Energy Efficient Cluster Head Selection Using Squirrel Search Algorithm in Wireless Sensor Networks

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Abstract**—**The structure of the wireless sensor network for energy management is an investigating area of research since the power resource of the sensor nodes is considered as a battery. Clustering-based methods are introduced through information aggregation to stabilize energy utilization for efficient communication amid the nodes of sensor networks. Clustering is the technique of splitting the sensing region into a number of sensor groups and allocating a leader node (Cluster Head) for that group. To enhance the search efficiency and optimal coverage the Squirrel search algorithm (SSA) is offered for cluster head election. SSA mimics the energetic searching and gliding behavior of flying squirrels (FSs). The specialty of SSA like Gliding, Seasonal monitoring condition and Predator presence probability overcomes the inconsistent tradeoffs between exploration-exploitation and global search constraints of the existing meta-heuristics algorithm. The network's performance is analyzed in terms of the overall lifespan of the nodes. The simulation results show the proposed SSA provides an improvement in residual energy and throughput by 77.66% and 28.60% respectively, than the PSO algorithm.

Index Terms**—**Cluster head selection, SSA, wireless sensor network, clustering

I. Introduction

The precise development in a wireless system is facilitating the assortment of improvements in wireless sensor networks (WSNs). Accurate sensing abilities and reliable wireless communication offer Wireless sensor networks as a vital factor in different applications. The sensor node comprises various modules such as energy module, detecting module, memory and information processing module and information interactive module [1]. Sensor nodes are densely deployed in the very critical environment to amassing the info, process the info at the end transmit/receive info to the destination node (BS). Recharging battery is very difficult and impossible in some cases. The efficient utilization of existing power sources is considered as the necessary criteria in a wireless sensor network.

All sensor nodes interconnect straight with the base station in the Direct Transmission (DT) method. So every node passes the amassed info to BS individually. This process forces the sensor nodes at a loftier distance from the endpoint (BS) may culvert their energy earlier when compared to nodes that are neighboring to the endpoint (BS). Direct transmission methodology can perform the communication process efficiently only in a small range of communication. To achieve balanced energy consumption among the sensor nodes, similar nodes (cluster members) are assembled together and election the best node (cluster head) among them is considered as clustering. Cluster head will perform the energy efficient process like gathering the info from member nodes, aggregating the collected info and direct it to endpoint (BS).

The energy consumption parameter determines the overall lifespan of wireless sensor networks. Each sensor node loses its available energy throughout the info broadcast. After some interval, a node may miss its available energy completely and it will be inactive. The sensor node energy level and conversation range are contrarily related. For large conversation range between the sensor node and base station is consumed high energy. The energy source used for information transmission is restricted and efficient utilization of existing power sources is considered an important research task in the wireless sensor network [2]-[5].

Election of Cluster head acts as a life-threatening role in cluster based communication. In many applications, the head of the cluster is altered for better results during definite iteration [6]. This encouraged many researchers to explore multiple aspects of wireless sensor networks such as suitable CH selection, low energy routing protocols design and appropriate network coverage [7–9]. This research paper describes certain commonly available Wireless sensor network clustering algorithms and offers a CH selection procedure for wireless sensor networks using meta-heuristics optimization techniques. Meta-heuristic algorithms have a tendency to find the global optimal resolution wherever the examination aimed at an optimal resolution is intensive [10]-[11]. In order to be efficient, meta-heuristic algorithms should cover the search space where the global optimum is present and also enhance the new solution over the complete iteration. All meta-heuristic algorithms should a necessity to jump from the local minima or maxima [12]-[14]. The literature section covers some exploration (global optima) and exploitation (local optima) meta-heuristic algorithms used in WSN.

The continuing sections of the research paper are organized in the following manner: Section 2 recollects the works associated with cluster head selection using meta-heuristic algorithm; Section 3 describes the network

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model followed in WSN; Section 4 presents the proposed SSA algorithm. All the simulation results are inferred in terms of network efficiency is discussed in Section 5, and Section 6 concludes the foremost outcomes of the proposed algorithm and a space for the future work.

II. Related Work

The Enhanced research based on the classical protocol (Direct Diffusion), Geographical and Energy-aware Steering protocols (position-dependent), clustering hierarchical protocol (LEACH) was performed within the literature [15]-[16]. To prolong the life span of a WSN, sensor nodes are determined to sleep energetically by the Sleep Scheduling (SS) mechanism. Basically, Sensor nodes are very lucky to sleep consuming Sleep Scheduling mechanisms organized by the base station to expand energy efficient management [17]. LEACH uses a dynamic methodology of agglomeration somewhere nodes 'n' are arbitrarily selected as cluster heads depend on the threshold value of sensor nodes. LEACH suffers from the possibility that during some rounds nobody (sensor node) present in the available network will be elected as head of the cluster. The cluster head finding is therefore not energy balanced and the establishment of clusters eats more energy during each round [18].

In recent years several investigators have established natural inspiration based optimization technique that imitates certain genetic actions or physical occurrences. Hussain *et al*. investigated smart techniques using a genetic algorithm (GA) for cluster construction and control. The optimal cluster head selection process is carried out at the base station using GA [19]. Multiple energy efficient parameters are grouped to design a fitness function. The authors in [20]-[22] have proposed a Particle Swarm Optimization (PSO) algorithm that is founded on the natural activities of a group of birds. The PSO uses the cumulative effect of personal best and global best to generate a new direction for each particle in the search region. This algorithm does not consider probabilistic phenomenon and seasonal condition to enhance the optimal broader search of the algorithm. Due to this reason the algorithm tapped towards local minima.

The authors in [23] have suggested an Artificial bee colony algorithm (ABC), which imitates the scavenging procedure composed of employed bee, onlooker bee, and scout bee. Every employed bee is associated with high quality food resources and tries to find new improved food sources of nectar in the nearby search space. It broadcast the position of new improved food source to onlooker bees which are near the dancing area of hive only if its quality is higher than the current food source. Based on the received information, Onlooker bees decided to move towards the optimal available resource. An employed bee may also turn as the scout bee, once the present food source is completely utilized and to find a different optimal food source. In ABC, random relocation of scout bee initiated only if the predefined value of iteration is overdone, but SSA adaptively updates the random relocation of search agents during run-time using seasonal monitoring condition to avoid stuck in local optima.

Yang [24] proposed a Firefly algorithm, supported the thought of flashing light making by fireflies. To draw in the partners or to notify the predator, fireflies create the light by the development of bioluminescence. The attraction is straightly related to their brightness. Low intensity fireflies have a tendency to travel towards the brighter one. The random relocation of firefly takes place due to the absence of a brighter one. To enhance the Firefly algorithm, a single pattern matrix is updated through courses of iteration [25]. Whereas under different scenarios, SSA the pattern matrix is effectively divided into three section and corresponding updates are followed. Firefly algorithm regularly updates the location of fireflies to increase the capability of exploration, but SSA familiarized the climate checking criteria.

The authors in [26] proposed a cluster head selection scheme based on Fuzzy relevance to resolving the problems of node distribution. The main motive of this study is to decrease the overhead and stabilize the network. However, this method does not concentrate on optimizing the formation of clusters. The authors in [27] presented an energy efficient scheme of hierarchical clustering for WSN. The nodes form clusters in a hierarchical manner for maximizing coverage and minimizing energy consumption. This method of clustering is decentralized. As an extension, this approach can be formulated as a centralized clustering scheme for improving energy efficiency. The authors in [28] formulated cluster head selection using a random approach called LEACH protocol. The protocol consumes around 25% of the whole energy consumption of the network for data transmission. The overhead of this approach is relatively high and so the network lifetime is relatively short. The authors in [29] proposed an Equalized Cluster Head Election Routing Protocol (ECHERP) as an effort to establish a balanced clustering mechanism in WSN. This model used the Gaussian elimination approach for calculating the node combinations which were selected as the CHs.

In Multi-objective optimization (MOO), the trade-off among two or many contradictory objectives is taken into consideration to design the optimal fitness function. An objective function may compromise on multiple dissimilar objectives to achieve a single fitness function. The outcomes of multi-objective optimization fitness function need to balance among all the objectives present in the fitness evaluation. A way to handle such issues is 'Pareto-optimality' [30]. In 'Pareto-optimal front', multi-group of optimal values replaces the single set which composed of 'non-dominated value' since not at all dominated by others [31]. To exhibits enhancement in the lifespan of the WSN, the integration of popular meta-heuristics based cluster header node selection is achieved [32], [33].

The authors in [34] proposed a hybridization of a great exploitation algorithm (HSA) with an energetic exploration algorithm (PSO) to pick the optimal cluster head among the sensor nodes in the cluster. Clustering permits the cluster head node to remove redundant information gather from its group members and it transmits only the aggregated information to the sink node (BS). The limitations of the traditional network are replaced by recreating the participation of member nodes involved in data transmission and its information. In wireless sensor networks, the clustering tool efficiently decreases the cost of communication in terms of distance and increasing the lifespan by optimizing the energy consumption of sensor nodes. This research suggested a squirrel search optimization algorithm (SSA) to pick out optimal cluster heads.

III. Network Model

To calculate the complete energy consumption of a wireless sensor network, a first-order free space network model is considered. In which transmitter unit contains transmit electronics with a suitable amplifier for data transmission and receiver unit contains receive electronics with a separated distance (d). The communication energy of the sensor network is calculated using the following equation (1-2). An optimal number of sensor nodes is scattered in the monitoring area on rectangular fashion [13]. The subsequent characteristic is assumed to design the wireless sensor network:

- Quasi-stationary nodes construct the wireless sensor network.
- Sensor nodes are ignorant of the position.
- Initial stage every node is considered to be homogeneous.
- The nodes are self-sorting out and need not be checked after the arrangement.
- Constant power level is fixed for all the nodes in the network

$$E_{Tx}(l,d) = \begin{cases} l * E_{elec} + l * \varepsilon_{fs} * d^2 \,, & d \le d_0 \\ l * E_{elec} + l * \varepsilon_{mp} * d^4 \,, & d \le d_0 \end{cases} \quad (1)$$

$$E_{Rx}(l) = l * E_{elec} \quad (2)$$

where E_{elec} is the energy spent to transmit one bit of data; the transmitter unit amplification coefficient (ε_{fs}) is considered when the distance is lower than the threshold distance; l is the total data being sent. The field region of ‘100x100’ m^2 sensor network contains randomly scatted 100 nodes in the observation area. The following objective function is used to find the optimal ‘K’ cluster heads (3).

$$f_{obj} = \varepsilon \times f_1 + (1-\varepsilon) \times f_2 \quad (3)$$

where f_1 and f_2 are calculated by

$$f_1 = max_k \left\{ \sum_{\forall\, node\, i\, \epsilon\, C_k} \frac{d(node_{i\,,} CH_k)}{\|Cluster_k\|} \right\} \quad (4)$$

$$f_2 = \frac{\sum_{i=1}^{N} E(node_i)}{\sum_{j=1}^{k} E(CH_j)} \quad (5)$$

The scaling factor ε varies from 0 to 1. The first objective function f_1 is the maximum Euclidean distance between a node to cluster head $d(node_{i\,,} CH_k)$ and the total number of nodes that belong to the cluster ($\|Cluster_k\|$).

IV. Squirrel Search Algorithm

Flying squirrels are an expanded gathering of arboreal and nighttime sort of rodents that are especially adjusted for gliding locomotion. A parachute-like layer (patagia) of flying squirrels is viewed as energy efficient refined, that comforts the flying squirrel move smoothly from one tree to subsequent and styles them proficient in the ever-changing lift and drag [35]. The foraging behavior of flying squirrels initiates the search process in the squirrel search optimization algorithm. An energy efficient characteristic of flying squirrels is called as Guiding. In fact, the flying squirrels do not fly; they follow a special locomotion technique in order to travel large distances resourcefully and rapidly [36]. During autumn the squirrel gliding from one tree to another for finding the food resources to meet their daily needs (acorn nuts) in the forest. After achieving their daily needs, they start foraging for hickory nuts (optimal food resource) that will help them in winter.

Storage of optimal food (hickory nuts) will help them in preserving their energy needs in especially cruel climate (winter) and decrease the high foraging journeys and increase the probability of lifespan. At the end of winter climate, flying squirrels become active again. Flying squirrels repeat the above process and continue throughout the lifecycle and formulate the SSA. The flow diagram of the proposed SSA scheme is displayed in the Fig. 3. To implement the mathematical model of SSA, the following assumptions are considered.

- The forest contains ‘n’ number of flying squirrels and assuming that each tree having one squirrel.
- The forest region consists of three types of trees such as hickory tree (optimal food), acorn tree (second optimal food) and normal tree (no food).

V. Mathematical Model of SSA

Similar to population-based algorithms; SSA begins with the random deployment of flying squirrels in d dimensional search space beside the position of flying squirrel is denoted by a vector.

A. *Initialize the Squirrel Matrix*

The position of the entire (n) flying squirrel is represented by the following squirrel matrix (6).

$$FS = \begin{bmatrix} FS_{1,1} & \cdots & FS_{1,d} \\ \vdots & \ddots & \vdots \\ FS_{n,1} & \cdots & FS_{n,d} \end{bmatrix} \tag{6}$$

To construct a squirrel search matrix, the required number of the population (flying squirrel) in the forest is n. Where $FS_{i,j}$ denotes the i[th] flying squirrel in the j[th] dimension. The upper and lower limits of the search space are FS_{UB} and FS_{LB}. To assign the initial position of all flying squirrel the following formula is used (7).

$$FS_i = FS_{LB} + U(0,1) \times (FS_{UB} - FS_{LB}) \tag{7}$$

B. Evaluation of Fitness Function and Sorting

After random distribution, flying squirrels are evaluated by substituting the corresponding squirrel position value in the objective function and results are updated in the squirrel search matrix. The standard of food source describes by the objective value of the position of every flying squirrel. There are three types of food resources in the forest such as the hickory nut tree (best food resource), acorn tree (second food resource) and normal tree (no food resource). Objective values of all flying squirrels position are ranked in the climbing order, the least value of fitness function is selected as an optimal food source named as a hickory tree (FS_{ht}). The subsequent fitness values of flying squirrel position are considered as acorn nuts trees (FS_{at}) and expected to travel in the direction of the hickory tree (FS_{ht}). The rest squirrel declared as normal trees (FS_{nt}). Assuming that some normal trees flying squirrel's (FS_{nt}) may already complete their regular needs and wishes to travel on the way to a hickory nut tree (FS_{ht}). In order to achieve regular food demand, the remaining normal trees flying squirrel (FS_{nt}) will travel in the direction of acorn nuts trees (FS_{at}). The existent of hunters is continuously disturbing the natural scavenging deeds of a flying squirrel which is described by predator presence probability (P_{dp}).

C. Generation of New Locations

Flying squirrels glides throughout the forest and effectively find its favorite food. Due to the presence of predator, they forced to use slow random movement to find food in a nearby location. The mathematical modeling of foraging behaviour of flying squirrels can be formulated as follows:

Scenario1: Certain flying squirrels (acorn trees) tend to travel in the direction of the hickory tree. The new flying squirrel position is designed in equation (8):

$$FS_{at}^{t+1} = \begin{cases} FS_{at}^{t} + d_g \times G_c \times (FS_{ht}^{t} - FS_{at}^{t}), & R_1 \geq P_{dp} \\ Random\ location & otherwise \end{cases} \tag{8}$$

where d_g is random gliding distance, R_1 denotes the random number in the range of [0, 1]. The balance between exploitation and exploration is achieved by the gliding constant G_c declared in the mathematical model.

Scenario 2: In order to achieve the daily energy requirements, certain flying squirrels (normal trees) tend to travel in the direction of acorn trees. The new position of flying squirrels is designed in equation (9):

$$FS_{nt}^{t+1} = \begin{cases} FS_{nt}^{t} + d_g \times G_c \times (FS_{at}^{t} - FS_{nt}^{t}), & R_2 \geq P_{dp} \\ Random\ location & otherwise \end{cases} \tag{9}$$

where R_2 is a number selected randomly within the interval [0, 1].

Scenario 3: To balance the food scarcity, certain flying squirrels (normal trees) considered to traveling in the direction of a hickory tree assuming that its regular necessities are already fulfilled. The new flying squirrel position is designed in equation (10):

$$FS_{nt}^{t+1} = \begin{cases} FS_{nt}^{t} + d_g \times G_c \times (FS_{ht}^{t} - FS_{nt}^{t})\ R_3 \geq P_{dp} \\ Random\ location \quad otherwise \end{cases} \tag{10}$$

where R_3 is a number selected randomly within the interval [0, 1]. Predator presence probability P_{dp} is assumed as 0.1.

D. Gliding Distance

Gliding is an energy-efficient technique help to travel the FSs for large distances. The gliding technique of flying squirrels may be defined as balance glide. The resulting force (R) is generated by the addition of lift (L) and drag (D) force. The magnitude of R is equivalent to flying squirrel's mass (Mg) and direction is inverse to Mg. Accordingly, R offers a linear route gliding to flying squirrel at a steady speed (V) as shown in Fig. 1.[35]. The Flying squirrel gliding at a constant speed with inclines to the horizontal axis at an angle ϕ. The mathematical model of the gliding approach is shown in Fig. 2. Equation (11) provides lift-to-drag ratio or glide ratio expression [36]:

$$\frac{L}{D} = \frac{1}{\tan\phi} \tag{11}$$

The glide path of FSs may improve by forming a lower glide degree (ϕ) and thereby increasing the glide ratio [36]. Due to plunging deflection of air transient over the pinion results the lift force and is described as (12):

$$L = \frac{1}{2\rho C_L C^2 A} \tag{12}$$

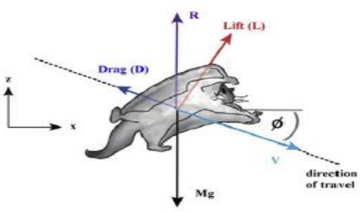

Fig. 1. Equilibrium gliding of flying squirrel

where ρ (=1.204 kgm−3) describes air density, C_L and C_D represent the lift and frictional drag coefficient; C (=5.25 ms−1) describes Constant speed and body area of the squirrel is A (=154 cm^2) [36]. At low speed, the frictional drag is very large while at high speed D becomes lesser and is described as (13):

$$D = \frac{1}{2\rho C_D C^2 A} \tag{13}$$

$$d_g = \left(\frac{h_g}{\tan\phi}\right) \tag{14}$$

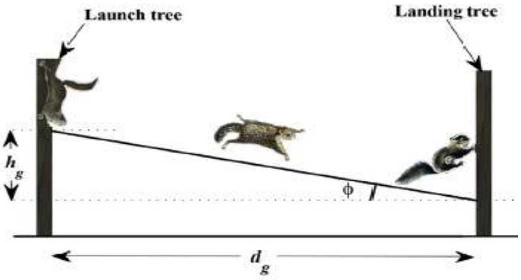

Fig. 2. Mathematical model of gliding approach

where h_g (=8 m) is the misfortune in height that happened in the wake of gliding. Flying squirrel may change its glide distance (d_g) by basically changing the lift-to-drag proportion according to the ideal arrival area. The simulations are implemented by irregular varieties in $C_L(0.675 \leq C_L \leq 1.5)$ and C_D is viewed as fixed at 0.60.

In all scenarios, gliding distance d_g lies between 9 - 20m [35]. However, the high value of gliding distance may produce more disquiets in (8) - (10) and hence algorithm has a chance to perform insufficiently. To overcome this disadvantage, the high value of gliding distance is normalized by a scaling factor (S_f) and its value is selected to be 18 [36].

E. Monitoring the Seasonal Condition

Flying squirrels searching activity is considerably suffered by climate variations. Winter season force the flying squirrels to be less active as compared to summer. Climatic changes may affect the flying squirrels movement and presence of such behavior can offer a reliable attitude to balance exploration and exploitation of the optimization algorithm. Hence, Climatic checking condition is included in the squirrel search optimization algorithm to avoid optimal solutions being trapped from local minima. Seasonal monitoring condition can be checked by the following steps:

- Calculate the seasonal constant (S_c) (15) and minimum value of seasonal constant (S_{min}) (16)
- Verify the seasonal checking condition i.e. $S_c < S_{min}$

If the condition is satisfied, then winters are completed and exploration of flying squirrels may happen at the end of winter.

$$S_c^t = \sqrt{\sum_{k=1}^{d}\left(FS_{at,k}^t - FS_{ht,k}^t\right)^2} \tag{15}$$

$$S_{min} = \frac{10\, e^{-6}}{(365)^t/(t_m/2.5)} \tag{16}$$

F. Random Relocation of Flying Squirrels

Due to less scavenging costs, FSs become active at the completion of the winter period. The flying squirrels that have not been able to walk around the forestry in winter for searching the optimal resource and have survived can discover the best food resource in new directions location. By the following equation, the random relocation of flying squirrels is designed (17).

$$FS_{nt}^{new} = FS_{LB} + Le\acute{}vy(n) \times (FS_{UB} - FS_{LB}) \tag{17}$$

where the distribution of Lévy promotes better and more effective exploration of the search region. Lévy flight is described as a strong measurement tool used to enhance the global exploration capabilities of different meta-heuristic algorithm [36]. It is a sort of random walk used to identify new solutions far from the present best solution. The mathematical expression of Lévy flight is given in equation (18):

$$Le\acute{}vy(n) = 0.01 \times \frac{r_a \times \sigma}{|r_b|^{1/\beta}} \tag{18}$$

where r_a and r_b are considered as normally distributed arbitrary variable lies between [0,1], β is taken as 1.5 and σ is obtained as (19):

$$\sigma = \left(\frac{\Gamma(1+\beta)\times\sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right)\times\beta\times 2^{\left(\frac{\beta-1}{2}\right)}}\right)^{1/\beta} \tag{19}$$

VI. Cluster Head Selection Using SSA

For energy-efficient clustering, the energy of the sensor nodes is considered to be like that of the food source of squirrel in SSA algorithm implementation. Likewise, the movement of the squirrel in SSA is similar to the change in the location of the cluster head. The movements of flying squirrels from acorn or normal tree to hickory are mapped to the clustering of less energy nodes move towards higher energy nodes.

The optimal cluster heads are elected using fitness factors found from the sensor nodes energy and distance between the interactive elements is the main concern of energy consumption. The wireless sensor network is modeled with n sensor nodes and k optimal cluster heads, the cluster head selection is obtained as the following steps:

Step 1: Initialize the network population with k arbitrarily nominated cluster heads.

Step 2: Evaluate the objective function of every sensor node in the network.

Step 3: Sort the node's location in ascending order and divide the nodes into three locations.

Step 4: Generate the new location of the nodes using the squirrel search optimization algorithm

Step 5: Check the seasonal monitoring condition of the cluster heads.

Step 6: If seasonal monitoring condition is true, random relocation the nodes using the $Le\acute{}vy$ distribution.

Step 7: Steps 2 to 6 are repeated up to the maximum limit of the round is reached.

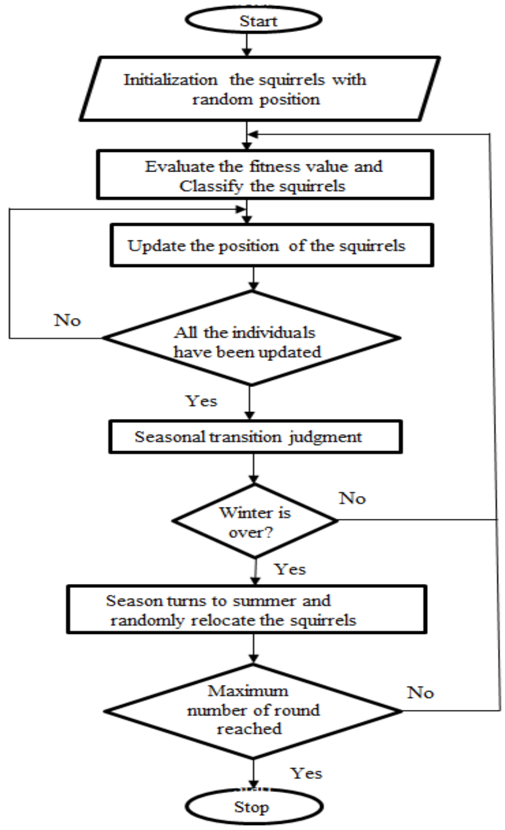

Fig. 3. Flowchart of SSA

Pseudo code of the SSA

Initialize the input parameters
Randomly generate the squirrel position using Equation (7)
Evaluate the fitness using Equation (3)
Sort the squirrel location in ascending order
Divide the squirrel into three locations
While $I_{ter} < I_{termax}$
Update the new locations
for i = 1: n1 (n1 = total number of FSs travels to hickory trees)
$if\ R_1 \geq P_{dp}$
$FS_{at}^{t+1} = FS_{at}^{t} + d_g \times G_c \times (FS_{ht}^{t} - FS_{at}^{t})$
else
$FS_{at}^{t+1} = Random\ location$
end
end
for t = 1: n2 (n2 = total number of FSs travels to acorn trees)
$if\ R_2 \geq P_{dp}$
$FS_{nt}^{t+1} = FS_{nt}^{t} + d_g \times G_c \times (FS_{at}^{t} - FS_{nt}^{t})$
else
$FS_{nt}^{t+1} = Random\ location$
end
end
for t = 1: n3 (n3 = total number of FSs travels to hickory trees)
$if\ R_3 \geq P_{dp}$
$FS_{nt}^{t+1} = FS_{nt}^{t} + d_g \times G_c \times (FS_{ht}^{t} - FS_{nt}^{t})$
else
$FS_{nt}^{t+1} = Random\ location$
end
end
if $< S_{min}$
$FS_{nt}^{new} = FS_L + Le'vy(n) \times (FS_U - FS_L)$
end
Calculate fitness value of new location
$I_{ter} = I_{ter} + 1$
end

VII. Result and Discussion

This chapter analyze the overall achievement of every algorithm dependent on the succeeding network parameters, explicitly, residual energy and throughput of the network, the measure of dead and alive nodes. Table I shows the necessary initial parameter for different algorithms.

TABLE I: SIMULATION PARAMETERS OF SSA

Parameter	Value
Sensor field region (m^2)	(100*100)
Number of nodes (n)	100
Initial energy of a node(E_o) (J)	0.5
Data packet length (*l*) (bits)	4096
E_{elec} (nJ/bit)	70
E_{amp} (pJ/bit/m^2)	120
Energy data aggregation(nJ)	5
Number of rounds(r_{max})	2000
Number of iterations	5
Number of Cluster Heads (k)	5
Predator presence probability (P_{dp})	0.1
Density of air (ρ)	1.204 kg/m^3
Speed(V)	5.25 m/s
surface area of body (S)	154 Cm^2
Lift coefficient (C_L)	$0.675 \leq C_L \leq 1.5$
drag coefficient (C_D)	0.6

The Residual energy of the wireless sensor network meant for different algorithms is shown in Fig. 4. It is obvious that in clustered WSN, the SSA has the highest energy optimization outcomes as compared to other existing algorithms. It is determined that the residual energy falls to zero in direct transmission by the side of a primary level (about 315 rounds) due to the fact that every sensor node is participated in the communication process. The large participation of the sensor node may growths the network complexity in terms of redundancy. LEACH algorithm provides improved efficiency than direct transmission to some extent due to the existence of a clustering scheme; it includes the arbitrary election of header nodes for the cluster and survives for only about 715 rounds. HSA algorithm can extend it better perform nearby 905 iterations because of its greater searching ability and the consideration of various criteria for the choice of cluster heads. To improve the search process of exploration and exploitation, a new harmony vector is generated by mutation or crossover of the existing vector. HSA involves the restriction of the search process towards a particular area. In high dimensional search space, PSO faces the exploration and exploitation problem to attain local optima (maxima or minima) and survives around 1230 rounds. This problem is being eliminated in SSA, which might modify squirrels gliding - pathway distance or d_g by adjusting the ratio of lift-to-drag towards an optimum solution. In SSA, predator presence probability (p_{dp}) immediately redirects the node to explore towards the optimal direction. To avoid local optimal search value, the climate checking condition makes SSA appeal to start exploration in multiple directions and therefore continues nearly 1637 rounds. The proposed SSA shows 95.84% and 77.66% enhancement in the residual energy over the HSA and PSO algorithms, respectively. The comparison of various implemented algorithms for Residual Energy is tabulated in Table II.

TABLE II: COMPARISON OF VARIOUS IMPLEMENTED ALGORITHM FOR RESIDUAL ENERGY

Algorithm	Residual Energy (J)			
	300 rounds	1000 rounds	1200 rounds	1500 rounds
DT	0	0	0	0
LEACH	9.687	0	0	0
PSO	37.7	9.008	0.8096	0
HSA	32.13	0	0	0
Proposed SSA	33.15	6.746	3.625	0.3645

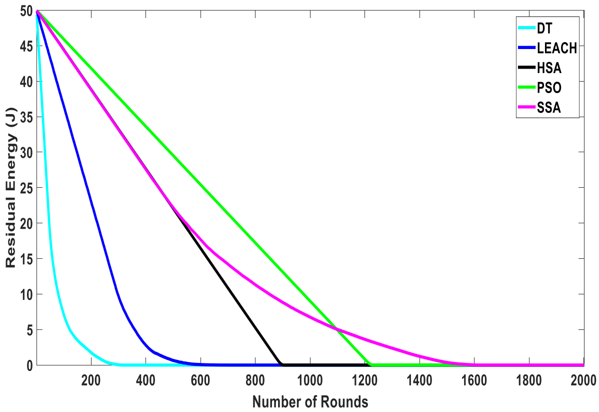

Fig. 4. Comparison of residual energy obtained for various algorithms

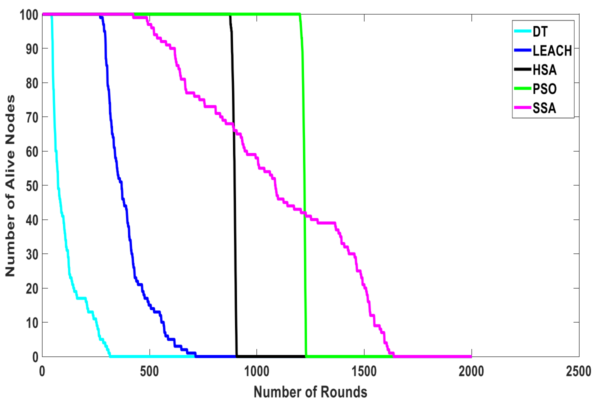

Fig. 5. Comparison of alive nodes obtained for various algorithms

The Fig. 5 provides the alive nodes sustained for different algorithms. An alive node shows the network's lifespan directly. This means that the network's lifetime will be improved as long as large sensor nodes are active. It is evident that the nodes stay alive up to 315 rounds for DT due to more nodes involved in transmission. The arbitrary election of cluster heads attempts to increase the nodes stay alive in LEACH protocol till 715 rounds compared to the DT. The meta-heuristic search algorithms such as PSO and HSA sustain alive nodes up to 1230 and 905 rounds respectively. The suggested SSA technique of CHS, sustains the nodes to stay alive up to 1637 rounds. The offered SSA attains 46.48% and 25.46% enhancement in preserving the nodes alive compared to the HSA and PSO algorithms, respectively.

The throughput achieved for various algorithms is presented in Fig. 6. The network's throughput improved as the amount of living nodes increases in WSN. It is obvious that 0.41 Mbps is an extreme throughput of different algorithms. On the other hand, the range of rounds goes the outcome decreases. The throughput of DT drops to zero around 315 rounds. The LEACH protocol indications enhancement compared to the DT, where the throughput drips to zero about 715 rounds since the randomized election of CH. Then meta-heuristic search algorithms such as PSO and HSA algorithms create throughput that descents to zero nearby 1230 and 905 rounds respectively. The offered SSA yields a throughput that persists up to 1637 rounds. The proposed SSA shows 34.52% and 28.60% enhancement in the residual energy over the HSA and PSO algorithms, respectively. The comparison of various implemented algorithms for throughput is tabulated in Table III.

TABLE III: COMPARISON OF VARIOUS IMPLEMENTED ALGORITHM FOR THROUGHPUT

Algorithm	Throughput (bps)	
	300 rounds	1500 rounds
DT	12290	0
LEACH	348200	0
PSO	409600	0
HSA	409600	0
Proposed SSA	409600	86020

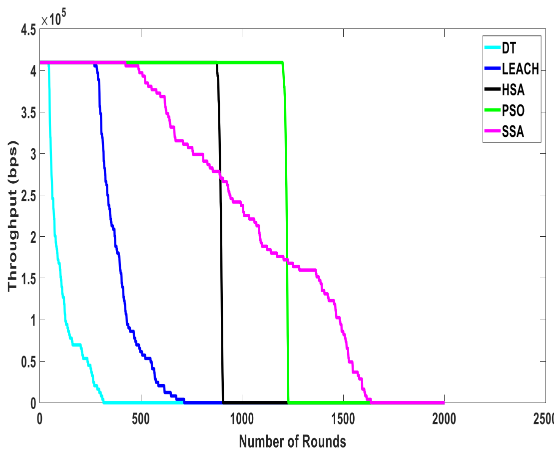

Fig. 6. Comparison of throughput obtained for various algorithms

The Fig. 7 affords the dead nodes for varies algorithms. It is evident that the first node dies at 44 rounds and ultimately all the nodes die in 315 rounds for DT. The LEACH protocol shows upgrading than the DT, in which, the first dead node is established at the round 270 and all the nodes come to be dead in 715 rounds. Then meta-heuristic search algorithms such as PSO and HSA begin the first node to die at the round 1201 and 876 respectively, and all the nodes to dead in 1230 and 905 rounds respectively. The proposed SSA begins all the nodes to dead in 1637 rounds. The qualitative and quantitative outcomes are delivered in Table IV.

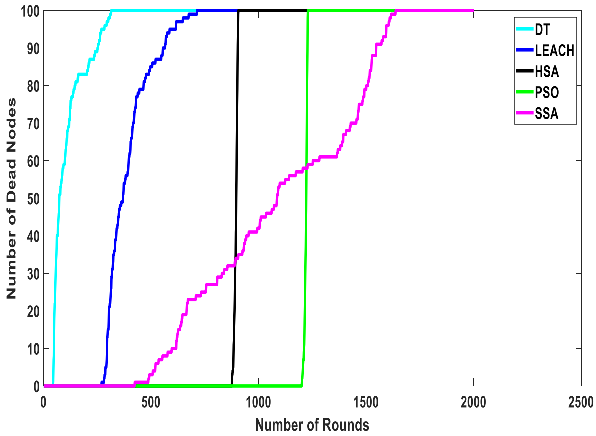

Fig. 7. Comparison of dead nodes obtained for various algorithms

TABLE IV: COMPARISON OF VARIOUS IMPLEMENTED ALGORITHM FOR FND AND LND

Algorithm	First node dead (FND)	Last node dead (LND)
DT	44	315
LEACH	270	715
PSO	1201	1230
HSA	876	905
Proposed SSA	424	1637

VIII. CONCLUSION

In this paper, a different algorithm such as direct transmission (DT), LEACH, HSA, PSO and SSA have been implemented and analyzed the energy efficiency of the network in terms of first node death, last node death, throughput, and efficiency. The fast searching capability of HSA building exploration - exploitation faster and results are better than LEACH. The HSA suffers from the drawback of being bound to only a specific search area. In PSO, the particle traverses from area to area in search of an optimal solution. However, the PSO suffers from the issue with exploitation and exploration in high dimensionality. Unlike HAS and PSO, the proposed algorithm introduced seasonal monitoring condition to prevent SSA being stuck in local optima and proper balance between exploration and exploitation capabilities. In addition, gliding constant (G_c) and possibility of predator existence unexpectedly redirects the position of any flying squirrel and thus enhances the algorithm's exploration capability. Hence, the proposed SSA generates better Cluster Heads than other algorithms using seasonal monitoring condition, gliding constant and Predator presence probability (P_{dp}). The scope for future work lies in the hybridization of SSA with different algorithm to enhance the energy efficiency of the Wireless Sensor Networks.

CONFLICT OF INTEREST

"The authors declare no conflict of interest".

AUTHOR CONTRIBUTIONS

N. Lavanya conducted the research and wrote the manuscript; T. Shankar analyzed the data; all authors had approved the final version.

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