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Energy Aware Clustering System for Wireless Sensor Networks utilizing Rider Sunflower Optimization Approach

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Abstract—Wireless Sensor Networks (WSN) are spatially disseminated sensors that are utilized for monitoring physical or environmental factors, like sound, temperature, pressure, and so on, to collectively drive their information from the networking to the base station. The WSN is composed of hundreds or thousands, where all the nodes are interconnected with other Sensor Node (SN). Clustering is the most popular topology management technique in WSN, grouping nodes to manage them or execute different tasks in a distributed manner, like resource management. It includes grouping sensors and selecting Cluster Heads (CHs) for every cluster. Therefore, this study presents a new Rider Sunflower Optimizing Model-Based Energy Aware Clustering Approach (RSFOA-EACA) for WSNs. The prime goal of the RSFOA-EACA technique is in the optimum selection of CH for data transmission in the WSN. With Rider Optimization Algorithm (ROA) and Sunflower Optimization (SFO) incorporation, the RSFOA-EACA technique mainly depends upon the RSFOA. Furthermore, the RSFOA-EACA algorithm derives a Fitness Function (FF) by the computation of distance, Residual Energy (RE), Node Degree (ND), and network coverage. The CH selecting enables proper inter-cluster transmission in the network. The experimental analysis of the RSFOA-EACA method is investigated by implementing a sequence of simulations. The simulation values emphasized the promising energy efficiency outcomes of the RSFOA-EACA approach.

Keywords- Clustering; Fitness function; Wireless sensor networks; Rider sunflower optimization; Energy efficiency

I. INTRODUCTION

In the modern era, the utility of ad-hoc networks has spread vastly with the tremendous growth of new technologies. Autonomous technological gadgets are utilized as a single mechanism, in peer-to-peer and decentralized architectures, WSN are considered as one instance [1]. Such networks contain a set of spatially dispersed sensor devices that record and monitor the physical circumstances of their atmosphere. The data gathered by such SNs are transferred to the server side through base station nodes [2]. WSN serves a crucial role in surveillance and tracking applications namely natural disaster prevention, environmental monitoring, precision agriculture, smart cities, disaster management, weather forecasting, border surveillance, and many more [3]. As there are limited non-rechargeable batteries, the nodes' energy must be used effectively. Hence, the model of WSN protocols must be flexible, simple, and energy-efficient for changing environmental conditions [4].

The clustering method segregates the groups of nearby nodes and networks into clusters. From each cluster, a CH selection depends on certain criteria [5]. Uniform distribution of energy amongst the nodes is impossible because of the arbitrary deployment of the nodes. The process of clustering is considered to be an NP hard optimized issue and the metaheuristics consumption has severely increased the capability to solve unremitting optimizing issues [6]. Computational intelligence approaches like evolutionary algorithms, neural networks, swarm intelligence approaches, fuzzy logic and reinforcement learning will be utilized to solve many design problems in WSN like security and CH selection [7]. As the nodes are inter-reliant to one another with inter-related metrics, cluster formation utilizing predefined rules cannot be allied. The main problem in clustering-related techniques is the selection of the appropriate CH for all clusters among multiple SNs [8]. The CH selection process is dependent on many network parameters. Suitable and optimal coefficients for all parameters were gained through mathematical techniques, which is a complicated issue that needs further processing. The CH selection procedure can be considered an NP-hard matter and swarm intelligence techniques are utilized to resolve it [9]. So, metaheuristic techniques offer a substitute for wide search and deterministic methods that solve appropriate optimized issues by finding an optimal solution utilizing limited computing sources in a reasonable period. Moreover, metaheuristic techniques, in contrast to deterministic and greedy techniques, may escape the trap of local optima in initial iterations and have balanced performance in the exploiting and exploring stages [10].

This study presents a new Rider Sunflower Optimization Algorithm-Based Energy Aware Clustering Approach (RSFOA-EACA) for WSN. The prime goal of the RSFOA-EACA model is in the optimum selection of CH for data transmission in the WSN. With Rider Optimization Algorithm (ROA) and Sunflower Optimization (SFO) incorporation, the RSFOA-EACA technique mainly depends upon the RSFOA. Furthermore, the RSFOA-EACA method derives a fitness function by the computation of distance, Residual Energy (RE), Node Degree (ND), and network coverage. The CH selecting enables proper inter-cluster transmission in the network. The experimental analysis of the RSFOA-EACA method is investigated by implementing a sequence of simulations.

II. LITERATURE REVIEW

Al-Otaibi et al. [11] establish a fusion of a metaheuristic clustering based routing system for WSN. The proposed scheme originally takes an innovative optimizer with levy dispersion-based clustering procedure implementing an FF including 4 parameters like length to BS and neighbours, energy, and load of the network. Moreover, a hill-climbing based routing method utilizing water wave optimizer which was executed to better choose the routes. Wang et al. [12] examine a clustering method that employs CHs utilizing an advanced Artificial Bee Colony (ABC) technique. During the network initializing method, every node has a similar energy level, enhanced ABC technique was utilized for optimizing FCM clustering to define a better clustering system. The authors also present an energy-effective routing technique dependent upon an enhanced ant colony optimizer for routing betwixt BS and CH.

Subramani et al. [13] focused on planning the metaheuristic clustering based routing system for WSN. The proposed approach contains the planning of cultural emperor penguin optimizing based on cluster systems for constructing clusters. In addition, the Multi-Hop Routing (MHR) with Grasshopper Optimizer Algorithm (MHR-GOA) system was developed utilizing input parameters. The authors [14] propose a Hybrid Metaheuristic Technique-Related Clustering with MHR (HMA-CMHR) for WSN. The projected method incorporated diverse phase hashes like node initialization, routing, data broadcast, and clustering. Primarily, the HMA-CMHR system utilizes Quantum HSA (QHSA) depending on the clustering system for choosing the best CH subset. Next, the Improved CS (ICS) scheme-related route system has been employed for the best route chosen.

Lakshmanna et al. [15] present an advanced metaheuristic-driven energy aware clustering-based routing approach for IoT-aided WSN. For that reason, this scheme initially plans an IAOAC scheme for CH selection and clustering management. Besides, the TLBO-MHR method was executed to better chosen of routes to target. In [16], a new energy-effective cluster routing method for WSN dependent upon Yellow Saddle Goatfish Algorithm (YSGA) was presented. The network considers a BS and a group of CHs from their cluster infrastructure. The cluster infrastructure of networks is reconfigured by YSGA for guaranteeing an improved dispersion of CHs and a decrease in transmission distance.

III. THE PROPOSED MODEL

In this research, a state-of-the-art RSFOA-EACA model for clustering in WSN is developed. The intention of the RSFOA-EACA model is in the optimal selection of CH for data transmission in the WSN. The proper selection of CHs enables proper inter-cluster communication in the network. Fig. 1 represents the comprehensive RSFOA-EACA approach process.

A. System Model

The following assumption was used for developing the network structure [17]:

- Concerning energy and processing time, WSN sensor is identical to each other;
- The principle of Euclidean Distance (ED) is considered to measure the width between the SNs;
- When the width can be measured, the SNs are positioned in the networking field;
- BS considered the distance and node RE to select the CH, utilizing a proper selection of the CH method. For the WSN setup, the abovementioned constraints and qualities are considered.

The distance between other nodes and the BS was measured by comparing the strength of the received signal. Consequently, with location services like GPS, no other systems are needed. Likewise, nearby CH a node linked the cluster. Based on the first-order radio technique, the energy utilization of the receiver and transmitter nodes is calculated.

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B. Algorithmic Design of RSFOA

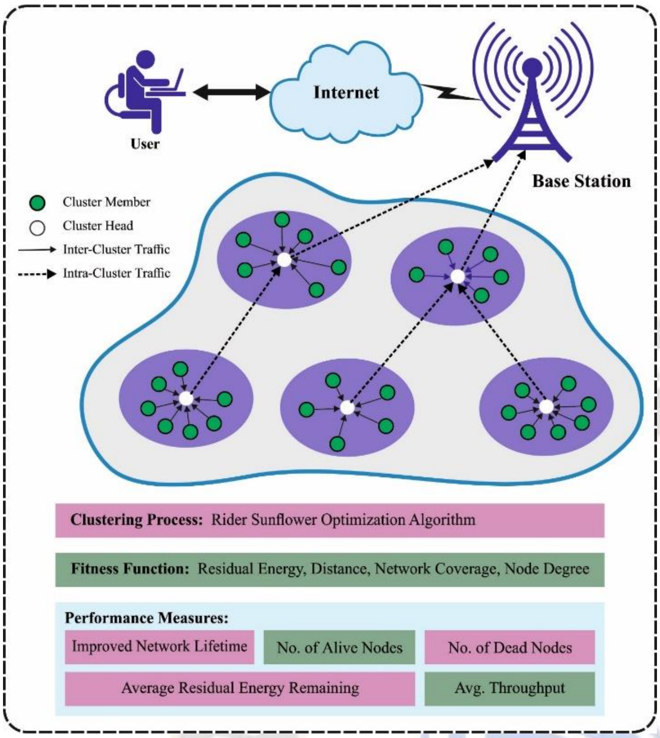

Figure 1. Comprehensive process of RSFOA-EACA system

The RSFOA-EACA technique mainly depends upon the RSFOA, which is integrated by the use of the ROA and SFO algorithms. This presented RSFOA receive the award of both SFO and ROA to yield the best cluster solution with a fast convergence rate [18]. ROA performs by the behaviours of various kinds of riders to the destination. Now, there remain four various rider's attacker types, follower, overtaker, and Bypass Rider (BR), correspondingly. Then, SFO performs by the sun's rotation. SF often stimulates the rotation that is nature-inspired optimizing. This algorithm determines the better location for better accomplishment. Concurrently, it exploits higher computational difficulty because of the highest computation step. To accomplish a global optimum solution with a faster outcome and best computation step, the study applied the hybrid ROA technique along with SFO. Fig. 2 exhibits the application of ROA.

The hybrid K-Means based rider SFO technique is shown below:

Step1. Initializing the parameter

Step2. Assess FF using Lagrangian optimization principles that are provided below:

$$M=\sum_{p=1}^{K}\sum_{q=1}^{g}(w_{qp}\|d_p-l_p\|^2+\rho\ln w_{qp}+\rho\ln\|d_q-l_p\|^2))$$
$$=\sum_{q=1}^{g}\eta_q\left(-1\sum_{p=1}^{k}w_{qp}\right) \quad (1)$$

In Eq. (1), d_q represents the data object, the constant which is a user-defined value is represented as ρ, lp indicates the cluster centre, l_p shows the fuzzy membership function, K denotes the overall centres of the cluster, and g represents the overall data as follows:

$$(\frac{\partial M}{\partial w_{qp}})=\|d_q-l_p\|^2+\frac{\rho}{w_{qp}}-\eta_q=0 \quad (2)$$

$$w_{qp}=\frac{\rho}{(\eta_q-\|d_q-l_p\|^2)}$$

Since $\sum_{p=1}^{k}W_{qp}=1$, which is shown below

$$\sum_{p=1}^{K}[\frac{1}{\eta_q}-\|d_q-l_p\|^2]=\frac{1}{\rho} \quad (3)$$

We have to make sure $w_{qp}\geq 0\geq 0$.

Step3. Upgrade rider group's location

For location updating, we applied a BR to exploit the attainment rate. BR often tracks and follows the typical path without the information of other riders. The position update based on the BR is given below:

$$B_{t+1}(r,p)=\theta\big[B_t(t,p)*m(p)+B_t(\mu,p)*[1-m(p)]\big] \quad (4)$$

Now, variables θ, t, m, and μ are the randomly generated number inside the range [0,1]. Next, k specifies the iterating number that is described by the end-user. Let $\mu=r$, the formula is modified as

$$B_{t+1}(r,p)=\theta\big[B_t(t,p)*m(p)+B_t(r,p)*[1-m(p)]\big] \quad (5)$$

The SFO update the solution space or location by the sun's revolution. SF frequently stimulates the sun's rotation. The updated SFO position is shown below:

$$B(r,p)=B_t(r,p)+y_r\times g_r \quad (6)$$

In Eq. (6), $B_t(r,p)$, and $B_{t+1}(r,p)$ indicates the present and upgraded location at t, and $t+1$ time, $B_{t+1}(r,p)$ indicates the SF stages, and g_r denotes the SF path.

$$B_t(r,p)=\frac{B_{t+1}(r,p)}{y_r}\times g_r \quad (7)$$

Substitute (8) for position updating is location updating of SFO (6) is location updating of rider optimization.

$$B_{t+1}(r,p)=\theta B_t(t,p)*m(p)+\left(\frac{B_{t+1}(r,p)}{y_r}\right)\times g_r$$
$$*[1-m(p)] \quad (8)$$

$$B_{t+1}(r,p)=\theta B_t(t,p)*m(p)+B_{t+1}(r,p)[1-m(p)]$$
$$-y_r\times g_r$$
$$*[1-m(p)] \quad (9)$$

Next, rearrange (8) and (9), and we get

$$B_{t+1}(r,p)=\theta B_t(t,p)*m(p)+B_{t+1}(r,p)-$$
$$\frac{B_{t+1}(r,p)m(p)}{y_r g_r}+y_r g_r m(p)$$

$$\frac{B_{t+1}(r,p)}{B_{t+1}(r,p)\theta}+\theta B_{r+1}(r,p)m(p)=\theta\left[\frac{B_t(t,p)*m(p)}{y_r t_r+y_r t_r m(p)}\right] \quad (10)$$

$$B_{t+1}(r,p)[1-\theta+\theta m(p)]=\theta[\frac{B_t(t,p)*m(p)}{y_r t_r+y_r t_r m(p)}]$$

Following, the last formula would be formulated by

$$Bt+1(r,p)=\frac{1}{[1-\theta[1-m(p)]]}\left[\frac{\theta[Bt(t,p)*m(p)]}{y_r t_r[1-m(p)]}\right] \quad (11)$$

Step4. Define the better solution

Now, the greatest fitness values are assumed as a better solution and upgrading the ROA parameter for the better solution.

Step5. Terminating criteria

The 2 to 4 steps are reiterated until the ending condition is reached.

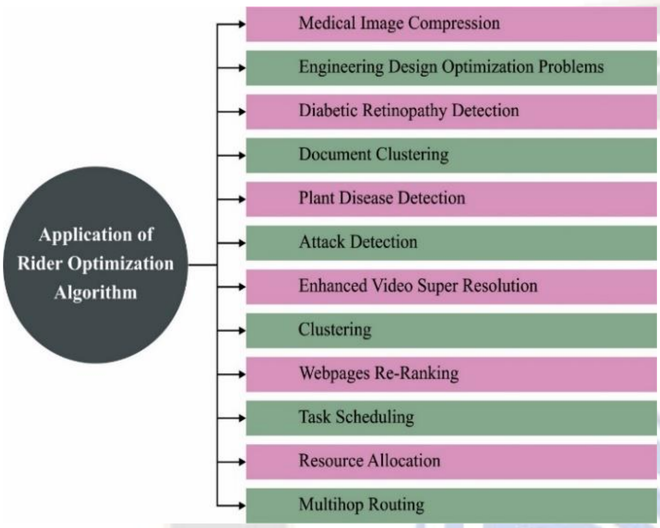

Figure 2. Application of ROA

C. *Process Involved in Choosing CH*

In this work, the RSFOA-EACA approach derives an FF by the computation of distance, RE, ND, and network coverage. In a traditional technique, the non-CH node is just attached to the CH by considering the distance aspect that produces an imbalanced CH load, and results in high energy utilization [19]. Now, the presented technique is used for the cluster method with FF diverse parameters to generate a lower time and computation difficulty, and higher stability speed of optimization.

The basic aim of the RSFOA-EACA-based clustering approach is to choose the better node numbers in the vicinity namely CHs. The objective is to accomplish appropriate fitness by computing distance, RE, ND, and network coverage.

RE can be defined by:

$$RE=\sum_{i=1}^{m}\frac{1}{E_{CHi}} \quad (12)$$

The consideration of energy consumption, the sensors are completely controlled by the broadcast distance. Once the BS is distant from the mobile nodes, it needs additional energy for completing the process. Consequently, the CHs with the least ED commencing from the BS are highly preferred. As a result, intra and inter -cluster purposes are stated as $D1$ and $D2$ that could be minimized and formulated as follows:

$$D1=\sum_{i=1}^{m}\left(disl\left(CH_j,BS\right)\right) \quad (13)$$

$$D2=\sum_{j=1}^{q}\left(\sum_{i=1}^{cm_i} dis2\frac{s_i,CH_j}{cm_j}\right) \quad (14)$$

Where the cm_j characterizes the existing node numbers in the cluster and $dis2(s_i,CH_j)$ signifies the distance between the i^{th} and j^{th} CHs. The network coverage is determined as:

$$N_{cov}=r(N_i) \quad (15)$$

where $r(N)$ signifies the radius covered by the node.

$$N_{cov}=\frac{1}{N_T}\sum_{i=1}^{N}N_{cov}\left(N_i\right)$$

ND is defined as the non-CH applicant's quantity who goes to the exact transferrable node.

$$D_N=\sum_{i=1}^{m}I_i \quad (16)$$

Consequently, the normalization process $(F(x))$ is used for all the objectives $\alpha_1,\alpha_2,\alpha_3,\alpha_4,\alpha_5$ as follows.

$$F(x)=\frac{f_i-f_{\min}}{f_{\max}-f_{\min}} \quad (17)$$

where $f_i$is function value, f_i and $f_{\max}$ denote the minimal and maximal fitness values, correspondingly. An FF was introduced that implies a tradeoff is preserved within the specified objective. Lastly, the different goals are transformed as a sole objective function via the supplement of increased value. Now, a multiobjective FF was introduced by RSFOA-EACA which is provided below.

$$fitness\ =\alpha_1 RE+\alpha_2 D1+\alpha_3 D2+\alpha_4 N_{cov}+\alpha_5 D_N \quad (18)$$

$$where\ \sum_{i=1}^{5}\alpha_j=1, and\ \alpha_j\in(0,1) \quad (19)$$

α_j represent the weighted parameter, and all the dimensions of weighted parameters are initialized by the random integer within [0,1] that is allocated to all the FFs as $(\alpha_1=0.4,\alpha_2=0.3,\alpha_3=0.2,\alpha_4=0.05,\alpha_5=0.05)$. The broadcast distance through the WSN is minimalized by considering the RE and distance while selecting the node with the maximum RE. Consequently, the FF is employed for determining the optimal data broadcast direction. Afterwards choosing the CH, the cluster forms based on energy and distance.

IV. RESULTS AND DISCUSSION

The presented RSFOA-EACA technique put under simulation process by employing the MATLAB tool. In Table 1 and Fig. 3, a relative Number of Alive Nodes (NOAN) assessment of the RSFOA-EACA approach with recent methods is provided [20]. The outputs specified that the RSFOA-EACA approach reaches improving NOAN values under the total execution rounds. As a sample, with 100 rounds, the RSFOA-EACA approach attains growing NOAN of 99.51% while the

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HAS-PSO, FFOCR, FFC-GWO, and HABC-MBOA approach attain decreasing NOAN of 96.69%, 96.95%, 99%, and 99.76% respectively. Meanwhile, with 500 rounds, the RSFOA-EACA technique obtain an improving NOAN of 97.97% while the HAS-PSO, FFOCR, FFC-GWO, and HABC-MBOA techniques achieve reduced NOAN of 59.08%, 64.71%, 79.30%, and 97.20% respectively. Furthermore, with 1000 rounds, the RSFOA-EACA technique offers enhanced NOAN of 72.39% while the HAS-PSO, FFOCR, FFC-GWO, and HABC-MBOA techniques provide lower NOAN of 9.96%, 16.87%, 20.71%, and 45.52% respectively.

TABLE I. NOAN EVALUATION OF RSFOA-EACA METHOD WITH RECENT SYSTEMS UNDER CHANGING ROUNDS

Alive Node Numbers (in %)					
Round Count	**HAS-PSO**	**FFOCR**	**FFC-GWO**	**HABC-MBOA**	**RSFOA-EACA**
0	97.20	98.23	99.51	99.00	99.51
100	96.69	96.95	99.00	99.76	99.51
200	93.62	96.44	98.48	98.23	99.25
300	89.53	94.39	96.18	97.46	98.74
400	80.32	82.11	90.04	97.72	99.25
500	59.08	64.71	79.30	97.20	97.97
600	43.48	51.41	65.48	96.95	98.48
700	31.97	45.78	53.46	83.90	97.46
800	23.52	30.69	41.94	69.32	95.16
900	12.01	23.01	34.78	67.53	83.13
1000	9.96	16.87	20.71	45.52	72.39
1200	0.75	5.10	15.08	30.94	58.57
1400	0.24	0.24	6.64	22.24	47.83
1600	0.00	0.00	0.24	13.80	29.92
1800	0.00	0.00	0.00	0.50	11.50
2000	0.00	0.00	0.00	0.00	8.68

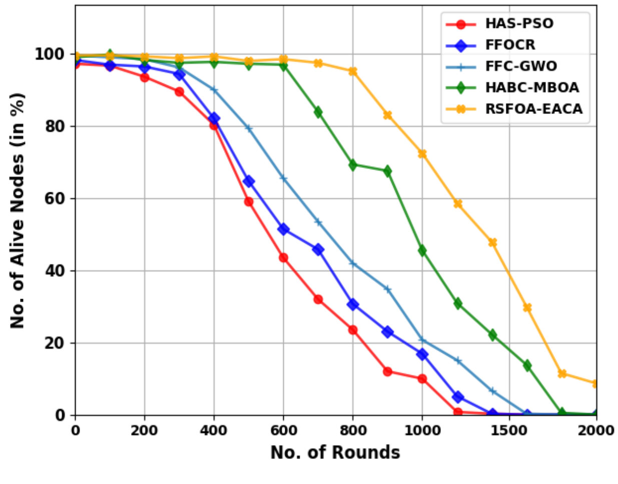

Figure 3. NOAN evaluation of RSFOA-EACA method under changing rounds

In Table 2 and Fig. 4, an elaborate Average Throughput (ATHRO) analysis of the RSFOA-EACA approach with present approaches are provided. The outputs exhibited the RSFOA-EACA method reaches improving values of ATHRO under all SN of execution. For example, with 100 SN, the RSFOA-EACA approach gains an increasing ATHRO of 8.17Mbps while the HAS-PSO, FFOCR, FFC-GWO, and HABC-MBOA methods attain decreasing ATHRO of 1.88Mbps, 3.34Mbps, 3.97Mbps, and 6.28Mbps correspondingly. Temporarily, with 500 SN, the RSFOA-EACA method obtain an improving ATHRO of 25.80Mbps while the HAS-PSO, FFOCR, FFC-GWO, and HABC-MBOA methods achieve a reducing ATHRO of 8.59Mbps, 10.69Mbps, 13.84Mbps, and 20.76Mbps correspondingly. Furthermore, with 1000 SN, the RSFOA-EACA method provides enhanced ATHRO of 57.06Mbps while the HAS-PSO, FFOCR, FFC-GWO, and HABC-MBOA methods provide lower ATHRO of 19.50Mbps, 24.54Mbps, 31.67Mbps, and 51.40Mbps correspondingly.

TABLE II. ATHRO ANALYSIS OF RSFOA-EACA METHOD WITH RECENT SYSTEMS UNDER VARYING SNS

Average Throughput (Mbps)					
No. of SNs	**HAS-PSO**	**FFOCR**	**FFC-GWO**	**HABC-MBOA**	**RSFOA-EACA**
100	1.88	3.34	3.97	6.28	8.17
200	3.55	5.02	7.12	9.01	11.32
300	5.44	6.49	9.22	13.00	17.82
400	7.54	8.17	10.48	16.56	21.60
500	8.59	10.69	13.84	20.76	25.80
600	9.64	13.63	16.98	26.22	29.57
700	13.21	15.93	20.97	30.83	35.03
800	15.51	16.77	24.96	34.61	42.16
900	18.03	19.92	28.52	40.06	50.77
1000	19.50	24.54	31.67	51.40	57.06

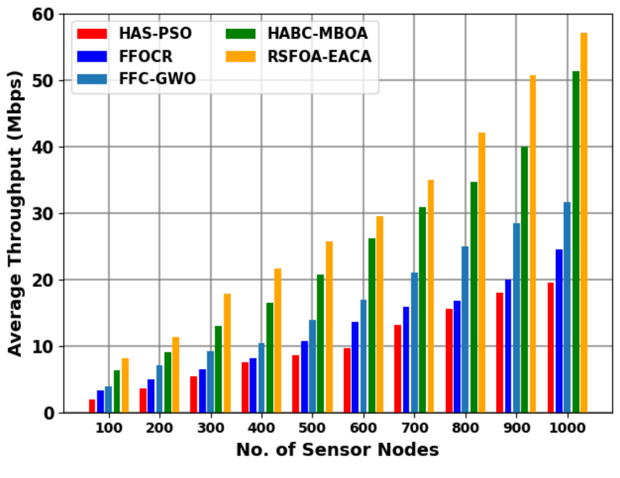

Figure 4. ATHRO analysis of RSFOA-EACA approach under changing SNs

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In Table 3 and Fig. 5, a relative Average Residual Energy Remaining (ARER) examination of the RSFOA-EACA approach with present methods are provided. The outputs show that the RSFOA-EACA approach reaches improving ARER values under all SN of execution. For example, with 100 SN, the RSFOA-EACA approach gains an increasing ARER of 24.44% while the HAS-PSO, FFOCR, FFC-GWO, and HABC-MBOA methods attain decreasing ARER of 9.79%, 13.43%, 16.91%, and 22.18% correspondingly. In the meantime, with 500 SN, the RSFOA-EACA method has to improve ARER by 18.05% while the HAS-PSO, FFOCR, FFC-GWO, and HABC-MBOA methods achieve a reducing ARER of 5.74%, 6.80%, 10.03%, and 14.32% correspondingly. Besides, with 1000 SN, the RSFOA-EACA approach renders an enhanced ARER of 11.41% while the HAS-PSO, FFOCR, FFC-GWO, and HABC-MBOA approaches provide lower ARER of 0.73%, 2.02%, 4.61%, and 7.61% correspondingly.

TABLE III. ARER ANALYSIS OF RSFOA-EACA METHOD WITH RECENT SYSTEMS UNDER VARYING SNS

Average Residual Energy Remaining (in %)					
No. of SNs	**HAS-PSO**	**FFOCR**	**FFC-GWO**	**HABC-MBOA**	**RSFOA-EACA**
100	9.79	13.43	16.91	22.18	24.44
200	8.50	11.81	15.05	19.50	22.18
300	7.77	9.87	12.62	18.05	20.48
400	7.04	7.61	10.52	16.27	19.50
500	5.74	6.80	10.03	14.32	18.05
600	4.77	5.58	8.33	12.22	16.10
700	3.80	5.02	7.44	10.76	14.00
800	2.75	3.96	6.88	9.79	13.92
900	1.86	2.99	5.10	8.82	13.03
1000	0.73	2.02	4.61	7.61	11.41

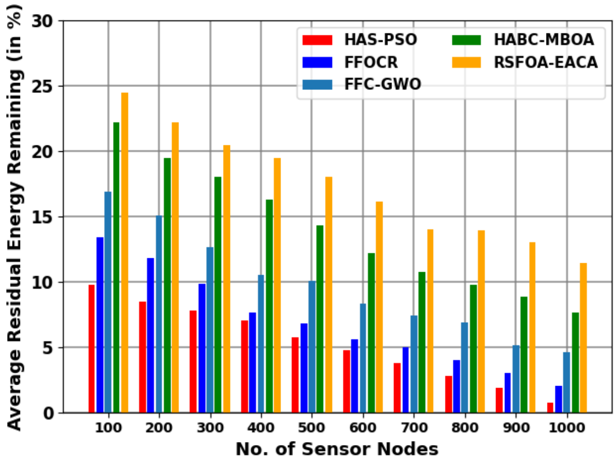

Figure 5. ARER analysis of RSFOA-EACA approach under changing SNs

In Table 4 and Fig. 6, a comparatively Improved Network Lifetime (INLT) analysis of the RSFOA-EACA approach with current models are provided.

The outputs depicted that the RSFOA-EACA algorithm reaches improving values of INLT under all SN of execution. For example, with 100 SN, the RSFOA-EACA approach gains an increasing INLT of 38.95% while the HAS-PSO, FFOCR, FFC-GWO, and HABC-MBOA methods attain decreasing INLT of 21.47%, 26.63%, 29.68%, and 37.89% correspondingly. In the meantime, with 500 SN, the RSFOA-EACA algorithm has improved INLT by 31.66% while the HAS-PSO, FFOCR, FFC-GWO, and HABC-MBOA techniques achieve reducing INLT of 12.85%, 16.30%, 21.33%, and 26.76% correspondingly. Additionally, with 1000 SN, the RSFOA-EACA method offers enhanced INLT of 23.32% while the HAS-PSO, FFOCR, FFC-GWO, and HABC-MBOA approaches provide lower INLT of 5.70%, 9.68%, 14.97%, and 20.54% subsequently.

TABLE IV. INLT EVALUATION OF RSFOA-EACA MODEL WITH RECENT SYSTEMS UNDER VARYING SNS

Improved Network Lifetime (in %)					
No. of SNs	**HAS-PSO**	**FFOCR**	**FFC-GWO**	**HABC-MBOA**	**RSFOA-EACA**
100	21.47	26.63	29.68	37.89	38.95
200	19.74	21.47	27.56	34.98	36.83
300	17.36	19.74	26.10	31.80	34.31
400	15.24	18.68	23.45	29.55	32.46
500	12.85	16.30	21.86	29.41	31.66
600	12.19	14.44	21.33	26.76	30.21
700	9.81	12.59	20.14	24.91	28.09
800	8.22	11.13	19.08	22.79	24.38
900	6.36	10.07	16.70	21.60	24.25
1000	5.70	9.68	14.97	20.54	23.32

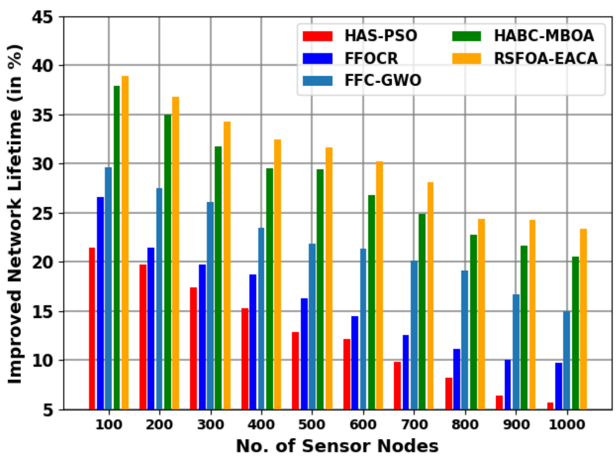

Figure 6. INLT analysis of RSFOA-EACA method under changing SNs

TABLE V. DCOH ANALYSIS OF RSFOA-EACA APPROACH WITH RECENT SYSTEMS UNDER VARYING SNS

Decreased Communication Overhead (in %)					
No. of SNs	**HAS-PSO**	**FFOCR**	**FFC-GWO**	**HABC-MBOA**	**RSFOA-EACA**
100	15.82	19.87	25.23	33.86	36.87
200	14.64	17.91	22.49	31.64	34.25
300	12.42	17.52	21.83	29.68	32.55
400	10.72	16.08	21.18	25.36	30.20
500	9.94	15.82	19.87	23.79	27.19
600	9.15	13.21	18.96	21.83	24.71
700	6.54	9.94	13.34	19.22	21.96
800	6.02	8.76	10.98	16.60	18.83
900	3.27	6.93	10.33	14.90	17.78
1000	2.49	5.88	9.15	13.07	15.56

In Table 5 and Fig. 7, a relative Decreased Communication Overhead (DCOH) analysis of the RSFOA-EACA approach with current methods are given. The outputs highlighted that the RSFOA-EACA approach reaches improving values of DCOH under all SN of execution. For example, with 100 SN, the RSFOA-EACA approach gains an increasing DCOH of 36.87% while the HAS-PSO, FFOCR, FFC-GWO, and HABC-MBOA methods attain decreasing DCOH of 15.82%, 19.87%, 25.23%, and 33.86% correspondingly.

Meanwhile, with 500 SN, the RSFOA-EACA method gain improved DCOH by 27.19% while the HAS-PSO, FFOCR, FFC-GWO, and HABC-MBOA methods achieve reducing DCOH by 9.94%, 15.82%, 19.87%, and 23.79% correspondingly. Also, with 1000 SN, the RSFOA-EACA technique offers enhanced DCOH of 15.56% while the HAS-PSO, FFOCR, FFC-GWO, and HABC-MBOA approaches provide lower DCOH of 2.49%, 5.88%, 9.15%, and 13.07% correspondingly.

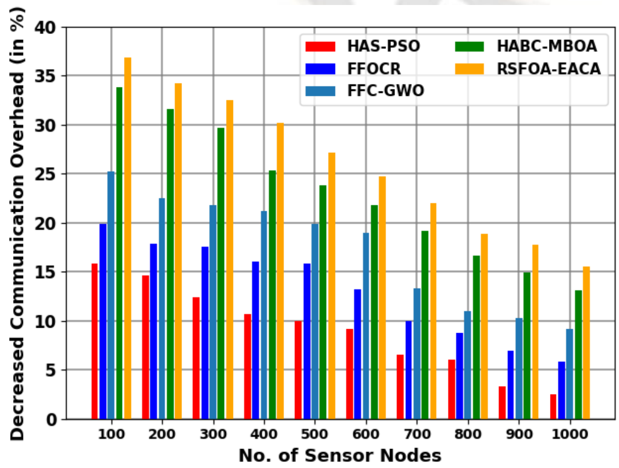

Figure 7. DCOH analysis of RSFOA-EACA method under changing SNs

V. CONCLUSION

In this research, a novel RSFOA-EACA approach has been formulated for clustering in WSN. The prime goal of this model is in the optimum selection of CHs for data transmission in the WSN. With ROA and SFO incorporation, the RSFOA-EACA technique mainly depends upon the RSFOA. Furthermore, the RSFOA-EACA method derives an FF by the computation of distance, RE, ND, and network coverage. The proper selection of CHs enables proper inter-cluster transmission in the network. The experimental analysis of the RSFOA-EACA method is investigated by implementing a sequence of simulations. The experimental result highlighted the promising energy efficiency outcomes of the RSFOA-EACA technique. In the coming days, multihop routing procedures can be established for optimizing the performance of the network.

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