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ORIGINAL RESEARCH PAPER

Hybrid grey wolf sunflower optimisation algorithm for energy-efficient cluster head selection in wireless sensor networks for lifetime enhancement

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Abstract

Wireless sensor networks (WSNs) are expected to find extensive applicability and accelerating deployment in the future. However, the main challenge faced in WSN is its perishing lifetime. The process of clustering a network is a popular mechanism employed for the purpose of extending the lifespan of WSNs and thereby making efficient data transmission. The main aim of a clustering algorithm is to elect an optimal cluster head (CH). The recent research trend suggests meta-heuristic algorithms for the selection of optimal CHs. Meta-heuristic algorithms possess the advantages of being simple, flexible, derivation-free, and avoids local optima. This research proposes a novel hybrid grey wolf optimiser-based sunflower optimisation (HGWSFO) algorithm for optimal CH selection (CHS) under certain factor constraints such as energy spent and separation distance, such that the network lifetime is enhanced. Sunflower optimisation (SFO) is employed for a broader search (exploration) where the variation of the step-size parameter brings the plant closer to the sun in search of global refinement, thus increasing the exploration efficiency. Grey wolf optimisation (GWO) is employed for a narrow search (exploitation), where the parameter coefficient vectors are deliberately required to emphasise exploitation. This balances the exploration-exploitation trade-off, prolongs the network lifetime, increases the energy efficiency, and enhances the performance of the network with respect to overall throughput, residual energy of nodes, dead nodes, alive nodes, network survivability index, and convergence rate. The superior characteristic of the suggested HGWSFO is validated by comparing its performance with various other existing CHS algorithms. The overall performance of the proposed HGWSFO is 28.58%, 31.53%, 48.8%, 49.67%, 54.95%, 70.76%, and 87.10%, better than that of GWO, SFO, particle swarm optimisation (PSO), improved PSO, low-energy adaptive clustering hierarchy (LEACH), LEACH-centralised, and direct transmission, respectively.

1 | INTRODUCTION

Wireless sensor network (WSN) consists of low-power and low-cost sensor nodes (SNs). The SNs are located in a specific region and organise themselves to generate a WSN. In many fields, the WSNs have identified a variety of uses that include surveillance in the battlefield, industrial observation units, threat detection, healthcare monitoring and so forth due to their efficient communication. Furthermore, the energy, computational abilities, and bandwidth are few numbers of the sources that facilitate the overall WSN control. In such a way, a WSN has systematised accurate sensing and signifies incorporation of wireless communications with numerous nodes. WSN has got several benefits like communication flexibility, deployment flexibility, low cost, and less consumption of power [1–3].

WSN comprises numerous SNs. These SNs run on a non-rechargeable battery. Hence, for providing the object of load balancing, fault tolerance as well as network connectivity, node grouping is necessary. Clustering is the procedure for partitioning SNs into groups depending on a variety of parameters, and the choice of a group leader from all groups. The groups are known as clusters while group leaders are known as cluster heads (CHs) of the clusters. Factors for creating the clusters comprise the intra-cluster communication cost, the distance among CH and its members, location of nodes with respect to the base station (BS), residual energy of SNs and so forth [4].

Different schemes were employed in addressing the problem of CH selection (CHS). These schemes can be categorised into, normal CHS methods and optimal CHS methods. The optimal CHS methods can still be categorised into meta-heuristic and heuristic techniques [5]. These techniques are established to bring solutions to an optimisation problem with compact and simple theories, often based on empirical nature. Numerous heuristic algorithms were recommended in the literature to handle the heterogeneity. The shortcoming found in the heuristic approaches is the numerical inefficiency of the search process, especially for high-dimensional and large scale problems. In contrary, the meta-heuristic schemes of optimisation have become more popular over the recent decades. Meta-heuristic algorithms are developed to solve big-dimensional complex optimisation problems and to bring improved evolution in the search region [6]. The major advantages of metaheuristic algorithms are flexibility, simplicity, local optima avoidance, and derivation-free mechanism [7].

1. Flexibility is known as the applicability of the meta-heuristic techniques to several optimisation problems lacking distinct modifications in the procedure's structure. Meta-heuristics are applicable readily to several problems because these methods often consider the problems as the black boxes.
2. Meta-heuristics are generally very simple. They are developed from the inspiration of very simple ideas. These inspirations are often associated with some physical phenomena, animals' behaviours, or evolutionary concepts.
3. Meta-heuristics possess superior capabilities to prevent local optima when compared to the traditional approaches of optimisation. This is because of the stochastic behaviour of meta-heuristic protocols that permit them to prevent from being stuck in the local best optima and explore the whole search space widely. A majority of meta-heuristic algorithms have techniques without any derivations. Contradictory to the gradient-based techniques of optimisation, the meta-heuristic algorithms optimise problems in a stochastic manner.

Generally, meta-heuristic protocols may be categorised into two major types: Population- and single-solution-based types. These can also be categorised based on nature inspiration into evolutionary-based, physics-based, and bio-inspired algorithms. Irrespective of the dissimilarities among the meta-heuristic protocols, a common attribute helped in the segmentation of the search procedure into two stages: Exploitation and exploration [8, 9]. The exploration stage is the method of inspecting promising areas of entire search location extensively. On the other hand, exploitation is defined as the local searching ability around the promising areas attained in the stage of exploration. Determining an appropriate stability among exploration and exploitation is considered a challenge because of the stochastic behaviour of meta-heuristic techniques. Among the numerous techniques proposed by researchers, most of the techniques were employed to perform the CHS in WSNs. However, stabilisation of energy and enhancement of the lifetime of WSNs require further improvements. With the motivation of meta-heuristics into play, this study proposes a hybrid grey wolf optimiser based sunflower optimisation (HGWSFO) scheme for the energy-efficient selection of optimal CHs in WSNs.

Grey wolf optimisation (GWO) algorithm is the latest renowned optimiser unit that works on the hunting nature of grey wolves (GWs). These GWs have the capacity of locating preys and encircling them. This hunting behaviour is an inspiration for GWO algorithm. Hence for exploitation, GWO algorithm is employed. For a further broader search, sunflower optimisation (SFO) is employed in the proposed study. SFO algorithm is based on the peculiar behaviour of sunflowers and examines their finest alignment of facing the direction of the sun. The primary aim of the integration is the prolonged lifespan of modelled WSN by employing GWO for exploitation and SFO for exploration. This proposed HGWSFO technique combines the advantages of both SFO and GWO, bringing the balance between the exploitation and exploration phases of optimisation, resulting in better performance of the network.

The remaining portions of the research article are arranged in a manner listed as Section 2 that explains the associated studies proposed in the literature. Section 3 elaborates on the method suggested; Section 4 explains the outcomes and discussion of the simulation; Section 5 presents the conclusion of the study implemented and scope to extend further.

2 | LITERATURE REVIEW

Several studies are available in the literature that attempted an effort to enhance the lifespan of network and efficiency of WSNs energy using clustering approaches. These methods are categorised in Figure 1.

2.1 | Normal CHS methods

Heinzelman et al. [10] proposed a protocol called centralised low-energy adaptive clustering hierarchy (LEACH-C) on which the decisions like the selection of CH, information distribution and formation of a cluster to the network was performed. Because of the fact that the steady-state phase is entirely implemented at the BS, SNs are not affected by overheads during the time of formation of the cluster. Handy et al. [11] proposed LEACH-deterministic CHS (LEACH-DCHS) for

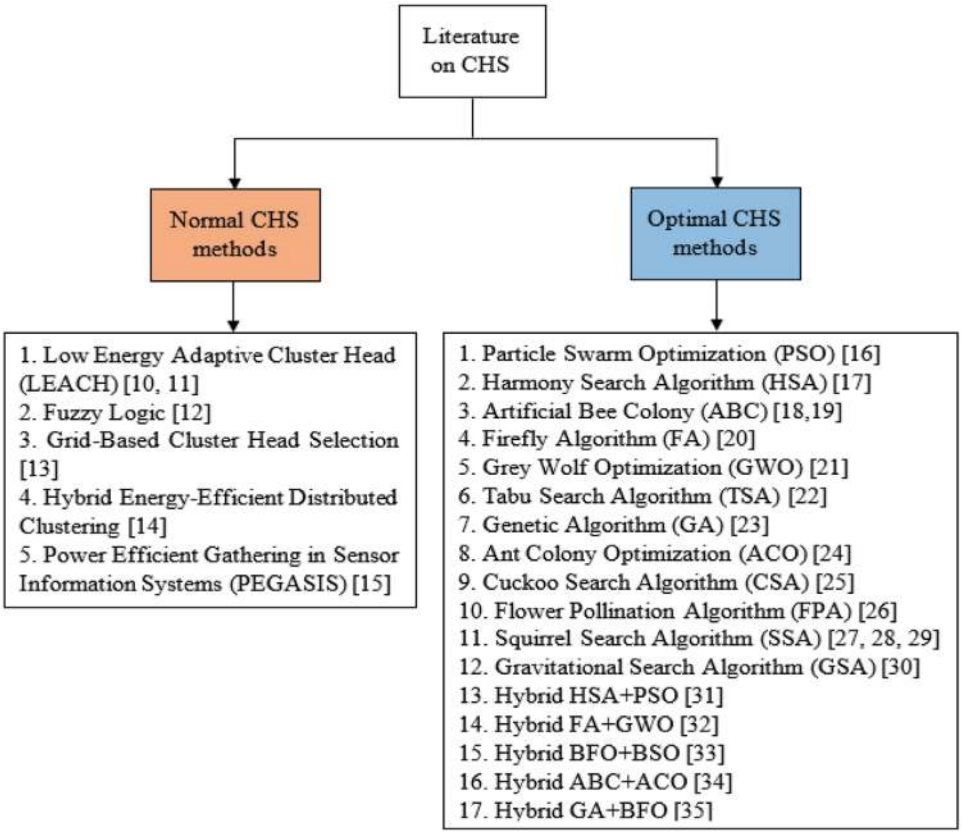

FIGURE 1 Classification of clustering algorithms

prolonging the lifetime of the network. This is achieved by making two alterations in the protocol of LEACH: (i) Modifying the CHS threshold value by multiplying the balance factor of energy, and (ii) using rotational CHs to extend the network lifetime. The negatives of LEACH protocol are that it performs random CHs selection, which leads to bad CHS and hence leads to inefficient energy and lifetime retention by the network.

Devulapalli and Nayak [12] proposed a fuzzy inference engine, using which, a super CH was chosen among CHs that can transfer the data to mobile BS through opting the best descriptors like mobility of BS, remaining battery power and cluster centrality. The network encounters energy depletion faster during data transmission to the BS. Haseeb et al. [13] presented a grid-based CHS technique through segmenting the field of the network into $M \times N$ dividers of uniform sizes that focus to reduce the dissipation of energy of sensors and enhancing network lifetime. This method works in a centralised fashion and requires details of the location of the network nodes, such that all nodes send their locations to the sink node. Energy is not considered for the process of CHS.

Younis and Fahmy [14] proposed a hybrid energy-efficient distributed (HEED) algorithm. The nodes intra-communication rate and residual energy are two main factors that have been utilised in this approach for the CH chosen in SN. HEED provides even distribution of CHs, and the chances for two nodes within the same communication range can be selected as CHs is very low. The major drawback found in this method is the overhead caused by energy dissipation. Lindsey and Raghavendra [15] presented a power-efficient gathering in sensor information systems, an enhanced variant of LEACH. It creates a chain of a group of SNs and every node receives and transmits information from the neighbouring node and takes a turn being a leader for transmission to the destination. Only one node can send the data to the destination at a time. However, latency is found to be high in this approach. This method of CHS does not consider the energy of nodes.

2.2 | Optimal CHS methods

Rao et al. [16] proposed an energy-efficient CHS (ECHS) protocol that is developed using particle swarm optimisation (PSO) called PSO-ECHS. This protocol is designed with an effective mechanism for encoding particles and objective function. In order to improve the energy efficiency of the suggested PSO algorithm, numerous constraints are considered, namely, sink distance, residual energy and intra-cluster distance between SNs. The drawback of this approach is that a set of nodes are selected initially as candidates for CHs in a random manner. Following this random selection, PSO-based CHS was formulated.

Tabibi and Ghaffari [17] developed PSO-based selection of optimal rendezvous points for a network as an effort to efficiently manage the resources of the network. This is done by calculating weights for each node on the basis of the total number of packets received from the rest of the nodes in the network. Dong and Zeng [18] developed an Improved harmony search-based energy-efficient routing protocol for WSNs. This work improves the performance of harmony search algorithm (HSA) by introducing dynamic adaptation to the parameter harmony memory-considering rate (HMCR). The method focused on improving accuracy; however, the speed of convergence is not enhanced.

Ahmad et al. [19] presented an approach for CHS based on an optimisation technique called artificial bee colony (ABC) method. The ABC's fitness function is evaluated on the basis of three parameters, that is, intra-cluster length, sink station distance and residual energy. Wang and Dong [20] presented a reliable and efficient clustering algorithm to WSNs on the basis of ABC algorithm for node density, the energy consumption of balanced network and increasing the network lifetime. The work focused on data acquisition and network clustering of mobile WSN. The disadvantage of the ABC algorithm is that it converges at a slow speed during the search process. Baskaran and Sadagopan [21] proposed an altered firefly heuristic and synchronous firefly optimisation to enhance the network performance. Firefly algorithm has the advantage of avoiding multiple local optima. Hence, it performed better when compared to LEACH algorithm. The CH gathers the information before forwarding it to BS. This additional work leads to a high drain of energy resulting in uneven network deprivation. Daneshvar et al. [22] proposed a clustering technique that chooses CHs by GWO. For selecting CHs, the results are determined by anticipated energy consumption and the residual energy of all nodes. For the purpose of improving the efficiency of energy, the suggested scheme utilises the same method of clustering for numerous consecutive stages. This encourages the algorithm to conserve the energy that is required for reforming the clustering algorithm. In this approach, the first node dies in less than 200 rounds; hence, improvement is required for prolonging the network lifespan. Varsha et al. [23] used REAC-IN (regional energy-aware clustering by isolated nodes) protocol for clustering in WSN. In REAC-IN, the selection of the CH is made by weight and weight is measured by residual energy of every sensor and average regional energy of all SNs in the clusters. The technique proposed in this work has the ability for overcoming the limitation of REAC-IN routing protocol by using clustering and Tabu search.

Yuan et al. [24] provided a GA-based, self-organising network clustering (GASONeC) framework for optimising WSN clusters dynamically. In GASONeC, residual energy, BS distance, estimated expenditure of energy, the total count of the SN are applied in the search for a dynamic, optimal structure. The time taken for performing optimisation is long in this approach. Kim et al. [25] proposed inter-cluster ant colony optimisation (ACO) protocol that depends on ACO algorithm in order to route data packet in WSN, and the effort was taken for reducing the attempts wasted in transmitting the information forwarded through SNs that lie in nearness in an intensely deployed WSN. In this method, the nodes start to die in less than 1000 rounds of data transmission.

Sekhar and Prasad [26] presented a cuckoo search algorithm (CSA) for selecting the optimal CHs in trust predicted routing framework. This framework was established to secure mobile ad hoc networks. Khabiri and Ghaffari [40] proposed CHS scheme based on CSA. In this work, the optimal selection of CHs depends on four parameters, namely, residual energy of nodes, distance from the node to the BS, distance within clusters, and the distance between clusters. Search solutions falling into local optima very easily is one of the drawbacks found in CSA. Mittal et al. [27] proposed an improved flower pollination algorithm for accelerating threshold sensitive energy-efficient clustering protocol in WSNs. This was aimed at maintaining the stability of the network for a prolonged time duration. In the proposed protocol, though the last node dies later, the first node dies earlier than the existing models. Another recent and evolving optimisation algorithm is the squirrel search algorithm [28], inspired by the foraging behaviour of flying squirrels and is employed in applications such as micro electronic mechanical systems (MEMS) [29], memory populations [30] and so forth. Zahedi and Parma [31] proposed the energy-aware trust-based gravitational search algorithm (ETGSA) in WSN for energy-saving issues, increasing the trustworthiness against attacks in the network and reduction of computational overhead. They suggested evaluating the ETGSA technique in clustered WSN with multiple sink nodes. The drawback of GSA algorithm is that it takes a long time for the convergence of the optimal solution.

Several works suggested the integration of two optimisation algorithms to overcome the disadvantages of algorithms working independently. Shankar et al. [32] suggested a hybrid HSA-PSO, bringing exploration-exploitation trade-off in the optimisation problem of CHS in WSNs. This method combines HSA's high search efficiency and PSO's dynamic nature to produce an improved performance. The performance in terms of the initial dead node (DN) is good. However, the last DN round number needs improvement. Murugan and Sarkar [33] proposed a hybrid optimisation using firefly algorithm and grey wolf optimisation, called firefly cyclic grey wolf optimisation. The work focused on the regulation of energy and lowering of separation distance and minimisation of delay. Rajagopal et al. [34] suggested the integration of bacterial foraging optimisation (BFO) with bee swarm optimization, for optimal CHS problem, to improve data aggregation. The work aims to elect optimal CHs with minimum transmission cost and energy. The death of the first node for this method occurs in less than 500 rounds of data transmission. Kumar and Kumar [35] presented a hybridisation of swarm intelligence algorithms such as ABC and ACO. The hybrid algorithm works on three phases: (1) Selection of an optimal number of clusters, (2) selection of CHs using ABC, and (3) data transmission using ACO. But balance among exploration and exploitation is not taken into consideration in this work. This leads to the death of the last node earlier than the LEACH algorithm. Kapoor et al. [36] suggested a hybrid scheme that uses Quadrature LEACH with optimisation algorithms: genetic algorithm (GA) and BFO. Hybrid QLEACH-GA and QLEACH-BFO were employed for

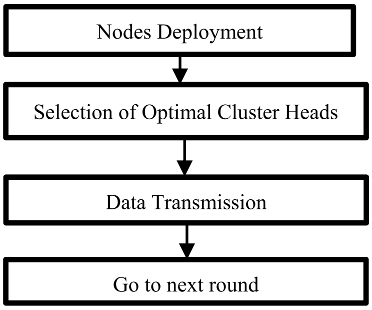

FIGURE 2 The framework of the proposed method

choosing optimal CHs. BFO and GA have their own drawbacks where BFO is vulnerable in perceiving the environmental changes, and the performance of GA depends completely on the fitness function.

The single optimisation methods either excel in the exploration phase of optimisation or the exploitation phase but lags at bringing any balance among exploitation and exploration phase. The hybrid optimisation techniques require improved performance in enhancing network lifespan. Hence, the proposed work presents the hybridisation of SFO and grey wolf optimization (GWO) for balancing exploration and exploitation, thereby providing better performance in the optimal selection of CHs in WSN.

3 | PROPOSED METHODOLOGY

This study focuses on extending the lifetime of the network by choosing optimal CHs for data transmission. The flow chart of the entire work is displayed in Figure 2.

3.1 | Network model

WSN comprise of various SNs where every SN is motionless and has equivalent skills. Throughout the information communication, nodes may perform both as a CH and functioning sensor. All in all, the WSN module is related by radio correspondence, sensor allocation, information sensing, topology features and energy consumption. In area utilisation, a sensor might be situated arbitrarily or physically. The way-gathering SNs may be named as clustering. It is an eminent strategy to expand the future of WSN. In the procedure of clustering, clusters are shaped through collecting the SNs. This pattern of CHS is made for all the clusters present in the network. The nodes in a specific group are shaped dependent on the state of minimum CH distance. Throughout the activity, all SNs gather data from a territory and move to CH. Moreover, a specific CH takes the data to BS.

3.2 | Distance model

At first, the whole CHs inside the system transfers advertisement packet to pronounce that they possess the role of CH. In this condition, each SN in the system finds out the CH distance. In this way, a node has a place with the specific cluster by guaranteeing that its transmission distance from CH of the particular cluster is low, and hence it transfers the information to CH. The SNs transfers the information straightforward to BS if the transmission distance among CH and the node is greater than transmission distance between BS and node. This is the configuration of shaping a cluster on basis of calculation of close transmission distance. Thus, nodes may be re-bunched in the system by the chosen CH utilising a transmission distance and determined utilising the equation below:

$$d = \cos(\theta) = (XY) / \|X\| \, \|Y\| \tag{1}$$

where X is the coordinate of the node and Y is the coordinate of the CH.

3.3 | Energy model

Energy consumption is a primary issue in WSN. WSN battery cannot be recharged that means that there is a chance for no power supply when the battery is removed. Additional energy is needed for transferring information from SNs to BS. The network takes a huge quantity of energy since it does multiple operations like reception, transmission, aggregation and sensing. The module of energy necessary for information transition is explained in the below equation:

$$E_{TX}(N:d) = \begin{cases} (E_{elec} \times N) + \left(E_{fs} \times N \times d^2\right), & \text{if } d < d_0 \\ (E_{elec} \times N) + \left(E_{pw} \times N \times d^4\right), & \text{if } d \geq d_0 \end{cases} \tag{2}$$

where $d_0 = \sqrt{\frac{E_{fs}}{E_{pw}}}$ is the threshold distance, $E_{elec} = E_{TX} + E_{agg}$, $E_{TX}(N{:}d)$ indicates the entire energy consumption needed for transmitting packets of N bytes to a d distance, E_{fs} is the amplification coefficient of the transmission amplifier for the free space model, E_{pw} is used when the distance is greater than the threshold distance, E_{elec} specifies the electronic energy based on diverse factors include spreading, digital coding, filtering and so forth.

3.4 | Cluster head selection

3.5 | Objective function

The transmission distance among the selected CH and node and energy needed for transmitting the information among nodes should be low. The energy in the network must be huge, that is, it must spend limited energy when data passing on. The following constraints are considered for designing the WSN for the simulation work.

(i) Alive node constraint: A sensor node in the network is said to be alive when its energy is higher than zero.

$$E_i > 0 \quad i = 1, 2, \ldots, n$$

(ii) Distance constraint: f_{dis} is the maximum of the distance of nodes '$node_i\ \forall_i \in cluster\ Cluster_k$' to their cluster heads 'CH_k' and '$\|Clusterk\|$' is the number of nodes that belong to cluster '$Clusterk$'.

$$f_{dis} = \max_k \left\{ \sum_{\forall, node, i \in C_k} \frac{d\,(node_i, CH_k)}{||Cluster_k||} \right\};$$

(iii) Energy constraint: f_{en} is the ratio of the initial energy of all nodes alive, $E(node_i)$ in the network with the total current energy of the cluster head $E(CH_j)$ in the current round.

$$f_{en} = \frac{\sum_{i=1}^{N} E\,(node_i)}{\sum_{j=1}^{k} E\,\left(CH_j\right)};$$

The objective function of the suggested selection of cluster is mentioned as

$$f_{obj} = \left(\sigma_1 \times f_{dis}\right) + \left(\sigma_2 \times f_{en}\right) \tag{3}$$

where $\sigma_2 = 1 - \sigma_1$;

The value of σ_1 should be in the range of $0 < \sigma_1 < 1$. The fitness evaluation of each search agent in the proposed algorithm of CH selection is computed using Equation (3). This fitness depends on two parameters, distance and energy, expressed in f_{dis} and f_{en}.

3.5.1 | Grey wolf optimization

Grey wolf (GW) is known as the apex predator, which means that they represent the top of the biological food chain. GWs often choose to survive. The average size of a group is 5–12. The pack leaders are female and a male termed as alpha (α) wolves. The α wolf usually takes the decision about the place of sleeping, time of waking, hunting and so forth. The decisions made by the α are being informed to the whole pack. Nonetheless, some democratic behaviour is also seen. The α wolf leads other wolves in packs. In gatherings, the entire pack identifies the α through holding their extremities. It shows the discipline and organisation of the pack that are considerably significant than its strength [37]. The beta (β) wolves are secondary wolves that aid the α in other activities or in making decisions. The β wolf may be female or male, and he/she is most likely the better one if the α wolves reach old age or die. The β wolf must respect the α and also commands the bottom-stage wolves. It undertakes the role of disciplining the pack and also a consultant to α. The β enforces the α's directions through the pack and passes the response to α. The least arranged GW is omega (ω) and it undertakes the job of a scapegoat. The ω is not essential and is separate in the pack; however, the entire pack faces interior battling and issues in the absence of ω. It helps in fulfilling the whole pack and keeping up the predominance configuration. If a wolf is not α, β, or ω, then he/she is termed delta (δ). The δ wolves should submit to β and α wolves, however, it dominates ω. Sentinels, scouts, hunters, caretakers and elders belong to this group. Scouts watch the territory boundaries and warn pack of danger. The following steps are implemented in the GWO algorithm:

Encircling prey

In GWO algorithm, hunting is done on the basis of α, β, and δ wolf's location. The x wolves tail these three wolves. The GW surrounds the prey while in hunt. The encircling behaviour of GW is mentioned in the following equation:

$$E = \left|F \cdot X_p\,(i) - X\,(i)\right| \tag{4}$$

$$X\,(i+1) = X_p\,(i) - BE \tag{5}$$

where i indicates the current iteration, B and F are coefficient vectors, X_p is the prey's position vector, and X indicates the GW's position vector. The vectors B and F are computed in the following manner:

$$B = 2a \cdot rand_1 - a \tag{6}$$

$$F = 2 \cdot rand_2 \tag{7}$$

The variable a is linearly decremented from 2 to 0 during the search iterations; $rand_1$ and $rand_2$ are randomly generated vectors in [0, 1].

Hunting

The ability of prey-position recognition helps the GW to surround the prey. The successful hunt is regularly directed through the α. In addition, the δ and β may contribute to the hunting behaviour intermittently. For investigating the hunting behaviour of GW, the α, β, and δ should have awareness about the position of prey. Hence, the first three finest values achieved so far are stored, and the rest of the search agents are subjected to update on their own locations with respect to the location of finest search agents. The expressions given below are being suggested [7].

$$E_\alpha = \left|(F_1 \cdot X_\alpha) - X\right| \tag{8}$$

$$E_\beta = \left|(F_2 \cdot X_\beta) - X\right| \tag{9}$$

$$E_\delta = \left|(F_3 \cdot X_\delta) - X\right| \tag{10}$$

$$X_1 = X_\alpha - (B_1 \cdot E_\alpha) \tag{11}$$

$$X_2 = X_\beta - (B_2 \cdot E_\beta) \tag{12}$$

$$X_3 = X_\delta - (B_3 \cdot E_\delta) \tag{13}$$

$$X(t+1) = \frac{X_1 + X_2 + X_3}{3} \tag{14}$$

The α, β, and δ evaluate the location of prey, and the rest of the wolves randomly update their locations around the prey.

Attacking prey

When the prey stops the movement, the GW initiates the prey-attacking process. For the purpose of modelling the process of the imminent attack of the prey mathematically, the range of a is decreased to taper the B from the maximum value. In further $|B| < 1$ pushes the GW to attack (exploitation) in the direction of the prey. This increases the efficiency of the GWO for performing a local search.

Search for prey

GWs generally search for the best candidate based on the locations of α, β, and δ wolves. They are diverged (exploration) from each other for searching the prey and are converged (exploitation) together to attack the prey. The random coefficient vector (B) lies above 1 or below –1 to force the search agent to diverge from prey. In addition, the random coefficient vector F also contributes GWO to obtain better random behaviour during optimisation and prevent local optima. It is notable that F is non-linearly reduced, unlike the parameter B. The parameter F is deliberately needed for providing randomly generated values every time for the purpose of emphasising exploration phase.

Sunflower optimisation

The pattern of the sunflower is consistent: They daily go with the sun like the clock needles. Around evening time, they travel the other way to stand by again for their departure of the following morning. Yang [38] suggested a flower pollination algorithm dependent on the bloom fertilisation procedure of blossoming plants considering the natural reproduction process. The researcher focuses on the speciality of sunflowers' motion in the exploration for the finest orientation in the direction of the sun. The random fertilisation is considered between the marginal distances of sunflower i and i+1. In general, millions of pollen gametes is frequently released by every flower patch. For easiness, we consider that every sunflower generates only one gamete of pollen and reproduces individually. Another significant point about nature-based optimisation is the inverse square law radiation. The law states that the received power is inversely related to the square of separation and it takes larger step values to orient towards the sun (global optimum) [39].

The quantity of received power for all sunflowers is specified by

$$Q_i = \frac{P}{4\pi r_i^2} \tag{15}$$

where P is the source power and r_i the distance among the present best and the plant i.

The sunflowers orientation in the direction of the sun is

$$s_i = \frac{X^* - X_i}{X^* - X_i}, \quad i = 1, 2, \ldots, n \tag{16}$$

The step of the sunflowers towards the sun is computed by

$$d_i = \lambda \times P_i (X_i + X_{i-1}) \times X_i + X_{i-1} \tag{17}$$

where λ describes an 'inertial' displacement of the plants, $P_i(X_i + X_{i-1})$ is the pollination probability.

The maximum step size followed by the sunflowers to enhance the exploration is given as

$$d_{max} = \frac{X_{max} - X_{min}}{2 \times N_{pop}} \tag{18}$$

where X_{max} and X_{min} are the upper and lower bounds values, and $N_{pop}$is the total count of plants of the overall population.

The updated location of the sunflower (new plantation) is given as

$$X_{i+1} = X_i + (d_i \times s_i) \tag{19}$$

The algorithm starts with the arbitrary initialisation of a population of individuals in the search region. The fitness values of all the individual are evaluated and best among all the individual is nominated as the sun. Then, the entire individual in the population will update its location towards the sun. The step-size variation emphasises the exploration phase by bringing the plant closer to the sun in search of global refinement. This variable deliberately is needed for the purpose of emphasising exploration phase not only in the initial iterations but also in the final search iterations. It allows the solution to escape from local optima and to improve the global optimum prediction of the algorithm.

3.5.2 | Proposed HGWSFO algorithm for CHS

In the considered application scenario, 100 SNs are deployed randomly and 5% of the total nodes act as cluster head [21, 32, 33 and 35]. The cluster head selection process for the proposed study is carried out by integrating the best characteristics of SFO and GWO algorithm using an index search. The sunflower method follows the inverse square law radiation to minimise the distance between the plant and the sun to get sunlight and to stabilise them in its vicinity. In addition, the variation of the step-size parameter brings the plant closer to the sun in search of global optima, thus increasing the exploration efficiency. Even though SFO can perform the global optimal, it suffers from slow convergence and has poor local searchability. In GWO, exploration and exploitation are controlled by coefficient vectors (B and F). The GWO algorithm excels in the exploitation phase; the wolves attack the prey (exploitation) when the coefficient vectors are less than one. On the other hand, the GWO algorithm performs lesser in the exploration when compared to the exploitation since the information of candidate solutions from search space as limited information is shared among the solutions in the pack. A critical index value of 5 is set with reference to [33], to choose between SFO and GWO method of CHS. The index search enables the exploration for the best fitness (index <5) to find the global best CH using the SFO method and other fitness (index >5) to perform the GWO algorithm (exploitation). This process is repeated for each round of data transmission. The narrow process of search starts by creating a grey wolf's arbitrary population in the GWO algorithm. During the search iterations, α, β, and δ wolves calculate the possible prey. Every solution of candidate updates their distance with respect to the prey. The parameter a is minimised from 2 to 0 for emphasising the phase of exploration. Candidate solutions are more likely to diverge from the prey under the condition $|B| > 1$ and are more likely to converge towards the prey under the condition $|\mathrm{B}| < 1$.

The α, β, and δ wolves' positions are updated. The GWO algorithm is terminated by the satisfaction of a convergence criterion. For a broader search, a random population of plants is created. These plants are oriented towards the sun, and the fitness of each plant is calculated. The mortality rate is monitored for removing the dead plants. Steps are calculated, and the process of pollination is carried out for generating new plants. The fitness values of the new plants are evaluated. The best fit plant is set as the sun node. The SFO algorithm is completed by the satisfaction of a convergence criterion. The following steps are implemented in the HGWSFO and the flowchart of the proposed algorithm is provided in Figure 3.

Step 1. Nodes deployment: A total of 100 nodes are deployed in the network model where each sensor is stationary and homogeneous fashion.

Step 2. Evaluate fitness: Fitness is evaluated for each node by energy and distance. The values are sorted consistent with the ascending order of the index.

Step 3. Index check: If the index is less than 5, SFO is initiated. If the index is greater than or equal to 5, then GWO is initiated.

Step 4. Optimal Cluster head selection: (1) GWO: Initialise GWO population. The population of GWs is initialised. These GWs are the search agents that find the best solution in the exploitation region.

Evaluate Fitness: Fitness for each GW is evaluated and sorted. The first best search agents are categorised as α wolves, whereas the second and third best agents are categorised as β and δ wolves, correspondingly.

Update GWO parameters: The values *a, B,* and *F* are updated according to Equations (6) and (7).

Update α, β and δ positions: The final positions of α, β and δ wolves are updated with respect to the obtained fitness values.

Optimal solution: The first five nodes having minimum fitness values are set as CHs.

ALGORITHM 1 GWO algorithm for CHS

r_{max} ← Number of iterations for data transmission
NI ← Internal iteration for CHS using GWO
for t ← 1 to r_{max} **do**
To construct an arbitrary determination of normal nodes
for i ← 1 to *NI* **do**
GWO(j,:) ← Arbitrarily chosen CH for *GWO.*
$f_{Obj}(j)$ ← Fitness standards for *GWO(j,:)*
Update *Alpha_score, Beta_score* and *Delta score*
Update a, A and C values
Update the positions of Alpha, Beta, and Delta wolves
end
Selecting the best Cluster heads from the Alphas for
Data Transmission
end

Stop criterion: The procedure is repeated for a predefined number of search iterations.

(2) SFO: Initialisation of SFO population. The population of plants is initialised. These plants are the search agents that find the global best solution.

Evaluate Fitness: The orientation of each plant is done in the direction of the sun. The fitness of each plant is calculated. The mortality rate is monitored, and the dead plants are removed. Steps are calculated according to Equation (17). Pollination is carried out for the generation of new plants, followed by the evaluation of fitness for those new plants using the Equation (19).

Update SFO parameters: The plant with the best fitness value is transformed into the sun.

Optimal solution: The first five nodes having minimum fitness values are set as CHs.

Stop criterion: The procedure is recurrently executed for a defined number of search iterations.

Step 5. Data Transmission: Data transmission is initiated between the optimal CHs and the sink node. This procedure is repeated for every round of data transmission and is continued until the iteration reaches a maximum number of rounds.

Pseudocode for GWO algorithm:
Pseudocode for SFO Algorithm:
Pseudocode for HGWO-SFO algorithm:

4 | RESULTS AND DISCUSSION

The experimental of optimal CHS in WSN is carried out in MATLAB R2018a. The parameters considered for the simulation and the initialised values are listed in Table 1 given below.

The performance of the proposed HGWSFO technique of selecting cluster heads is related with other existing algorithms

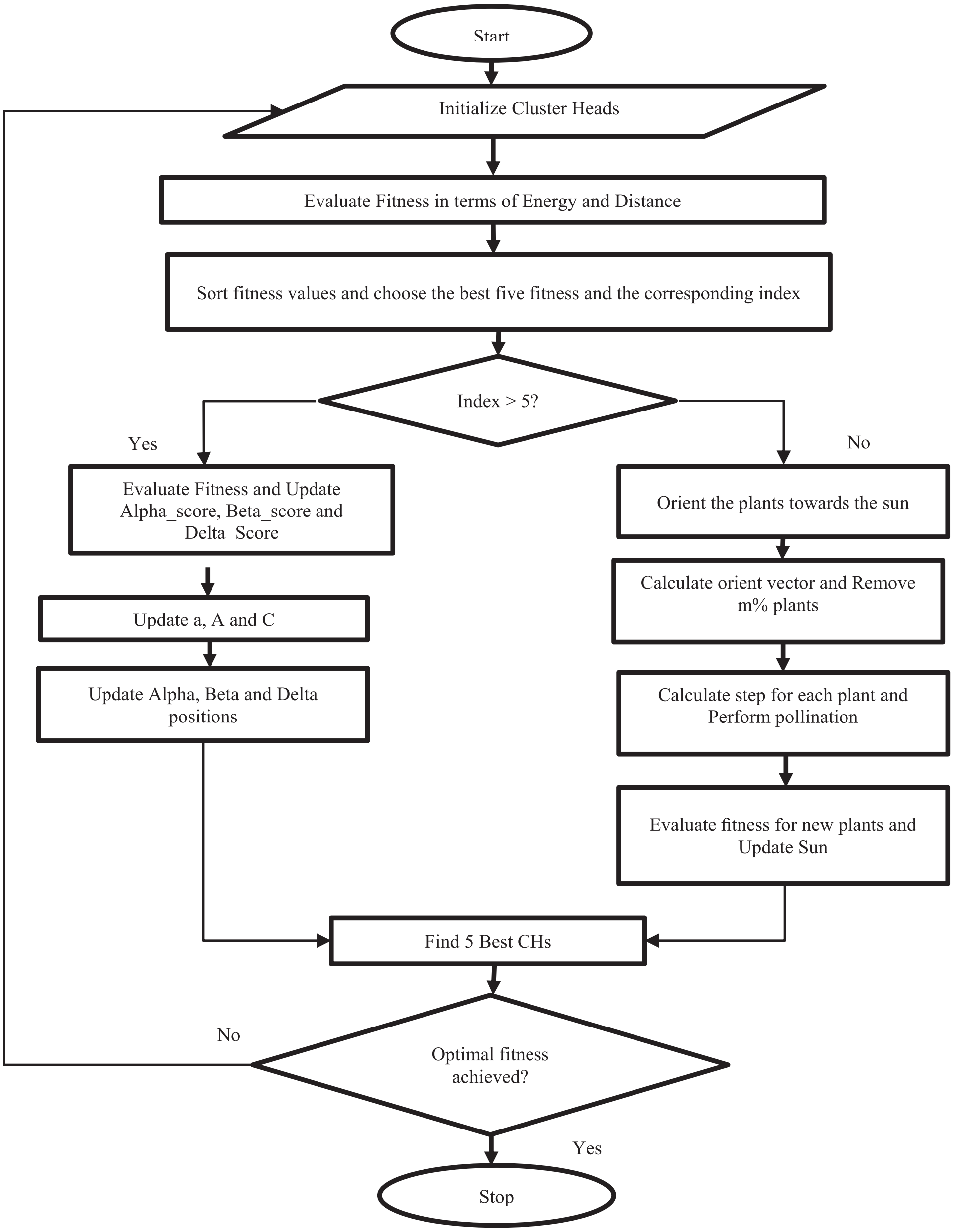

FIGURE 3 Flowchart of hybrid grey wolf optimisation (GWO)-based sunflower optimisation (SFO) cluster head selection (CHS) algorithm

like DT, LEACH, LEACH-C [41], PSO, improved PSO [42], GWO, and SFO.

The performances of these different algorithms are assessed in terms of six parameters such as throughput produced by the network, number of alive nodes, number of DNs, residual energy of the network, network survivability index (NSI), and convergence rate. Throughput of the network is defined as the number of alive nodes at a particular round and is multiplied by the data packet length (bits). A node is said to be dead when its energy is dropped to zero. The number of alive nodes is found by calculating the total number of nodes that are alive. And the number of DNs is found by calculating the total number of nodes that are drained out of energy (i.e. dead). The residual energy of the networks is defined as the sum of the remaining energy of all the nodes present in the network at a particular round. Network lifetime is defined in many ways; however, in the proposed study, we consider it as the number of rounds until the last node death. NSI can be defined as the ratio of the number of nodes that are alive to the total number of nodes in the network. The convergence rate describes how quickly the optimisation algorithm finds the global best without being struck in the local minima or maxima.

The DT method permits the nodes in the network to communicate with the BS directly. In contrast, the LEACH protocol follows a random selection of CHs. Hence, the performances of these two methods were poorer than the meta-heuristics. The PSO-CHS method faces high-dimensional optimisation limitation; it is difficult to explore every possible region of the search space (poor exploitation). In SFO, the variation of the step-size parameter brings the plant closer to the sun in search of

ALGORITHM 2 SFO algorithm for CHS

r_{max} ← Number of iterations for data transmission
NI ← Internal iteration for CHS using SFO
for t ← 1 to r_{max} **do**
To construct an arbitrary determination of normal nodes
Calculate fitness and sort according to the index value
for i ← 1 to *NI* **do**
SFO(j,:) ← Randomly chosen CH for *SFO.*
$f_{Obj}(j)$ ← Fitness values for *SFO(j,:)*
Update the positions of *Plants* using *SFO* parameters
Update the position of best *Plant* as the *Sun*
end
Selecting the best CHs from the positions of the Sun
for data transmission
end

TABLE 1 Simulation parameters

Parameter	Value
Area covered by wireless sensor networks (m^2)	200 × 200
E_o (Initial energy of nodes) (J)	0.5
E_{amp} (pJ/bit/m^2)	120
E_{elec} (nJ/bit)	100
Energy data aggregation (nJ)	5
Number of cluster heads selected	5%
Number of rounds	3000
Number of search iterations	5
Exploration control parameter (a)	Decreases from 2 to 0
Coefficient vector 'F'	Range [0, 2]
Mortality rate 'm' (%)	0.1
Pollination rate 'p' (%)	0.05

ALGORITHM 3 HGWO-SFO algorithm for CHS

Initialise the parameters of SFO and GWO.
r_{max} ← Number of iterations for data transmission
NI ← Internal iteration for CHS
for t ← 1 to r_{max} **do**
To construct an arbitrary determination of normal nodes
Calculate fitness and sort according to the index value
if index > 5 Begin GWO exploitation
for i ← 1 to *NI* **do**
GWO(j,:) ← Randomly chosen CH for *GWO.*
$f_{Obj}(j)$ ← Fitness values for *GWO(j,:)*
Update *Alpha_score, Beta_score* and *Delta score*
Update a, A and C values
Update the positions of Alpha, Beta, and Delta wolves
end
else Begin *SFO* Exploration
for j ← 1 to *NI* **do**
SFO(j,:) ← Randomly chosen cluster head for *SFO.*
$f_{Obj}(j)$ ← Fitness values for *SFG(j,:)*
Update the positions of *Plants* using *SFO* parameters
Update the position of best *Plant* as the *Sun*
end
end

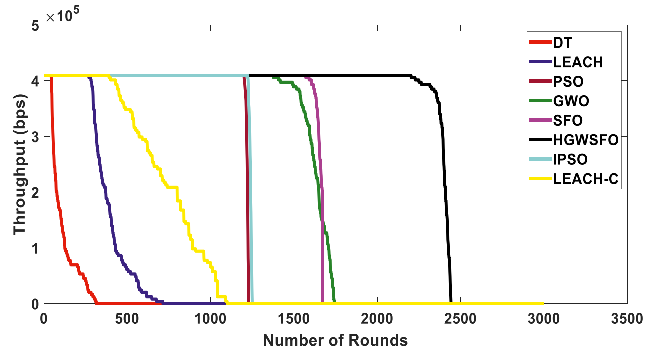

FIGURE 4 Comparison of throughputs obtained for different CHS algorithms

global optima, thus increasing the exploration efficiency. Even though SFO can perform the global optimal, it suffers from slow convergence and has poor local searchability. In GWO, the exploration and exploitation is controlled by coefficient vectors (B and F) and the wolves attack the prey (exploitation) when the coefficient vectors are less than 1. On the other hand, the performance of GWO in exploration is poorer compared to exploitation. These single optimisation methods either excel in the exploration phase of optimisation or the exploitation phase but lags at bringing any balance between the exploitation-exploration and fast convergence. Hence, the CHS process for the proposed study is carried out by integrating the best characteristics of SFO and GWO algorithm using index search.

Figure 4 shows the comparative illustration of the performance of the different algorithm in terms of throughput obtained in bps for an increasing number of rounds of data transmission. The throughput in the WSN for all the algorithms at the initial round is 409,600 bps. When 1600 rounds are reached, the throughput of the proposed HGWSFO is 409,600 bps, whereas for the algorithms, GWO and SFO, the throughputs are 294,900 and 401,400 bps, respectively. The throughput of IPSO, PSO, LEACH-C, LEACH, and DT at the round number 1600 is 0 bps. The throughput of the proposed HGWSFO declines to zero at the round number 2442, while the algorithms GWO, SFO, IPSO, PSO, LEACH-C, LEACH, and DT, declines at 1744, 1672, 1250, 1229, 1100, 714, and 315, respectively. The throughput lifetime of proposed HGWSFO is 28.58% more than the GWO algorithm, 31.53% more than the SFO algorithm, 48.8% more than IPSO algorithm, 49.67% more than the PSO algorithm, 54.95% more than LEACH-C

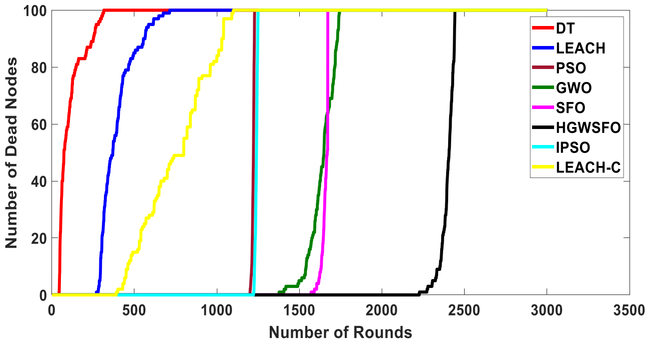

FIGURE 5 Comparison of dead nodes obtained for different CHS algorithms

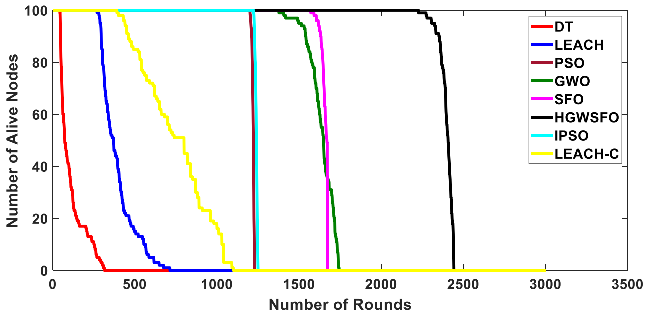

FIGURE 6 Comparison of alive nodes obtained for different CHS algorithms

protocol, 70.76% more than the LEACH protocol, and 87.10% more than the DT.

Figure 5 shows the comparative illustration of the performance of the different algorithm in terms of count of the DNs for an increasing number of rounds of data transmission. The first node in the WSN for the proposed HGWSFO dies at the round number 2227, whereas for the algorithms GWO, SFO, IPSO, PSO, LEACH-C, LEACH, and DT, the nodes die at 1377, 1571, 1223, 1201, 391, 270, and 44, respectively. Half of the total number of nodes in the WSN for the proposed HGWSFO die at the round number 2407, whereas for the algorithms GWO, SFO, IPSO, PSO, LEACH-C, LEACH, and DT, the nodes die at 1649, 1669, 1240, 1222, 830, 370, and 74, respectively. All the nodes in the WSN for the proposed HGWSFO die at the round number 2442, whereas for the algorithms GWO, SFO, IPSO, PSO, LEACH-C, LEACH, and DT, the nodes die at 1744, 1672, 1250, 1229, 1100, 714, and 315, respectively. The lifetime of the nodes for the proposed HGWSFO lasts 38.16% more than the GWO algorithm, 29.45% more than the SFO algorithm, 45.08% more than the IPSO algorithm, 49.07% more than the PSO algorithm, 82.44% more than the LEACH-C protocol, 87.87% more than the LEACH protocol, and 98.02% more than the DT.

Figure 6 shows the comparative illustration of the performance of the different algorithm in terms of count of the alive nodes for an increasing number of rounds of data transmission. The first node in the WSN for the proposed HGWSFO is alive till the round number 2227, whereas, for the algorithms: GWO,

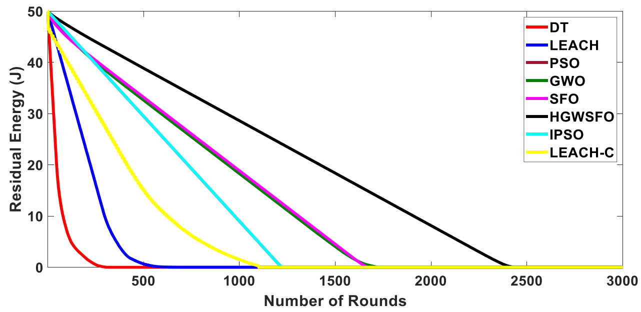

FIGURE 7 Comparison of residual energy obtained for different CHS algorithms

SFO, IPSO, PSO, LEACH-C, LEACH, and DT, the nodes die at 1377, 1571, 1223, 1201, 391, 270, and 44, respectively. Half of the total number of nodes in the WSN for the proposed HGWSFO are alive till the round number 2407, whereas for the algorithms GWO, SFO, IPSO, PSO, LEACH-C, LEACH, and DT, the nodes die at 1649, 1669, 1240, 1222, 830, 370, and 74, respectively. All the nodes in the WSN for the proposed HGWSFO stay alive till the round number 2442, whereas for the algorithms GWO, SFO, IPSO, PSO, LEACH-C, LEACH, and DT, the nodes stay alive till 1744, 1672, 1250, 1229, 1100, 714, and 315 rounds, respectively. The lifetime of the nodes for the proposed HGWSFO lasts 28.58% more than the GWO algorithm, 31.53% more than the SFO algorithm, 48.8% more than IPSO algorithm, 49.67% more than the PSO algorithm, 54.95% more than LEACH-C protocol, 70.76% more than the LEACH protocol, and 87.10% more than the DT.

Figure 7 shows the comparative illustration of the performance of the different algorithm in terms of residual energy in J for an increasing number of rounds of data transmission. The residual energy in the WSN for all the algorithms at the initial round is 50 J. When 1600 rounds are reached, the residual energy of the proposed HGWSFO is 16.33 J, whereas for the algorithms GWO and SFO, the residual energies are 1.564 and 1.667 J, respectively. The residual energies of IPSO, PSO, LEACH-C, LEACH, and DT become zero at the round number 1600. The residual energy of the proposed HGWSFO declines to zero by the round number 2442, while for the algorithms GWO, SFO, IPSO, PSO, LEACH-C, LEACH, and DT, the residual energy declines at 1744, 1672, 1250, 1229, 1100, 714, and 315, respectively. The residual energy of proposed HGWSFO lasts 28.58% more than the GWO algorithm, 31.53% more than the SFO algorithm, 48.8% more than IPSO algorithm, 49.67% more than the PSO algorithm, 54.95% more than LEACH-C protocol, 70.76% more than the LEACH protocol, and 87.10% more than the DT.

Figure 8 shows the comparative illustration of the performance of the different algorithm in terms of NSI. NSI is calculated for each round of transmission for all the algorithms. The NSI value will be 1 if there are no dead nodes in the network. The NSI for the proposed HGWSFO stays 1 till the round number 2227, whereas for the algorithms GWO, SFO, IPSO, PSO, LEACH-C, LEACH, and DT, the NSI starts falling from 1377, 1571, 1223, 1201, 391, 270, and 44, respectively.

TABLE 2 Table of comparison

Algorithm	First dead node (DN; round number)	Half DNs (round number)	Last DN (round number)	Residual energy after 1600 rounds (J)	Throughput after 1600 rounds (bits/round)
Direct transmission	44	74	315	0	0
Low energy adaptive clustering hierarchy (LEACH)	270	370	714	0	0
LEACH-centralised	391	830	1100	0	0
Particle swarm optimisation (PSO)	1201	1222	1229	0	0
Improved PSO	1223	1240	1250	0	0
Grey wolf optimisation	1377	1649	1744	1.564	294,900
Sunflower optimisation (SFO)	1571	1669	1672	1.667	401,400
Proposed hybrid HGWSFO	2227	2407	2442	16.33	409,600

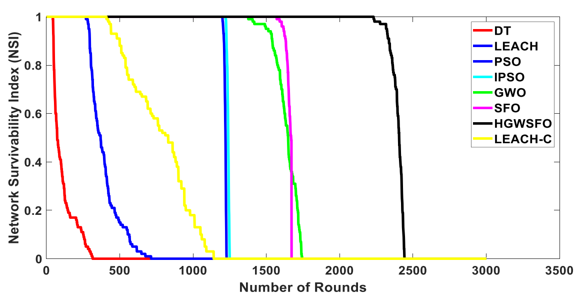

FIGURE 8 Comparison of network survivability index obtained for different CHS algorithms

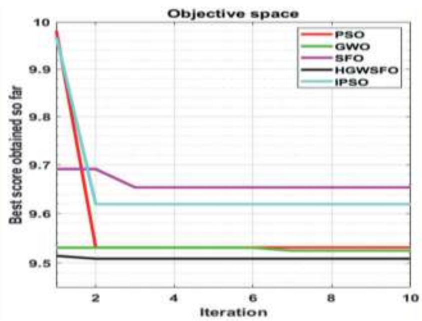

FIGURE 9 Convergence curve of different CHS algorithms

The NSI becomes 0 for the WSN for the proposed HGWSFO at the round number 2442, whereas for the algorithms GWO, SFO, PSO, LEACH, and DT, the NSI falls to 0 at 1744, 1672, 1250, 1229, 1100, 714, and 315 rounds, respectively. The survivability of the network for the proposed HGWSFO lasts 28.58% more than the GWO algorithm, 31.53% more than the SFO algorithm, 48.8% more than IPSO algorithm, 49.67% more than the PSO algorithm, 54.95% more than LEACH-C protocol, 70.76% more than the LEACH protocol, and 87.10% more than the DT.

The convergence curve of the proposed HGWSFO and existing algorithms such as IPSO, PSO, SFO, and GWO are shown in Figure 9. The curves illustrate the converging property of different optimal CHS algorithms for increasing number of iterations. The convergence of minimum best score to minimum number iterations can be seen for the proposed HGWSFO algorithm. Table 2 shows the comparative analysis of the performance of various CHS methods.

5 | CONCLUSION

This study proposes HGWSFO for the optimal selection of CHs in WSN based on the index value of CHs. The HGWSFO algorithm integrates the superior behaviour of two meta-heuristic algorithms, namely, SFO and GWO. The energy consumption and separation distance are considered for selecting optimal CHs. The coefficient vectors of the GWO algorithm enhances the efficiency of exploitation, whereas the global search inefficiency of GWO is compensated in a better way by the SFO algorithm under the variable step size of the plants. The superior performance of the proposed HGWSFO is validated by comparing its performance with various other existing CHS algorithms in terms of throughput, residual energy, alive nodes, DNs, NSI, and convergence rate. It is found that the lifetime of the WSN guided by the proposed HGWSFO CHS shows 28.58%, 31.53%, 48.8%, 49.67%, 54.95%, 70.76%, and 87.10%, enhancement when compared to GWO, SFO, IPSO, PSO, LEACH-C, LEACH, and DT methods, respectively. The total time complexity of the proposed HGWSFO scheme is $O(N \times d \times maxIter)$where N is the size of the population, d represents the dimensionality of the problem and $maxIter$is the maximum iteration. Although the complexity of the proposed scheme is higher than older algorithms like DT, LEACH and PSO, the proposed scheme is found to exhibit better efficiency and is able to keep the network alive for a longer period of time. In the future, this study can be extended in the design of Internet of Things for sensing applications and beyond 5G networks.

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