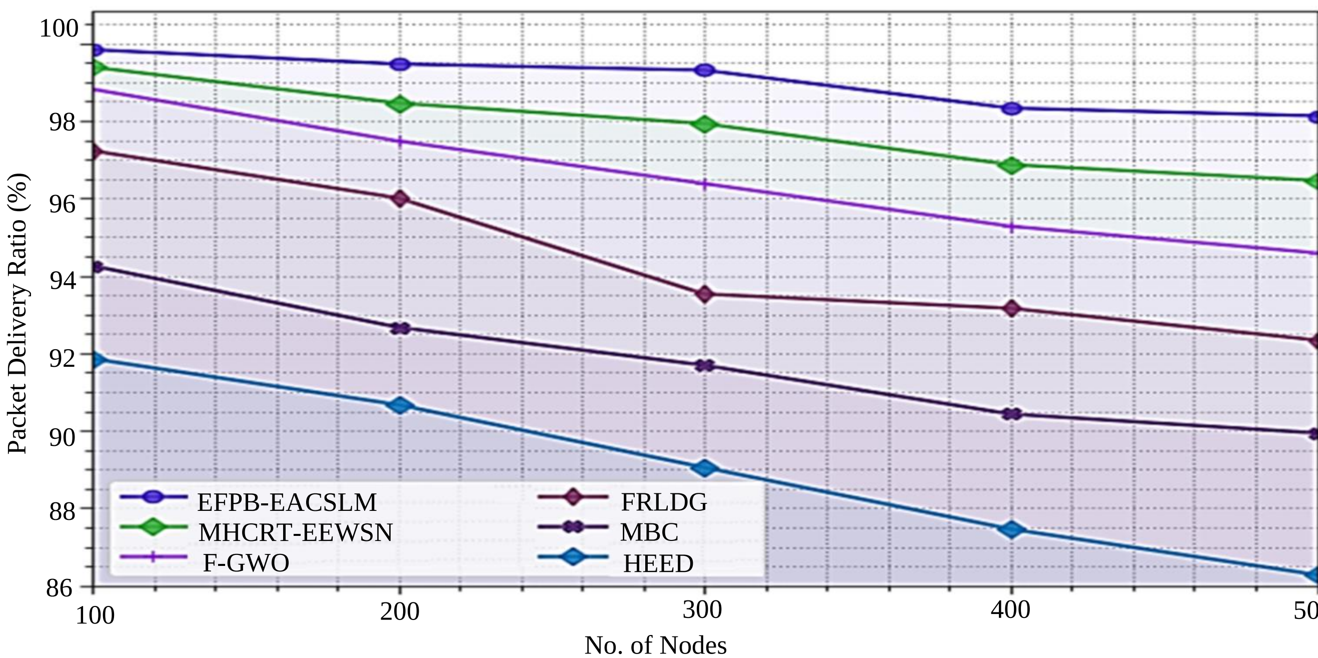

Fig. 4 PDR investigation of EFPB-EACSLM methodology under changing SNs

Table 3. PLR evaluation of the EFPB-EACSLM method with other techniques under varying SNs

Packet Loss Rate (%)						
Number of Nodes	**EFPB-EACSLM**	**MHCRT-EEWSN**	**F-GWO**	**FRLDG**	**MBC**	**HEED**
100	0.16	0.61	1.18	2.77	5.74	8.14
200	0.53	1.54	2.52	3.99	7.33	9.33
300	0.69	2.07	3.62	6.47	8.31	10.95
400	1.67	3.13	4.72	6.84	9.57	12.54
500	1.87	3.54	5.41	7.66	10.06	13.72

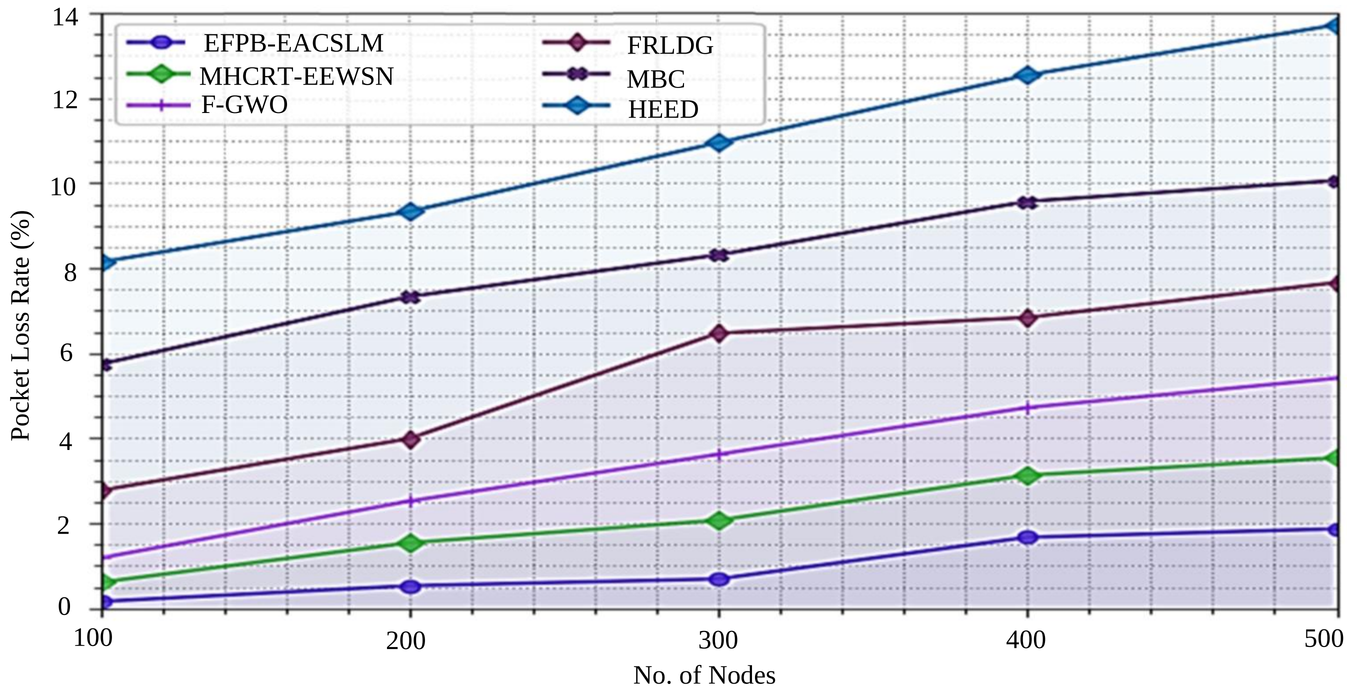

Fig. 5 PLR investigation of EFPB-EACSLM methodology under varying SNs

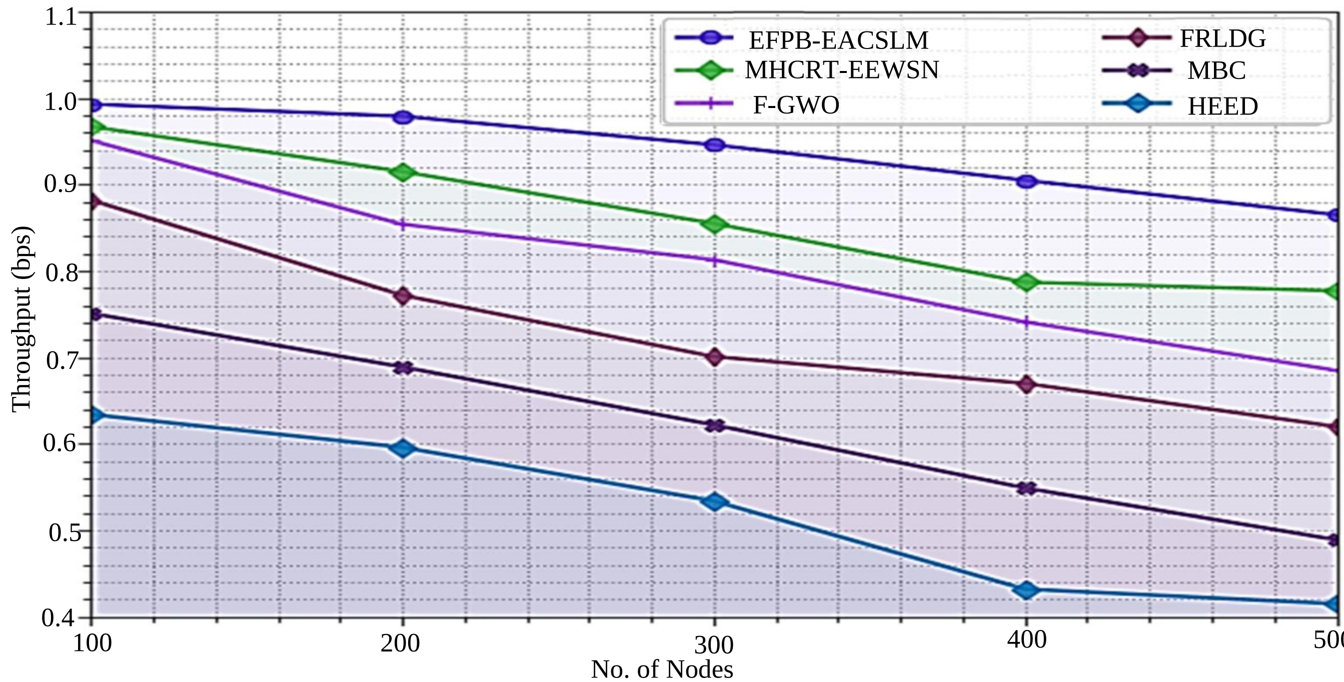

Fig. 6 THRO investigation of EFPB-EACSLM methodology under changing SNs

The THRO investigation of the EFPB-EACSLM values with current models under several SNs is illustrated in Table 4 and Figure 6. The acquired values conclude that the EFPB-EACSLM approach improves THRO values. For the sample, with 100 SNs, the EFPB-EACSLM approach accomplishes a maximum THRO of 0.993bps while the MHCRT-EEWSN, F-GWO, FRLDG, MBC, and HEED techniques achieve minimal THRO of 0.967bps, 0.951bps, 0.882bps, 0.751bps, and 0.634bps correspondingly. Also, with 500 SNs, the EFPB-EACSLM methodology accomplishes a maximum THRO of 0.865bps, while the MHCRT-EEWSN, F-GWO, FRLDG, MBC, and HEED techniques achieve minimal THRO of 0.777bps, 0.685bps, 0.620bps, 0.489bps, and 0.415bps respectively.

Table 4. THRO evaluation of the EFPB-EACSLM method with other models under varying SNs

Throughput (bps)						
No. of Nodes	**EFPB-EACSLM**	**MHCRT-EEWSN**	**F-GWO**	**FRLDG**	**MBC**	**HEED**
100	0.993	0.967	0.951	0.882	0.751	0.634
200	0.979	0.915	0.854	0.772	0.689	0.596
300	0.946	0.855	0.813	0.701	0.622	0.534
400	0.905	0.787	0.741	0.670	0.549	0.432
500	0.865	0.777	0.685	0.620	0.489	0.415

Table 5. ECON investigation of the EFPB-EACSLM method with other models under varying SNs

Energy Consumption (mJ)						
No. of Nodes	**EFPB-EACSLM**	**MHCRT-EEWSN**	**F-GWO**	**FRLDG**	**MBC**	**HEED**
100	12.26	27.16	50.76	69.38	109.74	142.64
200	22.82	47.65	68.14	100.42	135.19	163.75
300	38.96	71.24	99.80	137.05	155.68	176.17
400	63.17	99.18	133.33	155.06	173.06	196.03
500	81.80	115.94	157.54	169.34	192.93	230.80

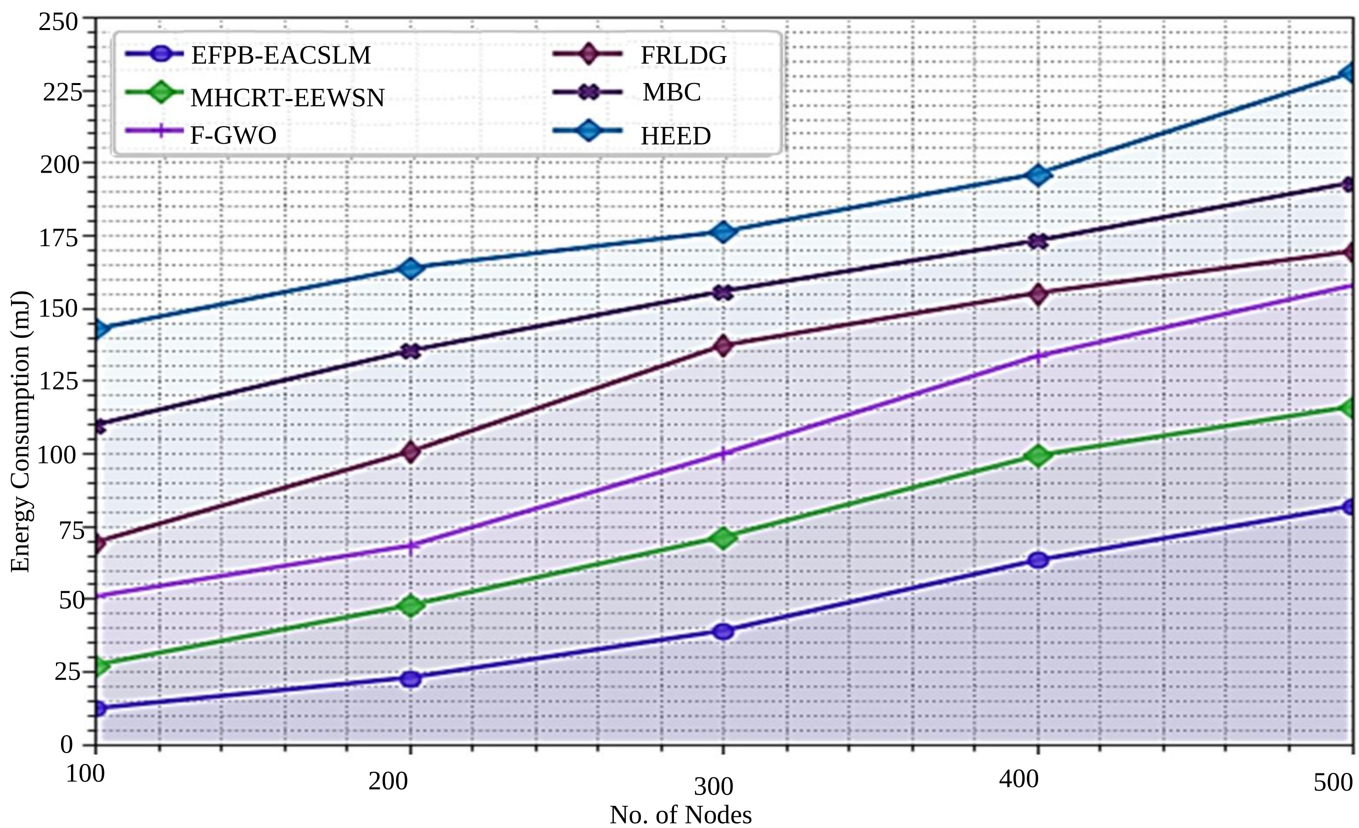

Fig. 7 ECON investigation of EFPB-EACSLM methodology under varying SNs

Table 5 and Figure 7 show an elaborate ECON evaluation of the EFPB-EACSLM model. The outcomes portray that the EFPB-EACSLM model reaches reduced values of ECON. For the sample with 100 SNs, the EFPB-EACSLM technique gains a lower ECON of 12.26mJ while the MHCRT-EEWSN, F-GWO, FRLDG, MBC, and HEED techniques accomplish higher ECON of 27.16mJ, 50.76mJ, 69.38mJ, 109.74mJ and 142.64mJ correspondingly. In the meantime, with 500 SNs, the EFPB-EACSLM approach gains a lower ECON of 81.80mJ while the MHCRT-EEWSN, F-GWO, FRLDG, MBC, and HEED techniques accomplish higher ECON of 115.94mJ, 157.54mJ, 169.34mJ, 192.93mJ and 230.80mJ respectively.

The NLT inspection of the EFPB-EACSLM approach with existing models under several SNs is represented in Table 6 and Figure 8. The values gained denote that the EFPB-EACSLM approach improves the values of NLT. For sample, with 100 SNs, the EFPB-EACSLM technique accomplishes a maximum NLT of 5467 while the MHCRT-EEWSN, F-GWO, FRLDG, MBC, and HEED techniques achieve minimal NLT of 5437, 5215, 4741, 4435 and 4091 respectively. Besides, with 500 SNs, the EFPB-EACSLM technique accomplishes a maximum NLT of 5161, while the MHCRT-EEWSN, F-GWO, FRLDG, MBC, and HEED techniques achieve minimal NLT of 5008, 4573, 4030, 3747 and 3120 respectively.

Table 6. NLT investigation of the EFPB-EACSLM method with other models under changing SNs

Network Lifetime (Rounds)						
Number of Nodes	**EFPB-EACSLM**	**MHCRT-EEWSN**	**F-GWO**	**FRLDG**	**MBC**	**HEED**
100	5467	5437	5215	4741	4435	4091
200	5421	5314	5001	4680	4320	3892
300	5345	5138	4726	4351	3961	3380
400	5253	5077	4642	4122	3801	3128
500	5161	5008	4573	4030	3747	3120

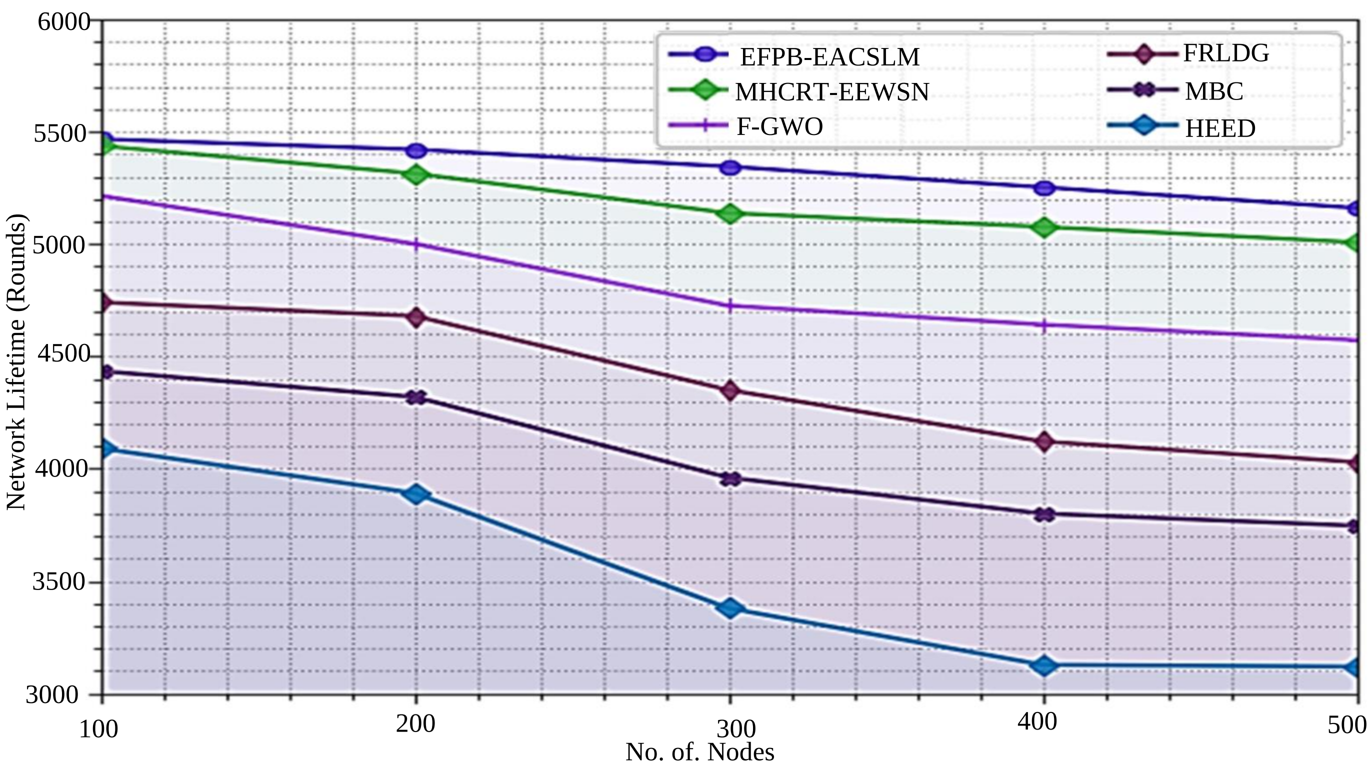

Fig. 8 NLT analysis of EFPB-EACSLM approach under changing SNs

Table 7 and Figure 9 show an elaborate BER valuation of the EFPB-EACSLM approach. The outcomes portray that the EFPB-EACSLM technique reaches reduced BER values. For the sample with 100 SNs, the EFPB-EACSLM technique gains a lower BER of 0.3348 while the MHCRT-EEWSN, F-GWO, FRLDG, MBC, and HEED techniques accomplish higher BER of 0.3918, 0.4331, 0.5446, 0.6029 and 0.6502 correspondingly. In the meantime, with 500 SNs, the EFPB-EACSLM technique gains a lower BER of 0.2620 while the MHCRT-EEWSN, F-GWO, FRLDG, MBC, and HEED methods accomplish higher BER of 0.3482, 0.4088, 0.4573, 0.5495 and 0.5895 correspondingly. These outputs demonstrated that the EFPB-EACSLM approach achieves more achievement than other approaches.

Table 7. BER analysis of the EFPB-EACSLM system with other techniques under varying SNs

Bit Error Rate						
No. of Nodes	**EFPB-EACSLM**	**MHCRT-EEWSN**	**F-GWO**	**FRLDG**	**MBC**	**HEED**
100	0.3348	0.3918	0.4331	0.5446	0.6029	0.6502
200	0.3251	0.3712	0.4561	0.5459	0.5713	0.6502
300	0.3118	0.3603	0.4500	0.5216	0.5604	0.6405
400	0.2948	0.3445	0.4282	0.4925	0.5434	0.6198
500	0.2620	0.3482	0.4088	0.4573	0.5495	0.5895

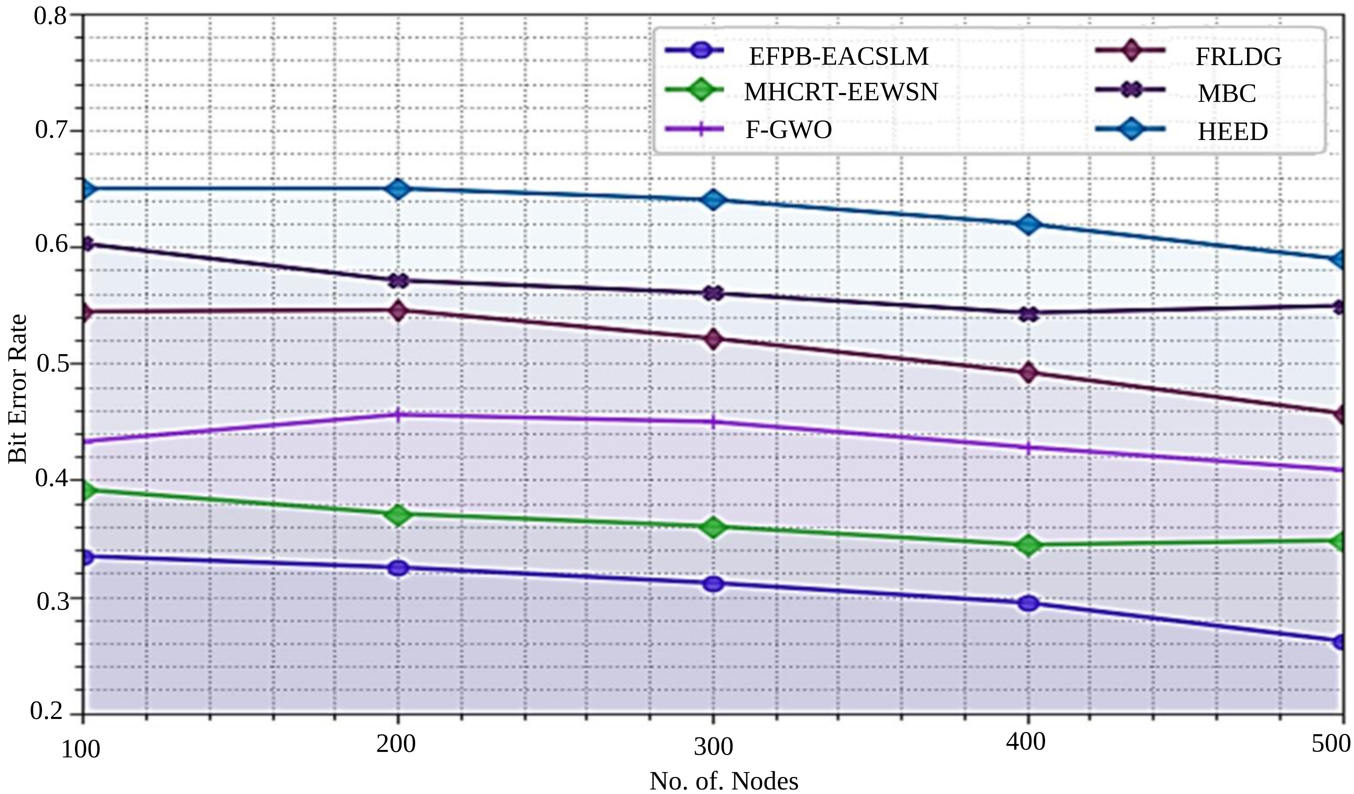

Fig. 9 BER analysis of EFPB-EACSLM approach under varying SNs

5. Conclusion

In the present article, a novel EFPB-EACSLM model for WSN. The primary aim of the EFPB-EACSLM method is to correctly build the clusters in WSN and effectively classify the CHs in the network. In the presented EFPB-EACSLM technique, the first-order radio energy method was employed. Besides, the EFPB-EACSLM technique computes an FF to mitigate energy consumption and increase lifespan. For validating the performance of the EFPB-EACSLM technique, numerous evaluation of the simulation is achieved, and the experimental outcomes undergo comparison with current methods. The acquired results portrayed a proficient achievement of the EFPB-EACSLM methodology through diverse measuring. In the future, unequal clustering techniques can advance the energy efficacy of the EFPB-EACSLM methodology.

References

[1] Irin Loretta G, and V. Kavitha, "Privacy Preserving using Multi-Hop Dynamic Clustering Routing Protocol and Elliptic Curve Cryptosystem for WSN in IoT Environment," *Peer-to-Peer Networking and Applications*, vol. 14, no. 2, pp.821-836, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[2] Ikram Daanoune, Baghdad Abdennaceur, and Abdelhakim Ballouk, "A Comprehensive Survey on LEACH-Based Clustering Routing Protocols in Wireless Sensor Networks," *Ad Hoc Networks*, vol. 114, p. 102409, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[3] Maryam Shafiq et al., "Systematic Literature Review on Energy Efficient Routing Schemes in WSN – A Survey," *Mobile Networks and Applications*, vol. 25, no. 3, pp. 882-895, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[4] R. Manoj Kumar, and S. Sridevi, "A Survey on Localization Methods in Wireless Sensor Networks," *SSRG International Journal of Computer Science and Engineering*, vol. 4, no. 4, pp. 13-17, 2017. [Publisher Link]

[5] Asha Jerlin Manuel et al., "Optimization of Routing-Based Clustering Approaches in Wireless Sensor Network: Review and Open Research Issues," *Electronics*, vol. 9, no. 10, pp. 1-29, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[6] Awadhesh Kumar Maurya et al., "Improved Chain Based Cooperative Routing Protocol in WSN," *Journal of Physics: Conference Series*, vol. 1478, no. 1, pp. 1-8, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[7] A. Nageswar Rao, B. Rajendra Naik, and L. Nirmala Devi, "On the Relay Node Placement in WSNs for Lifetime Maximization through Metaheuristics," *Materials Today: Proceedings*, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[8] Uma Maheswari Durairaj, and Sudha Selvaraj, "Two-Level Clustering and Routing Algorithms to Prolong the Lifetime of Wind Farm-Based WSN," *IEEE Sensors Journal*, vol. 21, no. 1, pp. 857-867, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[9] Alma Rodríguez et al., "Robust Clustering Routing Method for Wireless Sensor Networks Considering the Locust Search Scheme," *Energies*, vol. 14, no. 11, pp. 1-29, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[10] Deepak Mehta, and Sharad Saxena, "Hierarchical WSN Protocol with Fuzzy Multi-Criteria Clustering and Bio-Inspired Energy-Efficient Routing (FMCB-ER)," *Multimedia Tools and Applications*, vol. 81, pp. 35083-35116, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[11] Sercan Yalçın, and Ebubekir Erdem, "TEO-MCRP: Thermal Exchange Optimization-Based Clustering Routing Protocol with A Mobile Sink for Wireless Sensor Networks," *Journal of King Saud University-Computer and Information Sciences*, vol. 34, no. 8, pp. 5333-5348, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[12] Nitin Mittal, "An Energy-Efficient Stable Clustering Approach using Fuzzy Type-2 Bat Flower Pollinator for Wireless Sensor Networks," *Wireless Personal Communications*, vol. 112, pp. 1137-1163, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[13] D. Lubin Balasubramanian, and V. Govindasamy, "Energy-Aware Farmland Fertility Optimization-Based Clustering Scheme for Wireless Sensor Networks," *Microprocessors and Microsystems*, vol. 97, p. 104759, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[14] E. Gajendran, J. Vignesh, and S. R. Boselin Prabhu, "Prolonging Network Lifetime in Wireless Sensor Networks using Enhanced Integrated Clustering," *International Journal of P2P Network Trends and Technology (IJPTT)*, vol. 7, no. 4, pp. 6-11, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[15] Vrajesh Kumar Chawra, and Govind P. Gupta, "Memetic Algorithm-Based Energy Efficient Wake-Up Scheduling Scheme for Maximizing the Network Lifetime, Coverage and Connectivity in Three-Dimensional Wireless Sensor Networks," *Wireless Personal Communications*, vol. 123, pp. 1507-1522, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[16] S. Jaya Pratha, V. Asanambigai, and S. R. Mugunthan, "Hybrid Mutualism Mechanism-Inspired Butterfly and Flower Pollination Optimization Algorithm for Lifetime Improving Energy-Efficient Cluster Head Selection in WSNs," *Wireless Personal Communications*, vol. 128, no. 3, pp. 1567-1601, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[17] Nitin Mittal et al., "An Energy-Efficient Stable Clustering Approach using Fuzzy-Enhanced Flower Pollination Algorithm for WSNs," *Neural Computing and Applications*, vol. 32, pp. 7399-7419, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[18] Nitin Mittal et al., "Trust-Aware Energy-Efficient Stable Clustering Approach using Fuzzy Type-2 Cuckoo Search Optimization Algorithm for Wireless Sensor Networks," *Wireless Networks*, vol. 27, pp. 151-174, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[19] C. Murugesh, S. Murugan, "Artificial Ecosystem Optimizer with Convolutional Recurrent Neural Network for Intrusion Detection System in Wireless Sensor Networks," *SSRG International Journal of Electronics and Communication Engineering*, vol. 10, no. 5, pp. 62-75, 2023. [CrossRef] [Publisher Link]

[20] Rakesh Kumar Yadav, and Rajendra Prasad Mahapatra, "Hybrid Metaheuristic Algorithm for Optimal Cluster Head Selection in A Wireless Sensor Network," *Pervasive and Mobile Computing*, vol. 79, p. 101504, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[21] M. Supriya, and T. Adilakshmi, "Secure Routing using ISMO for Wireless Sensor Networks," *SSRG International Journal of Computer Science and Engineering*, vol. 8, no. 12, pp. 14-20, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[22] K. Umamaheswari, and A. Kiran Kumar, "Energy Aware Metaheuristics Based Path Planning Technique with Mobile Sinks for Wireless Sensor Networks," *Mathematical Statistician and Engineering Applications*, vol. 71, no. 3, pp. 1111-1127, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[23] G. Rajeswarappa, and S. Vasundra, "Self-Adaptive Cuckoo Search-Based Cluster Head Selection for Maximizing Network Lifetime in Wireless Sensor Networks," *In Proceedings of International Conference on Recent Trends in Computing*, Springer, Singapore, pp. 599-611, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[24] Rakesh Kumar Yadav, and R. P. Mahapatra, "Energy-Aware Optimized Clustering for Hierarchical Routing in A Wireless Sensor Network," *Computer Science Review*, vol. 41, p. 100417, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[25] Panimalar Kathiroli, and Kanmani Selvadurai, "Energy-Efficient Cluster Head Selection using Improved Sparrow Search Algorithm in Wireless Sensor Networks," *Journal of King Saud University-Computer and Information Sciences,* vol. 34, no. 10, pp. 8564-8575, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[26] Hui Wang, Kangshun Li, and Witold Pedrycz, "An Elite Hybrid Metaheuristic Optimization Algorithm for Maximizing Wireless Sensor Networks Lifetime with A Sink Node," *IEEE Sensors Journal*, vol. 20, no. 10, pp. 5634-5649, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[27] Thi-Kien Dao et al., "A Hybridized Flower Pollination Algorithm and Its Application on Microgrid Operations Planning," *Applied Sciences,* vol. 12, no. 13, pp. 1-27, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[28] 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, p. 102317, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[29] Sweta Kumari Barnwal, Amit Prakash, and Dilip Kumar Yadav, "Improved African Buffalo Optimization-Based Energy Efficient Clustering Wireless Sensor Networks using Metaheuristic Routing Technique," *Wireless Personal Communications*, vol. 130, pp. 1575-1596, 2023. [CrossRef] [Google Scholar] [Publisher Link]