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Clustering and routing using spiral exploration mechanism with honey badger optimization in wireless sensor network

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ABSTRACT

Wireless sensor network (WSN) contains a huge number of spatially distributed sensor nodes that are connected by wireless to monitor and record information from the environment. The WSN nodes are battery-powered, thus reducing energy after a certain period which affects the network lifetime. To overcome this issue, this research proposed a spiral exploration mechanism with honey badger optimization (SEM-HBO) for cluster head (CH) and route path selection in WSN. The objective of this research is to reduce energy consumption and enhance network lifespan in WSN. The distance, communication cost, residual energy and cluster density are considered as fitness functions for selecting CH and route path in WSN. Through the SEM-HBO search behavior, it explores different routes and recognizes best one for reducing energy consumption and delays thereby enhancing network lifetime. The SEM-HBO performance is calculated based on packet delivery ratio (PDR), delay, energy consumption (EC), network lifetime (NL), and throughput for 100-500 nodes. The SEM-HBO performance is efficient and it achieves 99.62% and 99.59% of PDR for 100 and 200 nodes when compared to harmony search algorithm and competitive swarm optimization (HSA-CSO).

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1. INTRODUCTION

An extensive distribution of numerous sensor nodes (SNs) within a particular area establishes a wireless sensor network (WSN) [1]. The processing data gathered from sensors for event handling is WSN's primary task. The data is collected from the particular area through SNs and transferred to the base station (BS) in WSN [2], [3]. The effectiveness of WSN extends to different military and civil applications such as combat field surveillance, security and disaster management [4]. The duration of time till the desired area or point which are no longer covered is defined as WSN network lifetime [5]. A geo-clustering process through sink position as the basis, in which every cluster obtains a group of geo-cluster heads that include initial cluster head (CH) and several subordinate CHs [6], [7]. The network SNs' high-power utilization and unbalanced usage of energy are a main factor in network lifetime reduction [8]. To respond to hotspot concerns through inter-cluster traffic, clusters placed near to sink are allocated through the large set of geo-CHs than clusters positioned far away from sink [9]-[11]. The clustering hierarchy-based protocols are developed to lower WSN energy consumption. The protocol enables data to be gathered and transferred to BS from nodes through high residual energy [12], [13]. Through, these protocols did not enhance energy efficiency that minimizes network lifetime [14]. The transmission power associated with transmission range predicts under high topology in that SNs directly transmit to BS depending on physical topology to enable scalability [15]-[18]. The presence of sensors in this protocol presents significant complexity particularly if the node is terminated, every network will be lost which makes it undependable [19]. The receiver is an energy component of SN and it is ineffective and unable to balance energy usage within the network [20]. The existing approaches have drawbacks like minimizing energy after a certain period because the WSN nodes are battery-powered thereby reducing the network lifetime. To tackle this problem, this research proposed an SEM-HBO for clustering and routing in a WSN environment.

Various research has introduced numerous clustering and routing techniques for data transmission. Some recent research for CH and route path selection are analyzed in this section in the WSN environment. Kumar *et al.* [21] developed an optimal CH selection through harmony search algorithm and competitive swarm optimization (HSA-CSO) for WSN. The HAS-CSO has huge search efficiency and dynamic CSO ability which extends nodes' lifespan. The number of dead nodes, alive nodes, throughput, and residual energy are considered to calculate the performance. The HSA-CSO were circulated data packets over the short path which used to reduce latency. However, it considered energy as fitness that fails to utilize distance, thus the path with huge distance reduces the network lifetime. Asiri *et al.* [22] implemented improved duck and traveller optimization-enabled cluster-based multi-hop routing (IDTOMHR) for WSN. The artificial gorilla troops optimization (ATGO) algorithm was used to determine optimal routes to the destination subset. Both techniques derive fitness functions through the presence of input parameters. IDTOMHR was efficient in achieving a better balance for WSN. However, it does not consider the distance in the route path which leads to high energy consumption due to the selection of long routes. Farooq *et al.* [23] introduced a probabilistic weight-based energy-efficient cluster routing (POWER) for WSN. Initially, it developed a probabilistic weighted metric that generates an efficient way to select CH dynamically according to large priority weight. The node degree weight, distance, hop weight and residual energy were considered for determining the weights. Then, it developed cluster and routing by load balancing through determining node access according to the probabilistic weighted average. The weighted average-based CH and route path selection were utilized to obtain better balance in the network however, this model required restricted transmission for transmitting data through nodes due to bandwidth constraints which increased the delay.

Mishra and Verma [24] presented a reliable routing with optimized scheduling and routing for WSN. The GridCosins chain clustering was used which clusters nodes according to its distance and creates tree topology chaining for minimizing transmission range and enhancing network lifespan. The turtle search algorithm-desert cat swarm optimization (TSA-DCSO) was developed to obtain data from un-clustered network nodes. The TSA-DCSO reduced the energy consumption within a network however, it did not consider cluster density which resultant in less packet delivery ratio due to the possibility of selecting the attack node as CH. Almasri and Alajlan [25] suggested a modified golden eagle optimization (M-GEO) for cluster-based routing in WSN. The M-GEO selects an optimum CH by using residual energy, node degree, distance, and node centrality. Moreover, yellow saddle goatfish (YSG) was used for producing the optimum route path from CH to BS. It detects the shortest routing path thus reducing energy consumption. However, performances of M-GEO were affected because of inappropriate fitness function parameter selection which reduces lifespan because it leads to inefficient resource utilization. From the above investigation, the existing techniques have advantages and struggled from the several flaws. Energy is perceived as fitness that does not use the distance; therefore, the path with a higher distance reduces the network lifetime. It does not consider the distance in the route path which leads to high energy consumption due to the long route selection. Restricted transmission are needed to send data through nodes which enhances delay due to bandwidth constraints. Not consider the cluster density which results in packet drop over the network due to the increased probability of selecting an attack node as CH. The network lifetime is minimized by considering inappropriate fitness function parameters due to inefficient resource utilization. Based on this investigation, this research proposed an SEM-HBO for energy-efficient CH and route path selection in WSN. The following are major contributions of this research:

- The distance, communication cost, residual energy and cluster density are considered as fitness functions for selecting CH. Additionally, distance and residual energy are taken as fitness functions for selecting a route path that enhances the network lifespan and reduces energy consumption.
- Through the SEM-HBO search behavior, it explores different routes and recognizes the best one for reducing energy consumption and delay thereby enhancing network lifetime.

The organization of this research paper is given in the following section: the research method detailed explanation is provided in section 2. The results and discussion are given in section 3 and the conclusion of the work is provided in section 4.

2. RESEARCH METHOD

In this work, the data transmission is performed through the spiral exploration mechanism with honey badger optimization (SEM-HBO) in a WSN environment. It comprises four various stages like node initialization, CH selection, cluster formation, and route path selection. Here, the distance, communication cost, residual energy and cluster density are considered as fitness functions for selecting CH. Additionally, the distance and residual energy are considered as fitness functions for selecting route paths. Figure 1 signifies the process of the proposed methodology.

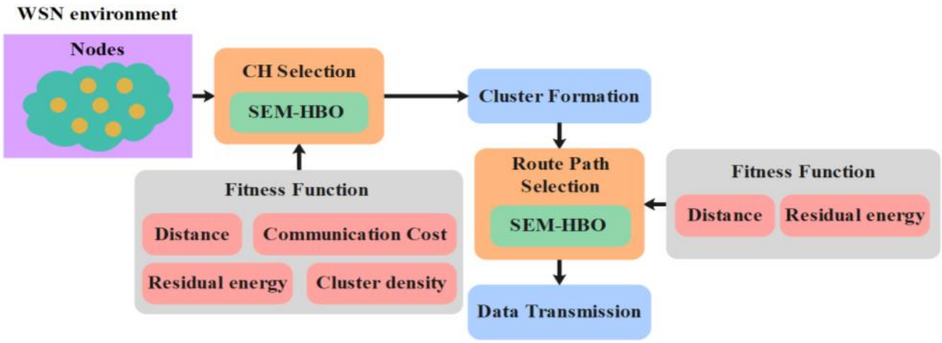

Figure 1. Process of proposed methodology

2.1. Node initialization

In WSN, nodes are located randomly and optimal CH and route paths are selected by SEM-HBO. The SEM-HBO is applied to obtain reliable and energy-efficient data transmission in the network. The selection of CH and route paths are described in the subsequent section.

2.2. CH selection using SEM-HBO algorithm

The CH from nodes is recognized by SEM-HBO with various fitness due to it managing huge data that is suitable for real-world applications when SNs are required to be identified. The selection of CH is important for optimizing energy and increasing data transmission which provides better performance. Here, the optimization algorithm is used to find a suitable node to act as CH for improving overall performance. The HBO is a bio-inspiration algorithm taken from the type of animal named Badger in finding the honey prey. The dynamic search behavior for mining and searching for honey is stimulated to update its processing equations. Due to their fearless nature, honey badgers will not hesitate to involve high predators when escaping situations. It employs a rat sniffing method to walk gradually and frequently searching prey mining per day. The HBO process includes population initialization, updating search agent position, prey attraction, and density factor.

Population initialization: it is generated randomly in the initial location of honey badger through search space boundaries. Every candidate solution location is presented as vectors in dimension D as (1). Where, r_1 is a random number within $[0, 1]$, ub and lb are upper and lower bounds of search space.

$$X_{ij} = lb + r_1 \cdot (ub - lb) \tag{1}$$

Updating search agent position: it has dual stages such as mining and enjoining honey stages. Before moving to location updates of honey badgers in mining and enjoining honey stages, a few factors are taken such as prey attraction and density factor for defining expressions. It is related to the intensity of prey concentration and distance between prey and jth honey badger. The K_j is an odor intensity that is exposed in (2).

$$K_j = r_2 \cdot \frac{S}{4\pi d_j^2} \tag{2}$$

Where, S and d_j are known as source intensity and distance among prey and jth honey badger which is expressed in (3) and (4). The density factor minimizes slowly through number of iterations to ensure smooth translation from exploration to exploitation. The reducing factor is updated through the number of iterations to minimize the randomization which is expressed in (5).

$$S = (X_j - X_{j+1})^2 \tag{3}$$

$$d_j = X_p - X_j \tag{4}$$

$$\alpha = C_o \cdot \exp\left(\frac{-l}{l_{max}}\right) \tag{5}$$

Where, C_o is a constant in a range equal to or greater than 1, l and l_{max} are current and maximum iterations. The mining stage in the process for honey prey is expressed in (6). Where, X_p is the best prey location, β is equal to or greater than 1 which can capability of honey badgers to attain food, d_j is the distance among prey and jth honey badger, r_3, r_4, and r_5 are three various random number within $[0, 1]$, K is an odor intensity, F is a search path of agent to alter search path strictly as (7). The honey stage is the next position update procedure through honeyguide as birds which has essential supportive and mutual relationship. The update expression is exposed in (8). The spiral exploration mechanism (SEM) is used to overcome these limitations which is used through population to update its location. The updated formula is expressed in (9).

$$X_{new} = X_p + F \cdot \beta \cdot K \cdot X_p + F \cdot r_3 \cdot d_j \cdot |\cos(2\pi r_4)\,[1 - co\,s(2\pi r_5)]| \tag{6}$$

$$F = \begin{cases} 1, r_6 \leq \frac{1}{2} \\ -1, r_6 \leq \frac{1}{2} \end{cases} \tag{7}$$

$$X_{new} = X_p + F \cdot r_7 \cdot \alpha \cdot d_j \tag{8}$$

$$X_{new} = X_p + F \cdot \beta \cdot K \cdot X_p + F \cdot r_8 \cdot d_j \cdot |\cos(2\pi a)| \cdot b \cdot \exp\,(a \cdot n) \tag{9}$$

Where, X_{new} is a new position, X_p is the best prey location, F, α, and d_j are parameters which are estimated in updating honey badger searches at a location near to X_p location. At the global exploration stage of HBO, the population explores search space utilizing the motion trajectory of a heart-shaped curve. Through, in early-stage iteration, the heart-shaped line of traversal range is limited and global exploration capability is inadequate. The a is a random number among $[-1,1]$ that reflects the optimization trajectory of the helix, b is a population search range, n is a spiral shape size, r_8 is a random number among $[0,1]$. After constructing the position updating formula of population, honey badger recognizes the prey position in search space through trajectory which enhances the overall population searchability.

2.3. Fitness function estimation

The CH and route path fitness enable to improvement of network lifetime and reducing energy consumption which generates conditions for estimating different performances. Arranging nodes by high energy optimizes and preserves fitness functions efficiently for contributing to improving network lifespan. The residual energy (FF_1), distance (FF_2), communication cost (FF_3), and cluster density(FF_4) are used to select CH by SEM-HBO which is converted as one objective function (F) as (10). Where, F is the overall fitness function, ρ_1, ρ_2, ρ_3, and ρ_4 are weight metrics of each fitness. The detailed definition of each fitness is given in the upcoming subsections:

$$F = \rho_1 \times FF_1 + \rho_2 \times FF_2 + \rho_3 \times FF_3 + \rho_4 \times FF_4 \tag{10}$$

2.3.1. Residual energy and distance

Here, huge energy is used for data collection, preprocessing, transmission and path selection in CH due to the node considered high energy as the route path. The residual energy (FF_1) is assessed by (11). WSN consumes high energy when transmitting data from CH to BS, here the consumption of energy is linearly related to transmitted energy. Hence, it is required to select CH through a minimum distance from BS. The distance (FF_2) is assessed by (12). Where, E_{CH_i} is an ith CH sustain energy, $dis(CH_i, BS)$ is an ith CH and BS distance.

$$FF_1 = \sum_{i=1}^{D} \frac{1}{E_{CH_i}} \tag{11}$$

$$FF_2 = \sum_{i=1}^{D} dis(CH_i, BS) \tag{12}$$

2.3.2. Communication cost and cluster density

The data is transmitted through the power which is related to its respective distance between source and nodes. The communication cost (FF_3) is assessed by (13). It is stated as a node that recognizes how to interconnect less in a simple route. Here, density is linearly related to entire nodes as (14).

$$FF_3 = \frac{d_{avg}^2}{d_0^2} \tag{13}$$

$$FF_4 = \frac{1}{M}\sum_{i=1}^{A}|Y_i| \tag{14}$$

Where, d_{avg} is a node and neighbors' average distance, d_0 is a node circulation radius. M and A are network nodes and the number of CH, $|Y_i|$ is an ith cluster node. The failure of a node is estimated through energy, and the transmitted distance is minimized between dual nodes. Additionally, cluster density is used to enhance energy efficiency when increasing network security contrary to attack nodes.

2.4. Cluster formation

After the selection of CH by SEM-HBO, every active node transfer control packets to its sink node. During cluster formation, SNs are utilized to select CHs and the cluster formation happens by selecting residual energy and distance which are considered sensor potential in the formation process. It is numerically presented in (15). Where, E_{CH} and $dis(s_i, CH)$ are a CH energy and distance among CH and ith sensor.

$$Sensor\ potential\ (s_i) = \frac{E_{CH}}{dis(s_i, CH)} \tag{15}$$

2.5. Route path selection

After forming clusters, the path selection process is initialized to determine optimal path for transmitting data from source of destination. By using SEM-HBO, path is selected with CH and BS path production is taken as final gateway. Distance and residual energy are used as fitness function for selecting route paths thereby network performance is enhanced. Initially, route initialization is diverse and flexible to allow SEM-HBO to fine-tune by iterations. This process is helpful for discovering best route path that adopts to alter network conditions. The steps for route selection are outlined:

- The CH and BS paths are considered as primary solutions for selecting route paths, where each resultant dimensions are related to number of CH in routes.
- Additionally, fitness functions such as distance and residual energy are utilized for updating positions which are presented in (16).

$$fitness = \gamma_1 \times \sum_{i=1}^{D} dis(CH_i, BS) + \gamma_2 \times \sum_{i=1}^{D} \frac{1}{E_{CH_i}} \tag{16}$$

Where, γ_1, γ_2, and γ_3 are weighted parameters assigned to every route objective generation. These functions help in identifying route paths that maximize residual energy and minimize distance. Hence, the energy of nodes is reduced by SEM-HBO thereby network lifespan is enhanced.

3. RESULTS AND DISCUSSION

The SEM-HBO performance is stimulated by MATLAB2020a with the configuration of processor i7, RAM 16 GB, and OS Windows 10. The performance is evaluated with metrics like PDR, delay, EC, NL, and throughput which is numerically given in (17)-(21). Where, $E_{transmitted}$ and $E_{received}$ define the transmitted and received node energy; actual and approximate remaining energy is denoted as σ_0 and $E_{estimate}[E_{RE}]$; consumed energy is denoted as $E[E_{CE}]$, fixed power consumption is denoted as CP. The SEM-HBO comprises 100-500 nodes in the area of 1,000 m×1,000 m. The SEM-HBO explores different routes and recognizes best one for reducing energy consumption and delay thereby enhancing network lifetime. Table 1 signifies simulation parameters.

Table 1. Parameters for simulation

Parameter	Value
Clustering and routing technique	SEM-HBO
Area	1,000 m×1,000 m
Simulation time	100s
Number of nodes	100, 200, 300, 400, and 500
Initial energy	0.5J

$$PDR = \frac{Number\ of\ received\ packets}{Number\ of\ transmitted\ packets} \times 100 \quad (17)$$

$$Delay = \frac{Sum\ of\ transmitting\ and\ receiving\ time\ of\ packets}{Total\ number\ of\ packets} \quad (18)$$

$$EC = E_{transmitted} + E_{received} \quad (19)$$

$$Network\ Lifetime = \frac{\sigma_0 - E_{estimate}[E_{RE}]}{CP + \#E[E_{CE}]} \quad (20)$$

$$Throughput = \frac{Total\ number\ of\ packets \times size\ of\ 1\ packet}{Time} \times 100 \quad (21)$$

3.1. Quantitative and qualitative analysis

The SEM-HBO performance is evaluated with metrics like PDR, delay, EC, NL, and throughput. The existing CH and route path selection algorithms like salp swarm algorithm (SSA), vortex swarm optimization (VSO), tunicate swarm algorithm (TSA) and HBO are evaluated in comparison with SEM-HBO. The SEM-HBO explores different routes and recognizes best one for reducing energy consumption and delay thereby enhancing network lifetime.

From Table 2, the SEM-HBO performance is evaluated through PDR with different nodes in terms of 100-500. The SSA, VSO, TSA, and HBO performance are evaluated for different no. of nodes. The SEM-HBO performance is efficient and it achieves 99.62%, 99.59%, 99.51%, 99.43%, and 99.37% for 100-500 nodes in comparison with SSA, VSO, TSA, and HBO. From Table 3, the SEM-HBO performance is evaluated through a delay with different nodes in terms of 100-500. The SSA, VSO, TSA, and HBO performance are evaluated for different no. of nodes. The SEM-HBO performance is efficient and it achieves 0.016 ms, 0.018 ms, 0.021 ms, 0.025 ms, and 0.027 ms for 100-500 nodes in comparison with SSA, VSO, TSA, and HBO. From Table 4, the SEM-HBO performance is evaluated through delay with different nodes in terms of 100-500. The SSA, VSO, TSA, and HBO performance are evaluated for different no. of nodes. The SEM-HBO performance is efficient and it achieves 0.13 J, 0.15 J, 0.18 J, 0.21 J, and 0,25 J for 100-500 nodes in comparison with SSA, VSO, TSA, and HBO.

Table 2. Result evaluation of PDR (%)

Methods	No. of nodes				
	100	200	300	400	500
SSA	93.82	93.76	92.65	92.50	92.44
VSO	94.37	94.33	94.29	94.21	94.14
TSA	96.61	96.54	96.45	96.31	96.28
HBO	98.58	98.46	98.39	98.25	98.16
SEM-HBO	99.62	99.59	99.51	99.43	99.37

Table 3. Result evaluation of delay (ms)

Methods	No. of nodes				
	100	200	300	400	500
SSA	0.028	0.031	0.034	0.038	0.041
VSO	0.025	0.027	0.030	0.033	0.037
TSA	0.023	0.026	0.028	0.031	0.034
HBO	0.019	0.022	0.024	0.027	0.029
SEM-HBO	0.016	0.018	0.021	0.025	0.027

Table 4. Result evaluation of EC (J)

Methods	No. of nodes				
	100	200	300	400	500
SSA	0.27	0.28	0.32	0.35	0.39
VSO	0.23	0.25	0.29	0.31	0.35
TSA	0.20	0.23	0.26	0.29	0.32
HBO	0.16	0.19	0.22	0.24	0.28
SEM-HBO	0.13	0.15	0.18	0.21	0.25

From Figure 2, the SEM-HBO performance is evaluated through delay with different nodes in terms of 100-500. The SSA, VSO, TSA, and HBO performance are evaluated for different no. of nodes. The SEM-HBO performance is efficient and it achieve 25637s, 27382s, 29521s, 31468s, and 33284s for 100-500 nodes in comparison with SSA, VSO, TSA, and HBO. From Figure 3, the SEM-HBO performance is evaluated through throughput with different nodes in terms of 100-500. The SSA, VSO, TSA, and HBO performance are evaluated for different no. of nodes. The SEM-HBO performance is efficient and it achieves 71.26 Kbps, 79.52 Kbps, 86.68 Kbps, 91.73 Kbps, and 98.36 Kbps for 100-500 nodes in comparison with SSA, VSO, TSA, and HBO.

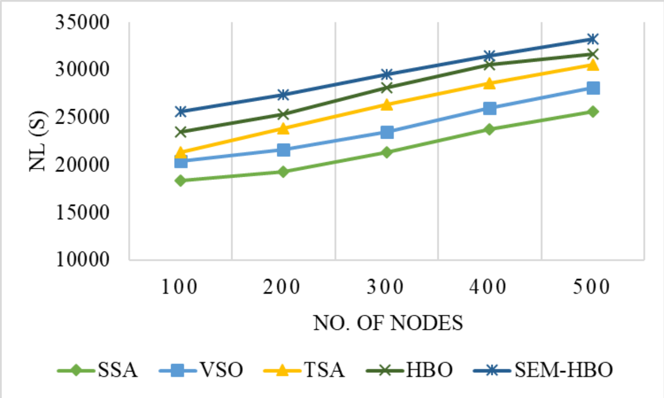

Figure 2. Result evaluation of NL (s)

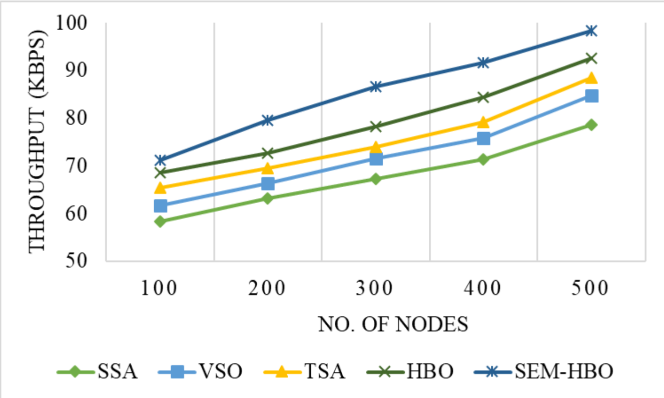

Figure 3. Result evaluation of throughput (Kbps)

3.2. Comparative analysis

The SEM-HBO performance is evaluated comparatively by existing research like HSA-CSO [21], IDTOMHR [22], and POWER [23] with a simulation area of 1000 m×1000 m. The SEM-HBO performance is efficient and it achieves 99.62% and 99.59% of PDR for 100 and 200 nodes. Table 5 signifies the parameters of different scenarios. In Table 5, scenario 1 is for HSA-CSO [21], scenario 2 is for IDTOMHR [22] and scenario 3 is for POWER [23]. The SEM-HBO performance is configured for the parameters mentioned in Table 5 for evaluating performance. Table 6 signifies a comparative result.

Table 5. Simulation parameters of different scenario

Parameters	Scenario		
	1	2	3
Sensor nodes	50, 100, 150, 200	50, 100, 150, 200, 250	100, 200, 300, 400, 500
Area	1,000 m × 1,000 m	1,000 m × 1,000 m	1,000 m × 1,000 m
Initial energy	1J	NA	0.5J

Table 6. Comparative result

Scenario	Performance metrics	Method	No. of nodes	
			100	200
1	PDR (%)	HSA-CSO [21]	94.5	97
		SEM-HBO	96.67	98.31
	Delay (ms)	HSA-CSO [21]	1.1	1.4
		SEM-HBO	0.8	1.1
	EC (J)	HSA-CSO [21]	0.19	0.16
		SEM-HBO	0.14	0.11
	NL (s)	HSA-CSO [21]	1950	1800
		SEM-HBO	2500	2300
2	PDR (%)	IDTOMHR [22]	96.28	95.90
		SEM-HBO	98.65	97.57
	Delay (ms)	IDTOMHR [22]	0.021	0.020
		SEM-HBO	0.017	0.014
	EC (J)	IDTOMHR [22]	3.34	7.43
		SEM-HBO	2.81	3.86
	NL (s)	IDTOMHR [22]	22854	20598
		SEM-HBO	23961	22493
	Throughput (Kbps)	IDTOMHR [22]	53	63
		SEM-HBO	68	71
3	PDR (%)	POWER [23]	99.1	99.4
		SEM-HBO	99.57	99.65
	Delay (ms)	POWER [23]	0.04	0.09
		SEM-HBO	0.02	0.05
	EC (J)	POWER [23]	2.26	2.42
		SEM-HBO	1.64	1.57
	NL (s)	POWER [23]	1545	2138
		SEM-HBO	2900	3500
	Throughput (Kbps)	POWER [23]	19.17	25.69
		SEM-HBO	54.67	67.85

3.3. Discussion

The existing clustering and routing techniques have drawbacks which are discussed in this section. In HSA-CSO [21] considered energy as fitness that fail to utilize distance, thus the path with huge distance reduces the network lifetime. IDTOMHR [22] requires an extensive number of control packets which are transmitted to the route selection that higher the routing load. POWER [23] required restricted transmission for transmitting data through nodes due to bandwidth constraints which increases the delay. TSA-DCSO [24] did not consider cluster density which resultant in packet drop over the network due to the increased probability of selecting the attack node as CH. M-GEO [25] has inappropriate fitness function parameters which minimized the network lifetime due to inefficient resource utilization. To overcome these flaws, this research proposed a SEM-HBO which explores different routes and recognizes best one for reducing energy consumption and delay thereby enhancing network lifetime. The SEM-HBO overcome these limitations through balancing distance and residual energy at CH and route selection which enhances the network performance. The result of this research supports scientific consensus on the significant of effective clustering and routing in WSN to enhance network performance. Moreover, this research addresses the limitations of existing techniques such as limited transmission range which leads to increase the delay due to inappropriate fitness function. The SEM-HBO optimizes resource utilization and network lifetime by considering factors like distance, communication cost, cluster density, and residual energy.

4. CONCLUSION

The SEM-HBO is proposed for the selection of CH and route path in WSN environment reduces the energy consumption and enhances the lifetime. It explores different routes and recognize best one for reducing energy consumption and delay thereby enhancing network lifetime. The distance, communication cost, residual energy and cluster density are taken as fitness for CH selection; additionally, distance and residual energy are taken as fitness function for selecting route path which enhances the network lifespan and reduces the energy consumption. By using SEM-HBO search behaviour, it explores different routes and recognize best one for reducing energy consumption and delay thereby enhancing network lifetime. By implementing SEM-HBO in WSN enhances the network lifetime and minimizes the energy consumption. This approach optimizes CH and route selection to offers robust solution for reliable and efficient data transmission in WSN. The SEM-HBO algorithm delivers robust solution for addressing energy consumption and network lifetime challenges in WSN which significantly enhances the reliability and efficiency of WSN in various applications. The SEM-HBO efficiently performed and achieved 99.62% and 99.59% of PDR for

100 and 200 nodes. Future research on SEM-HBO for WSN discover hybrid optimization algorithms, dynamic network conditions and scalability. The key experiments include real-world deployments, parameter sensitivity analysis and comparative analysis with innovative techniques. Moreover, incorporating SEM-HBO with internet of things (IoT) environments and testing fault tolerance provides practical applications.

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