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Article

Metaheuristics Enabled Clustering with Routing Scheme for Wireless Sensor Networks

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Abstract: Wireless Sensor Network (WSN) is a vital element in Internet of Things (IoT) as the former enables the collection of huge quantities of data in energy-constrained environment. WSN offers independent access to the target region and performs data collection in an effective manner. But energy constraints remain a challenging issue in WSN since it operates on in-built battery. The studies conducted earlier recommended that the energy spent on communication process must be considerably reduced to improve the efficiency of WSN. Cluster organization and optimal selection of the routes are considered as NP hard optimization problems which can be resolved with the help of metaheuristic algorithms. Clustering and routing are considered as effective approaches in enhancing the energy effectiveness and lifespan of WSN. In this background, the current study develops an Improved Duck and Traveller Optimization (IDTO)-enabled cluster-based Multi-Hop Routing (IDTOMHR) technique for WSN. Primarily, IDTO algorithm is exploited for the selection of Cluster Head (CH) and construction of clusters. Besides, Artificial Gorilla Troops Optimization (ATGO) technique is also used to derive an optimal set of routes to the destination. Both clustering and routing approaches derive a fitness function with the inclusion of multiple input parameters. The proposed IDTOMHR model was experimentally validated for its performance under different aspects. The extensive experimental results confirmed the better performance of IDTOMHR model over other recent approaches.

Keywords: Wireless sensor network; clustering; routing; metaheuristics; energy efficiency; lifetime

1 Introduction

Wireless Sensor Network (WSN) is an intermesh of Sensor Nodes (SN) that are linked with one another in a network via wireless means. WSN identifies application zones to observe the external and environmental statuses of remote locations [1]. It ensures wireless transmission of the data through limited computing capability. However, it has lesser energy sources which result in network failure issues [2]. Thus, it is considered as a prerequisite for WSNs to have SNs with inbuilt battery due to energy constraints. Therefore, the current research work is aimed at mitigating the power consumption of SNs [3]. Further, WSNs can be applied in large-scale in various domains such as environment monitoring, border control applications, and remote surveillance. In general, the sensor nodes are normally cheaper, possess low battery power and experience energy constraints [4,5]. Fig. 1 displays the infrastructure of WSN.

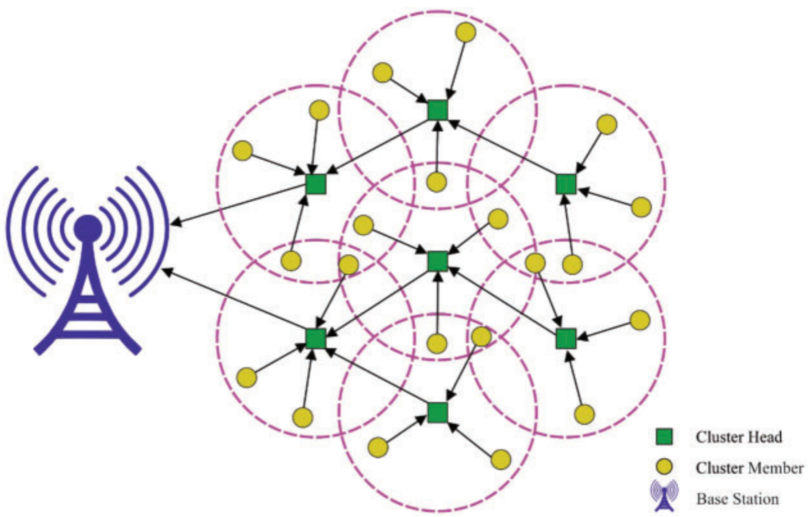

Figure 1: Structure of WSN

The main challenge in WSN is to increase the lifespan of network since the sensors do not possess the capability to transmit the data at the beginning to Base Station (BS) [6,7]. In data collection applications, every sensor is liable to sense and transmit the data packets to BS. The method of combining the data reduces data dissipation and saves power by clubbing unique incoming data packets into a single packet. Therefore, many applications are created to expand the lifespan of WSNs. Sensor Nodes function on the basis of in-built battery due to which WSNs experience energy-constraint issues [8–10]. Therefore, the dissipation of power is controlled to extend the lifespan of the network. Clustering is a process in which the sensors are grouped together in the network based on selected features. Each group is termed as a cluster; a Cluster Head (CH) exits in each cluster and is liable to each and every cluster member; further, it collects the data from other cluster member nodes and sends it to BS [11,12]. In order to reduce the power dissipation rate in WSN, an optimum route should be identified from the source to destination using routing protocol. This route is aimed at reducing the power utilization rate, whenever broadcasting the data [13]. Various routing protocols have been proposed earlier which function on the basis of power dissipation variable, whereas a few useful routing protocols has been examined by authors that are prominently utilized in the mitigation of power dissipation rate in WSN [14].

The researchers, in the study conducted earlier [15], proposed Moth Flame Optimization (MFO) algorithm based on Thresholding sensitive Energy-effective Clustering Protocol (TECP) to increase the lifetime of the network. MFO used multihop transmission between CHs and BSs to accomplish the optimum connectivity cost, reduction of energy and load balancing for distant CHs. In literature [16], a heterogeneous network-based cluster routing approach was introduced. It emphasized on resolving the problems involved in energy utilization and network lifespan so as to achieve better performance from the network. The presented method depends on probability approach in which node energy and CH selection possibility of distinct heterogeneous nodes are used in the selection of CHs.

In the study conducted earlier [17], a Light weight Trust Management Scheme (LTMS) was presented based on binomial distribution to defend from internal attacks. At the same time, the study also considered different domains such as energy, distance, environment, and security to present a Multi-dimensional Secure Clustered Routing (MSCR) protocol with the help of dynamic dimension weight in hierarchical WSN. In literature [18], Self-Organizing Map (SOM) NN was utilized to accomplish primary clustering on network node. In inter cluster routing phase, it is possible to achieve inter-cluster routing with the help of enhanced Ant Colony Optimization (ACO). The researchers [19] developed and analyzed an EE clustering-based routing method and selective-path priority table based on mobile sink application. The priority table can be generated by prioritizing the two shortest routes to the sink or CH in line with the rules.

The current study develops an Improved Duck and Traveller Optimization (IDTO)-enabled Cluster-based Multi-Hop Routing (IDTOMHR) technique for WSN. Primarily, IDTO algorithm is exploited for the selection of Cluster Head (CH) and construction of clusters. Besides, Artificial Gorilla Troops Optimizer (ATGO) technique is involved to derive an optimal set of routes to reach the destination. Both clustering and routing approaches derive a Fitness Function (FF) with the inclusion of multiple input parameters. The proposed IDTOMHR model was experimentally validated under different aspects.

2 The Proposed Model

In this study, a novel IDTOMHR technique has been developed to increase the energy effectiveness and lifespan of WSN. Initially, IDTO algorithm is exploited for effectual CH selection and cluster construction tasks. Next, ATGO technique is utilized to derive an optimal set of routes to reach the destination. Both clustering and routing approaches derive a Fitness Function with the inclusion of multiple input parameters.

2.1 Stage I: Cluster Construction Phase

Initially, IDTO algorithm is exploited for effectual CH selection and cluster construction tasks. The authors have conducted the current study to find a solution that improves the energy efficiency of WSNs. With energy constraint as the primary issue to be resolved, the current study is aimed at attaining the best possible solution for a specific period with maximum quality and minimum cost [20].

$$D_i^{new} = D_i + \alpha \oplus Terrif(\mu) \tag{1}$$

At this point, α refers to track dimensional parameter. $Terrif(\mu)$ signifies the distributing parameter to upgrade the place of the duck. α is computed based on the equation given below.

$$\alpha \oplus Terrif(\mu) \sim 0.01 \frac{a}{|b|^{\frac{1}{\mu}}} \left(D_i^t - D_{best}^t\right) \tag{2}$$

At this point, both the variables α and b are created in standard distribution, whereas

$$a \sim P\left(0, \phi_a^2\right), \ b \sim P\left(0, \phi_b^2\right) \tag{3}$$

$$\varphi_a = \left[\frac{\Gamma(1+\mu) \times \sin\left(\pi \times \frac{\mu}{2}\right)}{\Gamma\left[\frac{1+\mu}{2}\right] \times \mu}\right]^{\frac{1}{\mu}}, \phi_b = 1 \tag{4}$$

Here the gamma-adjusted function is developed. At this point $0 \le \mu \le 2$. In optimum search, the place (μ) is upgraded with the help of height *Tag* (Q_{wg}):

$$D_{best}^{new} = D_{best}^t \pm I_5 \times Q_{wg} \tag{5}$$

At this point, I_5 refers to the arbitrary number between 0 and 1. Q_{wg} signifies the height tag.

$$Q_{wg} = Q_{max}\, e^{(l \times m)} \tag{6}$$

$(Q_{\min})$ refers to the minimal number and Q_{max} demonstrates the maximal limit.

$$l = \left(\frac{\ln\left(\frac{Q_{min}}{Q_{max}}\right)}{M_{max}}\right) \tag{7}$$

Now, m implies the current iteration and (M_{max}) indicates the highest number of iterations.

The place of the concerned duck limits the separation of voyage, while it promotes the identification of prey. Speed > Distance = Capturing the prey in minimal time. Thus, the optimized value is attained at a minimum distance (traveling) and maximum speed (define the prey) by a flock of ducks.

$$S > P = P \tag{8}$$

Here S indicates the Speed and D denotes the distance utilized to attain P i.e., Prey. Here, force is calculated as follows.

$$F = m * a \tag{9}$$

At this point, m denotes the weight of the duck and is utilized to calculate distance/time^2 to update the speed (a).

Assume $fs = 1, 2, \ldots, \ n$ refers to n food sources that are assumed as graph nodes. Consider β_{jk} as the decision variable to connect the food source j to food source k (i.e., an edge from the graph in node j to node k) so that $\beta_{jk} = 1$ signifies the beginning of the duck travel at j and ends at k. Then, $\beta_{jk} = 0$ refers to the absence of connection along this edge. So, the cities procedure is set to be the V of vertice, and connection procedure is set to be E of the edge. Assume d_{i_j} as the distance between food path j and food path, k. Because of the symmetry, it is realized that $d_{jk} = d_{kj}$ and the graph is undirected. The objective is to minimize the distance.

$$\begin{aligned} f_s &= j, k \in \mathrm{E}, \quad j = k d_{jk} \beta_{kj} \\ A &= D^{s+1} = DTO\left(D^s, P(s), \in(s)\right) \end{aligned} \tag{10}$$

D^{s+1} = novel solution vector;

D^s = existing solution vector

P(s) = Parameters $P = (P_1, \ldots, P_u)$

$\in (s)$ = random variables $\varepsilon = (\varepsilon_1 \ldots,\ \varepsilon_v)$

s = scheduled time

In this technique i.e., IDTO, a novel and optimum solution D^{s+1} is the prime motto to be achieved so as to provide solutions to the existing problem D^s at iteration/schedule s. Mathematically speaking, an arbitrary walk is expressed as follows

$$R_{s+1} = R_s + p_s \tag{11}$$

R_s refers to the present solution; s signifies the steps and p_s refers to perturbation.

$$D_i^{s+1} = D_i^s + \mu_{oe^{-\gamma r^2 ij}} \left(D_{j^{-s}} - D_{i^s}\right) \tag{12}$$

The next generation is upgraded with the help of optimum function provided herewith.

The performance is maximized using the equation given below.

$$\xi = DTO\,(\phi,\ p,\ \varepsilon) \tag{13}$$

In order to increase the lifetime of WSN, several clustering methods are used to select the optimum CH and the effective solution resolves the problems. Fitness Function (FF) is the key for each technique and it determines the comparative significance of each and every model. A high appropriateness value represents that the model is effective. In current work, fitness function is constructed for IDTO algorithm and it considers power utilization and the distance between BS and the CH. Fitness function F can be determined using the following equation.

$$\text{Fitness Function} = \sum_i \left(w_j * f_i\right) \forall f_i \in \{E,\ D\} \tag{14}$$

The weight for fitness parameter is arbitrary allocated (w_i). Here w_1 and w_2 indicate the weight values of all the parameters. The weight value is upgraded based on the application's necessity. So, the overall power, utilized for transferring every gathered information to the BS, is determined as follows.

$$E = \sum_{i=1}^{m} E\,(i, ch) + \sum_{i=1}^{n} (m * R_X) + \sum_{i=1}^{n} E\,(i, bs) \tag{15}$$

Here, $E\,(i, ch)$ denotes the power utilization from i th node to respective CH, $(m * R_x)$ indicates the power utilized by CH to receive the message m from its members and $E\,(i, bs)$ signifies the power utilized for transmission of data from i th CH to the BS.

The overall distance can be determined as given below.

$$D = \sum_{i=1}^{m} D\,(i, ch) + \sum_{i=1}^{n} D\,(i, bs) \tag{16}$$

$D\,(i, ch)$ indicates the distance from node i to CH. $D\,(i, bs)$ denotes the distance from CH i to the BS. 'm' and 'n' indicates the cluster member and CH in 1[st] and 2[nd] terms of Eq. (15).

2.2 Stage II: Route Selection Phase

Once the clusters are constructed, ATGO technique is applied to derive an optimal set of routes to reach the destination [21]. This technique is simulated on the basis of group behavior of gorillas which is inclusive of five approaches. In exploration stage, three strategies are utilized such as migration in the direction of recognized place, migration towards unknown places, and moving towards other gorillas. The exploitation stage uses two approaches such as competition for adult females and following the silverback.

2.2.1 Exploration Phase

Each gorilla is regarded as a candidate solution in ATGO. Further, in every optimization phase, the optimal candidate solution is regarded as a silverback gorilla. Three distinct approaches are utilized for exploration stage such as migration toward an unknown location to increase the exploration of ATGO, migration towards another gorilla to increase the balance between exploration and exploitation stages and migration in the direction of recognized position to increase the ability of ATGO in terms of searching different optimization regions. These three approaches, in the exploration stage, are arithmetically expressed herewith.

$$GX\,(t+1) = \begin{cases} (UL - LL) \times r_1 + LL, \ rand < p, \\ (r_2 - C) \times X_r(t) + L \times H, \ rand \geq 0.5, \\ X\,(i) - L \times (L \times (X(t) - GX_r(t)) + r_3 \times (X(t) - GX_r(t)))\,, \ rand < 0.5 \end{cases} \tag{17}$$

whereas $X(t)$ and $GX\,(t+1)$ indicate the location vectors of the existing gorilla and candidate gorilla at t iteration correspondingly, whereas rand r_1, r_2, and r_3 signify the arbitrary values within [0,1].

$$C = F \times (1 - It/MaxIt), \tag{18}$$

$$F = cos(2 \times r_4) + 1, \tag{19}$$

$$L = C \times l, \tag{20}$$

$$H = Z \times X(t), \tag{21}$$

$$Z = [-C,\ C] \tag{22}$$

Here It and $MaxIt$ represent the existing and overall iteration values of the optimization method. cos and r_4 indicate the cosine function and arbitrary number within [0,1]. Moreover, l and Z represent the arbitrary numbers within [1,1] and $[-C,\ C]$, correspondingly. The cost of each GX solution is evaluated in the exploration stage. When the cost of $GX(t) < X(t)$, the $GX(t)$ solution replaces the $X(t)$ solution and becomes an optimal solution (silverback).

2.2.2 Exploitation Phase

Two approaches are applied in the exploitation stage of ATGO such as competition for adult females and following the silverback. With the application of C value in Eq. (19) and comparing it against the variable W, two approaches are selected as demonstrated in the following subsection. Silverback gorilla is the leader of a group that makes the decisions and guides other gorillas in the direction of food source. This approach is chosen, when $C \geq W$. It is arithmetically shown below.

$$GX\,(t+1) = L \times M \times (X(t) - X_{siverback}) + X(t). \tag{23}$$

$X_{silverback}$ characterizes the location vector of silverback gorilla that presents the optimal solution, and $X(t)$ characterizes the location vector of the gorilla.

$$M = \left(|\,(1/N) \sum_{i=1}^{N} GX_i(t)|^g \right)^{(1/g)} \tag{24}$$

$GX_i(t)$ demonstrates the location of candidate gorilla vector at t iteration, and N indicates the number of gorillas.

$$g = 2^L. \tag{25}$$

L is described in the abovementioned Eq. (21). Competition for adult females is the next approach followed during exploitation stage, when $C < W$. Once the younger gorilla becomes mature, it violently competes with others for the choice of adult females. Such behaviors are arithmetically expressed herewith. Fig. 2 illustrates the ATGO technique.

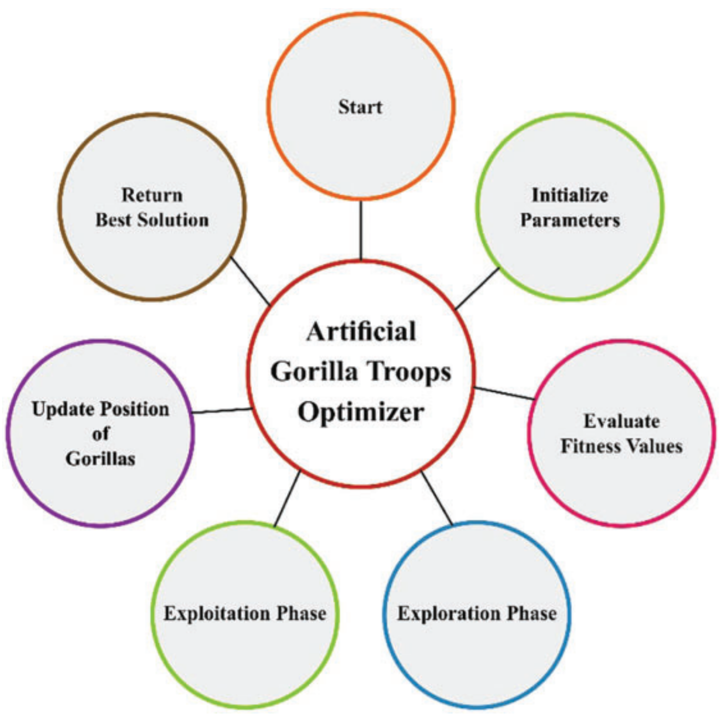

Figure 2: Flowchart of ATGO technique

$$GX\left(i\right) = X_{siverback} - \left(X_{siverback} \times Q - X\left(t\right) \times Q\right) \times A, \tag{26}$$

$$Q = 2 \times r_5 - 1, \tag{27}$$

$$A = \beta \times E, \tag{28}$$

$$E = \begin{cases} N_1 & rand \geq 0.5 \\ N_2 & rand < 0.5 \end{cases} \tag{29}$$

In order to define an optimum group of routes by ATGO algorithm, the given function is employed to determine the subsequent hop to BS and is calculated as follows.

$$f\left(x\right) = \left\{i,\ for\ which \left|\left(\frac{i}{k} - X_{i_f j}\right)\right| is\ minimum,\ \forall_i 1 \leq i \leq k\right. \tag{30}$$

The drive is to determine an optimal set of routes from CHs to BS using an FF that comprises of two parameters such as energy and distance. Primarily, the RE of next-hop nodes is determined and the node with high energy is fixed as relay node. Hence, the nodes with high RE are offered as next-hop nodes. A primary sub-objective $f1$ is offered as follows.

$$f1 = E_{CH} \tag{31}$$

In addition, the Euclidean distance is also executed to define the distance from CHs to BS. In general, minimized energy dissipation depends on the broadcasted distance. Thus, the node with lesser distances is chosen for relay nodes. Therefore, the next sub-objective, by means of distance i.e., $f2$ is formulated as follows.

$$f2 = \frac{1}{\sum_{i=1}^{m} dis\left(CH_i, NH\right) + dis\left(NH, BS\right)} \tag{32}$$

The above-mentioned sub-objective is revised to FF, whereas α_1 and α_2 signify the weights assigned to every sub-objective.

$$Fitness = \alpha_1\left(f1\right) + \alpha_2\left(f2\right),\ where \sum_{i=1}^{2} \alpha_i = 1\alpha_i \varepsilon (0, 1); \tag{33}$$

3 Results and Discussion

In order to ensure the enhanced performance of the proposed IDTOMHR model, the authors conducted multiple experiments and the results are discussed in this section. Tab. 1 provides the comprehensive comparative study results achieved by IDTOMHR model and other recent models [22] in terms of Network Lifetime (NLFT), Total Energy Consumption (TEC), and Average Residual Energy (ARE).

Table 1: Comparative analysis results of IDTOMHR technique and other existing approaches under different counts of SNs

No. of sensor nodes	EE-LEACH	EPSO-CEO	OQoS-CMRP	IDTOMHR
Network lifetime (sec)				
50	20019	21350	23317	23954
100	17589	19093	21466	22854
150	15448	16721	19614	21292
200	13191	15332	18109	20598
250	12612	14985	17589	20135
Total energy consumption (J)				
50	7.06	5.79	2.97	1.41
100	9.96	7.80	5.05	3.34
150	13.61	11.45	7.95	5.87
200	15.91	14.05	10.33	7.43
250	17.18	15.39	11.52	8.70
Average residual energy (J)				
50	2.86	2.89	2.93	2.95
100	2.90	2.92	2.94	2.97
150	2.91	2.93	2.94	2.97
200	2.92	2.93	2.95	2.98
250	2.93	2.94	2.95	2.98

Fig. 3 highlights the NLFT analysis results achieved by IDTOMHR model and other existing models under distinct SNs. The obtained values imply that the proposed IDTOMHR model accomplished an improved NLFT over other methods. For instance, with 50 SNs, IDTOMHR model offered a high NLFT of 23954 s, whereas EE-LEACH, EPSO-CEO, and OQoS-CMRP models reached the least NLFT values such as 20019 s, 13250 s, and 23317 s respectively. Moreover, with 150 SNs, the proposed IDTOMHR model achieved an improved NLFT of 21292 s, whereas EE-LEACH, EPSO-CEO, and OQoS-CMRP models achieved the least NLFT values such as 15448 s, 16721 s, and 19614 s respectively. At last, with 250 SNs, the proposed IDTOMHR model produced a superior NLFT of 20135 s, whereas EE-LEACH, EPSO-CEO, and OQoS-CMRP models reached less NLFT values such as 12612 s, 14985 s, and 17589 s respectively.

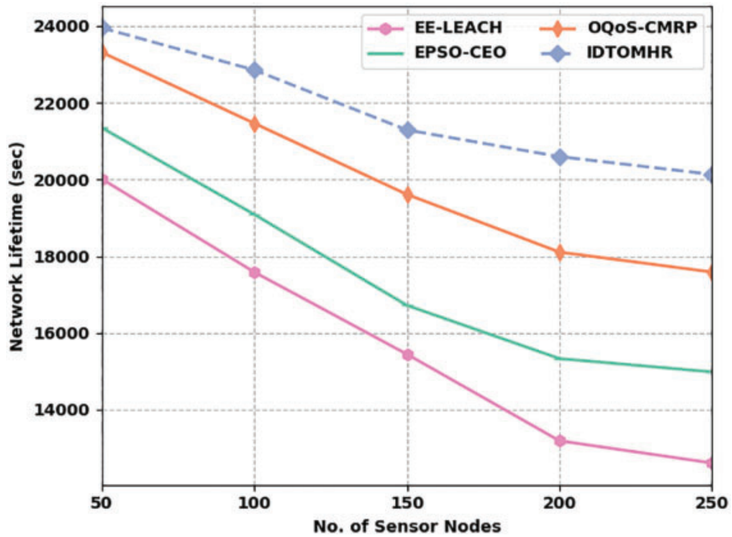

Figure 3: NLFT analysis results of IDTOMHR approach under different counts of SNs

Fig. 4 illustrates the TEC assessment results accomplished by IDTOMHR model and other existing models under dissimilar SNs. The figure portrays that the proposed IDTOMHR model produced the least TEC over other methods. For instance, with 50 SNs, the proposed IDTOMHR model reached a low TEC of 1.14 J, whereas EE-LEACH, EPSO-CEO, and OQoS-CMRP models attained the highest TEC values such as 7.06 J, 5.79 J, and 2.97 J respectively. Furthermore, with 150 SNs, the proposed IDTOMHR model accomplished the least TEC of 5.87 J, whereas EE-LEACH, EPSO-CEO, and OQoS-CMRP models achieved high TEC values such as 13.61 J, 11.45 J, and 7.95 J respectively. Lastly, with 250 SNs, IDTOMHR model attained the least TEC of 8.70 J, whereas EE-LEACH, EPSO-CEO, and OQoS-CMRP models accomplished high TEC values such as 17.18 J, 15.39 J, and 11.52 J respectively.

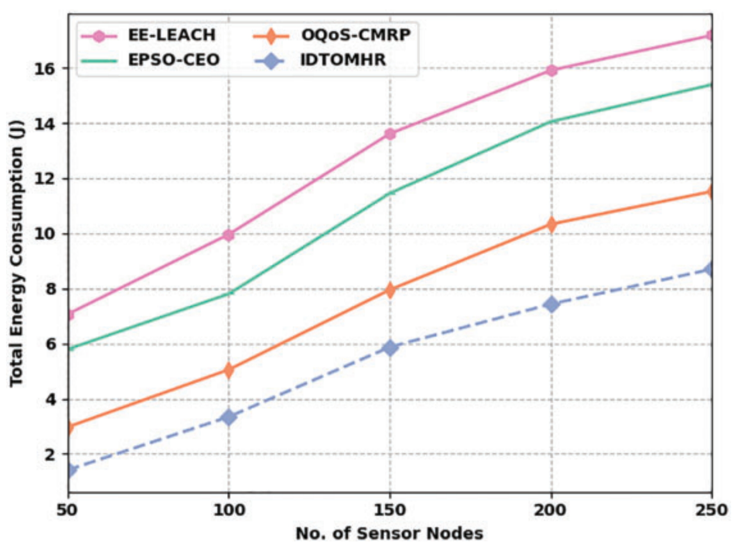

Figure 4: TEC analysis results of IDTOMHR approach under different counts of SNs

Fig. 5 portrays the ARE examination results achieved by IDTOMHR technique and other existing models under distinct SNs. The obtained values imply that IDTOMHR approach accomplished an enhanced ARE over other methods. For instance, with 50 SNs, IDTOMHR model offered an increased ARE of 2.95 J, whereas EE-LEACH, EPSO-CEO, and OQoS-CMRP approaches achieved the least ARE values such as 2.86 J, 2.89 J, and 2.93 J correspondingly. Furthermore, with 150 SNs, the proposed IDTOMHR model presented an improved ARE of 2.97 J, whereas EE-LEACH, EPSO-CEO, and OQoS-CMRP models obtained the least ARE values such as 2.91 J, 2.93 J, and 2.94 J correspondingly. Eventually, with 250 SNs, the proposed IDTOMHR model resulted in a superior ARE of 2.98 J, whereas EE-LEACH, EPSO-CEO, and OQoS-CMRP methods reached less ARE values such as 2.93 J, 2.94 J, and 2.95 J correspondingly.

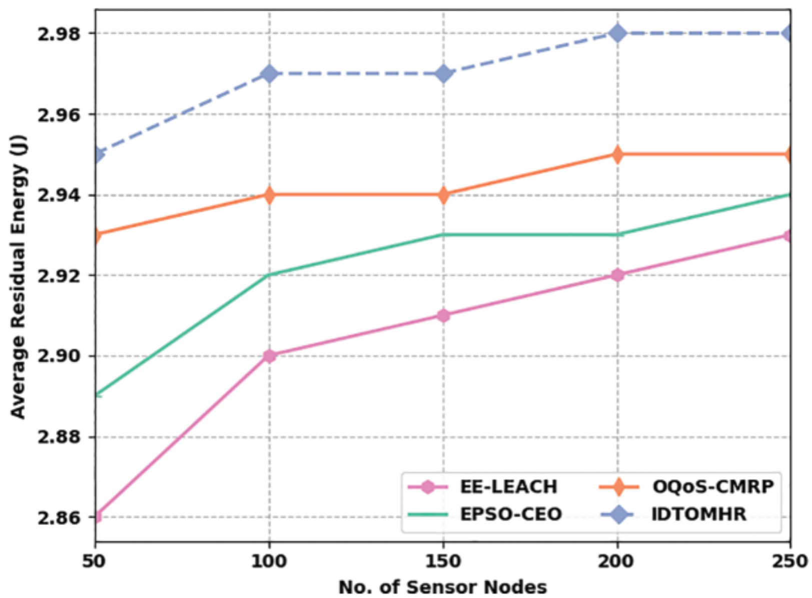

Figure 5: ARE analysis results of IDTOMHR approach under different counts of SNs

Tab. 2 demonstrates the results of comprehensive comparative analysis conducted between IDTOMHR technique and other recent models with respect to Packet Delivery Ratio (PDR) and Normalized Overhead (NO). Fig. 6 showcases the PDR analysis results achieved by IDTOMHR model and other existing models under distinct Simulation Time (ST). The values obtained from the analysis imply that the proposed IDTOMHR model accomplished an improved PDR over other methods. For instance, with 100 s STs, IDTOMHR model offered an increased PDR of 96.28%, whereas EE-LEACH, EPSO-CEO, and OQoS-CMRP approaches achieved less PDR values such as 84.29%, 88.04%, and 94.22% correspondingly. Furthermore, with 300 STs, the proposed IDTOMHR technique achieved an enhanced PDR of 94.78%, whereas EE-LEACH, EPSO-CEO, and OQoS-CMRP models offered less PDR values such as 79.23%, 83.73%, and 92.16% correspondingly. Finally, with 500 s STs, IDTOMHR model resulted in a superior PDR of 89.91%, whereas EE-LEACH, EPSO-CEO, and OQoS-CMRP models produced the least PDR values such as 75.86%, 79.80%, and 85.42% correspondingly.

Table 2: PDR and NO analyses results of IDTOMHR technique and other existing approaches

Packet delivery ratio (%)				
Simulation time (sec)	EE-LEACH	EPSO-CEO	OQoS-CMRP	IDTOMHR
100	84.29	88.04	94.22	96.28
200	81.29	86.35	92.72	95.90
300	79.23	83.73	92.16	94.78
400	77.74	82.42	87.85	92.72
500	75.86	79.80	85.42	89.91
Normalized overhead (%)				
No. of sensor nodes	EE-LEACH	EPSO-CEO	OQoS-CMRP	IDTOMHR
50	6.27	3.92	2.21	0.51
100	8.62	6.62	4.06	2.43
150	11.67	8.12	4.20	2.50
200	13.52	11.11	5.63	3.07
250	15.94	13.88	6.55	4.77

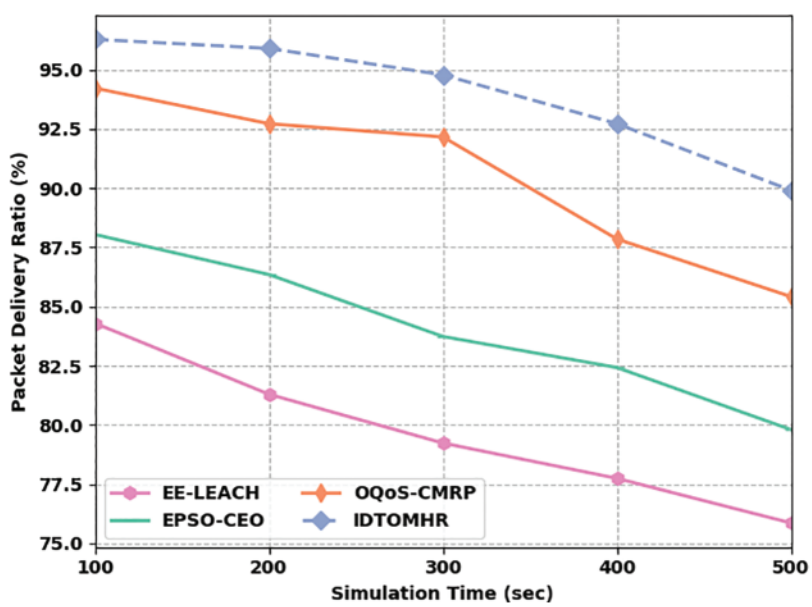

Figure 6: PDR analysis results of IDTOMHR approach under various STs

Fig. 7 defines the NO assessment results accomplished by IDTOMHR algorithm and other existing models under dissimilar SNs. The figure imply that the proposed IDTOMHR model produced the least NO compared to other methods. For instance, with 50 SNs, the proposed IDTOMHR system reached the least NO of 0.51%, whereas EE-LEACH, EPSO-CEO, and OQoS-CMRP models attained high NO values such as 6.27%, 3.92%, and 2.21% correspondingly. Also, with 150 SNs, the proposed IDTOMHR technique accomplished a less NO of 2.50%, whereas EE-LEACH, EPSO-CEO, and OQoS-CMRP techniques attained high NO values such as 11.67%, 8.12%, and 4.20% respectively. Followed by, with 250 SNs, the proposed IDTOMHR model attained the least NO of 4.77%, whereas EE-LEACH, EPSO-CEO, and OQoS-CMRP techniques accomplished high NO values such as 15.94%, 13.88%, and 6.55% correspondingly.

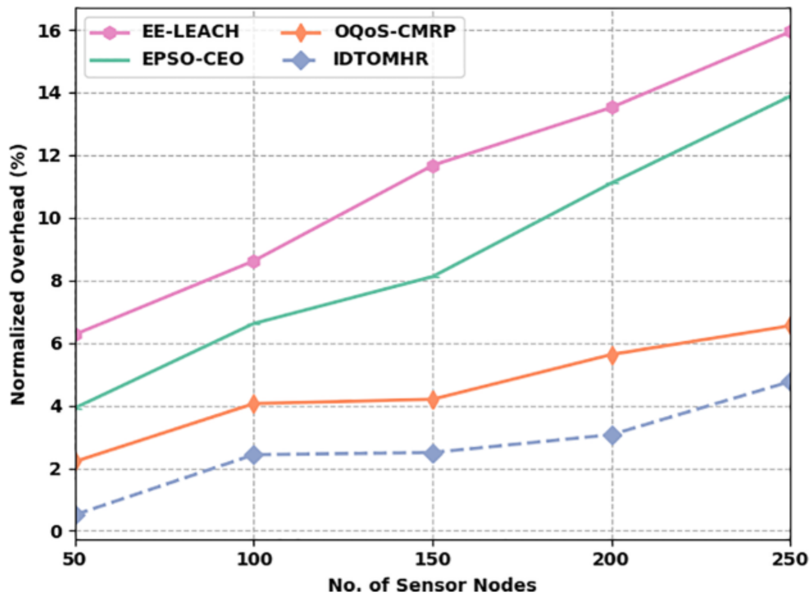

Figure 7: NO analysis results of IDTOMHR approach under various SNs

Tab. 3 shows the comprehensive comparative analysis results achieved by IDTOMHR model and other recent algorithms in terms of Throughput (THPT) and End to End Delay (ETED).

Table 3: Throughput and ETED analyses results of IDTOMHR technique and other existing approaches under different STs

Simulation time (sec)	EE-LEACH	EPSO-CEO	OQoS-CMRP	IDTOMHR
Throughput (Kbps)				
50	36	40	48	49
100	42	46	51	53
150	44	48	56	58
200	51	55	61	63
250	55	58	63	65

(Continued)

Table 3: Continued

Simulation time (sec)	EE-LEACH	EPSO-CEO	OQoS-CMRP	IDTOMHR
End-to-End delay (ms)				
50	0.032	0.029	0.021	0.012
100	0.043	0.037	0.030	0.021
150	0.050	0.041	0.031	0.019
200	0.051	0.045	0.032	0.020
250	0.054	0.047	0.035	0.025

Fig. 8 illustrates the THPT examination results achieved by IDTOMHR algorithm and other existing models under distinct STs. The obtained values imply that the proposed IDTOMHR system accomplished a high THPT over other algorithms. For sample, with 50 s STs, the proposed IDTOMHR model obtained an enhanced THPT of 49 Kbps, whereas EE-LEACH, EPSO-CEO, and OQoS-CMRP models reached low THPT values such as 36 Kbps, 40 Kbps, and 48 Kbps respectively. Moreover, with 150 s STs, the proposed IDTOMHR system achieved an improved THPT of 58 Kbps, whereas EE-LEACH, EPSO-CEO, and OQoS-CMRP methods offered low THPT values such as 44 Kbps, 48 Kbps, and 58 Kbps respectively. Finally, with 250 s STs, the proposed IDTOMHR model produced a superior THPT of 65 Kbps, whereas EE-LEACH, EPSO-CEO, and OQoS-CMRP models achieved less THPT values such as 55 Kbps, 58 Kbps, and 63 Kbps correspondingly.

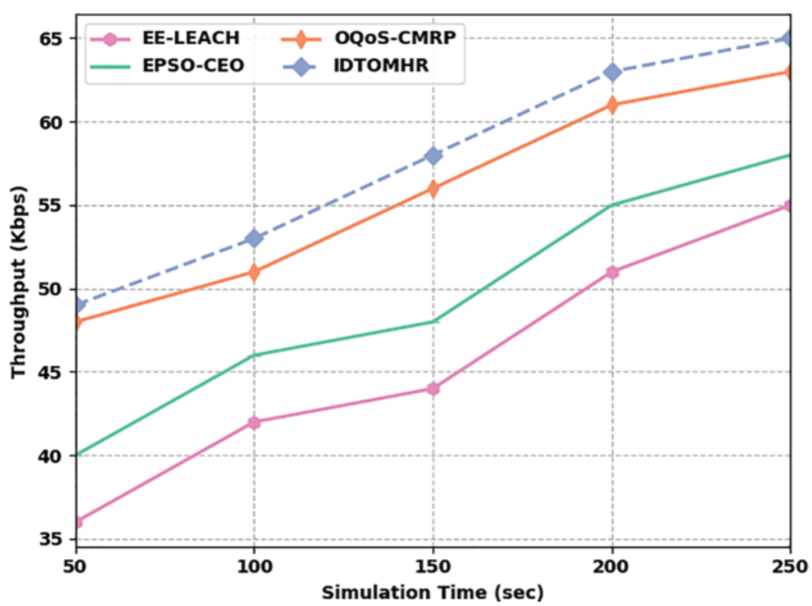

Figure 8: Throughput analysis of IDTOMHR approach under different STs

Fig. 9 exhibits the ETED analysis results accomplished by IDTOMHR model and other existing models under dissimilar STs. The figure shows that the proposed IDTOMHR model achieved the least ETED over other methods and showed excellent performance. For instance, with 50 s STs, IDTOMHR model reached a less ETED of 0.012 ms, whereas EE-LEACH, EPSO-CEO, and OQoS-CMRP models attained high ETED values such as 0.032 ms, 0.029 ms, and 0.021 ms respectively. Besides, with 150 s STs, the proposed IDTOMHR model accomplished a low ETED of 0.019 ms, whereas EE-LEACH, EPSO-CEO, and OQoS-CMRP models reached high ETED values such as 0.050 ms, 0.041 ms, and 0.031 ms correspondingly. At last, with 250 s STs, the proposed IDTOMHR model attained the least ETED of 0.025 ms, whereas EE-LEACH, EPSO-CEO, and OQoS-CMRP models accomplished high ETED values such as 0.054 s, 0.047 ms, and 0.035 ms respectively.

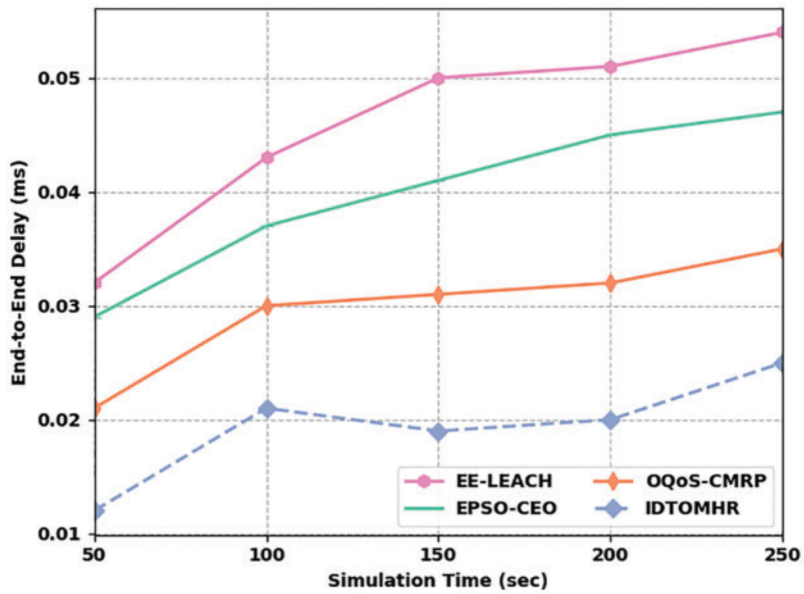

Figure 9: ETED analysis of IDTOMHR approach under different STs

After a detailed examination of the results, it is evident that the proposed IDTOMHR model improved the lifespan of WSNs compared to other methods.

4 Conclusion

In this study, a novel IDTOMHR approach has been developed to increase the energy effectiveness and lifespan of WSN. Initially, IDTO algorithm is exploited for effectual CH selection and cluster construction tasks. Next, ATGO approach is utilized to derive an optimum set of routes to reach the destination. Both clustering and routing approaches derive a fitness function with the inclusion of multiple input parameters. The proposed IDTOMHR technique was experimentally validated under different aspects. The extensive experimental results established the better performance of IDTOMHR technique over recent approaches. Thus, the presented IDTOMHR method can be utilized to improve overall network efficiency in WSN. In future, energy-aware data aggregation and intrusion detection schemes can be developed for WSN.

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