Received October 25, 2021, accepted November 3, 2021, date of publication November 8, 2021,
date of current version November 30, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3126537

An Improved Sunflower Optimization Algorithm for Cluster Head Selection in the Internet of Things

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ABSTRACT Due to the widespread of smart devices and services, the Internet of Things (IoT) has gained attention from researchers and is still in constant development. Many challenges face the IoT networks and need to be solved. Reducing energy consumption to increase the network lifetime is the main issue among these challenges. The clustering approach is one of the best solutions to solve this issue. Choosing the best Cluster Heads (CHs) can consume less energy in the IoT-WSN. Swarm Intelligence (SI) algorithms can help to solve complicated problems. In this paper, we propose a novel algorithm to select the best CHs in the IoT-WSN. The novel algorithm is called an Improved Sunflower Optimization Algorithm (ISFO). In the ISFO, we combine the Sunflower Optimization Algorithm (SFO) with the lèvy flight operator. Such invoking can balance the diversification and intensification processes of the proposed algorithm and avoid trapping in local minima. We compare the ISFO algorithm with six SI algorithms. The results of the proposed algorithm show that it can consume less energy than the other algorithms, also the number of nodes still alive for it is larger than alive nodes for the other algorithms. Hence, the ISFO algorithm proved its superiority in reducing the consumed energy and increasing the lifetime of the network.

INDEX TERMS Cluster head selection, Internet of Things (IoT), lèvy flight operator, network life time, sunflower optimization algorithm (SFO).

I. INTRODUCTION

Internet of Things (IoT) has attracted great interest from researchers in recent years and is still in constant growth. IoT is a kind of network that involves a large number of physical devices also called " Things " and these devices are connected with the internet. The IoT network's device resources own limited processing, storage volume, bandwidth, and battery power capabilities [38], [39]. Since IoT can interpret the physical world to a digital world with useful information, it becomes an important concept in our lives. IoT is a network of objects that can sense, process, and transmit information through the use of sensors that could be a portion of a Wireless Sensor Network (WSN).

Wireless sensor networks (WSNs) play a significant role in the internet of things where they can supply services of sensing to the devices in the IoT through the sensor nodes [3]. Also in the area of network technology, the WSN is seen as of fundamental importance [11] and It had been employed in diverse applications [1], [10]. Figure 1 shows the structure of WSN.

IoT has various applications in several fields that can include education, health care, transport, smart cities, manufacturing, agriculture, military, environmental monitoring, smart grid *et al.* In these various applications, data collection is the function of the IoT devices. The amount of data collected is enormous and must be sent to the cloud for processing. The cloud may be available at a remote IoT network location. Due to the IoT limited resources, we cannot send the collected data directly to the cloud because it will make the nodes consume their energy rapidly and the network will die. To solve this issue, we must send the collected data to another base station (BS) located near the sensor nodes, and then these (BSs) forward the data to the cloud.

The associate editor coordinating the review of this manuscript and approving it for publication was Amin Zehtabian.

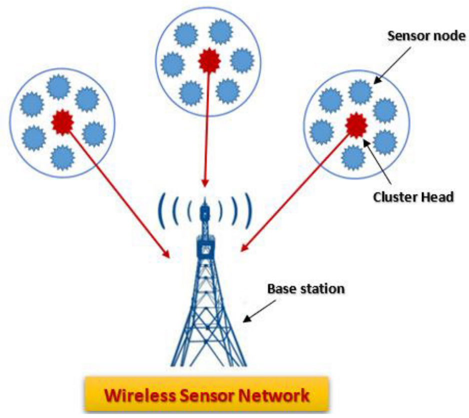

FIGURE 1. Wireless sensor network structure.

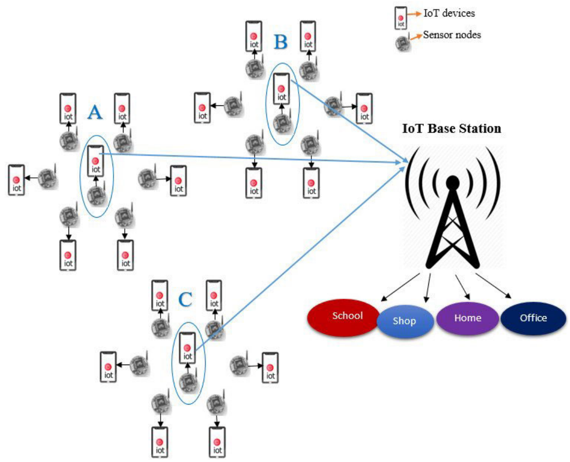

FIGURE 2. IoT network structure.

It is necessary to manage the limited IoT network resources. The main IoT challenge between these resources is energy management [20], [24], [35], and [41]. Several energy management protocols have been implemented in IoT networks. However, in some cases, these protocols may fail to function. For this reason, clustering techniques can be a good solution.

Network clustering splits the network into some groups known as clusters. Each cluster contains several sensor nodes. Among these nodes, there is one node is chosen to be the cluster head (CH). The CH works as a local BS, which is responsible for collecting the data from other nodes and send it back to the remote BS (as the cloud in IoT). Chosen the optimal CHs will conserve more energy over the IoT network, so the network will run for a longer period.

Figure 2 shows the structure of the IoT network, which contains an equal number of IoT devices and sensor nodes (SNs). where each SN is connecting to a specific IoT device. The function of each SN is to track and transfer the information to its IoT device. These devices and SNs are divided into clusters. In each cluster, there is one device is selected as a cluster head (CH) as A, B, C in Figure 2. Each CH is responsible for aggregating the data from other devices inside its cluster and then forwarding the aggregated data to the IoT BS (cloud).

Swarm intelligence (SI) algorithms have been utilized to solve complex problems [5]. In the last years, many SI algorithms have been applied in various fields and they have proved their superiority. In this paper, we proposed a distinct algorithm for the clustering process in IoT networks by merging the sunflower optimization (SFO) algorithm and the lèvy flight operator. The proposed algorithm is named ‘‘an Improved Sunflower Optimization Algorithm (ISFO) and its function is to determine the optimal cluster heads. Consequently, more energy will be saved and the IoT network lifetime will increase.

The main contribution of this paper can be summarized as follows.

- a new SI algorithm is proposed to minimize the energy consumption of the nodes and increase their lifetime.
- Invoking the lèvy flight operator in the proposed algorithm to avoid trapping in local minima.
- The proposed algorithm is proposed against six SI algorithms, the result of it can consume less energy than the other algorithms, also the number of nodes still alive for it is larger than alive nodes for the other algorithms.

The remainder of the paper is arranged as follows. We survey the related work in Section II, we present the problem formulation in Section III. In Sections IV and V, we present the standard sunflower optimization algorithm and the proposed ISFO algorithm. We analyze the numerical results in Section VI. Finally, we summarize the paper in Section VIII.

II. LITERATURE REVIEW

Reddy and Babu in [30] use the Gravitational Search Algorithm (GSA) with Artificial Bee Colony algorithm (ABC) and consider some parameters to select the CHs efficiently. Consequently, save more energy and extend the network lifetime. Cui *et al.* [9] developed the LEACH protocol which is used for the big data sensing system in the IoT. They introduce a novel algorithm called WHCBA that involves the Bat Algorithm with a weighted harmonic centroid strategy. Then they merge the WHCBA algorithm with the LEACH protocol to improve the process of the cluster head selection and reduce the consumed energy as the centroid strategy improves the local search. Also in [31] Reddy and Babu proposed a novel way using the self-adaptive whale optimization algorithm (SAWOA) for improving the clustering protocols and reducing the energy consumption in the WSN based IoT networks.

In [12] Farman *et al.* have proposed an upgraded scheme for more CH proper selection in the IoT-based WSNs. This scheme depends on multi-criteria which includes remaining energy for a node, the distance among the node and its neighbors in the same zone(cluster), distance from the middle of the zone(cluster), how many times the node became zone(cluster) head. Finally, the node was merged into another zone(cluster) or remained in its zone. The proposed scheme helped the network save more energy and extend its lifetime. A hybrid model has been produced in [32] by Reddy and Babu for selecting the cluster heads in the WSN-IoT network. The model combines Ant Lion Optimization (ALO) and Moth Flame Optimization (MFO) algorithms. The aim was to conserve more energy and reduce the delay, load, distance, and temperature of IoT devices to make the network work for a long time.

A novel algorithm called " R-LEACH " has proposed by Behera *et al.* in [3] to achieve an efficient selection for cluster heads (CHs) in the network. The R-LEACH algorithm enhances the LEACH protocol to suit the IoT applications by taking some parameters when selecting the CHs. These parameters involve the energy of the node, at the beginning, its residual energy after each round, and the suitable number of CHs.

Another hybrid algorithm for CH selection has proposed by Janakiraman in [19]. The algorithm combines Artificial Bee Colony and Ant Colony Optimization algorithms. It enhances the residual energy rate for the WSN-based IoT network, decreases the number of dead nodes. As a result, the network's lifetime has extended.

A new hybrid clustering algorithm has introduced by Kannammal and Suresh in [21] to improve the level of energy and the working period for the network. To achieve this improvement, the algorithm uses the LEACH protocol with the Firefly algorithm.

In 2020 Iwendi *et al.* [18] focused on reducing the consumed energy for the SNs in the IoT network to prolong the network lifetime. They proposed a hybrid algorithm named (WOA-SA). This algorithm aims to choose the most suitable CHs in the IoT network to reduce the consumed energy. The WOA-SA algorithm utilized the whale optimization algorithm and the simulated annealing together. the CHs chosen depend on some metrics involving the sensor residual energy, temperature, load, number of alive SNs, and the cost function.

Rajesh *et al.* [28] minimized the energy consumption in the IoT network by implementing "a multi-objective optimization routing algorithm" called BFOA-R. The BFOA-R algorithm utilizes the foraging way of M. Xanthus and E. coli bacteria to extend the network time.

A novel scheme for data routing in IoT networks has been proposed by Nguyen in [27]. The objective of this scheme is to save more energy by using the compressed sensing (CS) technique when transferring various kinds of data gathered from the devices linked to the IoT networks.

Muhammad *et al.* [26] suggested a hybrid energy-efficient algorithm for the IoT-based WSNs by applying the scheduling approach. The algorithm is called HABCA-EST where the artificial bee colony (ABC) algorithm is combined with an efficient schedule transformation.

Al-Shalabi, Mohammed, *et al.* in [2] have used a genetic algorithm for producing a novel method called Optimal Multi-hop Path Finding Method (OMPFM). This method aims to reach the optimal path from the source (cluster head) to the destination (base station) for less energy consumption and maximizing lifetime in WSNs.

In [4], Bhatt *et al.* have utilized the cuckoo search algorithm to produce an enhanced algorithm for WSN. The objective is to choose the most suitable node as the cluster head, thus achieve efficient use of the network energy and extending its lifetime.

In [7], Chauhan *et al.* have offered a different technique for determining cluster heads in heterogeneous WSN. The technique is called "DDMPEA-ANUM" which refers to Diversity-Driven Multi-Parent Evolutionary Algorithm with Adaptive Non-Uniform Mutation. The goal of the "DDMPEA-ANUM" is to save more remaining energy for the sensor nodes and make the traveled distance less. Thus, the network will work for a long time.

Sarkar *et al.* in [34] have employed the firefly optimization algorithm (FF) and Grey Wolf Optimization algorithm to produce two models for ensuring the selection of the proper cluster heads among other sensors in WSNs. Thus, save energy and work the network for a long time. The models have been called "Firefly Cyclic Randomization (FCR)" and "Firefly Cyclic Grey Wolf Optimization (FCGWO)".

Fouad *et al.* [13] have employed the traditional GWO to achieve accurately locate the sink node. When the results have compared to one of the previous WSN protocols, they have shown higher accuracy.

Snasel *et al.* [36] achieved greater accuracy for allocating the sink node in WSNs by employing a novel strategy that relies on CSO in addition to the greedy algorithm. Another different algorithm for the WSNs was used by Fouad *et al.* [14] in order to determine the optimal sink node position, which helps improve the network performance. Chen and Li in [8] have been concerned with the problem of determining the best place for the sink node in WSNs by employing different strategies that focus on the network's energy and lifetime. In [6], Cao *et al.* propose CSSO, a novel algorithm for optimizing the placement of sensor nodes in heterogeneous WSNs. For achieving optimal coverage, chaos technique and SSO (social spider optimization) algorithm have been utilizing in this algorithm.

For solving the problem of network coverage and lifetime, multiple upgraded algorithms have been utilizing depend on the PSO algorithm by Ling *et al.* in [23]. Based on the simulation data, it has been demonstrating that the upgraded algorithms perform well and have a good deployment effect. An advanced fish swarm optimization algorithm called AIFS has been employing by Qin and Xu in [37]. The objective of AIFS is to free the nodes from the local optimum and ensure that the monitoring area is effectively covered. Rajpoot and Dwivedi [29] have suggested a MADM strategy for choosing the fittest node placement with achieving the most region coverage, more connectivity, and lowest expense among a variety of choices.

We can summarize the current issues and problems in the IoT and WSN in Table 2 and the list of the used parameters abbreviations is shown in Table 1 as follows.

TABLE 1. List of parameters abbreviations in Table 2.

Abbreviation	Full form of a phrase
DR	Deployment Region
NSN	Number of Sensor Nodes
PS	Population Size
BL	Base station Location
IE	Initial Energy
ME	Max Energy
EFSM	Energy for Free Space Model
EMFM	Energy for Multi-path Fading Model
AE	Amplifier Energy
TE	Transmitter Energy
RE	Receiver Energy
TRE	Transmitter or Receiver Energy
EDA	Energy of Data Aggregation
SP	Size of a Packet
CR	Communication Range
SR	Sensing Range
TD	Threshold Distance
NR	Number of Rounds

III. PROBLEM DEFINITION

As energy is considered one of the most valuable resources in the IoT, our work aims to achieve effective management of energy utilization, which will lead to an expansion in the lifespan of the IoT network. We can do this by applying the clustering approach, where the optimal choice for the CHs in the IoT network will lead to consuming less energy. Consequently, The network will operate for a longer time. In our ISFO algorithm, clustering happens in two steps: Selection of CHs then formation of the clusters. We will explain these two steps in the following subsections.

A. SELECTION OF CLUSTER HEADS

The selection process of the CHs in the proposed ISFO algorithm takes place by applying a different fitness function, which based on a number of parameters as demonstrated in the following:

- **Average distance between CHs and SNs.** It refers to the summation of the distances between each CH $j(CH_j)$ and all SNs s_i. Then we calculate their average as shown in Equation 1

$$\frac{1}{m}\sum_{i=1}^{N} distance(s_i, CH_j) \tag{1}$$

  where m refers to the number of CHs and N is the total number of SNs.
  When each node transmits data to its CH, it consumes some energy. For that, we have to select CHs near all the remaining SNs to reduce the consumed energy.
- **Average distance between CHs and BS.** It points to the distance between each CH $j(CH_j)$ and the BS (BS) divided by the number of CHs (m) as written in Equation 2

$$\frac{1}{m}\, distance(CH_j, BS) \tag{2}$$

  Each CH collects the data from its SNs, and starts to forward these data to the BS. So it is better to pick the CHs that close to the BS. Consequently, we can merge Equation 1 and Equation 2 in Equation 3 (named it $f_{distance}$) because we want to minimize the distances between cluster heads and nodes and the distance between the base station and each cluster head.

$$Min\ f_{distance} = \sum_{j=1}^{m} \frac{1}{m}\left(\sum_{i=1}^{N} distance(s_i, CH_j) + distance(CH_j, BS)\right) \tag{3}$$

  Total energy for CHs. This parameter refers to the sum of the current energy for all the picked CHs. Our purpose is to maximize this sum to pick the optimal CHs. In another word, We aim to minimize the inverse of this sum as shown in equation 4 (named it f_{energy}). Because each node expenses some energy when transmitting the data. It is important to pick the CHs from the nodes that own more energy than other nodes.

$$Min\ f_{energy} = \frac{1}{\sum_{j=1}^{m}(E_{CH_j})} \tag{4}$$

  $E(CH_j)$ is the current value of energy for a cluster head j where $(1 \le j \le m)$.

From the previous two functions "$f''_{distance}$ and "f''_{energy} we can form the fitness function by merging these functions into one function called "$F''_{fitness}$ as shown in Equation 5

$$\begin{aligned}
&Min\ F_{fitness} = \alpha \times f_{distance} + (1-\alpha) \times f_{energy}\\
&\text{s.t. } distance(s_i, CH_j) \le R \quad \forall s_i \in SNs, \quad CH_j \in C\\
&\quad distance(CH_j, BS) \le R_{max} \quad \forall CH_j \in C\\
&\quad E_{CH_j} > TH_E, \quad 1 \le j \le m\\
&\quad 0 < \alpha < 1\\
&\quad 0 < f_{distance}, f_{energy} < 1
\end{aligned} \tag{5}$$

Where R is the maximum range of communication for each SN s_i, R_{max} is the maximum range of communication for each CH, SNs is the group of all the sensor nodes, C is the group of all CHs, $C = \{CH_1, CH_2, \ldots, CH_m\}$, TH_E refers to "threshold energy" to be a CH, α is a control parameter.

For selecting the optimal CHs, we aim to minimize the value of the fitness function in Equation 5. The smaller the fitness value, the best CH position we have.

B. FORMATION OF CLUSTERS

The formation of the clusters happens after the first step has been finished. Cluster formation takes place by using a weight function called " WeightF " this function depends on the following parameters:

- **Residual energy for the CH.** For a SN s_i, It should combine to a CH $j(CH_j)$ that owns more residual energy than

TABLE 2. Summary of the current issues and problems in the IoT and WSN.

Research Study	Objective	Algorithm Description	Parameters	Results	Limitation
Muhammad et al. [26]	Use the scheduling approach to achieve energy efficiency in IoT-based-WSNs.	They suggested a hybrid energy efficient algorithm called HABCA-EST where the artificial bee colony (ABC) algorithm is combined with an efficient schedule transformation.	$DR: 50m \times 50m$, $PS: 2$, Generation interval for scout bees: 10, various values for N, R, α, β	Enhancing the network's life via scheduling technique. The HABCA-EST algorithm is fast, guarantee that most significant points are covered	The effectiveness of the HABCA-EST algorithm has not been evaluating with a sufficient number of earlier scheduling techniques.
Reddy et al. [30]	Aims to choose a number of IoT devices as cluster heads in the WSN-IoT network to make the network reliable and transmit data in an efficient way.	They used the GSA (Gravitational Search Algorithm) with ABC (Artificial Bee Colony Algorithm).	$DR: 100m \times 100m$, BL: center, IE: 0.5, $EFSM: 10pJ/bit/m^2$, $AE: 0.0013pJ/bit/m^2$, TE: 50 nJ/bit/m, EDA: 5 nJ/bit/signal, NR: 2000.	Extend the network's life by clustering, enhancing the convergence, reduce the IoT device's load, temperature, and consumed energy.	They did not consider the possibility that the base station was outside the network, they only assumed the base station was in the network center.
Farman et al. [12]	Selection of zone heads for IoT-based-WSN by regarding some parameters that help in prolong the operational time.	They have proposed an upgraded scheme that depends on multi-criteria.	$DR: 100m \times 100m$, NSN: 100, IE: 0.25J, 0.5J, 1.0J, $AE: 100pJ/bit/m^2$, EDA: 5 nJ/bit/signal, TRE: 50 nJ/bit, D: 4, SP: 2000 bits, $W_1, W_2, W_3 and W_4$: 0.4, 0.36, 0.14 and 0.1	Choosing ZHs efficiently, decreases the quantity of energy used, the IGHND delivers higher network stability and extending its lifetime, the IGHND scheme has relatively better efficiency than some current techniques for clustering	They did not cover more parameters for selecting the ZH.
Janakiraman [19]	Effective selection of cluster heads by mutually removing the constraints of ACO and ABC.	Another hybrid algorithm for CH selection has been proposed. The algorithm combines Artificial Bee Colony and Ant Colony Optimization algorithms.	$DR: 100m \times 100m$, IE: 0.5, EFSM: 12 pJ/bit/sq AE: 0.00015 pJ/bit/sq, EDA: 10 pJ/bit/sq, TE: 55 pJ/bit/sq, NR: 2000.	CHs were selected from IoT devices effectively, the HACO-ABC-CHS increases the number of still alive nodes and the remaining energy and decreases the number of dead nodes compared to some algorithms.	The performance of the HACO-ABC-CHS has been compared only with two algorithms.
Reddy et al. [31]	The choice for cluster heads in the WSN-IoT network, which accomplishes efficient use for the network energy.	They proposed a novel way using the self-adaptive whale optimization algorithm (SAWOA).	$DR: 100m \times 100m$, BL: center, IE: 0.5, $EFSM: 10pJ/bit/m^2$, $AE: 0.0013pJ/bit/m^2$, $TE: 50nJ/bit/m^2$, EDA: 5 nJ/bit/signal, NR: 2000	Enhancing the network's life, keeps more energy and the number of still alive nodes, it achieves more network efficiency than others.	the base station location has assumed in the network center but, they did not consider if the base station was outside the network.
Behera et al. [3]	Prolong the network life through the controlling of the energy dissipated in it.	A novel algorithm called "R-LEACH " has been proposed, the R-LEACH algorithm enhances the LEACH protocol to suit the IoT applications.	$DR: 100m \times 100m$, NSN: 100, IE: 0.5 J, $AE: 100pJ/bit/m^2$, $RE: 0.0013pJ/bit/m^4$, $EFSM: 10pJ/bit/m^2$, EDA: 5 nJ/bit, NR: 3000	In terms of the delivery rate of packets to BS, the R-LEACH beats the LEACH protocol, based on throughput, remaining energy, and network life, the R-LEACH outperforms the LEACH protocol by about 60%, 64%, and 66%, respectively.	The performance of the R-LEACH has been compared only with the LEACH protocol.
Cui et al. [9]	Reduce the consumed energy of data sensing systems (BDSS), which are considered a critical part of the internet of things.	They introduce a novel algorithm called WHCBA that involves. The Bat Algorithm with a weighted harmonic centroid strategy. Then they merge the WHCBA algorithm with the LEACH protocol.	$DR: 100m \times 100m$, BL: center, IE: 0.5 J, TRE: 50 nJ/bit, $EFSM: 10pJ/bit/m^2$, $EMFM: 0.0013pJ/bit/m^4$, SP: 4000 bits, EDA: 5 nJ/bit, PCH: 0.05, N R: 2000, WHCBA parameters: Dimension: 2, NR: 200, $\alpha_1 = 0.9, \alpha_2 = 0.1$.	Fast convergence, enhances local search by employing the centroid strategy, LEACH-WHCBA conserves more energy than LEACH when selecting CHs.	The base station location has assumed in the network center but, they did not consider the possibility that the base station was outside the network.
Nguyen [27]	Save more energy by using the compressed sensing (CS) technique when transferring various kinds of data gathered from the devices linked to the IoT networks.	A novel scheme for data routing in IoT networks has been proposed.	$DR: 100m \times 100m$, BL: center, IE: 0.5 J, $EFSM: 10pJ/bit/m^2$, $AE: 0.0013pJ/bit/m^2$, $TE: 50nJ/bit/m^2$, EDA: 5 nJ/bit/signal	Significantly reduce the amount of energy used to transfer data. For diverse data kinds collecting by the IoT devices, this scheme can be applying.	They must consider more further applications to ensure its efficient use.

TABLE 2. ***(Continued.)*** **Summary of the current issues and problems in the IoT and WSN.**

Reddy et al. [32]	Enhancing the selection process of the cluster heads to reduce the consumed energy for the sensor nodes (SNs) in the IoT network.	A hybrid model has been produced. The model combines Ant Lion Optimization (ALO) and Moth Flame Optimization (MFO) algorithms.	$DR : 100m \times 100m$, BL: center, IE: 0.5 J, $EFSM : 10pJ/bit/m^2$, $AE : 0.0013pJ/bit/m^2$, $TE : 50nJ/bit/m^2$, EDA: 5 nJ/bit/signal, NR: 2000	Enhancing the convergence. Increases the number of still alive nodes and the remaining energy. Reduce the IoT device's load, temperature, distance and extend the network's life compared to some algorithms.	They overlooked the possibility that the base station was outside the network.
Al-Shalabi et al. [2]	Arrive at the optimal path from the source (cluster head) to the destination (base station) for less energy consumption and maximizing lifetime in WSNs.	They have used a genetic algorithm for producing a novel method called Optimal Multi-hop Path Finding Method (OMPFM).	$DR : 100m \times 100m$, BL: center, NSN: 100, IE: 0.5 J, 1 J, TE: 50 nJ/bit, RE: 50 nJ/bit, $AE : 13pJ/bit/m^2$, EDA: 5 nJ/bit, NR: 5000, SP: 500 bytes, S: 25 bytes, PS: 40, Rm, RC: 0.04, 0.8	The OMPFM method has aided in arriving at the best path. Based on consumed energy and network life, the OMPFM outperforms the LEACH protocol and similar other ways by about 50%.	The operations of GA lengthen the execution time.
Iwendi et al. [18]	Focus on reducing the consumed energy for the SNs in the IoT network to prolong the network lifetime.	They proposed a hybrid algorithm named (WOA-SA). The WOA-SA algorithm utilized the whale optimization algorithm and the simulated annealing together.	$DR : 100m \times 100m$, BL: center NSN: 100, IE: 0.5 J, NR: 2000	The WOA algorithm's exploitability improved via using simulated annealing. The method presented optimizes IoT network performance by the most suitable CHs selection. Efficient use of the node's energy and enhance network sustainability.	They assumed that the base station position in the network center. However, they overlooked the case of the base station being far away from the network.
Kannammal et al. [21]	Improve the level of energy and the working period for the IoT network.	A new hybrid clustering algorithm has been introduced. The algorithm uses the LEACH protocol with the Firefly algorithm.	The CH was chosen based on energy. On the basis of the size of a cluster, distance, and numbers of hops every single sensor determines its own CH.	Fast convergence. Diminishes the loss rate of packets. Reduces energy used and improves network life.	The algorithm's efficiency has not been evaluating with a sufficient number of previous methods.
Rajesh et al. [28]	The main goal is to minimize the expended energy while routing and enlarge the network life.	They are implementing "a multi-objective optimization routing algorithm" called BFOA-R. The BFOA-R algorithm utilizes the foraging way of M. Xanthus and E. coli bacteria.	$DR : 200m \times 200m$ NSN: 50 and 100, SN deployment: random. Movement of SN: dynamic, 5 m/s. The channel: Free space model was employed. Tr. E: 3 dBm, Energy: Friis loss model was employed. Mobility: random way point mobility model was employed.	In terms of the delivery rate of packets, remaining energy, total nodes still alive, and network life, the BFOA-R beats the PMSO algorithm considerably.	The performance of the BFOA-R has been compared only with the PMSO routing algorithm.
Bhatt et al. [4]	The objective is to choose the most suitable node as the cluster head, thus achieve efficient use of the network energy and extending its lifetime.	They have utilized the cuckoo search algorithm to produce an enhanced algorithm for WSN.	$DR : 100m \times 100m$, NSN: 100, IE: 120 J, NR: 8 Bellman ford algorithm was applied to determine the shortest path.	Chooses the most suited nodes to represent CHs, which reduce energy use and improves network life. When a node dead, the greedy technique is applied to find the best following route to flow information.	The previous methods have not been compared with the suggested algorithm.
Chauhan et al. [7]	The goal is to save more remaining energy for the sensor nodes and make the traveled distance less. Thus, the network will work for a long time.	They have offered a different technique for heterogeneous WSN. The technique is called "DDMPEA-ANUM" which refers to Diversity-Driven Multi-Parent Evolutionary Algorithm with Adaptive Non-Uniform Mutation.	$DR : 100m \times 100m$, BL: center, NSN: 100, IE: 0.5 J, TRE: 50 nJ/bit, $EFSM : 10pJ/bit/m^2$, $EMFM : 0.0013pJ/bit/m^4$, TD: 87 m, EDA: 5 nJ/bit/signal, SP: 2000 bits, Energy Heterogeneity: normal - intermediate - advanced	Based on consumed energy, total nodes still alive, dead nodes, the delivery rate of packets to BS, period of stability, and network life, the DDMPEA-ANUM algorithm beats other protocols that compared with it.	They did not assume the position of the base station may be far away from the network.
Sarkar et al. [34]	Guarantee the selection of the proper cluster heads among other sensors in WSNs. Thus, save energy and work the network for a long time.	They have employed the firefly optimization algorithm (FF) and Grey Wolf Optimization algorithm to produce two models called "Firefly Cyclic Randomization (FCR)" and "Firefly Cyclic Grey Wolf Optimization (FCGWO)".	NSN: 100, BL: center, IE: 0.5 J, $AE : 10pJ/bit/m^2$, $TE : 50nJ/bit/m^2$, EDA: 5 nJ/bit/signal NR: 2000.	Based on network energy, total nodes still alive, lifetime, and convergence, The FCR and FCGWO algorithms beat other previous methods compared with it.	They ignored the possibility that the base station was far from the network. They only assumed that the base station position in the network center.

TABLE 2. *(Continued.)* **Summary of the current issues and problems in the IoT and WSN.**

Cao et al. [6]	The aim is to optimize the placement of sensor nodes in heterogeneous WSNs, for achieving optimal coverage.	They have proposed an algorithm named CSSO. Chaos technique and SSO (social spider optimization) algorithm have been utilizing in this algorithm.	DR : $100m \times 100m$, NSN: 50, IE for normal SN: 1J, IE for heterogeneous SN: 5J, SR for normal SN: 10 m, SR for heterogeneous SN: 15m, $EFSM$: $10pJ/bit/m^2$, $EMFM$: $0.0013pJ/bit/m^4$, T.or $R.E$: $45 \times 10^{-9} J/bit$, S P: 4000bit, CSSO Parameters: PS: 50, N R: 50, PF: 0.5, $\sigma_m ax, \sigma_m in$: $0.9, 0.1$	Fast convergence. Owns the ability to avoid trapping in local minima. Reduce energy used, Costs, and achieve better network coverage. Increase network efficiency.	Through some areas, some nodes become overcrowded. These areas need to be reduced and more equally covered.
Ling et al. [23]	Resolving the issue of network coverage and lifetime.	Multiple upgraded algorithms have been utilizing depend on the PSO algorithm.	NSN: 32, 48, 64, K Coverage: 2, 3, 4, SR: 88 m, PS: 10, m: 10, NR: 5000	The upgraded algorithms (ICLPSO, QPSO, and SPSO) perform well and have a good deployment effect. ICLPSO is the best-upgraded algorithm. QPSO performs better than SPSO.	The presented algorithms require more upgrades to achieve cost-effectively.
Qin and Xu [37]	The objective is to free the nodes from the local optimum and ensure that the monitoring area is effectively covered.	An advanced fish swarm optimization algorithm called AIFS has been employing.	DR : $100m \times 100m$, NSN: 50, SR: 8 m, step_0,visual:8 m,26 m, α, β : $16m, 6.93m$, $C_{th}, V_{th}, Q_{th}, P_{th}, Y_{th}$: $10, 6m, 200, 0.5, 0.9$.	AIFS owns the ability to avoid trapping in local minima. Efficiency and rapid convergence. Coverage enhancing. Fewer costs.	Conservation of energy did not consider in this work.
Rajpoot and Dwivedi [29]	Guarantee the selection for the fittest node placement with achieving the most region coverage.	A MADM (Multi-Attribute Decision Making) method has been utilizing.	DR : $200m \times 200m$, NSN: variable, Position: variable, In. E: 1 J	The majority of the region is covered. Increased connectivity. Used less energy when transferring data. Fewer costs.	They have not covered the impact of the proposed method on the network's life.
Fouad et al. [13]	The aim is to achieve accurately locate the sink node for WSNs.	They have employed the Grey Wolves Optimizer (GWO).	DR : $600m \times 600m$, NSN - Module - Distribution: 100, 300, 500, 700, 900 - MICA2 Mote - Uniform CR: 100 m, SR: 20 m, IE and M. E: Uniform - 2000 mA-h, α_1, α_2 : $0.7, 0.3$	Determines the sink node position with high precision. Reducing the active nodes number, energy, and time complexity needed for topology construction.	They have not covered the impact of using more nodes and the network's life after topology building.
Snasel et al. [36]	The authors' goal is to achieve greater accuracy for allocating the sink node in WSNs.	They have applied a novel strategy that relies on cat swarm optimization (CSO) in addition to the greedy algorithm.	DR : $200m \times 200m$, PS: 16, NSN: 100, 200, 300, 400, 500, 600, CR: 40.	Reduces energy used in the entire network and enhances its life. Based on the required consumed energy for allocating the sink node, the CSO approach outperforms the PSO.	The authors compared the performance of their method with the PSO only. They did not concern with the other previous methods.
Fouad et al. [14]	Determine the optimal sink node position to accomplish efficient performance for the WSNs.	A novel topology was presenting by employing an improved PSO algorithm with a Gaussian jump.	DR : $600m \times 600m$, NSN: 100, 200, 300, 400, 500, 600, 700, SN model: Mica Mote, CR: 100 m, SR: 20 m Location, Energy distribution: Uniform, Uniform ME: 2000 mA-h, PSO parameters: $\alpha_1, \alpha_2, \alpha_3, \omega$: $0.4, 0.1, 0.5, 0.8 C_1, C_2, r_1, r_2$: $2, 2, 0.5, 0.5$	A topology control protocol's phases (topology construction and maintenance) have improved. Reduces the time it takes to build a topology. Enhancing the network's life.	The performance of the presented topology has been compared only with the A3 topology.
Chen and Li [8]	Concern with the problem of determining the best place for the sink node in WSNs.	Different strategies were utilizing that focused on the network's energy and lifetime. These strategies have based on the ant routing algorithm.	DR N. of SN:$400m \times 400m$: 100 nodes, DR - N. of SN: $600m \times 600$ m:370 nodes, DR N. of SN: $600m \times 600m$ 300 nodes, IE: 1 J, T. or R. E: 50 nJ, $Am.E$: $100pJ/m^2$, Ant Colony parameters: α, β, ρ : $1, 3, 0.5$.	In terms of network life extension, the strategy focused on network lifetime is more efficient than the strategy focused on network energy.	The strategies' efficiency has not compared to previous ones.

other CHs in its communication range. Consequently,

$$WeightF(s_i, CH_j) \propto E_{residual}(CH_j) \tag{6}$$

$E_{residual}(CH_j)$ is pointing to the residual energy for a CH j.

- **Distance between the SN and CH.** For a sensor node s_i, it should combine to the closest CH $j(CH_j)$ in its communication range. Where this will help in consuming less energy. Consequently,

$$WeightF(s_i, CH_j) \propto \frac{1}{distance(s_i, CH_j)} \tag{7}$$

- **Distance between the CH and BS.** CHs are responsible for receiving the data from the SNs, and forwarding them to the BS. For this reason, a SN s_i should combine to a CH that is closer to the BS than other CHs in its communication range.

$$WeightF(s_i, CH_j) \propto \frac{1}{distance(CH_j, BS)} \tag{8}$$

- **Degree of the CH node.** For a SN s_i, it should combine to a CH $j(CH_j)$ that owns the least node degree in its communication range. For this,

$$WeightF(s_i, CH_j) \propto \frac{1}{node\_degree(CH_j)} \tag{9}$$

We can merge the previous Equations 7, 8, 9 in Equation 10.

$$WeightF(s_i, CH_j) \propto \frac{E_{residual(CH_j)}}{distance(s_i, CH_j)} \times \frac{1}{distance(CH_j, BS)} \times \frac{1}{node\_degree(CH_j)} \quad (10)$$

Consequently, the final weight function for cluster formation as in Equation 11

$$WeightF(s_i, CH_j) = C \times \frac{E_{residual(CH_j)}}{distance(s_i, CH_j)} \times \frac{1}{distance(CH_j, BS)} \times \frac{1}{node\_degree(CH_j)} \quad (11)$$

where, C refers to a constant and its value is equal to 1. To form the clusters, each SN uses Equation 11 to calculate its "$WeightF''$ and then it must combine to a CH that owns the largest weight value.

IV. SUNFLOWER OPTIMIZATION ALGORITHM (SFO)

The Sunflower optimization algorithm (SFO) is a natural inspired algorithm proposed by G.F. Gomes *et al.* in 2019 [15]. The algorithm mimics the pollination process between the nearest two sunflowers during the movement toward the sun. In the next subsection, we highlight the characteristic of the SFO algorithm and the main processes of it.

A. THE NATURAL BEHAVIORS

Every morning, the sunflowers move toward the sun and the pollination process can happen between the nearest two sunflowers X_i and X_{i+1}. Each sunflower absorbs the radiation from the sun. The amount of aggregated radiation for each sunflower depends on its position to the sun. The longer distance between the sunflowers and the sun, the lower amount of the received radiation (heat) from it. The amount of the received heat for each sunflower from the sun can be represented as shown in Equation 12

$$Q_i = \frac{W}{4\pi c^2} \quad (12)$$

where Q_i is the amount of the received heat, W is the sun power and c is the distance between the best solution (sun) X^* and the sunflower X_i.

B. THE SUNFLOWER ORIENTATION ADJUSTMENT PROCESS

The orientation vector for each sunflower is calculated as shown in Equation 13.

$$\vec{s_i} = \frac{X^* - X_i}{\|X^* - X_i\|} \quad i = 1, 2, \ldots, N. \quad (13)$$

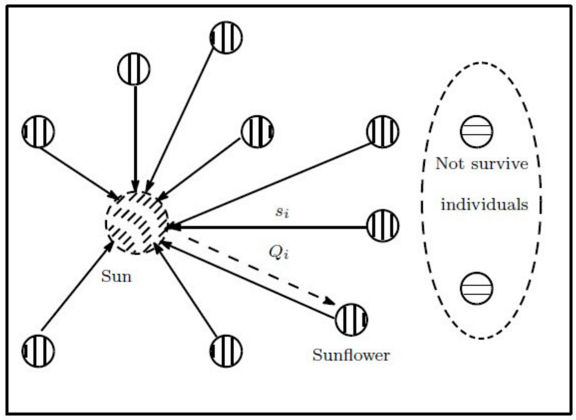

FIGURE 3. The sunflower orientation adjustment process.

where X^* is the global best solution, X_i is solution i, and N is the population size. The sunflower orientation adjustment process is shown in Figure 3.

C. STEP SIZE OF THE SUNFLOWERS TOWARD THE SUN

The step size of each sunflower X_i towards the sun is calculated as shown in Equation 14.

$$d_i = \alpha \times P_i(\|X_i + X_{i-1}\| \times \|X_i + X_{i-1}\| \quad (14)$$

where α represents the sunflower's inertial displacement, $P_i(\|X_i + X_{i-1}\|$ is the probability of the pollination between the closest two sunflowers X_i and X_{i+1}. The closer sunflowers to the sun take a smaller step to refine their positions (exploitation process) while the more distance sunflowers move randomly (exploration process). The step size for all sunflowers is restricted to the maximum step size d_{max} to avoid skipping from the boundary for each solution. The maximum step size for each sunflower is calculated as shown in Equation 15.

$$d_{max} = \frac{\|X_{max} - X_{min}\|}{2 \times N} \quad (15)$$

where X_{max} is the upper bound, X_{min} is the lower bound, and N is the population size.

D. FERTILIZATION PROCESS

The best sunflowers will fertilize around the sun to generate new individuals. The fertilization process for each sunflower can be represented as shown in Equation 16

$$X_{i+1} = X_i + d_i \times \vec{s_i} \quad (16)$$

where X_{i+1} is new generated sunflower.

E. THE SFO ALGORITHM

The main processes of the SFO algorithm are shown in Figure 4.

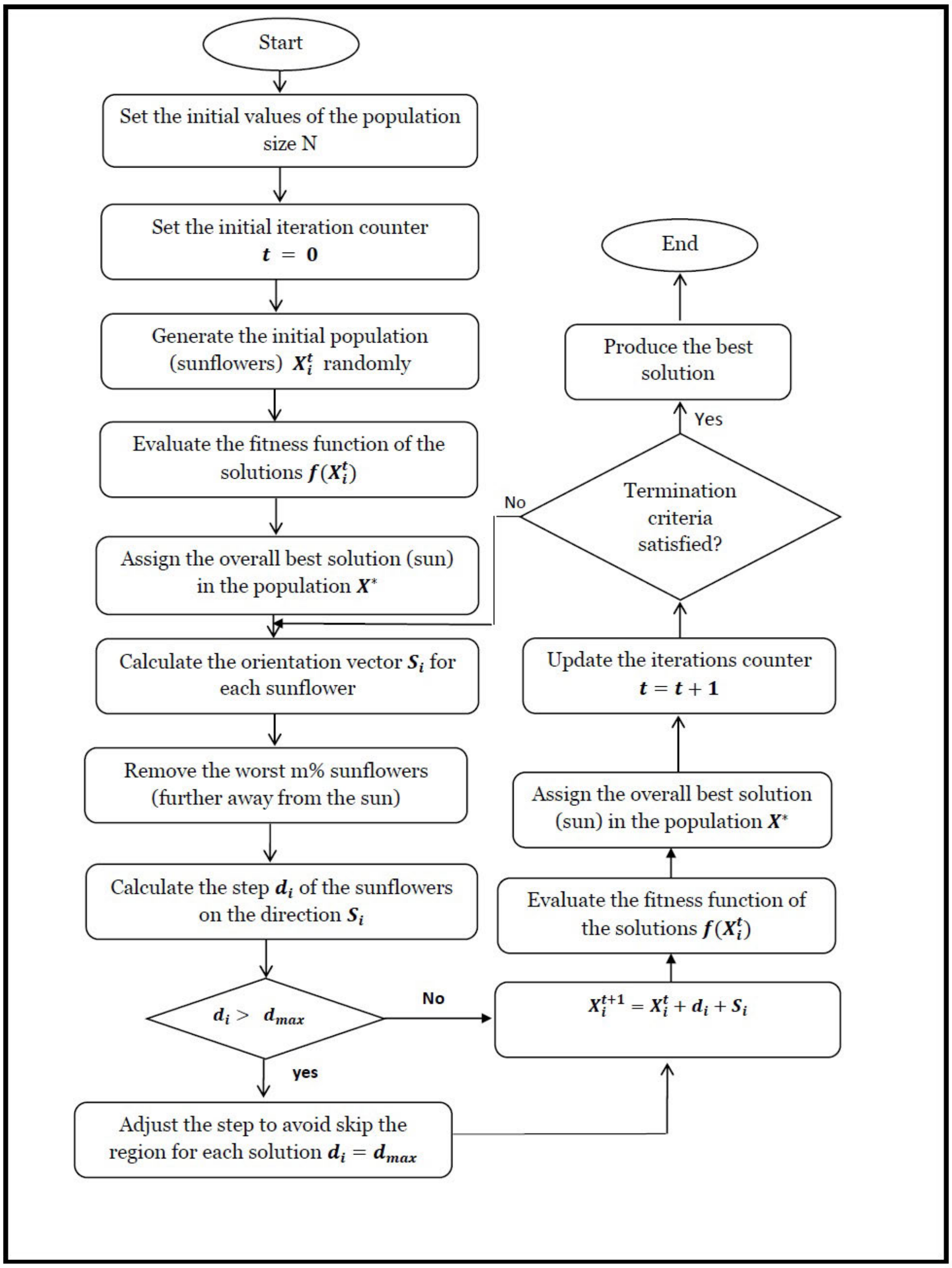

FIGURE 4. The SFO algorithm.

V. AN IMPROVED SUNFLOWER OPTIMIZATION ALGORITHM (ISFO)

The standard SFO algorithm like the other SI algorithms suffers from slow convergence and it can be trapped easily in local minima. To increase the diversity search in the standard sunflower optimization algorithm (SFO), we invoke the lèvy flight operator on it to produce a new version of the SFO algorithm, which is called an Improved Sunflower Optimization algorithm (ISFO). The lèvy flight operator is a random walk method that can help the SFO escaping from trapping in the local minima and avoid premature convergence. The main steps of the proposed ISFO algorithm are the same as the standard SFO algorithm except that we replace the step size in Equation 14 with the lèvy flight operator as shown in the following Equation.

$$X_{i+1} = X_i + levy(\nu) \times \vec{s}_i \tag{17}$$

where Levy (ν) is the lèvy distribution.

The structure of the proposed ISFO algorithm is presented in Algorithm 1.

We can summarize the steps of the proposed ISFO algorithm 1 as follow.

- **Parameter initialization.** The initial values of the parameters are setting such as the rate of mortality m,

Algorithm 1 The ISFO Algorithm

```
Initialize the parameter values for the rate of mortality m, population size N, the rate of pollination P and the maximum number of iteration max_itr.
Initialize the iteration counter t := 0.
The initial population X_i^(t) is generated randomly, i = 1, ..., N.
Calculate the fitness function for all solutions (sunflowers) in the population f(X_i^(t)).
The overall best solution is assigned X*.
repeat
    All solutions adjust their orientation toward the sun (best solution)X* as shown in Equation 13.
    The worst m% solutions are removed from the population and replaced with the new individuals.
    The solutions update their position based on the lèvy flight operator as show in Equation 17.
    Calculate the fitness function for the new solutions (sunflowers) in the population f(X_i^(t)).
    The new solutions are accepted if their fitness are better than the current solutions.
    Set t = t + 1.
until (t > max_itr).
The overall best solution is presented.
```

the population size N, the rate of the pollination P and the maximum iteration number max_{itr}.

- **Iteration counter initialization.** The counter for the initialization is initialized $t := 0$.
- **Solutions generation.** The solutions in the population are generated randomly $X_i^{(t)}$.
- **Solutions evaluation.** The Fitness function for each solution in the population is calculated $f(X_i^{(t)})$.
- **The global best solution.** The global best solution is assigned.
- **Solutions adjustment.** The solutions adjust their position toward the sun (best solution) as show in Equation 13.
- **The worst solution mortality.** The worst $m\%$ solutions are removed from the population and replaced with the new solutions.
- **Solutions update.** The solutions are update based on the lèvy flight operator to avoid trapping on the local minima and the premature convergence as show in Equation 17.
- **The new solutions evaluation.** The Fitness function for each new solution in the population is calculated $f(X_i^{(t)})$.
- **The new global best solution.** The new global best solution is assigned.
- **Iteration Counter increment.** The counter for the iteration number is increased $t = t + 1$.
- **Termination criteria satisfaction.** The processes are repeated until reaching to the maximum number of iterations max_{itr}.

TABLE 3. The network parameters.

Parameters	Definitions	Values
ND	Network Dimensions	200 x 200 m^2
BS	The location of BS (Sink node)	(100,100) (200,200) (300,300)
SN	Total number of SNs	300
CH_s	CHs percentage	10%
E_o	Initial energy for a node	2 J
E_{TX}	Energy dissipation for transmitting	50 nJ/bit
E_{RX}	Energy dissipation for receiving	50 nJ/bit
ϵ_{fs}	Energy dissipation for transmit amplifier	10 PJ/bit/m^2
ϵ_{mp}	Energy dissipation for transmit amplifier	0.0013 PJ/bit/m^4
R	Communication Range	100 m
d_o	The threshold distance	30 m
K	Length of packet	4000 bits
EDA	Data aggregation energy	5 nJ/bit

- **The global best solution.** The overall best solution is presented.

VI. EXPERIMENT RESULTS

We implemented the proposed ISFO algorithm by utilizing MATLAB R2019b and this on an Intel Core i5 processor 2.30 GHz, 8 GB RAM working on the operating system Windows 10 Pro (64-bit).

A. PARAMETER SETTING

In Table 3, we demonstrate the IoT network parameters. Where these parameter values have been utilized by Heinzelman *et al.* previously as in [17].

Where *ND* is the (size-diameter-target area-sensing) field of the IoT network and it equals ($200m \times 200m$). *BS* represents the position of the IoT base station and we have three cases at the points (100,100), (200,200), and (300,300). *SN* is the overall number of sensor nodes that are used in our IoT network and is equal to 300 nodes. CHs is the number of the selected CHs and it represents 10% of the total number for the SNs (i.e $300 \times 10\% = 30$ CHs). E_o refers to the initial energy amount for each *SN* and is equal to 2 Joules. E_{TX} and E_{RX} indicate the amount of energy dissipated for sending and receiving a bit of data respectively and are equal to 50 nJ/bit. ϵ_{fs} and ϵ_{mp} denote the amount of energy dissipated by the transmitting amplifier for both free space and multi-path models are equal to (10 PJ/bit/m2), (0.0013 PJ/bit/m4) respectively. R is the sensing radius that means the maximum range of communication for each SN and is equal to 100m. $d_o = 30$ m and it denotes the distance of threshold transmission. K means that the data package size = 4000 bits. Finally, *EDA* is the energy required to aggregate the data and is equal to 5 nJ/bit.

In Table 4, we demonstrate the values of the proposed ISFO algorithm parameters. Where the parameter values have been taken from the original paper of the sunflower optimization algorithm [15].

From Table 4, N refers to the number of populations (sunflowers) that equal to 30. $D = 30$ is the dimension of our problem that means the number of the selected CHs. P, m, and s indicate the rate of pollination, mortality, and survival

TABLE 4. The proposed ISFO algorithm parameters.

Parameters	Definitions	Values
N	Number of sunflowers	30
D	Problem dimension	30
UB	Upper bound	200
LB	Lower bound	1
P	The rate of Pollination	0.05
m	The rate of Mortality	0.1
s	The rate of Survival	$S = 1 - (P + m)$
α	Control Parameter	0.3
Max_{itr}	Maximum number of iterations	5000

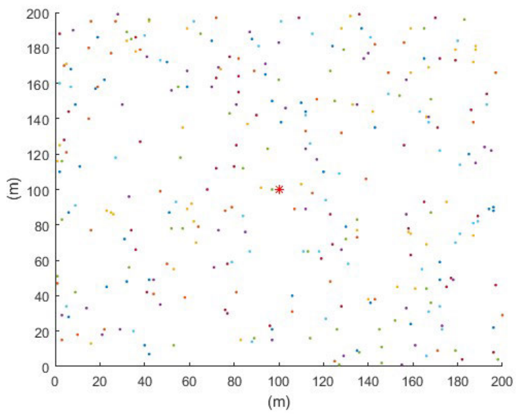

FIGURE 5. Random network deployment for 300 nodes where the BS at (100,100).

for the sunflowers respectively. α is a control parameter where the energy and distance parameters are controlled by α. Max_{itr} refers to the maximum number of iterations that equals 5000 iterations.

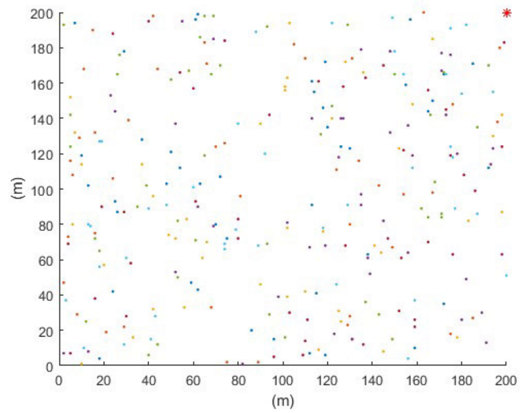

FIGURE 6. Random network deployment for 300 nodes where the BS at (200,200).

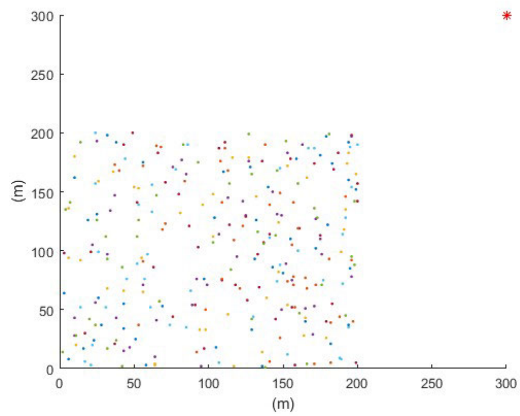

FIGURE 7. Random network deployment for 300 nodes where the BS at (300,300).

B. EXPERIMENT SETTING

We have distributed 300 nodes randomly where the network dimension $200 \times 200m^2$. There are three different scenarios of the BS location in our network. The network dimension is the same for all cases. The BS position is in the center of the network at (100,100) in the first case as shown in Figure 5, while the BS position is in the top right corner of the network at (200,200) in the second case as shown in Figure 6. Finally, the BS position is outside the network domain (300,300) as shown in Figure 7.

The following subsections show the efficiency of invoking the lèvy flight operator in the proposed ISFO algorithm then we compare its performance with other algorithms. We ran all algorithms 10 times.

C. TIME COMPLEXITY OF THE PROPOSED ISFO ALGORITHM

The time complicity of the ISFO algorithm can be computed as follow.

- **Initial population.** The time complexity of the initial population is $O(N \times D)$, Where N is the population size and D is the problem dimension.
- **Solution update.** The time complexity for all solutions in the population is $O(N \times D)$.
- **Fitness function evaluation.** The time complexity for calculating the fitness function of all solutions in the population is $O(N \times D)$.

The total time complexity is $O(N \times D \times Max_{itr})$, Max_{itr} is the maximum number of iterations.

D. THE PERFORMANCE OF THE PROPOSED ISFO ALGORITHM

From Equations 13 to 16, we can see that each solution in the population can update its position based on the position of the overall best solution. However, if the overall best solution gets in local minima, the rest of the population will trap in this region. Based on this issue, we invoke the lèvy flight operator in the proposed ISFO algorithm to increase the diversity of it. To show the diversity of the proposed ISFO algorithm, we show the convergence curves of the standard SFO and the proposed ISFO as shown in Figures 8, 9, 10, 11,12, 13.

Figures 8, 9, 10 show the relation between the number of round (iteration) versus the number operating nodes. The solid line represents the results of the ISFO algorithm,

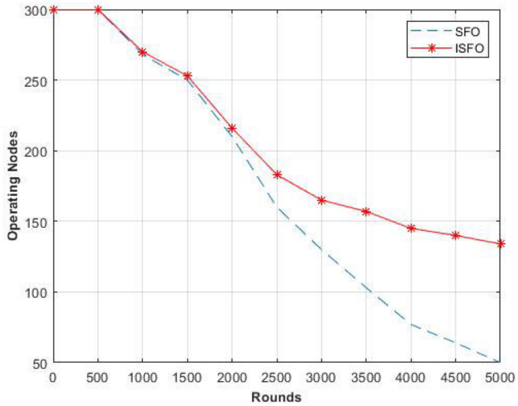

FIGURE 8. No. of operating nodes at BS (100,100).

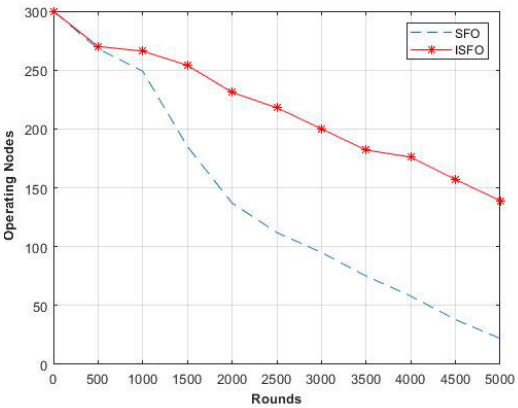

FIGURE 9. No. of operating nodes at BS (200,200).

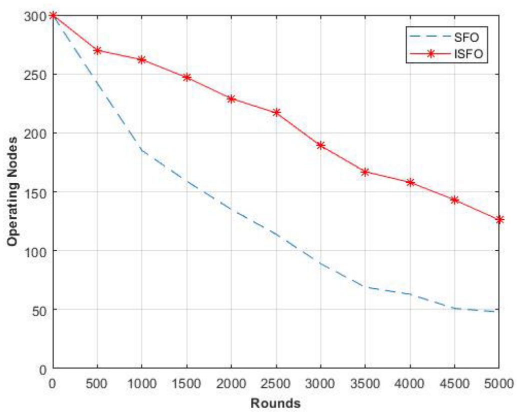

FIGURE 10. No. of operating nodes at BS (300,300).

while the dotted line represents the results of the standard SFO algorithm.

At the beginning of the search, both algorithms have the same diversity during the search, however, after a number of iterations, the solutions in the standard SFO algorithm get in local minima, while the proposed ISFO avoids trapping in local minima.

Figures 8, 9, 10 demonstrate the number of nodes that still alive (operating nodes) after 5000 rounds and the BS at the points (100,100), (200,200), and (300,300) respectively when using the SFO algorithm and the proposed (ISFO) algorithm.

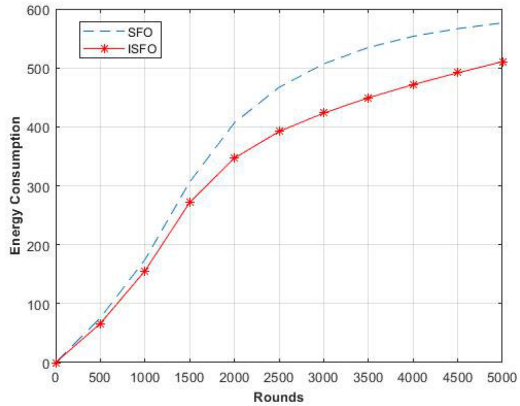

FIGURE 11. The total consumed energy after 5000 rounds and BS at (100,100).

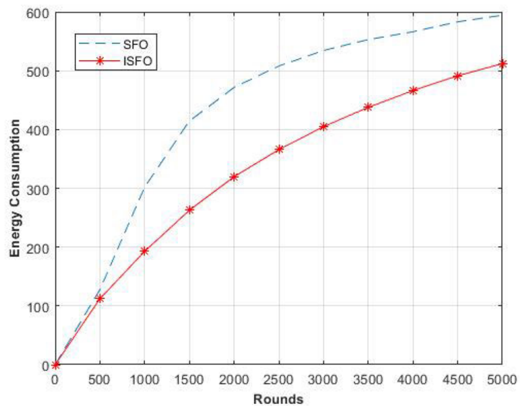

FIGURE 12. The total consumed energy after 5000 rounds and BS at (200,200).

From Figures 8, 9, 10, we can see that the number of nodes still alive for the ISFO algorithm is larger than alive nodes for the SFO algorithm.

We apply another test to verify the diversity of the proposed algorithm by plotting the relation between the energy consumption versus the round (iterations) as shown in Figures 11, 12, 13. In Figures 11, 12, 13, the solid line represents the results of the proposed ISFO algorithm while the dotted line represents the results of the standard SFO algorithm.

In Figures 11, 12, 13, at the beginning of the search, the convergence curves of both algorithms show that they have the same diversity effect. However, when the number of iterations increased, the diversity of the proposed ISFO increased while it decreased in the SFO algorithm. Figures 11, 12, 13 show the total consumed energy for the SFO and the proposed ISFO algorithms after 5000 rounds. The BS at the position (100,100), (200,200), and (300,300) respectively.

In Figures 11, 12, 13, it is clear that the consumed energy for the proposed ISFO algorithm is less than the consumed energy for the SFO algorithm.

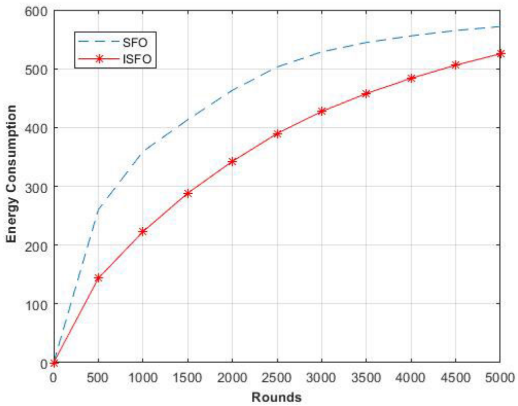

FIGURE 13. The total consumed energy after 5000 rounds and BS at (300,300).

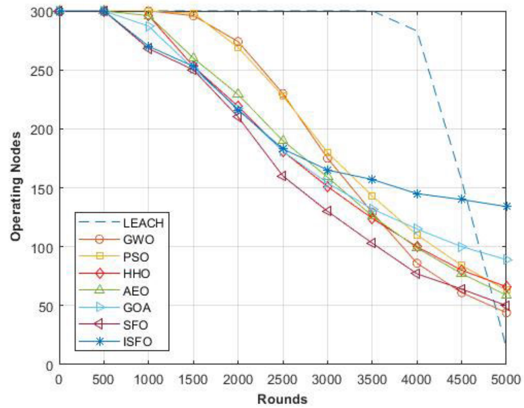

FIGURE 14. Operating nodes at BS (100,100).

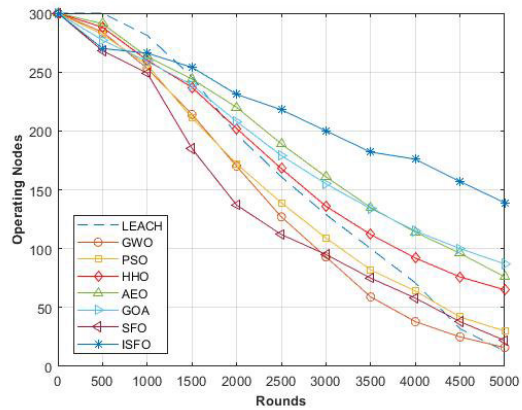

FIGURE 15. Operating nodes at BS (200,200).

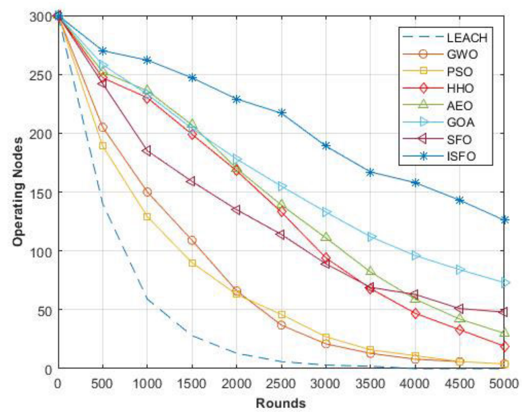

FIGURE 16. Operating nodes at BS (300,300).

We can conclude from the previous figures, that invoking the lèvy flight operator in the proposed ISFO, can increase its diversity and help it to avoid trapping in local minima.

E. THE COMPARISON BETWEEN LEACH, GWO, PSO, HHO, AEO, GOA, SFO, AND THE PROPOSED ISFO ALGORITHM

We compare the ISFO algorithm with the LEACH Protocol [17] and other SI to prove its superiority. The algorithms include Grey Wolf Optimizer (GWO) [25], Particle Swarm Optimization (PSO) [22], Harris Hawks Optimization (HHO) [16], Artificial ecosystem-based optimization (AEO) [40], Grasshopper Optimization Algorithm (GOA) [33] and Sunflower Optimization Algorithm (SFO) [15]. The results of the comparison are plotted in Figures 14, 15 and 16 according to the number of nodes that still alive (operating nodes) after 5000 rounds and the BS at the positions (100,100), (200,200), and (300,300) respectively.

The GWO, PSO, HHO, AEO, GOA, SFO are swarm intelligence and naturally inspired algorithms, which suffer from the slow convergence, and their solutions update their position based on the position of the overall best solution. If the best solution gets in the local optima, they follow it and can be trapped in that local minima.

Figures 14, 15 and 16 show the relation between the operation node and the round (iterations) by plotting the convergence curves of the proposed ISFO and the other algorithms.

From the Figures 14, 15 and 16, we can note that all algorithms have the same operation nodes, however, increasing the number of iterations reduces the number of operation nodes of all algorithms except the proposed ISFO algorithm because its diversity and ability to avoid trapping in local optima.

The diversity effect of all algorithms is verified also in Figures 17, 18 and 19 by showing the total energy consumption after 5000 rounds. All algorithms consume the same energy at the beginning of the search while increasing the number of iterations increases their consuming energy rapidly except the proposed ISFO algorithm has a lower consumed energy.

The numerical results of all algorithms concerning the average (Avg), minimum (Min), maximum (Max), standard deviation (Std) energy consumption after 5000 rounds are reported in Tables 6, 7 and 8, where the BS location at (100,100), (200,200), and (300,300), respectively.

From the results shown in Tables 6, 7 and 8, we can see that the consumed energy by the ISFO algorithm is less than the remaining algorithms, and it is superior to the other

TABLE 5. The number of operating and dead nodes at different BS position.

	BS at (100,100)		BS at (200,200)		BS at (300,300)	
Algorithms	Operating Nodes	Dead Nodes	Operating Nodes	Dead Nodes	Operating Nodes	Dead Nodes
LEACH	14	286	13	287	2	298
GWO	44	256	16	284	4	296
PSO	63	237	30	270	4	296
HHO	66	234	65	235	19	281
AEO	59	241	76	224	30	270
GOA	89	211	87	213	73	227
SFO	91	209	104	196	85	215
ISFO	**104**	**196**	**117**	**183**	**93**	**207**

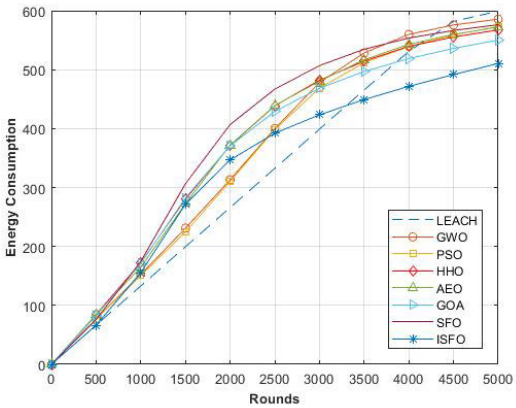

FIGURE 17. The total amount of energy consumed at BS (100,100).

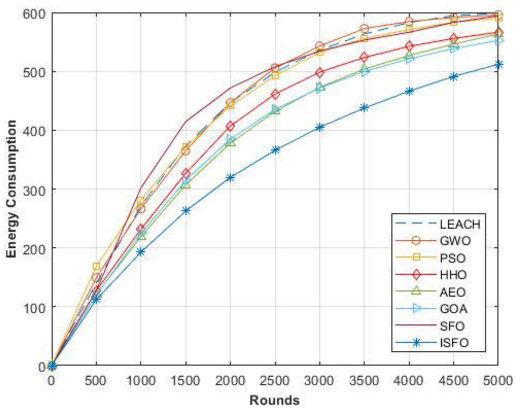

FIGURE 18. The total amount of energy consumed at BS (200,200).

TABLE 6. The energy consumption at BS location (100,100).

Algorithm	Min	Max	Avg	Std
LEACH	598.63	599.80	599.30	0.36
GWO	580.85	591.93	585.68	4.00
PSO	547.32	599.33	573.32	18.01
HHO	543.34	596.03	567.35	18.77
AEO	531.58	598.76	572.33	18.42
GOA	526.84	593.02	550.16	24.29
SFO	503.75	576.27	546.63	21.82
ISFO	510.48	575.23	**535.07**	18.81

algorithms and can help the network to operate a longer time than others.

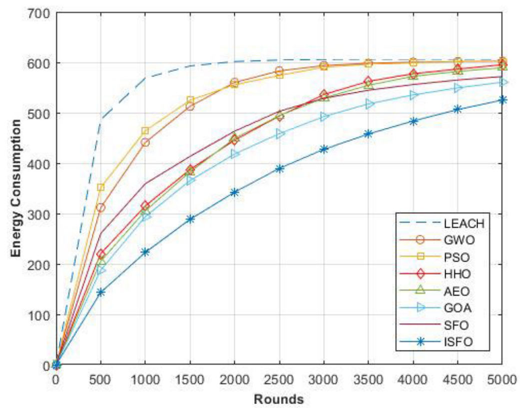

FIGURE 19. The total amount of energy consumed at BS (300,300).

TABLE 7. The energy consumption at BS location (200,200).

Algorithm	Min	Max	Avg	Std
LEACH	598.29	599.29	598.76	0.31
GWO	586.14	600.25	595.86	4.12
PSO	577.16	599.20	589.99	7.90
HHO	529.13	600.27	566.37	25.16
AEO	529.38	591.12	563.55	19.05
GOA	530.35	586.85	552.34	17.24
SFO	509.28	594.37	536.96	25.91
ISFO	511.96	556.37	**525.74**	13.90

TABLE 8. The energy consumption at BS location (300,300).

Algorithm	Min	Max	Avg	Std
LEACH	605.46	606.48	606.11	0.34
GWO	593.82	604.21	602.09	2.93
PSO	598.86	603.51	601.97	1.44
HHO	583.39	601.53	595.23	6.62
AEO	568.52	600.31	589.28	11.26
GOA	523.21	597.60	560.52	27.50
SFO	520.98	579.90	546.51	18.93
ISFO	522.63	597.38	**541.92**	23.03

VII. CONFLICT OF INTEREST

In the present work, we have not used any material from previously published. So we have no conflict of interest.

VIII. CONCLUSION AND FUTURE WORK

The network lifetime is the main issue that faces the IoT-WSN. To overcome this issue, we proposed a new algorithm to select the CHs in the IoT-WSN, which is an NP-hard problem. The proposed algorithm is called an Improved Sunflower Optimization Algorithm (ISFO). The ISFO algorithm is a hybrid algorithm between the standard SFO algorithm and the lèvy flight operator. The lèvy flight operator can increase the diversity search of the ISFO algorithm and help it to escape from local minima. The ISFO is compared with six SI algorithms at different BS positions. The results of the ISFO algorithm show that it can increase the network lifetime compared to the other algorithms. Our future work is to test the ISFO algorithm in a dynamic BS position and deal with real-time data and combining more operators into the ISFO algorithm to improve its performance.

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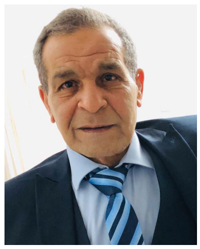

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