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Research Article

Cluster Head Selection for the Internet of Things Using a Sandpiper Optimization Algorithm (SOA)

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In recent years, our life has become broader and faster by adapting to the Internet of Things (IoT). In IoT, the devices distributed globally that are connected to the Internet improve productivity in various sectors. The network plays an important role for transferring data to the sink node by collecting from all other nodes in IoT. The IoT requires energy saving since it is connected to resource-constrained devices. Energy preservation is a difficult challenge to improve network lifetime in IoT. Clustering is one of the key techniques to extend the network's life. In that, cluster head selection is one of the promising techniques to extend the lifespan of the IoT network. Many researchers proposed various cluster head (CH) selection techniques in IoT. However, inappropriate CH selection quickly degrades a network battery and creates an energy-hole problem in the network. This paper proposes a novel sandpiper optimization algorithm (SOA) to select CH among the networks. Later, the cluster is formed by using the Euclidean distance. The proposed SOA's accomplishments are compared to fitness value-based improved grey wolf optimization (FIGWO), particle swarm optimization (PSO), artificial bee colony-SD (ABC-SD), and improved artificial bee colony (IABC). The proposed SOA extends the network lifespan by 3-18% and increases the throughput by 6-10%. Thus, the proposed SOA increases the network lifetime and throughput and decreases the energy consumption among the nodes in the network.

1. Introduction

The Internet of Things (IoT) is a new research field that has drawn researchers from academia and industry. The IoT is a new network paradigm that changed the traditional human lifestyle to sophisticated life. Kevin Ashton coined the term IoT in 1999 [1–3]. The IoT is a network of things that are linked to the Internet and that communicate with one another by exchanging information. The IoT applications are smart home, smart farming, smart grid, smart healthcare, smart transportation, smart cities, etc. [4–6].

Wireless sensor networks (WSN) contain an interconnected sensors that can exchange information wirelessly about the environment. With recent technological developments, small sensors and actuators with minimal cost and power consumption are now accessible. Each sensor node is made up of modules for sensing, data processing, and data transfer [7–9]. The WSN applications are personal health monitoring, environment monitoring, etc. Some applications require a large number of nodes. As a result, maintaining a high number of nodes requires efficient, scalable algorithms. The WSN may change the network structure dynamically due to its external causes or system designers. Therefore, it may suffer the routing process, delay, localization, etc. Hence, WSN requires redesigning a network to improve the overall network performance [10–12].

The WSN concepts can use various applications in real time. The network's nodes are powered by batteries. The energy consumed by wireless communication is proportional to the transmission distance; thus, nodes located in various places spend different amounts of energy [13, 14]. Thus, the network nodes maintain the uneven energy distribution. Routing is significant in the exchange of data between participants and sinks in WSN-based IoT. The routing problem suffers from the overall network lifetime. So, various routing protocols are proposed to improve network performance. The routing protocols are categorized based on network structure, node participation, and mode of functioning and clustering protocols [15, 16].

Clustering is one of the best choices for transmitting the data in WSN-based IoT due to its energy-saving capability. Clustering provides the data aggregation facility to reduce the redundant data transmission between cluster members (CMs) and sink in the network [17, 18]. In clustering protocol, the cluster head (CH) plays a significant role to choose the suitable CM among various other CMs. Numerous researchers proposed various CH selection strategies for finding the good CH in a network. However, optimization is the optimal strategy for determining the CH in a network.

The optimization algorithm is an iterative procedure that can repeatedly execute until it finds the best solution. Numerous researchers have developed a variety of optimization algorithms in the recent years, including ant colony optimization (ACO) [19], particle swarm optimization (PSO) [20], genetic algorithm (GA) [21], grey wolf optimization (GWO) [22], salp swarm algorithm (SSA) [23], krill herd (KH) optimization algorithm [24], and bat algorithm (BA) [25]. Nevertheless, many optimization methods require considerable convergence time during the CH selection process. Thus, the node's battery is depleting quickly after certain network rounds. In order to solve these issues, this paper suggests SOA to increase the network's life. Thus, the proposed SOA extends the network lifetime and throughput.

The primary contribution of this work is as follows:

(i) Design and development of SOA-CHS with the purpose of selecting the optimal CH in addition to extending the network's life and enhancing throughput

(ii) An extensive analysis was conducted with various optimization algorithms with respect to the proposed SOA-CHS algorithm to extend the network's lifespan

(iii) The simulation is run numerous times in order to evaluate the performance of the proposed SOA algorithm, and the sink node is placed in the center of the network region in order to examine its overall performance

(iv) To efficiently compute the fitness function, this paper makes use of the Euclidean distance, and the best sandpiper serves as CH throughout the given network round

The remainder of the paper is divided into the following sections: Section 2 outlines the related work on CH selection algorithms using optimization algorithms. Section 3 describes the proposed CH selection, which is based on the SOA algorithm. Section 4 elaborates on the results and discussion. Section 5 summarizes the paper and mentions future work.

2. Related Work

Wang et al. [26] suggested an improved artificial bee colony (IABC) algorithm to pick CH in IoT. In CH selection, the IABC algorithm considered the parameters, namely, CH energy, CH density, and CH location. The cluster is constructed using a fuzzy C-means algorithm. The CH is chosen using an IABC algorithm. In addition, the polling control mechanism is used to maintain the busy or idle states for intracluster communication. The IABC algorithm is compared to the PSO, ABC-SD, LACH-C, and FIGWO algorithms in terms of efficacy. Thus, it increased the lifespan of the network by 5-8%, respectively. However, the CH is far away from the sink; it consumes more energy than other nodes during the communication.

Alazab et al. [27] proposed a fitness averaged rider optimization algorithm (FA-ROA) for CH selection in IoT. The primary goal of this work is to decrease latency and extend the life of the network. The fitness function is computed utilising factors such as delay, energy, and distance. The proposed FA-ROA provides two sets of solutions. The first set is obtained by taking the average of the bypass rider values and follower rider values. The second set is based on the qualities of the riders who are attempting to overtake and attack. FA-ROA is being evaluated in comparison to ROA, SAWOA, WOA, MFO, and GFO to determine its effectiveness. As a result, the network's lifetime has been extended. However, it consumes more energy by considering the factors, namely, temperature, load, and data traffic. Also, it takes more time to converge during the CH selection. FA-ROA has improved the overall mean performance of alive nodes to 22.13% compared with existing optimization methods.

Bakshi et al. [28] adopted the glow-worm swarm optimization (GWSO) method for determining the CH in the Internet of Things. It provides the adaptive CH selection using the GWSO algorithm. Many existing algorithms form a cluster from the fixed nodes in the network. It is ineffective when there are a large number of dead nodes in the network. In the proposed clustering approach, the nodes are not fixed, and it changes the nodes in the cluster which is dynamic. Thus, it increases the lifespan of the network by 8-12%, respectively. Some nodes perished after a specific run owing to the cluster's dynamic nature.

Sankar et al. [29] proposed an efficient cluster-based routing protocol in IoT. It entails the selection of CHs as well as cluster formation. The sailfish algorithm is employed to pick the CH. The cluster is generated using the Euclidean distance. The SOA's effectiveness is evaluated in comparison to the EPSOCT, HCCHE, and IAB-COCT. The proposed SOA provides superior performance by means of network lifespan and throughput. In contrast to other algorithms, it has difficulties when it comes to trying to increase the number of rounds in the network, and it also takes significantly longer than other algorithms to converge when doing the CH selection process. The proposed SOA method improves network lifespan by 5-10% and decreases latency by 10-20%.

Zhang and Wang [30] proposed an energy-aware bioinspired algorithm in IoT to prolong the network's lifespan. This paper presented the PSO-WZ, which is adopted from the particle swarm optimization (PSO) algorithm. The CH is selected using PSO-WZ. Later, the division rule is used to form the cluster around the CH in the network. The simulation is conducted using MATLAB. The efficacy of the proposed PSO-WZ is compared to LEACH and PSO-C. The proposed PSO-WZ outperforms both LEACH and PSO-C by means of network lifetime and throughput. As a result, the network's lifetime has been improved by 5-10%. However, this type of algorithm is suitable for specific applications in WSN and IoT.

Khot and Naik [31] proposed particle-water wave optimization for CH selection in WSN. This paper presented the particle water wave optimization (PWWO) algorithm, which combines the PSO and water wave optimization (WWO) algorithms. The CH was selected using the PSO algorithm. The fitness value is computed using the parameters, namely, energy, trust, consistency factor, delay, and maintainability factor. After the CH selection, the path is established between CH and sink using the PWWO algorithm. The efficacy of the PWWO algorithm is compared to DICMLA and P-SMO. The proposed PWWO is provided superior performance by means of energy balancing index, network coverage, alive nodes, and left-out energy with values 0.9246, 99.9%, 144, and 0.666 J. As a result, the network's life span is extended. However, the fitness measure takes more time to compute the CH selection.

Shyjith et al. [32] proposed a dynamic CH selection in WSN to enhance the lifespan of the network. The selection of dynamic CH is a pivotal role in WSN to improve the network performances. This paper proposed rider-cat swarm optimization (RCSO) to pick the right CH in the WSN. The RSCO has setup, transmission, and measurement stages. The CH is elected using the RSCO algorithm. The threshold and CH selection are done on the basis of network parameters, namely, distance, delay, and energy. The data transmission stage ensures to exchange the data between CH and sink. Finally, during the measurement phase, the remaining energy of each node in the network is updated on a periodic basis. The proposed RCSO algorithm is compared to similar algorithms. The proposed algorithm improved the overall network performances such as throughput, alive nodes, and maximum provided energy with values 74.715%, 18, and 0.0351 J. During the CH selection process in the network, it takes some time for the network to converge.

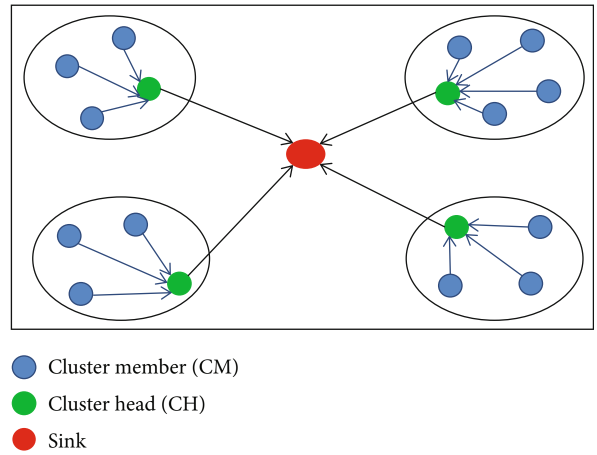

Figure 1: SOA network model.

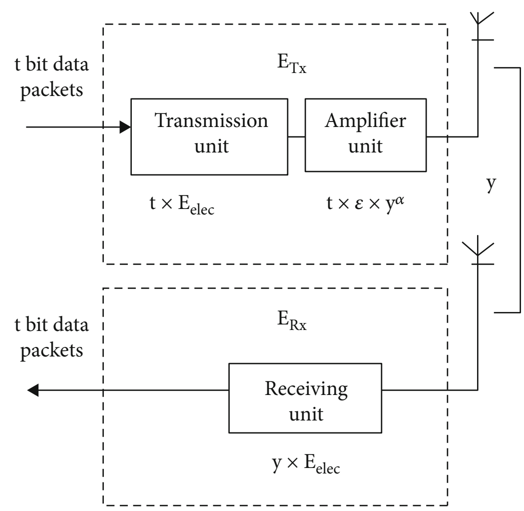

Figure 2: SOA energy model.

After conducting a review of related work, it was discovered that many optimization approaches for CH selection in WSN-based IoT have been presented. It is observed that the following limitations are as follows: (i) it takes more convergence time. (ii) It takes time to compute the fitness function. To solve these limitations, this paper proposes SOA-based CH selection to increase the network's lifespan.

3. System Model

3.1. Network Model. The network contains "N" nodes deployed randomly in monitoring areas. All the nodes are static and cannot move from one place to another after the deployment, and no intervention happens once the network is created. Each node in the network has a unique ID and is homogeneous with other nodes in terms of initial energy, processing, and communicational energies. The sink is located at the center of the network. The CH node is a focusing element in the network that affects the communication among sensor nodes. The CH selection algorithm runs in

Input: Network population is set of nodes "*N*".
Output: Best Sandpipers location act as CH.
1: while (true)
2: Initialize search agent S_p and movement of sandpiper S_m.
//migration phase.
3: Compute S_p and S_m for collision avoidance using Equations (4) and (5).
4: Compute best position of sandpiper using Equation (6).
5: Updating position of the best sandpiper using Equation (8).
// Attacking phase.
6: Create spiral behavior to attack the prey using Equation (9)-Equation (12).
7: Compute the fitness function Equation (16).
8: if sandpiper reaches its best search agent in the network then.
9: Best sandpipers act as CH
10: else.
11: Go to step 1
12: return CH.

ALGORITHM 1: CH selection using SOA.

the sink. The sink selects the optimal CH in the network nodes using SOA. Later, the clusters form on the basis of the Euclidean distance. The CH gathers the data and transfers the aggregated data to the sink. Figure 1 shows the SOA network model.

3.2. Energy Model. Figure 2 shows the SOA energy model which is followed by the standard WSN energy model [33]. The SOA follows the channel model according to the distance "*y*" between the transmitter "*s*" and receiver "*r*."

The amount of energy is consumed by "*t*" bits of data between transmitter "*s*" and receiver "*r*," and it is given in the following equation:

$$E_{\mathrm{TX}}(t, y) = tE_{\mathrm{elec}} + m\varepsilon \mathrm{y}(\mathrm{s}, \mathrm{r})^{\alpha} = \begin{cases} tE_{\mathrm{elec}} + t\varepsilon_{\mathrm{ft}} \mathrm{y}(\mathrm{s}, \mathrm{r})^2 \text{ where } \mathrm{y}(\mathrm{s}, \mathrm{r}) < \mathrm{y}_0 \\ tE_{\mathrm{elec}} + t\varepsilon_{\mathrm{mp}} \mathrm{y}(\mathrm{s}, \mathrm{r})^4 \text{ where } \mathrm{y}(\mathrm{s}, \mathrm{r}) \geq \mathrm{y}_0 \end{cases}, \quad (1)$$

where $t\varepsilon_{\mathrm{fr}}\mathrm{y}(\mathrm{s}, \mathrm{r})^2$ or $t\varepsilon_{\mathrm{mp}}\mathrm{y}(\mathrm{s}, \mathrm{r})^4$ is the energy consumption of the amplifier unit.

The threshold value y_0 is calculated in the following equation:

$$y_0 = \sqrt{\frac{\varepsilon_{\mathrm{ft}}}{\varepsilon_{\mathrm{mp}}}}, \quad (2)$$

where $\varepsilon_{\mathrm{ft}}$ is free space fading amplifier energy and $\varepsilon_{\mathrm{mp}}$ is multipath fading amplifier energy.

The receiver spends the amount of energy for receiving "*y*" bits from *r* to *s*, and its calculation is given in the following equation:

$$E_{\mathrm{RX}}(y) = yE_{\mathrm{elec}}, \quad (3)$$

where E_{elec} is the cost of circuit energy when transmitting or receiving one bit of data and *y* is the number of transmitted bits.

TABLE 1: Simulation setting and value.

Parameter	Value
Network area	$100 \times 100\mathrm{m}^2$
Sink location	(50, 50)
Number of sensor nodes	100, 200, and 300
Percentage of CH	5%
Control packet size	200 bits
Data packet size	4000 bits
ϵ_{fs}	100 PJ/bit/m^2
ϵ_{mp}	0.0013 PJ/bit/m^4

4. The Proposed Cluster Head Selection Using Sandpiper Optimization Algorithm

This paper proposes a sandpiper optimization algorithm (SOA) to choose the right CH in IoT [34]. The sink is situated in the network's center. The sink executes the SOA for choosing the best CH. Later on, a cluster is generated on the basis of the Euclidean distance between the nodes in the network.

Sandpipers are seabirds that reside in groups called colonies. They exploit their intellect to locate and attack their prey. It has two phases, namely, the migration and attacking phase.

4.1. Migration Phase (Exploration). It is a seasonal movement of sandpipers (S) from one location to another for eating food to gain energy. It follows the properties, and it is mentioned below.

(i) The sandpipers travel in a group during the migration phase. Initially, the entire sandpiper starts with different positions to avoid a collision

(ii) In a group, the entire sandpiper moves toward the sandpiper's optimum fitness value. The optimal

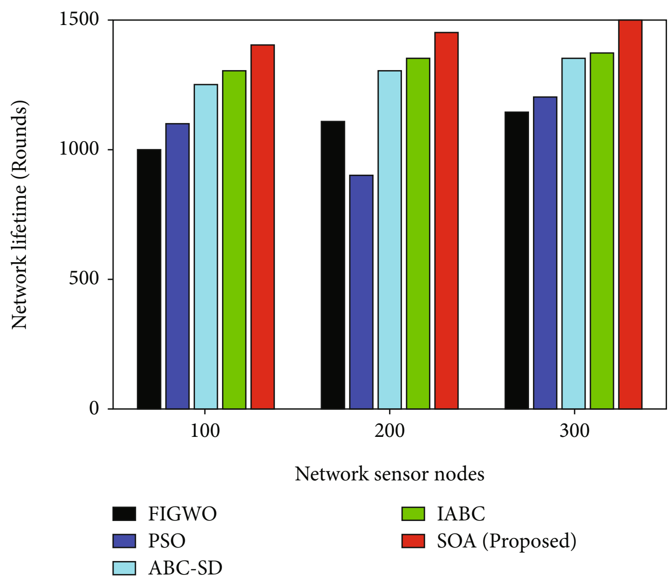

FIGURE 3: Network lifetime vs. network sensor nodes.

TABLE 2: Network lifetime vs. network sensor nodes.

Number of sensor nodes	Network lifetime (rounds)				
	FIGWO	PSO	ABC-SD	IABC	SOA
100	1000	1100	1250	1300	1400
200	1100	900	1300	1350	1450
300	1150	1200	1350	1375	1500

fitness value is the smallest in this case due to the minimization property

(iii) The sandpipers update their position based on the locations of the best sandpiper

The sandpipers need to satisfy three conditions during the migration phase.

4.1.1. Collision Avoidance. The sandpiper or search agent generates a new position without collision S_p, and it is given in the following equation:

$$S_p = S_m \times S_{cp}(t), \tag{4}$$

where S_m denotes the movement of the sandpiper, S_{cp} indicates the current position of the sandpiper, and t indicates the current iteration.

The movement of the sandpiper S_m is calculated, and it is given in the following equation:

$$\mathrm{S_m} = \mathrm{S_{cf}} - (\mathrm{t} \times (\mathrm{S_{cf}}/\mathrm{Maximum_{iterations}})), \tag{5}$$

where S_{cf} indicates sandpiper control frequency which is decreased from 2 to 0 and t indicates the iteration which varies the values from 0 to maximum iterations.

4.1.2. Converge the Best Position of the Sandpiper. In order to converge, the sandpipers move to the direction from the current position S_{cp} to best sandpiper S_{best}, and its calculation is given in the following equation:

$$M_s = S_{BC} \times (S_{best}(t) - S_{cp}(t)), \tag{6}$$

where S_{BC} denotes the random variable which is based on the exploration.

The S_{BC} is calculated, and it is given in the following equation:

$$S_{BC} = 0.5 \times \mathrm{rand}, \tag{7}$$

where rand is a random number that holds a value ranging between 0 and 1.

4.1.3. Updating the Position to the Best Sandpiper. Finally, the sandpiper updates its current position to the best sandpiper's position, and it is given in the following equation:

$$G_s = S_p + M_s, \tag{8}$$

where G_s indicates the gap between the sandpiper's position and the best location of the sandpiper.

4.2. Attacking Phase (Exploration). During the attacking phase, the sandpipers create the spiral behavior in the 3-dimensional plane, and its representation is given in the

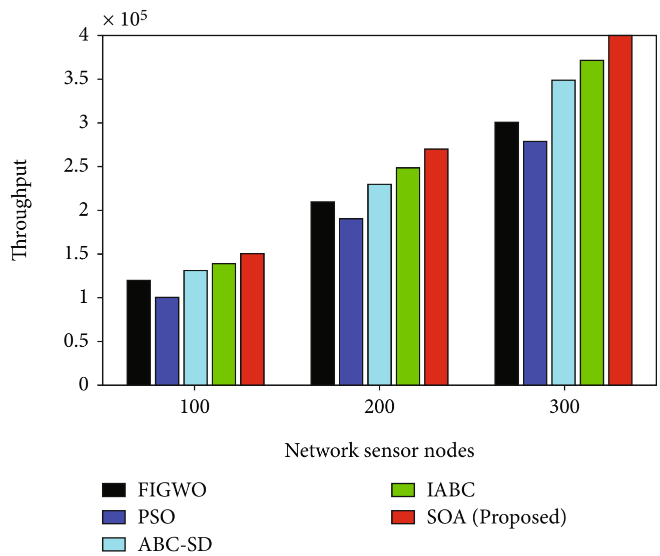

FIGURE 4: Throughput vs. network sensor nodes.

TABLE 3: Throughput vs. network sensor nodes.

Number of sensor nodes	Throughput (packets) FIGWO	PSO	ABC-SD	IABC	SOA
100	120000	100000	130000	140000	150000
200	210000	190000	230000	250000	270000
300	300000	280000	350000	370000	400000

following equations:

$$X' = r \times \sin(j), \tag{9}$$

$$Y' = r \times \cos(j), \tag{10}$$

$$Z' = r \times j, \tag{11}$$

$$r = l \times e^{km}, \tag{12}$$

where r indicates the radius of the spiral, j is a variable and its value between 0 and 2?, l and m are constant of the spiral value, and e is the base of the natural logarithm. Let l and m values set to be 1.

The updated position of the sandpiper $S_{p\_\text{new}}(t)$ is calculated, and it is given in the following equation:

$$S_{p\_\text{new}}(t) = \left(G_s \times \left(X' + Y' + Z'\right)\right) \times S_p(t). \tag{13}$$

4.3. Computing the Fitness Function. The average fitness denotes the average objective value of all the sandpipers in each iteration. The objective function is computed using the Euclidean distance. The SOA selection of the best position is based on the objective value which holds a minimum distance among various nodes in the respective iteration. The overall CH selection process is given in Algorithm 1.

4.3.1. Residual Energy (RER). The RER specifies total amount of energy available in network [35]. The following equation evaluates the remaining energy from spent energy and initial energy. It is given in the following equation:

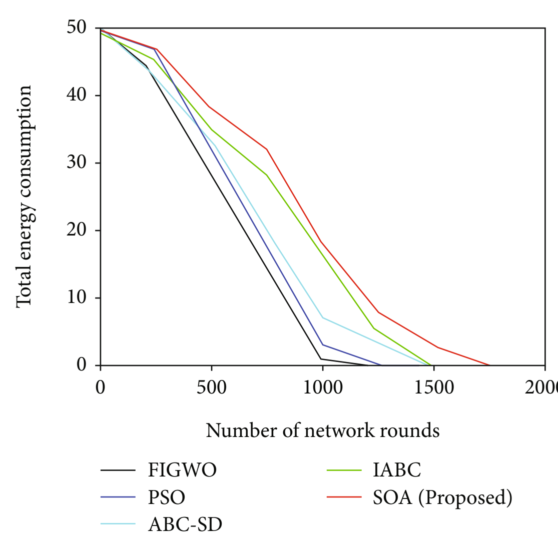

FIGURE 5: Total energy consumption vs. number of network rounds (network size is 100).

$$\text{RER}(n) = \frac{\text{Energy}_{\text{avail}}}{\text{Energy}_{\text{initial}}}, \tag{14}$$

where $\text{Energy}_{\text{avail}}$ and $\text{Energy}_{\text{initial}}$ are the currently available energy and initial energy of the network.

Table 4: Total energy consumption vs. number of network rounds (network size is 100).

Number of network rounds	Total energy (J) FIGWO	PSO	ABC-SD	IABC	SOA
0	50	50	50	50	50
250	43	47	43	45	47
500	28	32	33	35	38
750	15	18	20	28	32
1000	1	3	7	5	8
1250	0	0	3	5	8
1500	0	0	0	0	0
1750	0	0	0	0	0
2000	0	0	0	0	0

4.3.2. Distance. The distance between the sensor node (n_i) and sink node is calculated using the Euclidean distance [36]. It is given in the following equation:

$$\mathrm{dis}(n_i, \mathrm{sink}) = \sqrt{\sum_{i=1}^{n} (\mathrm{sink} - n_i)^2}. \quad (15)$$

The current position of the sandpiper fitness function $S_{p\_\mathrm{new}}(t)_{\mathrm{fitness}}$ is calculated in the following equation:

$$S_{p\_\mathrm{new}}(t)_{\mathrm{fitness}} = 0.5 \times \left(1 - \mathrm{RER}\left(S_{p\_\mathrm{new}}(t)\right) + 0.5 \times \left(1 - \mathrm{dis}\left(S_{p\_\mathrm{new}}(t)\right)\right.\right. \quad (16)$$

4.4. Cluster Formation. The network contains "N" number of nodes which are formed into various clusters after CH selection using the Euclidean distance, and it is given in the following equation:

$$\mathrm{dist}\left(S_{\mathrm{pi}}, S_{\mathrm{pj}}\right) = \sqrt{\sum_{i=1}^{n} \left(S_{\mathrm{pj}} - S_{\mathrm{pi}}\right)^2}, \quad (17)$$

where S_{pi} and S_{pj} are two nodes in the network space.

5. Result and Discussions

The performance of proposed SOAs is evaluated in comparison to FIGWO, PSO, ABC-SD, and IABC. The MATLAB 2019a simulator is unutilized for simulation [37]. We have considered the number of nodes as 100, 200, and 300 to prove the performance of the proposed algorithm. The nodes are randomly distributed throughout the network. The simulation network area is $100 \times 100\,\mathrm{m}^2$. The overall effectiveness of the proposed SOA is assessed by means of network longevity, throughput, and overall energy usage and compared with state of art works under the same simulation. Table 1 provides the simulation setting and values.

5.1. Network Lifetime. Figure 3 shows the network lifetime with respect to the network sensor nodes. In this simulation, we have taken 100, 200, and 300 nodes. For a network size of 100, it is found that the number of nodes that are dead in FIGWO, PSO, ASC-SD, IABC, and SOA is 1000, 1100, 1250,

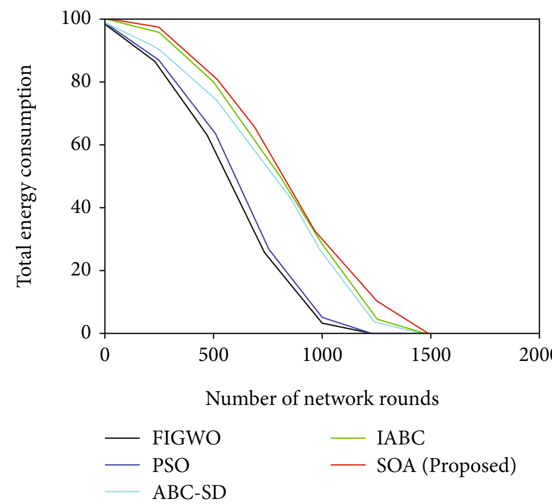

Figure 6: Total energy consumption vs. number of network rounds (network size is 200).

1300, and 1400, respectively. For a network of 200 nodes, the number of dead nodes in FIGWO, PSO, ASC-SD, IABC, and SOA is 1100, 900, 1300, 1350, and 1450, respectively. Similarly, for a network of 300 nodes, the number of dead nodes in FIGWO, PSO, ASC-SD, IABC, and SOA is 1150, 1200, 1350, 1375, and 1500, respectively. As previously stated, it is seen that the SOA enhances the lifetime in all the situations when the network size is 100, 200, and 300 nodes, respectively. It is due to the use of the sandpiper optimization algorithm, which reduces the amount of time required for convergence during the CH selection process.

Table 2 shows the network lifetime with respect to the network sensor nodes. It is noticed that the SOA enhances the lifetime in all the situations when the network size is 100, 200, and 300 nodes, respectively. It is due to the use of the sandpiper optimization algorithm, which reduces the amount of time required for convergence during the CH selection process.

5.2. Throughput. Figure 4 shows the throughput with respect to the network sensor nodes. For a network size of 100, the throughput in FIGWO, PSO, ASC-SD, IABC, and SOA are

Table 5: Total energy consumption vs. number of network rounds (network size is 200).

Number of network rounds	Total energy (J)				
	FIGWO	PSO	ABC-SD	IABC	SOA
0	100	100	100	100	100
250	85	87	90	95	97
500	60	63	75	80	82
750	25	28	55	57	59
1000	3	5	25	27	29
1250	0	0	3	5	10
1500	0	0	0	0	0
1750	0	0	0	0	0
2000	0	0	0	0	0

120000, 100000, 130000, 140000, and 150000 packets, respectively. For the network size of 200, the throughput in FIGWO, PSO, ASC-SD, IABC, and SOA are 210000, 190000, 230000, 250000, and 270000 packets, respectively. For the network size of 300, the throughput in FIGWO, PSO, ASC-SD, IABC, and SOA are 300000, 280000, 350000, 370000, and 400000 packets, respectively. As previously stated, the amount of packets delivered from participants to the sink is large in SOA when compared to all other similar algorithms, including FIGWO, PSO, ASC-SD, and IABC. It is because of the proposed optimization algorithm's major consideration that it takes less time to reach convergence during the CH rotation. In addition, the proposed algorithm enhances the network's lifetime. This is the reason to increase the throughput more than all other algorithms.

Table 3 shows the throughput with respect to the network sensor nodes. As previously stated, the amount of packets delivered from participants to the sink is large in SOA when compared to all other similar algorithms, including FIGWO, PSO, ASC-SD, and IABC. It is because of the proposed optimization algorithm's major consideration that it takes less time to reach convergence during the CH rotation.

5.3. Total Energy Consumption. Figure 5 shows the overall energy use proportional to the network size. The total number of nodes is 100. For the 1000th network rounds, it is found that the overall energy consumption in FIGWO, PSO, ABC-SD, IABC, and SOA is 1 J, 3 J, 7 J, 15 J, and 18 J, respectively. The proposed SOA consumes less energy than other algorithms. This is mostly due to the consideration of the SOA algorithm, which has a shorter convergence time.

Table 4 shows the overall energy use proportional to the network size of 100 nodes. The proposed SOA consumes less energy than other algorithms. This is mostly due to the consideration of the SOA algorithm, which has a shorter convergence time.

Figure 6 shows the overall energy use proportional to the network size. The total number of nodes is 200. For the 1000th network round, it is observed that the total energy consumption in FIGWO, PSO, ABC-SD, IABC, and SOA are 3 J, 5 J, 25 J, 27 J, and 29 J, respectively. It should be emphasized that the suggested SOA consumes less energy than other algorithms. This is mostly owing to the use of the SOA algorithm, which has a faster convergence time.

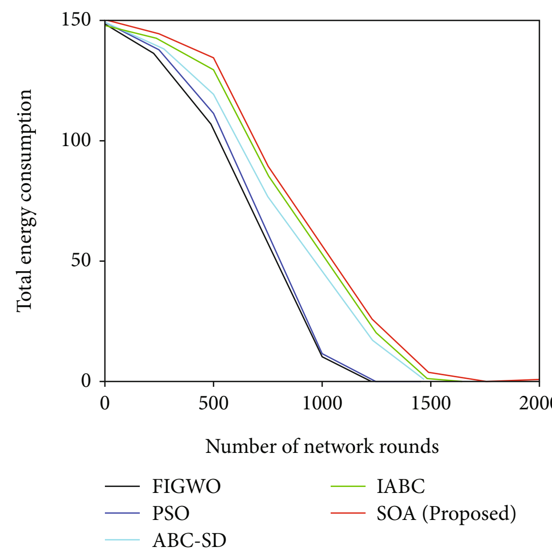

Figure 7: Total energy consumption vs. number of network rounds (network size is 300).

Table 5 shows the overall energy use proportional to the network size of 200 nodes. It should be emphasized that the suggested SOA consumes less energy than other algorithms. This is mostly owing to the use of the SOA algorithm, which has a faster convergence time.

Figure 7 shows the overall energy use proportional to the network size. The total number of nodes is 300. For the 1000th network round, it is observed that the total energy consumption in FIGWO, PSO, ABC-SD, IABC, and SOA are 10 J, 12 J, 45 J, 50 J, and 55 J, respectively. It should be emphasized that the suggested SOA consumes less energy than other algorithms. This is mostly owing to the use of the SOA algorithm, which has a faster convergence time.

Table 6 shows the overall energy use proportional to the network size of 300 nodes. It should be emphasized that the suggested SOA consumes less energy than other algorithms. This is mostly owing to the use of the SOA algorithm, which has a faster convergence time.

Table 6: Total energy consumption vs. number of network rounds (network size is 300).

Number of network rounds	Total energy (J)				
	FIGWO	PSO	ABC-SD	IABC	SOA
0	150	150	150	150	150
250	135	138	140	142	145
500	105	110	120	130	135
750	60	65	77	85	90
1000	10	12	45	50	55
1250	0	0	15	20	25
1500	0	0	0	0	3
1750	0	0	0	0	0
2000	0	0	0	0	0

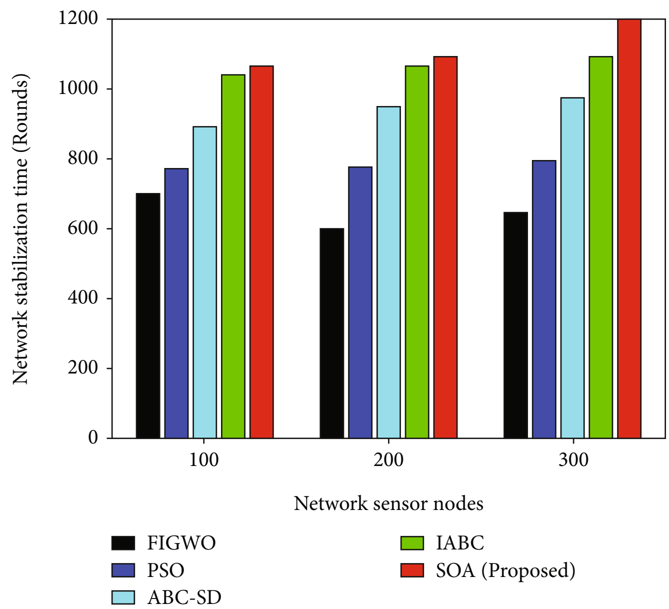

Figure 8: Network stabilization time vs. network sensor nodes.

Table 7: Network stabilization time vs. network sensor nodes.

Number of sensor nodes	Network stabilization time (rounds)				
	FIGWO	PSO	ABC-SD	IABC	SOA
100	700	775	900	1050	1075
200	600	780	950	1075	1100
300	650	800	975	1100	1200

5.4. Network Stabilization Time. Figure 8 indicates the network stabilization time with respect to network size. It is observed in Figure 8 that the proposed SOA algorithm which stabilizes the network is better than FIGWO, PSO, ABC-SD, and IABC. It is mainly due to fast convergence that consumes less energy in the network nodes. It is also noted that the proposed SOA algorithm is highly suitable for dense networks.

Table 7 indicates the network stabilization time with respect to network size. It is observed in Table 7 that the proposed SOA algorithm which stabilizes the network is better than FIGWO, PSO, ABC-SD, and IABC. For a network size of 300, the network is more stable in the 1200th round in SOA. It provides more stability and depletes energy more slowly than other existing algorithms.

6. Analysis and Discussion

The simulation results show that the proposed SOA algorithm provides superior performance than FIGWO, PSO, ABC-SD, and IABC. The simulation is conducted with different network sizes. The network sizes are varied in ranges such as 100, 200, and 300. The sink is located at (50 m and 50 m). The placing of the sink location plays a major role in WSN and IoT networks. The sink is executed the CH selection using SOA. From the simulations, we observed that the total network lifetime and throughput are high at a network size of 300 compared to 100 and 200. It is also noticed that the proposed SOA stabilized the network at a range of 1200th round, for the network size of 300. Hence, we conclude that the proposed SOA outperforms in the dense network than other algorithms.

7. Conclusion and Future Work

Energy saving is critical in the IoT, which connects devices with limited resources. Clustering is the most effective method of extending the life of a network. As a result of the incorrect CH selection in the network nodes, the battery is depleted prematurely. To overcome this issue, this paper proposes a novel sandpiper optimization algorithm (SOA) which considers distance and residual energy parameters to form a cluster and choose the appropriate cluster head node to enhance the longevity of the network. The simulation is conducted with different network sizes, and the sink is placed at the center of the network area. The proposed SOA's accomplishments are compared to FIGWO, PSO, ABC-SD, and IABC. The proposed SOA extends the network lifespan by 3-18% and increases the throughput by 6-10%. As a result, the network's overall performance is improved.

In the future, real-time network nodes will be deployed to assess the effectiveness of SOA in comparison to similar optimization algorithms. In addition, we can also expand it for multiobjective problems or dynamic problems.

Data Availability

The dataset used for this work is randomly generated in MATLAB.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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