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Adaptive Wind Driven Optimization based Energy Aware Clustering Scheme for Wireless Sensor Networks

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Abstract: Wireless Sensor Networks (WSNs) are utilised in a variety of applications due to their capacity to capture and transmit environmental data. Clustering has emerged as an efficient method for improving energy efficiency in WSNs. To resolve these issues, we propose an Adaptive Wind Driven Optimisation based Energy Aware Clustering Scheme (AWDO-EACS) for WSNs. The AWDO-EACS model presents an extended form of the Wind Driven Optimisation (WDO) algorithm, designated AWDO, with optimised inherent term values. The proposed model takes into account multiple objectives, such as energy consumption, distance, and end-to-end latency, in order to achieve superior energy efficiency and an extended network lifetime. To validate the efficacy of the AWDO-EACS model, extensive experiments with varying node counts were carried out. In terms of network stability, energy efficiency, end-to-end latency, packet delivery ratio, throughput, packet loss rate, and network lifetime, the results demonstrate that the AWDO-EACS outperforms contemporary clustering strategies. Specifically, the AWDO-EACS obtained a significant increase in energy efficiency, with a 27.35 percent improvement over existing clustering techniques for 20 nodes and an 83.41 percent improvement for 100 nodes. In addition, the end-to-end latency was considerably reduced, with a 96-round lifetime for 20 nodes and a 74-round lifetime for 100 nodes, compared to 37 and 20 rounds, respectively, for GA-LEACH and MW-LEACH. In addition, the AWDO-EACS demonstrated superior packet delivery performance, with a 99.32% delivery ratio for 100 nodes, eclipsing the 76.90% and 82.65% of GA-LEACH and MW-LEACH, respectively. Moreover, the AWDO-EACS model demonstrated a remarkably low packet loss rate of 0.68 percent for 100 nodes, compared to 23.10 percent for GA-LEACH and 17.35 percent for MW-LEACH. The effectiveness of the proposed AWDO-EACS model in enhancing the overall performance of WSNs is demonstrated.

Keywords: clustering; energy efficiency; metaheuristics; network stability; objective function; WSN

1 INTRODUCTION

Latest developments in the domain of integrated circuit (IC) and Information Technologies (IT) result in the progression of inexpensive and compacted sized sensor nodes (SNs). WSN is a fundamental portion of IoT [1]; it creates millions of gadgets to distribute data to improve environment user management. WSN consists of a collection of several SNs placed in adhocstyle for observing and interacting with the physical environment [2]. Every individual SN is composed of 4 elements such as power supply, microcontrollers, sensors, and transceiver. The sensor in the sensing unit measures the external variables in real-time namely acoustic signal, humidity, vehicular movement, vibration, pressure, infrared, etc [3]. The sensed values are prepared by processing unit and sent to the Base Station (BS) via single-hop or through intermediary sensors using communicating unit. WSN is generally utilized in environmental monitoring and tracking application areas like border control, industrial automation, disaster management, healthcare monitoring, agriculture, etc [4]. WSN is typically arranged in areas where human involvement is hard or impossible. Energy efficiency (EE), storage, and bandwidth are assumed to be key problems in the design of WSN. Owing to restricted and non-rechargeable battery units, the existing power of the sensors need to be used proficiently. Pointing out the features of WSN, power efficacy is the main concern that impacts the entire efficiency of the network. Hence, the designing of WSN protocols needs to be simple, flexible, and EE to various environmental conditions [5]. EE is a significant challenge that typically affects the entire efficiency of the network. WSN commonly wants to persist for a longer duration with the intrinsic battery due to the fact it is hard to recharge or replace batteries in harsh atmospheres. Earlier studies verified that the quantity of energy used by sensing and processing units is lesser and it is insignificant over the energy spent for interaction. It results in the requirement of enhancing EE methods to decrease the quantity of data transmission and communication cost [6]. Clustering is a familiar EE technique in WSN that merges closer nodes to produce clusters and a leader termed as cluster head (CH) is voted amongst the SNs. The residual nodes are named cluster members (CM) and it directs the original data to CH. Followed by, the CH transmits the data to BS next to totalling the received data [7]. Clustering approach reduces the quantity of data transmission and communication distances which leads to lower energy consumption and maximum network lifespan. Using Wind Driven Optimisation (WDO) as the foundation for clustering and extending it to construct AWDO with optimised inherent term values, the research introduces a novel approach. This innovative clustering technique seeks to improve the energy efficacy of WSNs by selecting cluster leaders based on their residual energy, thereby extending the network's lifetime. Multi-objective optimisation, which simultaneously factors energy consumption, distance, and end-to-end latency, is a significant contribution of this work. The AWDO-EACS paradigm improves energy efficiency without compromising network performance by establishing a balance between these objectives [8]. This exhaustive solution addresses key challenges in WSN management, making it useful for deployments in the field. The methodology of this study involves a comprehensive comparison with extant clustering strategies, such as GA-LEACH and MW-LEACH. The AWDO-EACS model outperforms these benchmarks in terms of network stability, energy efficiency, end-to-end latency, packet delivery ratio, throughput, packet loss rate, and network lifetime, as determined by rigorous experimentation and performance evaluations. This comparative analysis validates the scientific significance of the proposed model by demonstrating its superiority. In addition, the study investigates the scalability of the AWDO-EACS model by evaluating its efficacy in various node count scenarios [9].

The research establishes the model's scalability, which is essential for real-world applications in which network sizes may differ, by demonstrating its efficacy across varied network dimensions. The findings of this study have significant implications for WSN deployments from a practical standpoint. The enhanced energy efficiency and extended network longevity provided by the AWDO-EACS model can result in significant cost reductions and enhanced utilisation of WSNs across a variety of applications. This study's findings provide valuable guidance to network designers and researchers, thereby encouraging the development of more efficient and stable WSN solutions. In conclusion, the research paves the way for future developments in the realm of WSNs. The AWDO-EACS model serves as a basis for further investigation, where researchers can investigate additional optimisation techniques, such as multi-hop routing and data aggregation, to improve its performance [10]. This capacity for ongoing development contributes to the evolution of WSN research and management practices. This paper introduces an Adaptive Wind Driven Optimization based Energy Aware Clustering Scheme (AWDO-EACS) for WSN. The presented AWDO-EACS model intends to accomplish enhanced EE and lifetime in WSN. To achieve this, the AWDO-EACS model designs an extended form of WDO algorithm called AWDO algorithm by optimal selection of inherent term values. In addition, an objective with various constraints like energy, distance, and delay is considered into account. The experimental validation of the AWDO-EACS model is carried out under distinct number of node counts.

2 LITERATURE REVIEW

The researcher in [11] presented a fault-tolerant cluster-based routing approach for WSN with hybrid model named FAGWO-H that integrates Firefly Optimization (FA) and GWO. The FA was used for optimum clustering, and GWO selects the optimal route among the base station and the cluster head (CH). The presented approach employs two fitness functions (FF) for GWO and FA. Yang et al. [12] presented a fuzzy logic (FL) approach to additionally resolve the uncertainty of CH selection, incorporate the RE of CH node, and lastly realize the balance of node energy utilization and complete the reasonable distribution of CHs. To additionally decrease the overhead of communication between realized energy optimization and CHs, an inter-cluster routing optimization approach based on the ant colony technique was presented. Chu et al. [13] proposed a parallel fish migration optimization approach using compact technology (PCFMO) and designed a sequential transmission approach among groups and a compact technology to store memory space. In [14], authors presented a hybrid optimization approach for improving network lifetime and EE by integrating adapted PSO with GA. The two-stage method chooses the eligible node in the initial stage with GA and in the next level CH is chosen by the presented approach. In [15], an enhanced convolute system is utilized for predicting whether a node is trustworthy or malicious. The system employs training pattern to decrease the malicious node prediction-error rate. Dwivedi et al. [16] aims are to improve lifetime of the network by presenting an energy-effective layered-based routing approach for WSN utilizing the GWO (LBR-GWO) approach. The whole region of utilized node is separated into four layers. The researchers in [18] presented a fully connected energy effective clustering (FCEEC) method with the electrostatic discharge model for establishing an FC system with shortest path routing from sensors to CH in a multi-hop platform. The presented method improves network lifetime when obtaining energy effective full connectivity among sensors. Sathyamoorthy et al. [19] employ Q-learning approach to deploy sensors in proper cluster and CH selection. During the clustering stage, the node would be located in proper cluster-based computation of the mean value.

Research Gap. Despite the substantial contributions of the aforementioned research in proposing the "Adaptive Wind Driven Optimization-based Energy Aware Clustering Scheme" (AWDO-EACS) for Wireless Sensor Networks (WSNs), there are certain research gaps that require attention and further investigation. The absence of consideration for dynamic network scenarios and real-time adaptability is a notable research gap. While the AWDO-EACS model exhibits outstanding performance under a variety of node count scenarios, it is crucial to investigate how the clustering scheme responds to dynamic network changes, such as node failures, additions, and mobility. Another research gap is the limited examination of the efficacy of the AWDO-EACS model in large-scale WSNs. Although the research comments on scalability and evaluates the model under various node count scenarios, it does not completely address the difficulties that arise when WSNs include thousands or more nodes. Large-scale WSNs introduce complexities associated with communication overhead, data aggregation, and energy distribution, which can have a significant impact on the efficacy of the clustering scheme. Further research is required to determine how the AWDO-EACS model scales in such scenarios and whether modifications or enhancements are necessary to maintain its efficacy and stability. In addition, the research concentrates predominantly on energy efficiency and end-to-end latency as the primary optimisation goals. A clearer picture of the relative strengths and weaknesses of the AWDO-EACS model could be obtained by employing a broader array of existing clustering techniques in a comparative study. In conclusion, the research concentrates predominantly on the AWDO-EACS clustering scheme and its direct effect on WSN performance. However, it disregards the possibility of interactions with higher-layer network protocols and the internet of things (IoT) ecosystem. Investigating how the proposed clustering scheme integrates with other networking layers and how it affects the overall IoT architecture could yield additional insights and aid in the design of holistic and efficient WSN solutions.

3 SYSTEM MODEL

In our study, the system model comprises BS and SN that maintain uniform distribution based arbitrary utilization from the coverage region. For improving the network connectivity, the network was occupied by a large amount of sensors and is used within the coverage region. The hidden details and the subsection of the network are defined in the following. The network was fully static that comprises the sensor nodes and the BS. Initially, each node has equivalent energy. The BS has no energy limitation since its computational energy is very high. Based on the communication distance the energy has been enhanced by the node. For decreasing the energy utilization, sleep and wake node concept was introduced. The cluster head is multi weighted, that maintains the energy level. The node has the ability to transmit the address details to its neighboring nodes from the network.The CH and BS are located within the communication ranges from the network. Generally, single hop transmission dramatically affected the energy, hence *P*jump is an appropriate solution. At this point, the multi-weight clustering would be deliberated. That employs load balancing in clusters for reducing the energy utilization and to improve the EE of WSN.

3.1 Energy Model

In this method, two kinds of power loss are utilized, that is multi-path fading power loss d^4 and free space power loss d^2 and based on the communication distance among the source and the sink the network system was selected. The power consumption of the information depends on the distance factor, arithmetically shown below:

$$E_{TX}(l, d) = \begin{cases} l \cdot E_{energy} + l \cdot E_{em} + d^2, \text{ if } d \le d_{th} \\ l \cdot E_{energy} + l \cdot E_{am} + d^4, \text{ if } d > d_{th} \end{cases} \tag{1}$$

in which Energy represents overall dissipated energy of circuit for each bit, E_{tm} and E_{am} denote the transmitting and amplifying method of networks, and d_{th} indicates the threshold distance as follows:

$$d_{th} = \sqrt{(E_{tm}/E_{am})} \tag{2}$$

The power consumption of the sink is shown as follows:

$$E_{RX(l)} = l^{\wedge} \cdot E_{energy} \tag{3}$$

3.2 Energy Consumption Model

The energy consumption model is described in the following. The energy consumption of the transmitted node of l bits information to CH is arithmetically shown below.

$$E_{non-CH} = l \cdot E_{energy} + l \cdot E_{tm} d^2_{cn-CH} \tag{4}$$

in which d_{cn-CH} =Child node to CH distance.

Here the energy consumption of the CH is shown below.

$$E_{CH} = \left(l\left(\frac{n}{c} - 1\right) \cdot E_{energy} + \frac{n}{c} \cdot E_{con} \right) + E_{RX}(l, d) + \\ + E_{TX}(l, d_{CH-BS}) \tag{5}$$

whereas n denotes the number of alive nodes, c indicates the amount of clusters, E_{RX} represent the energy utilization of the CH, and d_{CH-BS} represent the BS to CH distance.

4 THE PROPOSED MODEL

In this study, a novel AWDO-EACS model has been developed to accomplish enhanced EE and lifetime in WSN. The AWDO-EACS model designed an extended form of WDO algorithm called AWDO algorithm by optimal selection of inherent term values. In addition, an objective with various constraints such as energy, distance, and delay are considered into account. Fig. 1 illustrates the overall process of AWDO-EACS technique.

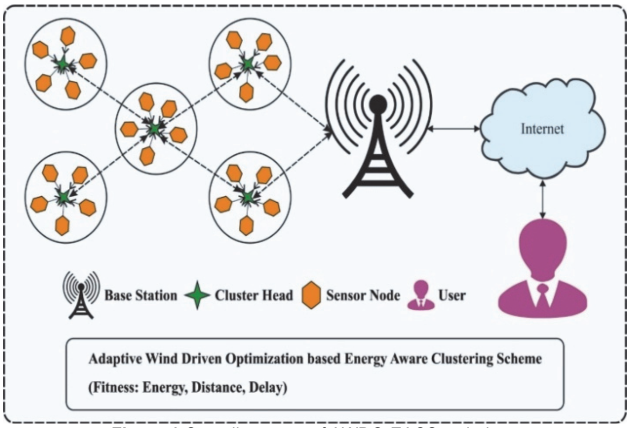

Figure 1 Overall process of AWDO-EACS technique

4.1 Design of AWDO Algorithm

The AWDO was established for eliminating the typical WDO techniques dependencies on user's input by choosing one of the suitable values for the inherent terms of velocity upgrade formulas from the typical WDO. At this point, the AWDO technique utilizes the covariance-matrix adaptation evolutionary strategy (CMAES) as an optimized technique for optimum choosing the inherent terms dependent upon the nature of all the problems. Fig. 2 displays the steps flow in WDO technique.

Figure 2 Flowchart of WDO technique

The typical WDO technique is established, in 2010, by Bayraktar et al. [20]. They expressed the atmospheric motion utilizing physical formulas that explain the air movement as a significance of pressure gradients based on temperature difference. These air parcels were determined as the position and velocity that signify an optimum solution or global optimal. During the AWDO technique, the velocity and position of air parcels are upgraded by the subsequent methods.

$$u_{new}^{i}=(1-\alpha)u_{cur}^{i}-gx_{cur}^{i}+\left(RT\left|\frac{1}{r}-1\right|\left(x_{opt}-x_{cur}^{i}\right)\right)+ \\ +\left[\frac{cu_{cur}^{other\ dim}}{r}\right] \tag{6}$$

$$x_{new}^{i}=x_{cur}^{i}+u_{new}^{i} \tag{7}$$

whereas i signifies the particle number, u_{cur}^{i} refers to the present velocity of air parcel, u_{new}^{i} stands for the novel velocity of air parcels, x_{pt} defines the global optimum position, x_{cur}^{i} stands for the existing position of air parcels, x_{new}^{i} demonstrates the novel place of the air parcel, and inherent terms (α, g, c and RT) are connected to physical method. At this point, the air parcel is in descending order based on its pressure.

For all dimensions, the typical WDO permits the air parcels for travelling only as to the range of −1 and 1 [21]. When some air parcel shows efforts for travelling outside of this range at some dimensional, their position in that dimensional is upgraded for sending the air parcel back to traveling range again. At this point, the velocity of some air parcels is restricted to a maximal value that purposes keeping air parcel to the searching space with preventing individual's parcels in ignored particular region and taking huge stages. When the velocity magnitude of some air parcel exceeded the restricted maximal value of velocity at some dimensional, next to the velocity in that dimensional was changed as:

$$u_{\text{new}}^{*}=\begin{cases}u_{\max} & if\ u_{\text{new}}<u_{\max}\\ -u_{\max} & if\ u_{\text{new}}<u_{\max}\end{cases} \tag{8}$$

in which $|u_{\max}|$ signifies the restricted maximal value of velocity at some dimensional, and u_{new}^{*} indicates the changed velocity. Thus, an AWDO technique was established for overcoming the restriction of typical WDO technique by employing the CMAES to optimum choice of the group of values to the inherent terms (α, g, c and RT). This purpose enhances the efficacy of the AWDO technique by avoiding being stuck in local optimum, pushing it for converging faster, and controlling higher noisy-specific optimized problem.

4.2 Process Involved in CH Selection

The primary purpose of the presented approach is to decrease the distance amongst the node and selected CH. Also, it focuses on minimizing the delay to transmit the information from one node to other nodes. In contrast, network energy needs to be higher, viz., it should exploit a small number of energies in transmitting data. At last, the node must tolerate the risk attained in network. The objective function of the adapted CH is given in Eq. (9), where the value of η needs to be dependent on $0 < \eta < 1$. Now, v_m and v_n denote the operation. The constraints on delay, energy, distance, and security are represented as σ_1, σ_2, σ_3 and σ_4. The condition of this constraint is represented as: $\sigma_1 + \sigma_2 + \sigma_3 + \sigma_4 = 1$. In Eq. (11), $Y^Z - S_S$ denotes the distance among the normal as well as sink nodes.

$$N_n=\eta v_n+(1-\eta)v_m \tag{9}$$

$$v_m=\sigma_1\cdot v_i^{dis}+\sigma_2\cdot v_i^{me}+\sigma_3\cdot v_i^{de}+\sigma_4\cdot v_i^{sec} \tag{10}$$

$$v_n=\frac{1}{b}\sum_{z=1}^{b}\left\|Y^K-S_J\right\| \tag{11}$$

Eq. (12) represents the FF for distance, where $ldi_J(m)$ is related to transmission of packet from the normal node (NLN) to CH and from CH to BS. Generally, v_i^{dis} ranges within zero and one, and value goes high when the distance among CH and the NLN is higher. Eq. (13) and Eq. (14) illustrate $v_{(m)}^{dis}$ and $v_{(n)}^{dis}$, where Y_Z denotes the NLN in zth cluster, G_Z indicates the CH of Zth cluster, the distance amongst the BS as well as CH represents $G_Z - S_s$, $G_Z - Y_y$ indicates the distance amongst the NLN and CH and $Y_Z - Y_y$ represent the distance among 2NLNs, M_z and M_y denotes the amount of nodes that exclude the Zth and yth cluster.

$$v_i^{dis}=\frac{v_{(m)}^{dis}}{v_{(n)}^{dis}} \tag{12}$$

$$v_{(m)}^{dis}=\sum_{z=1}^{M_z}\left[\left\|G_x-S_s\right\|+\sum_{y=1}^{M_y}\left\|G_Z-Y_y\right\|\right] \tag{13}$$

$$v_{(n)}^{dis}=\sum_{z=1}^{M_z}\sum_{y=1}^{M_y}\left\|Y_Z-Y_y\right\| \tag{14}$$

The FF of energy is shown below. The value v_i^{ene} will be high when compared to CH cumulative $v_{(m)}^{ene}$ and $v_{(n)}^{ene}$ concern the maximal energy value and the high amount of CH.

$$v_i^{ene}=\frac{v_{(m)}^{ene}}{v_{(n)}^{ene}} \tag{15}$$

Eq. (16) shows the FF of delay v_i^{del} that lies $[0, 1]$ v_i^{del} is directly proportionate to each node present in cluster. So, a delay gets reduced when the CH has a minimized amount of nodes. The numerator represents the high amount of CH and the denominator M_M indicates the entire amount of nodes in WSN.

$$v_i^{del}=\frac{\max\left(\left\|G_Z-Y_Z\right\|\right)_{z=1}^{M_c}}{M_M} \tag{16}$$

5 EXPERIMENTAL VALIDATION

In this section, a brief experimental validation of the AWDO-EACS model is tested under distinct aspects. Tab. 1 and Fig. 3 demonstrate a brief EE of the AWDO-EACS method over other approaches under distinct nodes. The results indicated that the AWDO-EACS system has gained increased performance over the other techniques.

Table 1 EE analysis of AWDO-EACS technique with existing approaches under distinct count of nodes

Energy Efficiency / %					
No. of Nodes	GA-LEACH	MW-LEACH	CSOGA	MWCSGA	AWDO-EACS
0	0.00	0.00	0.00	0.00	0.00
20	8.14	11.03	16.56	21.82	27.35
40	18.93	26.03	34.19	39.46	47.09
60	36.56	42.09	48.14	59.19	67.35
80	48.40	54.46	63.93	74.72	81.30
100	56.04	63.14	71.30	79.72	83.41

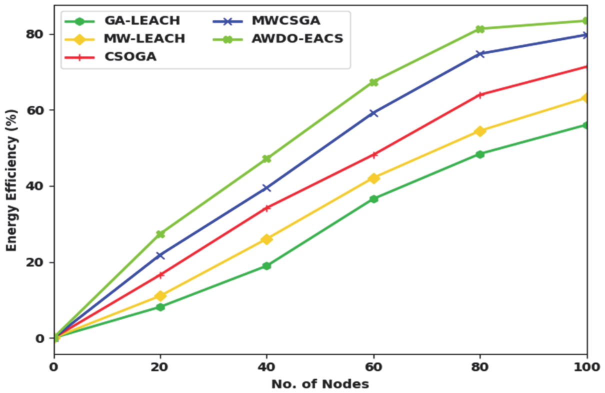

Figure 3 EE analysis of AWDO-EACS technique under distinct count of nodes

For sample, with 20 nodes, the AWDO-EACS model has offered EE of 27.35% whereas GA-LEACH, MW-LEACH, and CSOGA models have obtained lower EE of 8.14%, 11.03%, 16.56%, and 21.82% respectively. Along with that, with 60 nodes, the AWDO-EACS approach has offered EE of 67.35% whereas GA-LEACH, MW-LEACH, and CSOGA techniques have obtained lower EE of 36.56%, 42.09%, 48.14%, and 59.19% correspondingly. Moreover, with 100 nodes, the AWDO-EACS model has offered EE of 83.41% whereas GA-LEACH, MW-LEACH, and CSOGA methods have obtained reduced EE of 56.04%, 63.14%, 71.30%, and 79.72% correspondingly.

Table 2 ETED analysis of AWDO-EACS technique with existing approaches under distinct count of nodes

End-to-End Delay / ms					
No. of Nodes	GA-LEACH	MW-LEACH	CSOGA	MWCSGA	AWDO-EACS
0	0.00	0.00	0.00	0.00	0.00
20	6.60	5.83	3.43	1.46	0.61
40	11.49	7.80	7.03	3.26	2.15
60	13.97	11.83	8.83	6.43	4.20
80	21.34	17.06	11.66	8.49	5.58
100	27.34	23.22	15.68	9.94	7.29

A comparative ETED investigation of the AWDO-EACS model with recent models is provided in Tab. 2 and Fig. 4. The reached values imply that the AWDO-EACS methodology has resulted in reduced ETED over existing models. For instance, with 20 nodes, the AWDO-EACS model has provided lower ETED of 0.61 s whereas GA-LEACH, MW-LEACH, and CSOGA models have gained increased ETED of 6.60 s, 5.83 s, 3.43 s, and 1.46 s respectively. Also, with 100 nodes, the AWDO-EACS technique has provided reduced ETED of 7.29 s whereas GA-LEACH, MW-LEACH, and CSOGA models have gained maximum ETED of 27.34 s, 23.22 s, 15.68 s, and 9.94 s correspondingly.

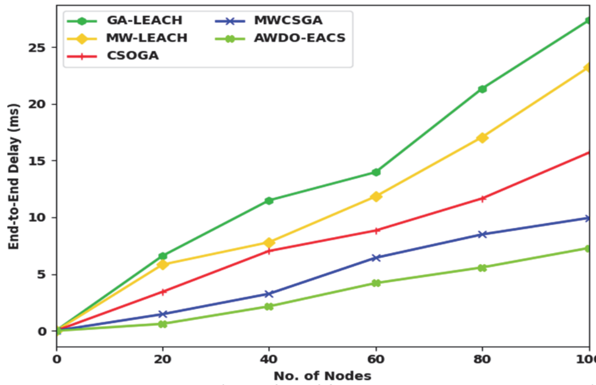

Figure 4 ETED analysis of AWDO-EACS technique under distinct count of nodes

Table 3 DROP analysis of AWDO-EACS technique with existing approaches under distinct count of nodes

DROP (PAC)					
No. of Nodes	GA-LEACH	MW-LEACH	CSOGA	MWCSGA	AWDO-EACS
0	0	0	0	0	0
20	141	120	61	29	18
40	267	223	126	52	33
60	434	314	200	96	56
80	552	451	257	134	73
100	632	535	335	158	107

A comparative DROP examination of the AWDO-EACS model with recent models is given in Tab. 3 and Fig. 5. The attained values imply that the AWDO-EACS model has resulted in reduced DROP over existing models. For instance, with 20 nodes, the AWDO-EACS model has provided lower DROP of 18PAC whereas GA-LEACH, MW-LEACH, and CSOGA techniques have reached increased DROP of 141PAC, 120PAC, 61PAC, and 29PAC correspondingly. Moreover, with 100 nodes, the AWDO-EACS approach has provided lower DROP of 107PAC whereas GA-LEACH, MW-LEACH, and CSOGA techniques have gained enhanced DROP of 632PAC, 535PAC, 335PAC, and 158PAC correspondingly.

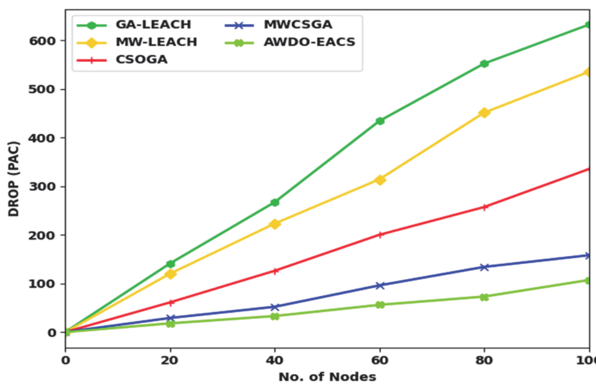

Figure 5 DROP analysis of AWDO-EACS technique under distinct count of nodes

Table 4 Throughput analysis of AWDO-EACS technique with existing approaches under distinct count of nodes

Throughput / Kbps					
No. of Nodes	GA-LEACH	MW-LEACH	CSOGA	MWCSGA	AWDO-EACS
0	0.00	0.00	0.00	0.00	0.00
20	23.62	84.26	112.24	161.22	247.52
40	67.93	151.90	210.20	296.50	422.45
60	121.57	203.21	357.14	578.72	641.69
80	147.23	259.18	455.10	669.68	760.64
100	179.88	352.48	536.73	679.01	753.64

Tab. 4 and Fig. 6 illustrate a brief throughput (THRT) of the AWDO-EACS model over other models under distinct nodes. The outcomes indicated that the AWDO-EACS model has gained maximal performance over the other algorithms. For instance, with 20 nodes, the AWDO-EACS approach has obtained THRT of 247.52 Kbps whereas GA-LEACH, MW-LEACH, and CSOGA models have obtained reduced THRT of 23.62 Kbps, 84.26 Kbps, 112.24 Kbps, and 161.22 Kbps correspondingly. Followed by, with 60 nodes, the AWDO-EACS system has accessible THRT of 641.69 Kbps while GA-LEACH, MW-LEACH, and CSOGA techniques have obtained lower THRT of 121.57 Kbps, 203.21 Kbps, 357.14 Kbps, and 578.72 Kbps correspondingly. Eventually, with 100 nodes, the AWDO-EACS system has accessible THRT of 753.64 Kbps whereas GA-LEACH, MW-LEACH, and CSOGA methodologies have obtained lower THRT of 179.88 Kbps, 352.48 Kbps, 536.73 Kbps, and 679.01 Kbps correspondingly.

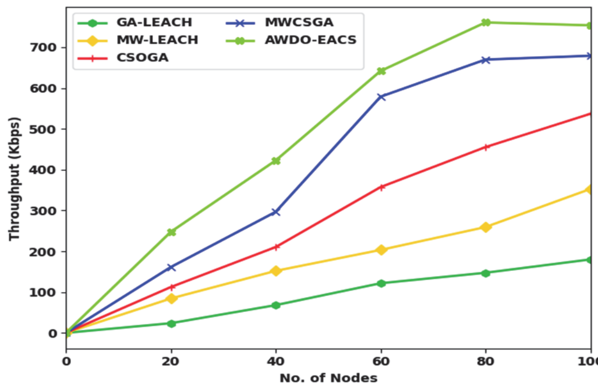

Figure 6 Throughput analysis of AWDO-EACS technique under distinct count of nodes

Table 5 PDR analysis of AWDO-EACS technique with existing approaches under distinct count of nodes

Packet Delivery Ratio / %					
No. of Nodes	GA-LEACH	MW-LEACH	CSOGA	MWCSGA	AWDO-EACS
0	0.00	0.00	0.00	0.00	0.00
20	5.05	6.85	14.39	25.17	35.59
40	14.03	19.78	29.84	47.80	57.50
60	37.74	46.36	56.42	63.97	79.06
80	60.02	66.48	76.18	84.09	93.78
100	76.90	82.65	90.91	97.17	99.32

Tab. 5 and Fig. 7 demonstrate a brief PDR of the AWDO-EACS technique over other models under distinct nodes. The results expose that the AWDO-EACS system has gained improved performance over the other techniques. For sample, with 20 nodes, the AWDO-EACS model has obtained PDR of 35.59% but GA-LEACH, MW-LEACH, and CSOGA methodologies have obtained lower PDR of 5.05%, 6.85%, 14.39%, and 25.17% correspondingly. Followed by, with 60 nodes, the AWDO-EACS model has offered PDR of 79.06% whereas GA-LEACH, MW-LEACH, and CSOGA models have obtained lower PDR of 37.74%, 46.36%, 56.42%, and 63.97% correspondingly. Furthermore, with 100 nodes, the AWDO-EACS model has accessible PDR of 99.32% whereas GA-LEACH, MW-LEACH, and CSOGA algorithms have obtained decreased PDR of 76.90%, 82.65%, 90.91%, and 97.17% respectively.

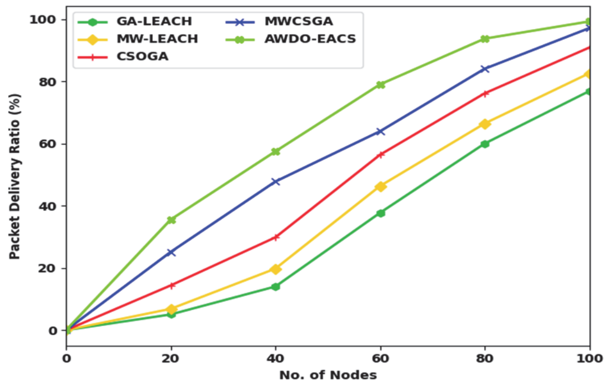

Figure 7 PDR analysis of AWDO-EACS technique under distinct count of nodes

A comparative PLR analysis of the AWDO-EACS model with recent algorithms is provided in Tab. 6 and Fig. 8. The achieved values implied that the AWDO-EACS methodology has resulted in lower PLR over existing models. For instance, with 20 nodes, the AWDO-EACS system has provided decreased PLR of 64.41% whereas GA-LEACH, MW-LEACH, and CSOGA models have gained enhanced PLR of 94.95%, 93.15%, 85.61%, and 74.83% correspondingly. Similarly, with 100 nodes, the AWDO-EACS methodology has provided lower PLR of 0.68% whereas GA-LEACH, MW-LEACH, and CSOGA approaches have gained increased PLR of 23.10%, 17.35%, 9.09%, and 2.83% respectively.

Table 6 PLR analysis of AWDO-EACS technique with existing approaches under distinct count of nodes

Packet Loss Rate / %					
No. of Nodes	GA-LEACH	MW-LEACH	CSOGA	MWCSGA	AWDO-EACS
0	100.00	100.00	100.00	100.00	100.00
20	94.95	93.15	85.61	74.83	64.41
40	85.97	80.22	70.16	52.20	42.50
60	62.26	53.64	43.58	36.03	20.94
80	39.98	33.52	23.82	15.91	6.22
100	23.10	17.35	9.09	2.83	0.68

Tab. 7 and Fig. 9 showcase a brief NLT of the AWDO-EACS technique over other models under various nodes. The results expose that the AWDO-EACS model has gained improved performance over the other methodologies. For instance, with 20 nodes, the AWDO-EACS approach has obtained NLT of 96 rounds while GA-LEACH, MW-LEACH, and CSOGA models have obtained lower NLT of 37, 49, 68, and 84 rounds correspondingly. Moreover, with 60 nodes, the AWDO-EACS system has offered NLT of 84 rounds whereas GA-LEACH, MW-LEACH, and CSOGA approaches have obtained reduced NLT of 32, 45, 56, and 69 rounds correspondingly. Furthermore, with 100 nodes, the

AWDO-EACS model has offered NLT of 74 rounds whereas GA-LEACH, MW-LEACH, and CSOGA techniques have obtained lower NLT of 20, 33, 49, and 66 rounds correspondingly.

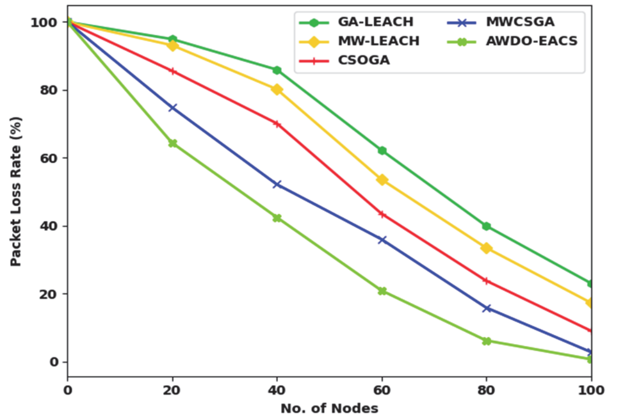

Figure 8 PLR analysis of AWDO-EACS technique under distinct count of nodes

Table 7 NLT analysis of AWDO-EACS technique with existing approaches under distinct count of nodes

Network Lifetime (Rounds)					
No. of Nodes	GA-LEACH	MW-LEACH	CSOGA	MWCSGA	AWDO-EACS
0	100	100	100	100	100
20	37	49	68	84	96
40	32	46	60	70	90
60	32	45	56	69	84
80	26	43	55	65	74
100	20	33	49	66	74

After examining the detailed results and discussion, it is apparent that the AWDO-EACS model is found to be effective over the other models.

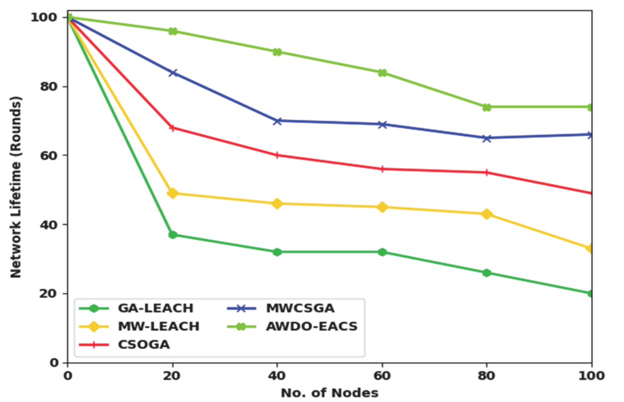

Figure 9 NLT analysis of AWDO-EACS technique under distinct count of nodes

6 CONCLUSION

In this study, a novel AWDO-EACS model has been developed to accomplish enhanced EE and lifetime in WSN. The AWDO-EACS model effectively addresses the energy efficiency and end-to-end latency optimization goals, demonstrating superior performance in comparison to the extant GA-LEACH and MW-LEACH clustering approaches. The incorporation of the adaptive wind-driven optimization algorithm enables clusters to be formed and maintained efficiently, resulting in longer network longevity and decreased data transmission latencies. However, there are still voids in the research that require further investigation. First, the AWDO-EACS model should be evaluated under dynamic network scenarios to determine its adaptability to real-time changes, such as node failures, additions, and mobility. In addition, it is essential to investigate the scalability of the model in large-scale WSNs, as this presents unique challenges that can affect clustering efficacy. To improve the AWDO-EACS model, a more thorough examination of the trade-offs between energy efficiency, security, reliability, and Quality of Service (QoS) is required. In addition, it is necessary to execute a more comprehensive comparative analysis, pitting the AWDO-EACS against other cutting-edge clustering algorithms. In addition, future research should evaluate the integration of the AWDO-EACS model with higher-layer network protocols and the IoT ecosystem as a whole.

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