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Honey Badger Algorithm Based Clustering with Routing Protocol for Wireless Sensor Networks

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Abstract: Wireless sensor network (WSN) includes a set of self-organizing and homogenous nodes employed for data collection and tracking applications. It comprises a massive set of nodes with restricted energy and processing abilities. Energy dissipation is a major concern involved in the design of WSN. Clustering and routing protocols are considered effective ways to reduce the quantity of energy dissipation using metaheuristic algorithms. In order to design an energy aware cluster-based route planning scheme, this study introduces a novel Honey Badger Based Clustering with African Vulture Optimization based Routing (HBAC-AVOR) protocol for WSN. The presented HBAC-AVOR model mainly aims to cluster the nodes in WSN effectually and organize the routes in an energy-efficient way. The presented HBAC-AVOR model follows a two stage process. At the initial stage, the HBAC technique is exploited to choose an optimal set of cluster heads (CHs) utilizing a fitness function involving many input parameters. Next, the AVOR approach was executed for determining the optimal routes to BS and thereby lengthens the lifetime of WSN. A detailed simulation analysis was executed to highlight the increased outcomes of the HBAC-AVOR protocol. On comparing with existing techniques, the HBAC-AVOR model has outperformed existing techniques with maximum lifetime.

Keywords: Cluster based routing; wireless sensor networks; objective function; lifetime; metaheuristics

1 Introduction

As an emerging paradigm of computing and networking, wireless sensor network (WSN) has been applicable and relevant in different areas namely military, medicine, climate forecasting, surveillance, environmental control, and so on [1]. Advances in networks and consistent development have empowered wide-ranging application of WSN. In recent times, WSN has been incorporated with other concepts, such as internet of things (IoT) [2]. A WSN is a network structure that comprises massive amount of diminutive, minuscule, low-cost autonomous devices represented as sensors that detect and monitor the environments for compiling information [3]. The information that is gathered from the environment is later transmitted to the sink node, a destination where information is redirected or processed locally to other networks for diverse applications [4]. Because of the node communication, accessible deployment, self-organization, and data transfer, WSN has various usage and advances, but also, they face certain difficulties [5].

A homogeneous network comprises nodes taking similar energy, physical, and software characteristics, whereas a heterogeneous network comprises nodes with distinct characteristics [6]. It is further effective to implement the installation of heterogeneous network for balancing the load and energy of the networks and to offer various features and amount of energy utilization of the node from the networks. The clustering is an organized group of sensors in the network according to provided features [7]. All the groups are determined as a cluster; A Cluster Head (CH) is presented in all the clusters i.e., accountable for cluster members (CMs) and collect information from other CMs and forward them to a static or Mobile Sink node (MS). An MS acts as a Base Station (BS) or BS might be distinct device with higher-level ability. Fig. 1 displays the overview of WSN.

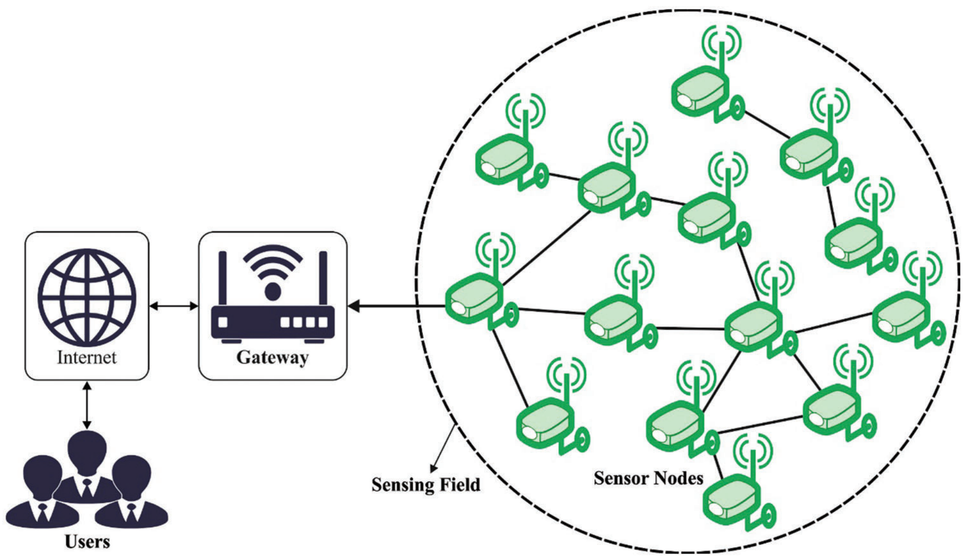


Figure 1: Overview of WSN

The clustering is very effectual in guaranteeing the energy utilization balance of WSN [8]. In that regard, CH reduces energy utilization by preventing each node from contributing to data communication because cluster node gathers the information they attain from the physical area. Simultaneously, CH delivers each information they gather to BS on neighboring CH or in a single-hop transmission. In the homogeneous WSN, communication ability of all the nodes is similar [9]. Since sensors have constraint balance between the energy, direct communication of the gathered information in the CH to the sink isn't an energy effective solution for the largescale WSN. Therefore, multihop routing protocol is needed for inter-cluster transmission and transport of the gathered information from the CH to the sink. Defining the energy balanced shortest way for these purposes is an NP-hard problem. In the current work, routing and clustering problems have been distinctly considered by many research workers [10].

Kiani et al. [11] progresses 3 meta-heuristic based techniques; gray wolf optimizer (GWO), incremental GWO, and expanded GWO. These techniques carry out different difficult procedures with high efficiency and much quicker. It contains cluster setup and data transmission stages. A primary stage concentrates on clusters formation and CHs selective, and the secondary stage attempts for determining routes for data broadcast. The researchers in [12] present a hybrid meta-heuristic approach in which optimum feature of

Artificial Bee Colony (ACO) and Differential Evolution (DE) is integrated for evaluating the optimum group of load-balanced CHs. The authors in [13] present a novel routing technique dependent upon teaching and learning based optimization algorithm (TLBO) that is an existing and robust model containing 2 important phases as Teacher and Learner. As TLBO is presented to continuous optimized problem, this case presents the first utilize of TLBO for distinct problems of WSN routing.

Wang et al. [14] presented an effectual routing technique dependent upon the elite hybrid meta-heuristic optimized technique. The presented technique comes as an original technique that newly brings together the global search capabilities of particle swarm optimization (PSO) technique, variance operator of differential technique, and pheromone of ant colony optimization (ACO) technique for avoiding local search and maintaining diversity of populations. In [15], a novel Mobile Clustering Routing Protocol (MCRP) dependent upon Thermal Exchange Optimization (TEO) simulated as Newton's cooling law is named as TEO-MCRP was projected for heterogeneous WSN. During the present protocol, 2 distinct techniques are presented for CH selective and MS way recognition with main function containing independent fitness parameters.

This study introduces a novel Honey Badger Based Clustering with African Vulture Optimization based Routing (HBAC-AVOR) protocol for WSN. The presented HBAC-AVOR model mainly aims to cluster the nodes in WSN effectually and organize the routes in an energy-efficient way. The presented HBAC-AVOR model follows a two stage procedure. At the initial stage, the HBAC technique is exploited to choose an optimal set of CHs utilizing a fitness function containing many input parameters. Next, the AVOR algorithm was executed for determining the optimal routes to BS and thereby lengthens the lifetime of WSN. A detailed simulation analysis was executed for highlighting the enhanced outcomes of the HBAC-AVOR protocol.

2 The Proposed Model

In this study, a new HBAC-AVOR algorithm was developed for energy aware cluster-based route planning process in WSN. The presented HBAC-AVOR model mainly aims to cluster the nodes in WSN effectually and organize the routes in an energy-efficient way. The presented HBAC-AVOR model follows a two stage process such as HBAC for cluster construction and AVOR based route selection.

2.1 Design of HBAC Technique

At the primary stage, the nodes in the WSN are initialized and communicated together. Then, the HBAC technique was executed to cluster the network and elect CHs [16,17]. The Honey badger algorithm (HBA) is a new meta-heuristic technique presented by Hashim et al. [16] dependent upon the hunting performance of honey badgers. This technique seeks for creating a balance amongst the exploration as well as exploitation stages by traveling the searching space rapidly and avoiding local optimal solutions. In addition, the HBA is proven effective from resolve empirical problems with difficult searching space. Important stages of HBA technique are summarized as follows:

During the exploration stage, the honey badger follows a honey guide bird for beehive and is estimated as:

$$x_{new} = x_{prey} + F \times r_1 \times \alpha \times d_j \tag{1}$$

whereas x_{new} refers the novel place of honey badger, x_{prey} signifies the optimum prey place, F stands for the flag which promotes exploration, d_i represents the distance amongst the prey and j^{th} badger, and r_1 defines the arbitrary value amongst zero and one. In addition, α demonstrates the arbitrary control variable which reduces the diversity of population and is computed as:

$$\alpha = 2 \times exp\left(\frac{-t}{\text{Max } It}\right) \tag{2}$$

During the exploitation stage, the honey badger digs from the cardioid-shaped motion and is estimated as:

$$x_{new} = x_{prey} + F \times \beta \times I_j \times x_{prey} + F \times r_2 \times \alpha \times d_i$$
$$\times |\cos(2\pi r_3) \times [1 - \cos(2\pi r_4)]| \tag{3}$$

In which I_j refers the intensity factor that is dependent upon the distance amongst all 2 neighboring searching agents and distance amongst the prey and honey badger. In addition, r_2, r_3 and r_4 are arbitrary variables in zero to one. The capability of honey badger for obtaining food was demonstrated as the parameter β that is taken as 6 under this case. An essential stage of the HBA technique is summarized as follows:

i) Initializing the amount of honey badgers (population size) with arbitrary places.
ii) Fixed the parameters $MaxIt$, d, and intensity factor I.
iii) Upgrade the reducing factor α.
iv) Estimate the fitness function (FF) of all honey badgers places.
v) Compute the honey badger place x_{new}.
vi) Estimate a novel place and allocate a novel FF f_{new}.
vii) Upgrade f_{new} still, the maximal count of iterations is obtained.

The aim of HBAC objective function (OF) is to allocate the node with minimal cost as CH and fitness parameter is determined in the following [17]. The residual energy (RE) is the fitness parameter, F_{res}. The amount of the ratio of RE of node i is related to E_{ri} and the overall energy of network E_t. It can be essential to estimate the RE of all the nodes for every iteration. Consequently, a balanced energy depletion can be accomplished from the networks.

$$F_{res} = \sum_{i=1}^{n} \frac{E_{ri}}{E_t} \tag{4}$$

In which n represent the overall amount of nodes. A node having lower F_{res} rises the possibility of selecting as a CH. Alternative of the fitness parameter is the average energy F_{avg} of node. This variable represents that node with higher primary energy are highly possibly that chosen CH. F_{avg} can be estimated in the following equation and normalized within the range of [0,1]. Now E_i represent the RE of node i.

$$F_{avg} = \frac{1}{n}\sum_{i=1}^{n} E_i \tag{5}$$

Another fitness parameter is the distance (F_{dist}) of node in the MS. The node nearer to the MS consumes lesser energy when transmitting information. Thus, it can be essential to take this variable as basis such that further accurate OF is estimated. F_{dist} can be shown as follows.

$$F_{dist} = \sum_{i=1}^{n} \frac{d(n_i toMS)}{d(navg_i toMS)} \tag{6}$$

In which $d(navg_i toMS)$ and $d(n_i toMS)$ denotes the average and euclidean distance of node i to the MS, correspondingly. The next parameter is the amount of neighbors near the node from the cluster. When the amount of nodes from the cluster rises, the data transmission problem rises. Then, there is need to consider the amount of neighbors near the node in CH selection. The fitness variable F_{neig} express the amount of neighbors of a node.

$$F_{neig} = \frac{\sum_{i=1}^{n_{cl}} d(i,j)}{n_{cl}} \tag{7}$$

whereas $d(i,j)$ denotes the distance amongst nodes i and j, and n_d indicates the amount of nodes in the cluster. At last, combining the objective function with fitness parameter is estimated by the following equation.

$$F_{obj} = \phi * F_{res} + \gamma * F_{avg} + \delta * F_{disf} + \theta * F_{neig} \tag{8}$$

Now ϕ, γ, δ and θ weight coefficient is multiplied with the fitness parameter and the sum is 1 $(\phi + \gamma + \delta + \theta = 1)$.

2.2 Design of AVOR Technique

Next to CH selection, the routes are optimally chosen by the use of AVOR technique. The AVO is a current metaheuristic approach is presented depending on the navigation and foraging behaviors of African vultures [18]. Furthermore, the AVO approach has lower computation difficulty and is more adaptable when compared to other metaheuristic approaches. As well, the exploration and exploitation stages of the AVO are given in the following:

In exploration phase, the probability of choosing the vulture to bring the other vultures to one of the optimal solutions in all the groups is calculated by:

$$P(i+1) = \begin{cases} R(i) - |X \times R(i) - P(i)| \times F & \text{if } P_1 \geq rand_{p_1} \\ R(i) - F + r_1 \times ((U - L) \times r_2 + L) & \text{if } P_1 < rand_{p_1} \end{cases} \tag{9}$$

whereas $P(i)$, $P(i+1)$ represents the location of the vulture in the existing and the subsequent iteration, correspondingly. Furthermore, F represent the satiation rate of vulture, U, and L indicates the upper and lower bounds of the searching agent, correspondingly, r_1, r_2 and X denotes arbitrary parameters and vector represents the arbitrary movement of vulture. Moreover, $rand_{p_1}$ denotes an arbitrary value within [0,1] i.e., generated for selecting the approach in the exploration stage, and $R(i)$ is represented by:

$$R(i) = \begin{cases} Best\ Vulture_1 & \text{if } P_i = L_1 \\ Best\ Vulture_2 & \text{if } P_i = L_2 \end{cases} \tag{10}$$

whereas $Best\ Vulture_1$ and $Best\ Vulture_2$ denotes the optimal solution of the 1st and 2nd groups in the existing iteration, correspondingly. The variables L_1 and L_2 are initialized beforehand the optimization search, within [0,1] and the sum of these two variables is 1. Fig. 2 showcases the steps involved in AVOR technique.

In exploitation phase, two approaches are proposed according to the satiation rate of the vulture (F). If $F \geq 0.5$, the vulture would compete for food in a rotational movement that is estimated as follows:

$$P(i+1) = \begin{cases} |X \times R(i) - P(i)| \times (F + r_3) - (R(i) - P(i)) & \text{if } P_2 \geq rand_{p_2} \\ R(i) - (S_1 + S_2) & \text{if } P_2 < rand_{p_2} \end{cases} \tag{11}$$

whereas S_1 and S_2 denotes the spiral flight movement and it is shown below:

$$S_1 = R(i) \times \left(\frac{r_4 \times P(i)}{2\pi}\right) \times cos(P(i)) \tag{12}$$

$$S_2 = R(i) \times \left(\frac{r_5 \times P(i)}{2\pi}\right) \times sin(P(i)) \tag{13}$$

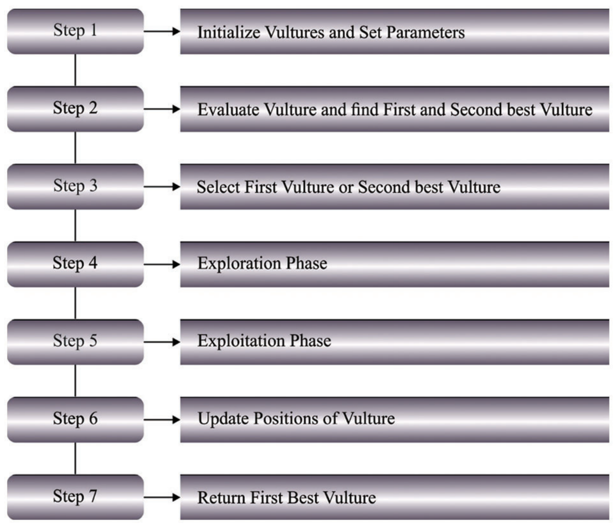


Figure 2: Steps involved in AVOR technique

In which r_3, r_4 *and* r_5 denotes arbitrary parameters, and $R(i)$ can be shown below. As well, $rand_{p_2}$ and $rand_{p_3}$ denotes arbitrary values within [0,1] that are generated for selecting the appropriate approach in the exploitation state. Furthermore, another vulture becomes aggressive at the time of foraging if $F < 0.5$ and it is estimated by the following formula:

$$P(i+1) = \begin{cases} \dfrac{A_1 + A_2}{2} & if\ P_3 \geq rand_{p3} \\ R(i) - |R(\mathrm{i}) - P(i)|^2 \times F \times Levy(X \times R(i)) & if\ P_3 < rand_{p3} \end{cases} \tag{14}$$

whereas A_1 and A_2 represents the movement of vultures and it is shown below:

$$A_1 = Best\ Vulture_1(i) - \frac{Best\ Vulture_1(i) \times P(i)}{Best\ Vulture_1(i) - P(i)^2} \times F \tag{15}$$

$$A_2 = Best\ Vulture_2(i) - \frac{Best\ Vulture_2(i) \times P(i)}{BestvVulture_2(i) - P(i)^2} \times F \tag{16}$$

Additionally, the Levy motion is utilized for increasing the efficacy of the AVO approach. At last, the AVO approach has proved efficient in resolving distinct optimization issues.

For determining the optimum group of routes, the dimensional of every AV is initiated that is equivalent to CH, and more place is located from the BS. Assume, $\theta^i = (\theta^i_1,\ \theta^i_2 | \theta^i_{p+1})$ is i^{th} fish, $\theta^i_{n_i}$ represents the real value lies from the interval of zero and one. Afterward, the provided function was utilized for determining the following hop to destination and is determined as:

$$f(x) = \{i,\ for\ which \left| \left(\frac{i}{k} - X_{i_f j} \right) \right| is\ minimum,\ \forall_i 1 \le i \le k \tag{17}$$

The purpose is for determining the optimum group of routes in CH for destination utilizing a FF including 2 parameters such as energy and distance. Primarily, the RE of next-hop node was defined and the node with maximal energy is preserved as relay node. The first sub-objective $f1$ is given as:

$$f1 = \sum_{i=1}^{m} E_{CHi} \tag{18}$$

In addition, Euclidean distance was executed for determining the distance in CHs to destination. The minimization of energy dissipation was mostly dependent upon the communication distance. Thus, the next sub-objective by means of distance is $f2$ that is demonstrated as:

$$f2 = \frac{1}{\sum_{i=1}^{\mathrm{m}} dis(CH_i,\ NH) + dis(NH,\ BS)} \tag{19}$$

The aforementioned sub-objectives are summarized as to a FF as provided under in which α_1 and α_2 refers the weighted allocation to all sub-objectives.

$$Fitness\ = \alpha_1(f1) + \alpha_2(f2),\ where \sum_{i=1}^{2} \alpha_i = 1\alpha_i \varepsilon(0, 1); \tag{20}$$

3 Results and Discussion

In this section, a detailed investigation of the results obtained by the HBAC-AVOR model is performed using two scenarios based on the position of sink. The position of sinks in scenarios 1 and 2 are (100, 100) and (200, 200) respectively. A comparative analysis is made with genetic algorithm (GA), ACO, PSO, and thermal exchange optimization-based clustering routing protocol (TEOMCRP).

Tab. 1 and Fig. 3 investigates the network lifetime (NLFT) examination of the HBAC-AVOR model with existing models under two scenarios. The experimental results indicated that the HBAC-AVOR model has resulted in improved NLFT over the other methods under two distinct scenarios. For instance, with scenarios 1 and 100 nodes, the HBAC-AVOR model has offered increased NLFT of 33712 rounds whereas the GA, ACO, PSO, and TEOMCRP algorithms have obtained reduced NLFT of 20109, 25159, 28869, and 31239 respectively. At the same time, with 200 nodes, the HBAC-AVOR model has provided maximum NLFT of 43709 rounds whereas the GA, ACO, PSO, and TEOMCRP algorithms have attained reduced NLFT of 31960, 35258, 39071, and 40411 respectively. Similarly, with 500 nodes, the HBAC-AVOR model has resulted in increased NLFT of 59683 rounds whereas the GA, ACO, PSO, and TEOMCRP algorithms have accomplished decreased NLFT of 52881, 55663, 57312, and 58137 rounds respectively.

Tab. 2 and Fig. 4 explore the comparative energy consumption (ECM) results of the HBAC-AVOR model and existing techniques. The achieved results specified that the HBAC-AVOR model has found reduced ECM under two scenarios and node count. For instance, with scenarios 1 and 5000 rounds, the HBAC-AVOR model has presented least ECM of 20 J whereas the GA, ACO, PSO, and TEOMCRP algorithms have gained increased ECM of 27, 24, 23, and 21 J respectively. Besides, with 25000 rounds, the HBAC-AVOR model has resulted in lower ECM of 94J whereas the GA, ACO, PSO, and TEOMCRP algorithms have reached higher ECM of 108, 104, 101, and 98 J respectively. Moreover, with 45000 rounds, the HBAC-AVOR model has led to minimal ECM of 132 J whereas the GA, ACO, PSO, and TEOMCRP algorithms have resulted in maximum ECM of 155, 150, 148, and 145 J respectively.

Table 1: Network lifetime analysis of HBAC-AVOR technique with existing algorithms under two scenarios

	Network lifetime (Rounds)				
No. of nodes	Genetic alg.	Ant colony opt.	Particle swarm opt.	TEOMCRP	HBAC-AVOR
Scenario-1 (Sink at (100, 100))					
100	20109	25159	28869	31239	33712
150	26395	30415	34434	36083	39587
200	31960	35258	39071	40411	43709
250	37422	39071	43194	45461	48553
300	40926	43709	46388	47728	50511
350	42472	46388	52056	52881	55148
400	47522	51850	54221	55663	58549
450	51026	54427	56797	57725	58858
500	52881	55663	57312	58137	59683
Scenario-2 (Sink at (200, 200))					
100	18368	22708	26578	29276	34085
150	23529	27986	32208	34788	39363
200	28220	33029	35492	39363	44523
250	31973	37251	41122	43819	47573
300	37251	40770	44758	46517	50270
350	40184	45579	48276	52147	55079
400	42998	47925	50739	54258	56838
450	45579	49684	53085	56017	57777
500	49332	52382	54727	57659	58598

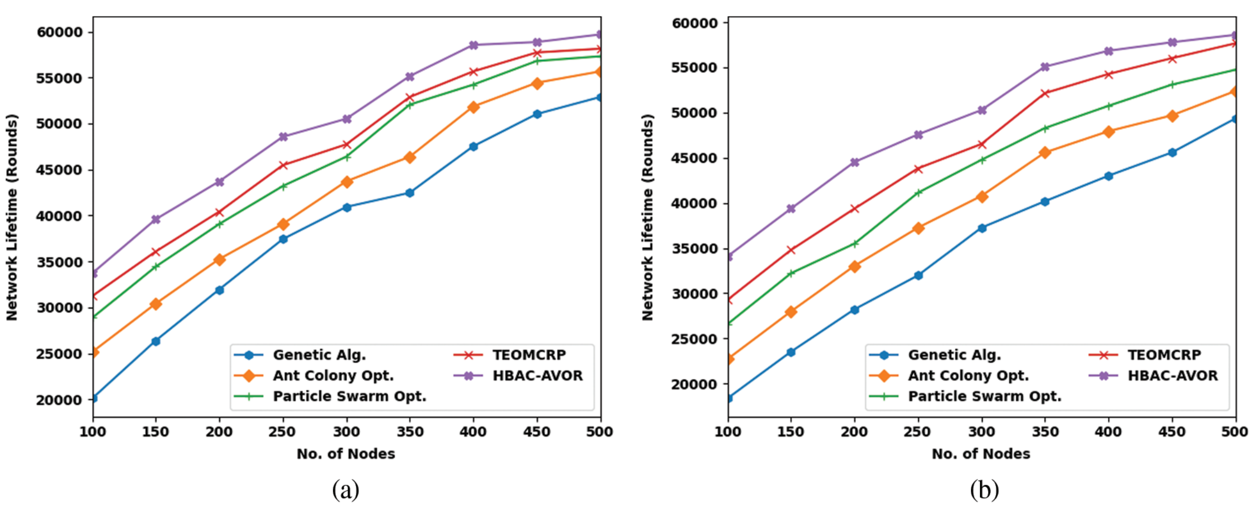
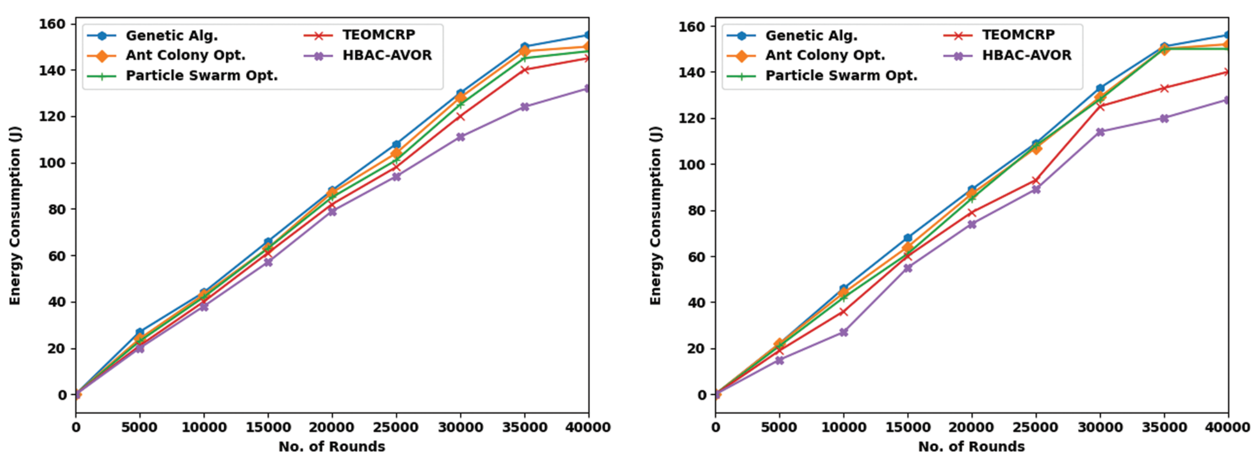


Figure 3: NLFT analysis of HBAC-AVOR technique under two scenarios

Table 2: Energy consumption analysis of HBAC-AVOR technique with existing algorithms under two scenarios

	Energy consumption (J)				
No. of rounds	Genetic alg.	Ant colony opt.	Particle swarm opt.	TEOMCRP	HBAC-AVOR
Scenario-1 (Sink at (100, 100))					
0	0	0	0	0	0
5000	27	24	23	21	20
10000	44	43	42	40	38
15000	66	63	63	61	57
20000	88	87	85	82	79
25000	**108**	**104**	**101**	**98**	**94**
30000	130	128	125	120	111
35000	150	148	145	140	124
40000	155	150	148	145	132
Scenario-2 (Sink at (200, 200))					
0	0	0	0	0	0
5000	22	22	21	19	15
10000	46	44	42	36	27
15000	68	64	61	60	55
20000	89	87	85	79	74
25000	109	107	108	93	89
30000	133	129	128	125	114
35000	151	150	150	133	120
40000	156	152	150	140	128



(a) (b)

Figure 4: ECM analysis of HBAC-AVOR technique under two scenarios

Tab. 3 and Fig. 5 investigate the packet delivery ratio (PDR) and packet loss rate (PLR) examination of the HBAC-AVOR technique with existing algorithms under two scenarios. The experimental results demonstrated that the HBAC-AVOR model has resulted in improved PDR over the other methods under two distinct scenarios. For instance, with scenarios 1 and 100 nodes, the HBAC-AVOR model has offered increased PDR of 99.83% whereas the GA, ACO, PSO, and TEOMCRP systems have obtained reduced PDR of 97.78%, 97.86%, 98.25%, and 99.68% correspondingly. Simultaneously, with 200 nodes, the HBAC-AVOR methodology has provided maximal PDR of 98.77% whereas the GA, ACO, PSO, and TEOMCRP approaches have attained reduced PDR of 95.86%, 96.75%, 97.98%, and 98.20% correspondingly. Likewise, with 500 nodes, the HBAC-AVOR model has resulted in increased PDR of 96.01% whereas the GA, ACO, PSO, and TEOMCRP algorithms have accomplished decreased PDR of 90.59%, 92.49%, 94.04%, and 94.73% correspondingly. Followed by, the achieved results specified that the HBAC-AVOR model has found reduced PLR under two scenarios and node count. For instance, with scenarios 1 and 100 nodes, the HBAC-AVOR model has presented least PLR of 0.17% but the GA, ACO, PSO, and TEOMCRP algorithms have gained increased PLR of 2.22%, 2.14%, 1.75%, and 0.32% respectively. Moreover, with 250 nodes, the HBAC-AVOR system has resulted in lower PLR of 1.77% whereas the GA, ACO, PSO, and TEOMCRP algorithms have reached higher PLR of 4.66%, 4.02%, 2.83%, and 2.05% correspondingly. In addition, with 500 nodes, the HBAC-AVOR model has led to minimal PLR of 3.99% whereas the GA, ACO, PSO, and TEOMCRP algorithms have resulted in maximal PLR of 9.41%, 7.51%, 5.96%, and 5.27% correspondingly.

Table 3: PDR and PLR analysis of HBAC-AVOR technique with existing algorithms under two scenarios

No. of nodes	Genetic alg.	Ant colony opt.	Particle swarm opt.	TEOMCRP	HBAC-AVOR
Packet delivery ratio (%)					
Scenario-1					
100	97.78	97.86	98.25	99.68	99.83
150	96.21	96.94	98.15	98.89	99.04
200	95.86	96.75	97.98	98.20	98.77
250	95.34	95.98	97.17	97.95	98.23
300	94.41	95.34	96.16	97.29	97.78
350	94.11	94.73	95.71	96.77	97.09
400	93.18	93.92	95.27	96.11	96.53
450	91.90	93.05	94.46	95.66	96.11
500	90.59	92.49	94.04	94.73	96.01
Scenario-2 (Sink at (200, 200))					
100	95.89	96.55	97.60	97.91	98.91
150	93.02	94.61	95.85	97.91	98.45
200	92.32	94.11	94.84	97.17	98.33
250	91.70	93.45	94.11	96.28	97.75
300	90.93	92.91	94.03	95.66	97.64
350	90.50	92.01	93.02	95.23	97.21
400	89.88	91.67	92.25	94.77	96.63
450	89.15	91.24	91.70	93.95	95.97
500	88.45	90.97	90.93	93.14	95.00

(Continued)

Table 3 (continued)

No. of nodes	Genetic alg.	Ant colony opt.	Particle swarm opt.	TEOMCRP	HBAC-AVOR
Packet loss rate (%)					
Scenario-1					
100	2.22	2.14	1.75	0.32	0.17
150	3.79	3.06	1.85	1.11	0.96
200	4.14	3.25	2.02	1.80	1.23
250	4.66	4.02	2.83	2.05	1.77
300	5.59	4.66	3.84	2.71	2.22
350	5.89	5.27	4.29	3.23	2.91
400	6.82	6.08	4.73	3.89	3.47
450	8.10	6.95	5.54	4.34	3.89
500	9.41	7.51	5.96	5.27	3.99
Scenario-2 (Sink at (200, 200))					
100	4.11	3.45	2.40	2.09	1.09
150	6.98	5.39	4.15	2.09	1.55
200	7.68	5.89	5.16	2.83	1.67
250	8.30	6.55	5.89	3.72	2.25
300	9.07	7.09	5.97	4.34	2.36
350	9.50	7.99	6.98	4.77	2.79
400	10.12	8.33	7.75	5.23	3.37
450	10.85	8.76	8.30	6.05	4.03
500	11.55	9.03	9.07	6.86	5.00

Tab. 4 and Fig. 6 demonstrate the comparative ETED results of the HBAC-AVOR system and existing techniques. The achieved results specified that the HBAC-AVOR methodology has found reduced ETED under node counts. For sample, with 100 nodes, the HBAC-AVOR model has presented least ETED of 0.99 ms whereas the GA, ACO, PSO, and TEOMCRP algorithms have gained increased ETED of 7.50, 4.57, 3.27, and 1.96 ms correspondingly. Moreover, with 250 nodes, the HBAC-AVOR methodology has resulted in lower ETED of 17.28 ms whereas the GA, ACO, PSO, and TEOMCRP algorithms have reached higher ETED of 57.68, 44, 31.62, and 25.75 ms correspondingly. Moreover, with 500 nodes, the HBAC-AVOR model has led to minimal ETED of 67.46 ms whereas the GA, ACO, PSO, and TEOMCRP algorithms have resulted in maximum ETED of 129.37, 108.19, 88.96, and 77.56 ms correspondingly.

Tab. 5 offers a brief examination of the results offered by the HBAC-AVOR model with existing models on two scenarios. The experimental values indicated that the HBAC-AVOR model has accomplished maximum number of received packets over the other methods. The HBAC-AVOR model enables to receiving of 681249 and 663815 packets under two scenarios. The experimental analysis indicated that the HBAC-AVOR model has resulted in effectual outcomes over the other methods.

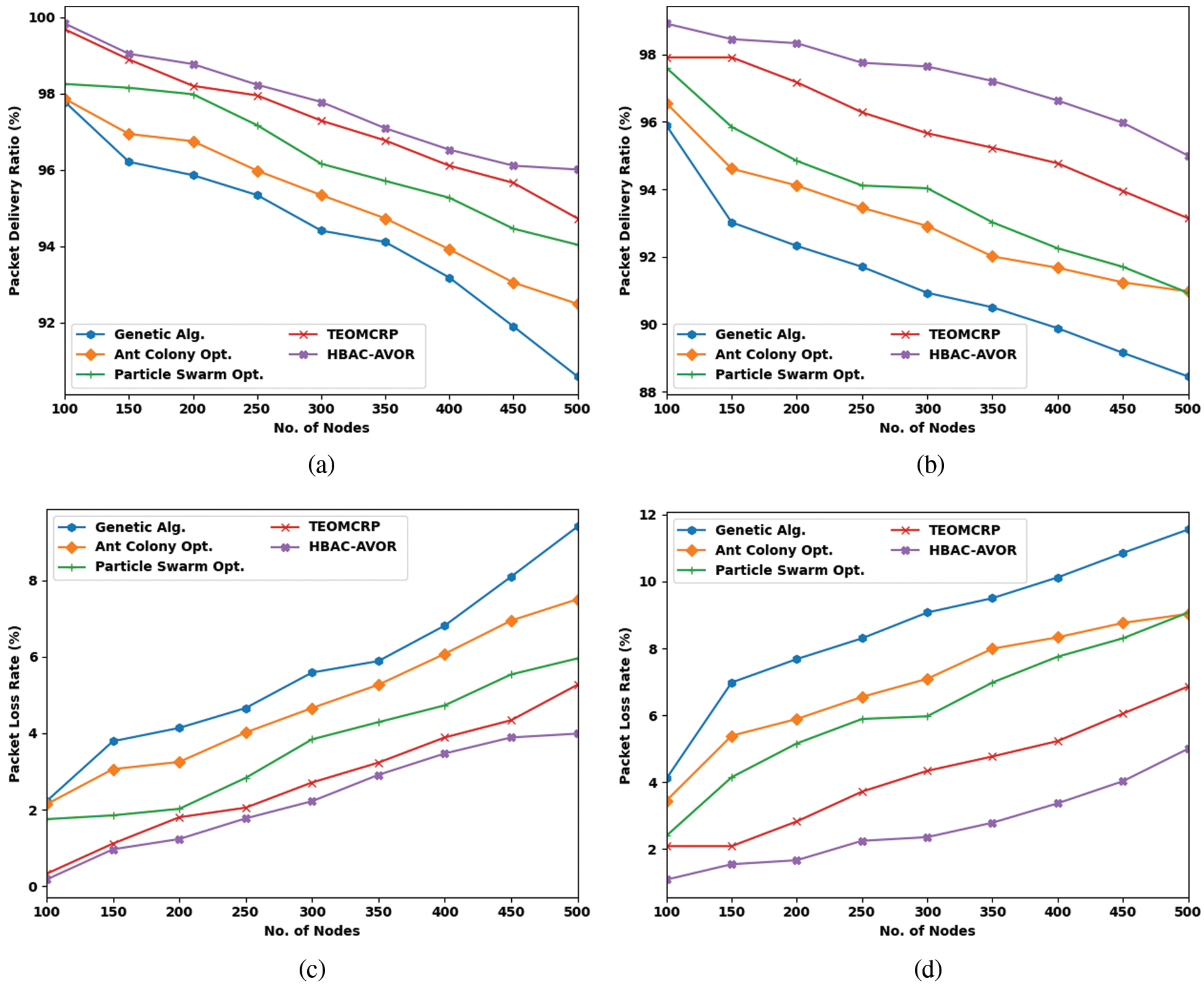


Figure 5: PDR and PLR analysis of HBAC-AVOR technique under two scenarios

Table 4: ETED analysis of HBAC-AVOR technique with existing algorithms

End to end delay (ms)					
No. of nodes	Genetic alg.	Ant colony opt.	Particle swarm opt.	TEOMCRP	HBAC-AVOR
100	7.50	4.57	3.27	1.96	0.99
150	23.47	16.63	12.72	8.16	4.90
200	30.96	25.10	22.49	12.72	8.81
250	57.68	44.00	31.62	25.75	17.28
300	62.57	53.12	41.07	32.27	24.77
350	74.63	58.99	46.28	37.16	30.31
400	81.47	66.48	57.03	44.65	38.46
450	100.69	85.38	68.44	60.29	52.47
500	129.37	108.19	88.96	77.56	67.46

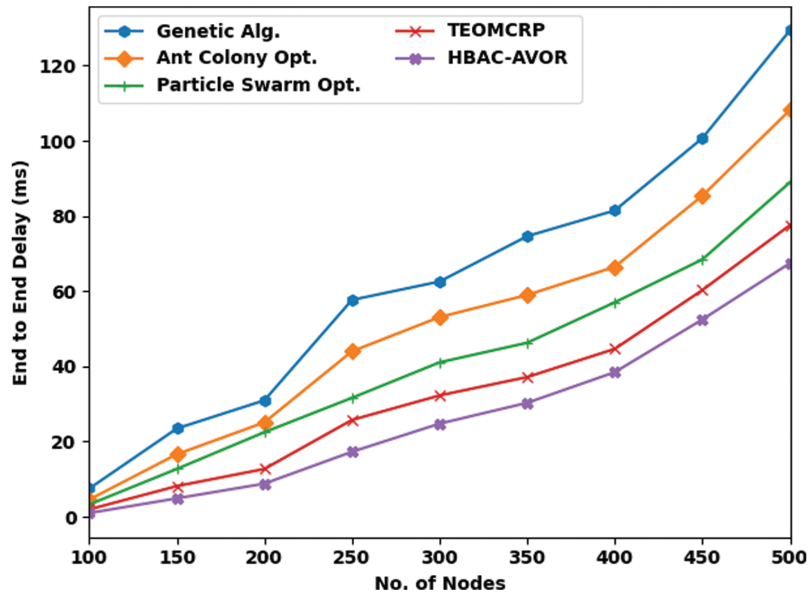


Figure 6: ETED analysis of HBAC-AVOR technique with existing algorithms

Table 5: Comparative analysis of HBAC-AVOR technique with existing algorithm under two scenarios

No. of packets received by base station		
Methods	Scenario-1	Scenario-2
Genetic alg.	547584	501673
Ant colony opt.	594658	542935
Particle swarm opt.	647542	612092
TEOMCRP	669626	652192
HBAC-AVOR	681249	663815

4 Conclusion

In this study, a new HBAC-AVOR algorithm was developed for energy aware cluster-based route planning process in WSN. The presented HBAC-AVOR model mainly aims to cluster the nodes in WSN effectually and organize the routes in an energy-efficient way. At the primary stage, the nodes in the WSN are initialized and communicated together. Then, the HBAC algorithm was executed for clustering the network and elect CHs. Next to CH selection, the routes are optimally chosen by the use of AVOR technique. The AVOR technique is applied for determining the optimal routes to BS and thereby lengthens the lifetime of WSN. A detailed simulation analysis was implemented to highlight the increased outcomes of the HBAC-AVOR protocol. On comparing with existing techniques, the HBAC-AVOR model has outperformed recent algorithms with maximal energy efficiency and lifetime. In future, data aggregation concepts can be improved for improving the overall performance.

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