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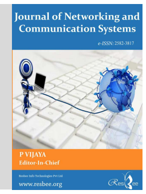

Adaptive Cuckoo Search and Squirrel Search Algorithm for Optimal Cluster Head Selection in WSN

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Abstract: In Wireless Sensor Network (WSN), clustering is considered as the primary model to prolong the life expectancy. Nevertheless, in WSN Cluster Head Selection (CHS) still residue the main confront on regarding energy stabilization. In this paper, the Adaptive Cuckoo Search and Squirrel Search Algorithm (ACS-SS) to simulate the optimal CHS model is presented. Here, the main aim is to choose the Cluster Head (CH) optimally by concentrating on the stabilization of energy, reduction of delay and reduction of distance among nodes. The proposed model is the hybridization of the Adaptive Cuckoo Search and Squirrel Search Algorithm to achieve optimal performance. Subsequent to the experimentation, the performance of the proposed technique compares with the existing techniques like the Genetic Algorithm (GA), Artificial Bee Colony (ABC), Group Search Optimization (GSO), and Firefly (FF) based CHS. Moreover, the performance analysis of the proposed technique seems to evaluate the energy efficiency, network lifetime, and statistics of dead nodes. The experimentation results exhibit the proposed CHS model is high effectual to extend the lifespan of the network.

Keywords: WSN; Cluster Head; Energy; Distance; Lifetime

Nomenclature

Abbreviations	Descriptions
WSN	Wireless Sensor Network
BS	Base Station
IoT	Internet of Things
SNs	Sensor Nodes
MCDM	Multi-Criteria Decision Making
CHs	Cluster Heads
FABC	Fractional ABC
GGWO	Grouped GWO
CSS	Cooperative Spectrum Sensing
GSA	Group Search Optimization
EBC	Entropy of Between's Centrality
LEACH	Low-Energy Adaptive Clustering Hierarchy
APTEEN	Adaptive Threshold-Sensitive Energy-Efficient Sensor Network
PEGASIS	Power-Efficient Gathering in Sensor Information Systems
ABC	Artificial Bee Colony
GWO	Grey Wolf Optimization
SI	Susceptible-Infected

1. Introduction

In both technical and economic circumstances, the advancement of modern applications creates the WSN appropriate [6] [7]. A distribution system which comprises of the few BS and sensor nodes and it is named as the WSN. The SNs have the ability to sense the nearby environments concerning the light, pressure, speed, temperature, changes in displacement and so forth. Therefore, these nodes possess the advantage of giving appropriate wireless communication and micro-sensing [1]. As mentioned above with specific characteristics, WSN can be exploited in various applications. In the network, every node directly communicates with the BS in the distribution of data. Since the transmission of data carries on the node with large distance expires more quickly than the other nodes by losing their energy [8] and [9]. For that reason, the clustering procedure is exploited, which collects the nodes as an assortment of a variety of clusters to resolve this problem [10].

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In maintaining the network topology, clustering models divide the network by gathering the nodes play an essential task ineffectual way. In conserving energy it is predictable to present a clustering protocol that is competent for hauling out the range of the network [11]. From SN data is communicated that is its origin to the sink or BS using multi-hop or single-hop model. Moreover, the investigational outcomes show that communication is costly when calculation and processing disperse minimum energy relatively. In each SN the number of energy is necessary for transporting a bit is corresponding to thousand processing operations. The energy expenditure by the sensor's sensing subsystem is dependent on the kind of sensor. In various scenarios, by transceiver and processor subsystem, it is fewer regarding the energy exhaustion. In a few scenarios, for data communication, sensing devours similar or even more than the energy necessary. The energy conservation algorithm highlights two mechanisms such as communication protocol and operation of SN are developed. A combination of different models can be used for the extensibility of the system existence [12].

In WSNs, there are primarily two types of routing protocols such as hierarchical architecture and flat architecture [21]. In Flat architecture, protocols undergo data overload while the nodes density increases and as a result in rough limited scalability and energy distribution. Accordingly, hierarchical routings encompass increased progressively global courtesy in modern years. For WSNs there are few hierarchical protocols presented like LEACH, APTEEN, and PEGASIS. Amid them, LEACH is the majority conventional and envoy one [13] [14].

For the SN, clustering models present a competent energy balancing technique [15]. In a clustering method, all the nodes in the network are practically divided into sub-networks named clusters. In every cluster, member nodes have one or more selected CHs. In a cluster, CH is the mainly significant component and it proceeds as a local coordinator for data transmission within the cluster and upholds the topology information and cluster members. On the other hand, on one occasion the malicious nodes are chosen as CHs, the performance of the system would be to a great extent affected as to all the member nodes based upon CHs for packet transmission to their own destinations. Additionally, a few CHs with maximum trust value will be repeatedly chosen, which drains their energy earlier. In this circumstance, chosen of trusted CHs with appropriate remaining energy becomes decisive for the complete performance of the network.

The main contribution of this paper is to present the Adaptive Cuckoo Search and Squirrel Search Algorithm (ACS-SS) -based CHS in WSN. Here, three parameters like delay, distance, and energy are considered. Moreover, the hybridization of ACS and SS methods can improve the performance of CHS with other well-known optimization methods.

2. Literature Review

In 2019, Trupti Mayee Behera et al [1], worked on WSN, which collects particular transducers that give sensing services to the IoT devices with restricted storage and energy resources. In sensor nodes as recharging or replacement of batteries was approximately not possible, power utilization becomes one of the vital design problems in WSN. Moreover, the clustering method plays a significant task for the energy-constrained network in power maintenance. In the network, selecting a CH can suitably balance the load thus minimizing energy utilization and improving lifetime. Moreover, this work concentrates on a competent CHS method which rotates the CH location between the nodes with a maximum energy level while comparing with others. The method contemplates remaining energy, initial energy, and the optimal value of CH to select the subsequent group of CHs for the network which ensembles for IoT applications.

In 2019, S. Murugaanandam and Velappa Ganapathy [2], presented an algorithm called reliability-based enhanced technique for the ordering of preference by similarity ideal solution (RE-TOPSIS) integrating with fuzzy logic that exploits MCDM algorithm assisting in the effectual and consistent chosen of CHs. Additionally, in each cluster, it exploits the existing LEACH protocol to allow one-time CH chosen or scheduling on the basis of the RE-TOPSIS rank index value. This procedure entirely eradicates the requirement of CHS procedure in every round of LEACH's setup state cycle. Moreover, they had considered for several criteria such as distances among neighboring nodes; energy consumption rates; remaining energy; availability of adjacent nodes; distances among the CHs and sink in addition to distances among CHs to member nodes; and the reliability index for entirely devising the novel method.

In 2018, Achyut Shankar et al [3], worked on WSN, which was considered as the resource constraint network in that the complete nodes encompass inadequate resources. Extending the network lifetime remains the unsolved point in WSN. For that reason, this work aims to present a hybrid GGWSO method to improve the performance of a CHS in WSN; hence the lifetime of the networks was extended. The developed algorithm concerns the major constraints related to delay, distance, security, and energy. This work evaluates the performance of the developed GGWSO with numerous existing methods such as fractional ABC, ABC, GSA, and GWO-based CHS.

In 2018, Muluneh M. Tulu et al [4], worked on a social network, which spreads information by the influential person in charge of the community was extremely precious. In device-to-device local communication, using effectual algorithms to recognize significant nodes will leverage cellular networks. In this work, EBC integrating the degree of the neighbor node and the degree of the node was presented as a metric to choose nodes from complex and large networks to distribute information effortlessly. Moreover, the EBC explains how the node was necessary to like two regions of the network. Here, nodes were recognized using EBC that was analyzed by exploiting the SI method. Therefore, in the SI model, if the source of infection was one node and the percentage of infected nodes was high.

In 2019, Akinbode A. Olawole et al [5], worked on cluster-based CSS in cognitive radio networks. It presents to reduce reporting delays, sensing error, and enhanced energy effectiveness, in a realistic network. Nevertheless, attaining these benefits based upon properly choosing a CH and developing a suitable fusion rule. Moreover, this paper examines a novel hard decision fusion rule that creates the CH non-cooperative sensing consequence an essential circumstance for obliging decision making. Also, this work proposes a relative numerical study of three conventional CHS strategies regarding their performance in CSS, in varying detection cluster's heterogeneity and thresholds. A generalized and robust CHS method which surmounts the limits of the conventional methods was subsequently presented. The performance of the conventional CHS methods based upon the distribution of secondary users.

3. CHS in WSN Model

3.1 Network Model

In WSN several sensor nodes (set as S_N) are considered, whereas every sensor is stationary and encompasses its equivalent effectiveness. A node can act as both a cluster head and as an active sensor at data transmission. Generally, the WSN model is related to radio communication, sensor allotment, energy utilization, data sensing, and topology features. A sensor can be placed in a random or manual way in an application area. For that reason, Fig. 1 exhibits the CHS model of WSN with a count of the centralized base station and sensor nodes. The procedure of collecting a set of sensor nodes can be referred to as clustering. It is a well-known algorithm to expand the lifetime of WSN. In the clustering procedure, clusters are produced by collecting the SNs, whereas a CH is selected, and the number of CHs is indicated C_H. Moreover, for all number of clusters, this outline of CHS is performed. In reality, the nodes in an exacting cluster are created on the basis of the circumstance of possessing minimum distance from CH. From the target area, all the SNs gather information and transport it to the CH during the operation. Additionally, the exacting CH broadcasts gathered information to the BS.

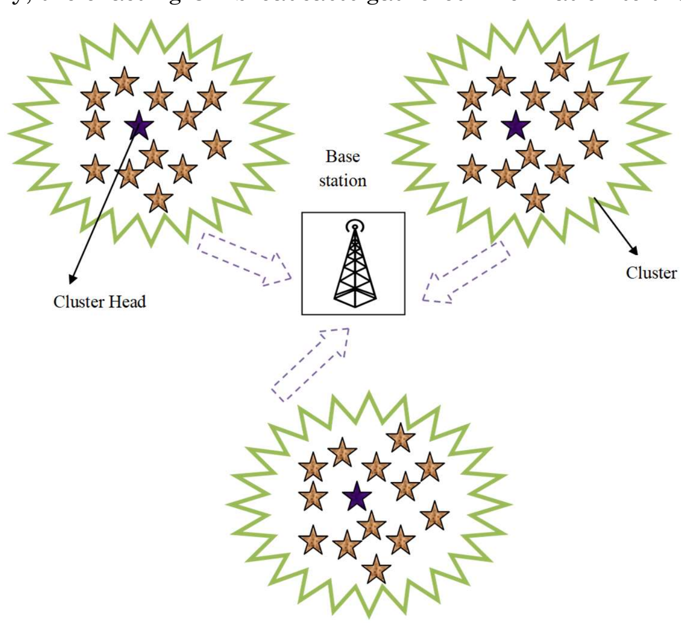

Fig. 1. *Diagrammatic representation of the WSN model*

The data transmission from one node to another is the major confront of WSN. On the other hand, the performance-related to the transmission of data can be improved to find the minimum path. In addition, the energy utilization by each node is contemplated as the other vital issue. Therefore, the major difficulty tends in distributing the information that owns the path with reduced energy and minimum length. Many researchers have recognized the algorithm to share the data packets among the base station and the nodes during the performance of several advanced routing protocols. The optimal CHS regarding position and energy is raised as the main confront in different routing protocols. Generally, a node demands high energy to transmit a high data quantity. The best way of placing the CH can minimize the energy, in order to create the exacting CH to transport plentiful information. Therefore, a node that is chosen as the CH has to help in the optimal position regarding the relative SNs with minimized energy utilization. In numerous optimization methods, energy or distance prolongs its maximum dependability when it comes to making a decision a CH. Consequently, it is essential to unease the multiple objectives improve the lifetime of nodes. Finally, the major parameters which are to be contemplated to choose the CH from a group of SNs are distance, delay, and energy.

3.2 Distance Model

At first, the complete selected CHs in the network transport the advert message to state that they proceed as the CH. In such a situation, every single SN of the network measures the precise distance from the CH. Hence a node fits into the exacting cluster merely, by guarantee its distance from the CH of that cluster is minimum and, additional, and it transmits the message to the equivalent CH. In contrast, the SN transmits the message directly to the BS, if the distance among the node and CH is greater than the distance among the BS and node. This is the layout of creating a cluster on the basis of the calculation of close distance. Therefore, in the network, the nodes can be reclustered with the chosen CH by exploiting a distance matrix $D_M(p*q)$ as stated in Eq. (1), whereas E_{C_H} states the Euclidean distance between a normal node and CH $y_1, y_2, ...y_n$ denotes the sensor nodes. Let us assume two SNs m (CH) and n (normal node) and their locations x and z, correspondingly. The equivalent Euclidean distance is measured by exploiting Eq. (2).

$$D_M(p*q) = \begin{bmatrix} d_{C_{H1},y_1} d_{C_{H1},y_2} .... d_{C_{H1},y_n} \\ d_{C_{H2},y_1} d_{C_{H2},y_2} .... d_{C_{H2},y_n} \\ : \\ : \\ d_{C_{H1},y_1} d_{C_{Hn},y_2} .... d_{C_{Hn},y_n} \end{bmatrix} \tag{1}$$

$$d_{m,n} = \sqrt{(m_x - n_x)^2 + (m_z - m_z)^2} \tag{2}$$

As stated in eq. (1), each element indicates the distance which subsists among the n^{th} node and m^{th} CH in the distance matrix. In the points of the matrix, the column which obtains the lowest value has the own connection with the equivalent one. Consider an element d_{C_{H2},y_1} engaging the first column of the matrix with less distance. Moreover, the node y_1 and CH C_{H2} associated with each other.

Additionally, a time slot is assigned using C_H to each sensor node in transmitting the data. Hence the major job of each C_H is to collect the data transmission from the complete sensor nodes that the clusters hold. From all the SNs subsequent to receiving data within the exacting cluster, C_H transfers the appropriate data to the BS or sink. The SN perseveres in sleep mode from 1 immediate to others, while C_H remnants at active state. The performance of data transmission and re-clustering is sustained from a count of cycles until the immediate that the complete SN turns dead. The two channels like multi-path fading and free space channels are exploited on the basis of the distance for the receiver from the sender. While the definite threshold value allocates a maximum value than the distance, the free space channel is used. On the other hand, the lesser thresholds exploiting the multipath fading channel. Eq. (3) indicates the threshold distance, whereas E_{fsm} denotes the energy need when using a free space model and E_{mps} denotes the power amplifier energy.

$$TH = \sqrt{\frac{E_{fsm}}{E_{pwm}}} \tag{3}$$

3.3 Energy Model

In WSN, the main problem is the energy utilization. In reality, in WSN, the battery exploited cannot be recharged, that is there is a state of not having any power supply, once the battery is minimal. Usually, high energy is needed to transmit the data from the complete SNs to the BS. Generally, the network utilizes high energy as it carries out diverse operations such as reception, transmission, aggregation, and sensing. Hence the model of complete energy obligation in transferring messages is stated in eq. (4), whereas $E_{TC}(N:d)$ indicates the total consumed energy necessary for transferring N packets bytes at a distance d and E_{ee} indicates the electronic energy on the basis of the various factors like spreading, filtering, digital coding, so on. The formulation of electronic energy, whereas E_{ag} denotes the data aggregation energy in eq. (5).

$$E_{TC}(N:d)=\begin{cases}E_{ee}*N+E_{fsm}*N*d^2, \text{if } d<TH\\ E_{ee}*N+E_{pwm}*N*d^2, \text{if } d\geq TH\end{cases} \tag{4}$$

$$E_{ee}=E_{TC}+E_{ag} \tag{5}$$

Eq. (6) portrays the total energy utilized need to receive N packets bytes at a distance d. Moreover, the energy utilized for the amplification principle is stated in eq. (7).

$$E_{RX}(N:d)=E_{ee}N \tag{6}$$

$$E_{ag}=E_{fsm}d^2 \tag{7}$$

Together, the total network energy is stated in eq. (8), whereas E_I indicates the necessary energy at the idle state and E_C indicates the energy cost at the time of sensing. It is essential to minimize the total energy as exhibited in eq. (8).

$$E_{total}=E_{TC}+E_{RC}+E_I+E_C \tag{8}$$

4. Proposed Methodology for CHS

4.1 Objective Model

According to the objective model of CHS, the distance between the chosen CH and node and delay to transfer the data from one node to the other must be less. Nevertheless, the energy stayed in the network must be maximum that is it must utilize minimum energy when transmitting data. For that reason, the objective model of the developed cluster chosen is stated in eq. (9), whereas α value must be in the range $0<\alpha<1$ and f_c as well as f_d indicate the functions as stated in eq. (10) and Eq. (11), correspondingly. The constraint parameters on the basis of the energy, distance, and the delay are indicated as λ_1, λ_2 and λ_3. The circumstance of those parameters is stated as $\lambda_1+\lambda_2+\lambda_3=1$. In Eq. (11), Y^y-B_s indicates the distance between the BS and normal node.

$$F_n=\alpha f_b+(1-\alpha)f_a \tag{9}$$

$$f_a=\lambda_1*f_i^{dis}+\lambda_2*f_i^{ene}+\lambda_3*f_i^{del} \tag{10}$$

$$f_b=\frac{1}{n}\sum_{y=1}^{n}\left\|Y^y-B_s\right\| \tag{11}$$

In eq. (12), the fitness model for distance is considered, whereas $f_{(a)}^{dis}$ is related to the transmission of a packet from the normal node to the CH and subsequently from the CH to the BS. The f_i^{dis} value must be within the range [0, 1]. The value of f_i^{dis} becomes maximum, while the distance among the CH and the normal node is maximum.

$$f_i^{dis}=\frac{f_{(a)}^{dis}}{f_{(b)}^{dis}} \tag{12}$$

$$f_{(a)}^{dis}=\sum_{y=1}^{N_y}\left[\left\|C_y-B_s\right\|+\sum_{x=1}^{N_x}\left\|C_y-Y_y\right\|\right] \tag{13}$$

$$f_{(b)}^{dis}=\sum_{y=1}^{N_x}\sum_{x=1}^{N_y}\left\|Y_y-Y_x\right\| \tag{14}$$

Eq. (13) and (14) represents the formulation of $f_{(a)}^{dis}$ and $f_{(b)}^{dis}$, correspondingly, whereas Y_y represents the normal node which fit in to y^{th} cluster, C^y denotes CH of y^{th} cluster, $C_y - B_s$ states the distance among the CH and BS, and $Y_y - Y_x$ indicates the distance among two normal nodes, $C_y - Y_y$ denotes the distance among the normal node and CH, N_y and N_x denotes the count of nodes which not be in the y^{th} and x^{th} cluster.

In Eq. (15) the fitness function of energy is represented. The value of f_i^{ene} becomes greater than 1 while the complete CH cumulative $f_{(a)}^{ene}$ and $f_{(b)}^{ene}$ considers energy to be of utmost value and the CH maximum count.

$$f_i^{ene} = \frac{f_{(a)}^{ene}}{f_{(b)}^{ene}} \tag{15}$$

Eq. (16) depicts the fitness function of delay that is directly proportional to the total count of nodes which fits into the cluster. Hence, the delay is less while the cluster holds only an adequate number of nodes. In Eq. (16), the utmost number cluster is exploited to minimize the delay. In the WSN the denominator N_N denotes the total count of nodes.

$$f_i^{del} = \frac{\max\left(\left\| C_y - Y_y \right\|\right)_{y=1}^{C_H}}{S_n} \tag{16}$$

The value of f_i^{del} should within the range [0, 1].

4.2 Cuckoo Search Algorithm

In [16], [17] developed the Cuckoo Search method enthused by the scrounging character of the cuckoo bird. This method is extensively exploited as an optimization method. It has a small number of parameters to the melody. Additionally, it has an inherent constraint-handling method. This creates it computationally competent and rapid. The CS method is presented on the following suppositions.

a. In a time a cuckoo bird lays a solitary egg and keeps it in an arbitrarily chosen nest.

b. An optimal nest with a better quality of eggs is viewed as a fit for the future generation.

c. The number of host nests is foreordained. Nevertheless, the host bird might identify the cuckoo's egg stated as a probability $P \in [0,1]$. In such a scenario, the host bird might fall the egg or it might depart the nest and create a new nest at another position. Here, an easy illustration of the CS method is pursued whereas every egg in a nest relates to a solution. In the nests, the fundamental aim is to use the new solutions to replacement the weak solution. Additionally, a cuckoo bird carries out a Levy flight whereas creating new solutions. For the next generation, the new solution is stated in eq. (17).

$$Y_i(h+1) = Y_i(h) + \delta \otimes \text{levy}(\sigma) \tag{17}$$

In eq. (17), $Y_i(h)$ indicates the current search position of cuckoo i and $Y_i(h+1)$ indicates the search position of similar cuckoo in the future generation. Moreover, δ indicates the step size typically represented 1 and $\otimes$ indicates element-wise multiplication operator the same as which exploited in PSO. Levy (σ) indicates the arbitrary walk by exploiting the Levy flight. The Levy distribution might be calculated as

Levy $\approx v = t^{-\sigma}$ for σ ranging from 1 to 3. The Levy step using the well-liked Mantegna's process [18] is described in eq. (18).

$$\text{Levy} = \frac{v}{|u|^{1/(\sigma-1)}} \tag{18}$$

4.3 Adaptive Cuckoo Search Algorithm

In [19], the ACS optimization algorithm is investigated. The Cuckoo Search method is done adaptive disregards the Levy distribution. A novel algorithm to control the step size is integrated to create the CS adaptive. For the current generation, the step size is indicated regarding the fitness value of individual nests in the search domain.

Hence, δ is disregarded which is fixed in the existing CS algorithm. Eq. (19) represents the adaptive step size.

$$\mathrm{step}_i(h+1)=\left(\frac{1}{h}\right)^{\left|\frac{f(h)-f_i(h)}{\mathrm{optimal}(h)-\mathrm{worst}\,f(h)}\right|} \tag{19}$$

In eq. (19) h indicates the current generation, $f_i(h)$ indicates the value of the fitness model of the i^{th} nest in the h^{th} generation, and optimal $f(h)$, as well as worst, $f(h)$ indicate the optimal objective model value and the worst fitness function value of the current generation, correspondingly. The above equation creates step size adaptive. It minimizes with maximizing in the number of generations. At present, the new solution for the next generation is indicated by using eq. (20).

$$Y_i(h+1)=Y_i(h)+\mathrm{randn}\times \mathrm{step}_i(h+1) \tag{20}$$

The ACS methods are faster than the conventional CS method as the requirement to describe the initial parameters and step size is eradicated. A clear description of the ACS method is stated in [19].

4.4 Squirrel Search (SS) Algorithm

The SS method is the most recent evolutionary computing method enthused by the searching ways of southern flying squirrels and effectual form of movement known gliding [20]. The squirrels exhibit a dynamic foraging method to optimally employ the resources of the nutrient.

a. The number of flying squirrels is n, and just a squirrel is perched on a tree.

b. Each squirrel searches for nutrition and exploits conventional resources independently.

c. Just three sorts of trees are available in a forest, that is usual, oak (acorn nut source), and hickory trees.

d. There are 1 hickory tree (optimal nutrient source) and 3 oak trees (usual nutrient source) in the forest area in unease.

In the forest area, the first location of every squirrel is uniformly distributed and it is indicated by exploiting the eq. (21).

$$FS_i = FS_L + rn(0,1)\times (FS_U - FS_L) \tag{21}$$

In eq. (21) FS_U and FS_L represents the upper and lower location limits respectively of the i^{th} flying squirrel. $rn(0,1)$ is a uniformly distributed arbitrary number ∈ [0, 1].

The nutrient source quality explored by a flying squirrel is indicated by the fitness value of its position. If a squirrel is on a hickory tree, it is represented as the optimal food source. If it is on an acorn/oak tree, subsequently it is represented as a usual food source. Otherwise, there is no nutrient source and the squirrel is on a normal tree. Additionally, the fitness value indicates the probability of survival of a squirrel.

If a squirrel possesses the least fitness value, subsequently it is represented to be on the hickory tree that is the best food source. On the basis of the fitness values, the following three squirrels are stated to be on the usual food source that is acorn nut trees.

It is for the reason that it is presumed which there are four food sources only. In the oak nut trees, the squirrels are relied upon to goes to the optimal food source that is a hickory nut tree. In the population, the remaining squirrels are supposed to be on usual trees without any food source. Few squirrels are arbitrarily chosen and affirmed to travel to the hickory tree offered which they encompass fulfilled their each day energy requirements.

The remaining squirrels will travel to the acorn nut trees for fulfilling they are each day's energy needs. The attendance of a predator constantly influences the exploring squirrel's behavior. In the model, this is taken care of in the update formulation exploiting a Predefined Predator Probability (P_{dp}). If the predator is not present, subsequently the flying squirrels move generously and find out the forest effectively for the optimal food source. The incidence of the predator be concerned with the squirrels, and they employ small arbitrary walk to discover a close hiding position. The dynamic searching performance of the flying squirrels for the best nutrition source is represented as eq. (22).

$$FS_{at}^{h+1}=\begin{cases} FS_{at}^{h} - d_h \times H_c \times \left(FS_{gt}^{h} - FS_{at}^{h}\right); & R_1 > P_{dp} \\ \text{Random location} & \text{O.W} \end{cases} \tag{22}$$

In eq. (22) d_h represents an arbitrary flying distance, R_1 represents an arbitrary range in 0,1, FS_{gt}^{h} represents the location of the squirrel accomplishment the best food source, FS_{at}^{h} represents the location of the squirrel in the acorn nut tree, H_c represents the gliding constant that balances the exploration and the exploitation, and h indicates the current iteration. For the foraging behavior, the same formulations are modeled for the flying squirrels on usual trees and while they go to the hickory tree for saving food for the prospect. Here the SS method obtains the global optimal with notable convergence capability as evaluated to numerous algorithms.

The synergistic behavior of Adaptive CS exploiting superior exploration and exploitation ability and the dynamic foraging behavior of SS has enthused to use the hybrid Adaptive Cuckoo Search-Squirrel Search method for this application. Additionally, this will improve the exploitation and exploration ability of ACS. It is the cause and exploited the hybrid algorithm of ACS-SS. Moreover, here, the constraint-handling method is also integrated into the developed algorithm consequently that the best thresholds attained are fine within the specified bounds.

5. Results and Discussions

5.1 Experimental Setup

In WSN the developed ACS-SS-based CHS experimented in MATLAB R2015a. The total count of nodes in the WSN is allocated as S_N, that are distributed in the area $100m \times 100m$, whereas the BS was positioned at the center. The relevant experimentation was performed from 0 to 2000 rounds. Based on [22], the experimentation was performed and attained the outcome. At the experimentation, the initial energy E_i is set as 0.5 and the energy of power amplifier E_{pw} is set as $10 pJ/bit/m^2$. In addition, the transmitter energy E_{TX} is allocated as $50 nJ/bit/m^2$ and the data aggregation energy E_{ae} is fixed as $5 nJ/bit/signal$. On the basis of these allocated values, the experimentation and the equivalent performance analysis were performed by analyzing the proposed ACS-SS algorithm with conventional methods such as GA, GSO, ABC, and FF.

5.2 Performance Analysis

Fig.2 demonstrates the performance evaluation of the proposed and existing methods such as GA, GSO, ABC, Firefly techniques on sustaining the number of alive nodes equivalent to the distance. Moreover, the performance of the proposed method is 13.23% superior to GA, 13.22% better than GSO, 15.11% superior to ABC, 24.14% superior to FF methods for 2000 rounds.

In Fig 3, the analysis of the proposed method with the existing methods on sustaining the number of alive nodes corresponding to a number of rounds is demonstrated. Here, the performance of the proposed method is 22% outperforms the GA, 15% outperforms the GSO, 28% outperforms the ABC, and 24% outperforms the FF methods for 2000 rounds.

The relative analysis of the proposed method and the existing algorithms for identifying the normalized energy from 0 to 2000 rounds is exhibited in Fig. 4. . Moreover, the performance of the proposed method is 32% superior to GA, 30% superior to GSO, 38% superior to the ABC, 16% superior to the FF methods for 2000 rounds.

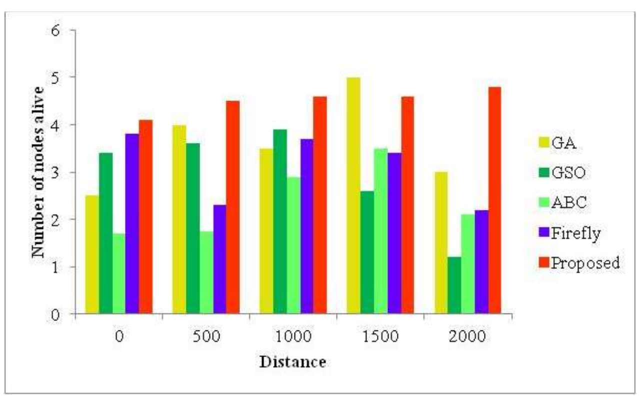

Fig. 2. *Performance analysis of the proposed model on sustaining a number of nodes alive regarding distance*

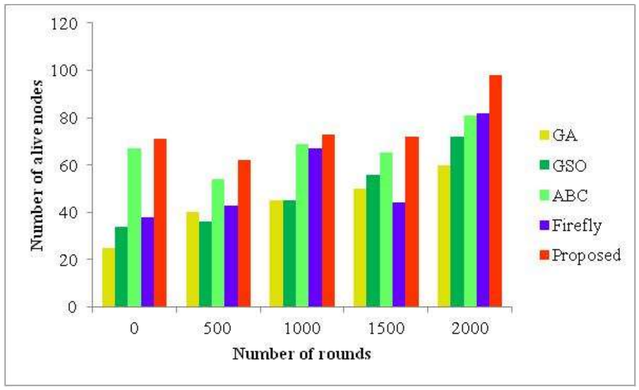

Fig. 3. *Performance analysis of the proposed model on sustaining a number of nodes alive regarding the number of rounds*

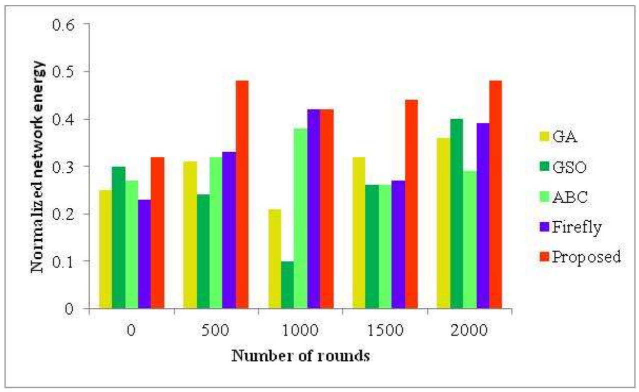

Fig. 4. *Performance analysis of the proposed model on sustaining normalized network energy*

6. Conclusion

Clustering is a significant approach for extending the network lifetime in WSNs. It involves grouping of sensor nodes into clusters and selecting CHs for all the clusters. CHs collect the data from the respective cluster's nodes and forward the aggregated data to the base station. In WSNs, a major challenge is to select suitable CHs. In this paper, a novel CHS method by exploiting the Adaptive Cuckoo Search and Squirrel Search Algorithm (ACS-SS) method were presented. Moreover, it had aspired to choose the optimal CH regarding the stabilization of energy, reduction of delay and reduction of distance among nodes. In reality, the optimal performance was obtained using hybridizing the ACS and SS method. Subsequently, in the experimentation, the performance of the proposed ACS-SS –based CHS method was evaluated with the GSO, GA, ABC, and FF algorithms. The lifetime of the network, energy efficiency and dead nodes statistics were evaluated by the comparative analysis.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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