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Dynamicity of the scout bee phase for an Artificial Bee Colony for optimized cluster head and network parameters for energy efficient sensor routing

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Abstract
Data transmitted to the base station from the sensor node by selecting an optimal cluster head is a massive challenge subjected to the routing protocol, in the case of the wireless sensor network. An energy efficient clustering method, depending on the Artificial Bee Colony (ABC) algorithm and the Fractional Artificial Bee Colony (FABC) algorithm, has a propensity to maximize the energy of the network and life time of nodes by the optimal cluster head selection (CHS). When conveying data, an ABC-Dynamic Scout bee algorithm is presented that multiplies the scout bee production to enlarge the number of alive nodes and the of CH energy. An assessment among the performances of the implemented ABC-based Dynamic Scout bee algorithm routing mechanism in opposition to that of ABC-based CHS and FABC-based CHS routing is done. The experimental outcome demonstrates that the implemented method increases the quantity of alive nodes with 25% of maximum energy for the normalized network compared with conventional protocols.

Keywords
Applications in science and engineering, computer networks, tools and technology, neural networks

1. Introduction

Wireless sensor network (WSNs) have an extensive range of applications in various fields,[1–3] owing to their efficient communication. Bandwidth, energy, and computational potentials are a few areas that facilitate control over the WSN. A WSN denotes an integration of wireless communications with various nodes that are exploited in a precise way for appropriate sensing.

For an excellent network performance, the measures of connectivity, coverage, and network lifetime must be considered. The cluster heads (CHs), together with the members, form the cluster. The major function of the CH is the coordination of the node between the clusters and transmission of data. Throughout the cluster head selection (CHS), the centrality, residual energy, and concentration should be focused. The attention denotes the number of nodes, and the centrality indicates the center of a node. The major algorithms associated with the clustering approach comprise the SEP protocol,[4] layered low energy adaptive clustering hierarchy (LEACH) protocol,[5] constrained coverage algorithm,[6] virtual force algorithm,[7] etc.

The disadvantages in the conventional clustering algorithms are increased energy consumption, unbalanced lifetime of nodes,[7] low network lifetime, poor stability,[8] a large-scale WSN,[9] information transmission delay,[10] less consideration to residual energy nodes,[4] less adaptation with the heterogeneous network[5] and less use in imbalanced energy nodes,[5] additional overhead and low coverage,[6] and death of nodes.[11] Hence, to prevail over these problems, several optimization algorithms have been established, and they are described in the next section. Even though many problems are optimized, still, there survives the crisis of stabilization energy and its efficiency, which maximizes the re-division of the monitoring area and network lifetime, and this should be considered for the effectual exploitation of WSN nodes.

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2. Literature review

2.1 Related works

In 2016, Jia et al.[12] presented the WSN's CH problem that directs to augmented usage of energy and inappropriate coverage. For solving this problem, they established a clustering algorithm that has the capability to preserve a balance in the network of the energy node. They investigated the developed dynamic CHS technique and utilized the Voronoi polygon technique to attain the separation of redundant and the clustering nodes. After discovering the initial type of node, a novel cluster node associated with the standard energy and residual energy equivalent to the nodes are chosen with the survival time evaluation algorithm. On comparing the recommended technique with the formerly existing LEACH method, the implemented method has been found to possess the capability of increasing the lifetime of a network and reducing the consumption of energy.

In 2015, Lin et al.[13] proposed a significant challenge in WSN, that is, maximizing the lifetime of a network with energy restraint in the nodes of the sensor. Considering the networks with large-scale sensor nodes, they introduced a clustering technique recognized as the fan-shaped clustering algorithm that has the capacity to separate the large-scale networks and change them into a variety of fan-shaped clusters. These fan-shaped clusters are exploited for detecting a solution to reduce the increased energy consumption, and the solutions are CHS and relay selection. From the experimental investigation, they demonstrated the implemented method to be one of the most excellent techniques for saving energy.

In 2017, Ni et al.[14] presented a solution-dependent fuzzy clustering pre-processing Particle Swarm Optimization (PSO). The implemented technique was utilized to improve the network lifetime on the basis of the CHS in hierarchical control of topology. Here, both the energy and distance utilization factors of the WSN were measured for the function of fitness. Depending on PSO, the CH nodes in hierarchical topology were demonstrated. Finally, the investigational results have confirmed that the implemented method attains better performance than the traditional methods.

In 2016, Khan et al.[15] worked on the routing technique for CHS depending on the Fuzzy-Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) with expected sink mobility that has an octagonal trajectory. Here, they measured the number of neighbor nodes, residual energy, energy consumption of the node rate, average distance between neighboring nodes, and distance from the sink. Finally, the investigational results showed that the implemented method increases the network lifetime when compared with the traditional methods.

In 2014, Hoang et al.[16] accomplished a harmony exploration algorithm that relies on the cluster-dependent protocols, which are centralized. The implemented technique is a music-dependent metaheuristic optimization technique that minimizes the distance that prevails between the CH as well as the related members and, thus, optimizes the distribution of energy in the WSN. The function is done in real time, and the execution is performed in Crossbow's IRIS hardware platform with the Tiny operating system (OS). The factors considered comprise the number of clusters, number of nodes, voltage threshold, sample time, etc. The presentation is evaluated by distinguishing with the conventional Fuzzy C-Means and LEACH-C clustering algorithms.

In 2012, Lee and Cheng[17] introduced a fuzzy logic-dependent clustering method in WSN assistance through the energy prediction technique. They improved this novel approach—LEACH-ERE—for maximizing the lifetime of a network with equal distribution of the workload. They concentrated on CHS with the distribution of energy consumption and high residual energy between the nodes equally. The desired residual energy is approximated by means of the consumption of energy, which is expected. The simulation is executed in network simulator-2, and the presentation that the recommended approach demonstrated is calculated by making an assessment against the traditional methods – LEACH LEACH Centralized and CHEF.

In 2010, Gautam and Pyun[18] concentrated on the problem of energy preservation and implemented an intelligent and distance aware clustering protocol. They established this technique to prevail over the restrictions of previously existing energy conservative algorithms, such as LEACH-C, LEACH, EEEAC, and BCDCP, that comprise unequal and high energy reduction of the CHS. For dealing with this problem, they separated the network as tiers and the collection of high energy CHS is executed later. They further proposed the consequence of distance that exists between the CH nodes and the base station, on consumption of energy. The investigational setup in this implemented method contains steps such as the schedule creation phase, network setup phase, data transmission phase, and routing path construction phase. The position of the base station, transmitter amplifier, number of CHs, primary energy of nodes, and number of nodes are the simulation factors studied, and the achieved results are compared against that of the existing approaches.

2.2 Review

The novel has come out with energy aware CHS algorithms and routing protocols for WSNs. The literature has come out with energy aware CHS algorithms and routing protocols for WSNs. They necessitate more enhancements since they lack ability in dealing with the recent practical scenarios. For example, the Voronoi partition for the clustering nodes[12] frequently results in calculating the complexity. In addition, the Voronoi partition can give out the nodes only on the basis of geographical characteristics, not on non-geographical characteristics such as lifetime, energy consumption, and capability of the nodes. Although a large-scale network has been focused on by Lin et al.,[13] it is non-adaptive and inaccurate to utilize fan-shaped clusters for a topologically self-determining problem space. Over the years, researchers have studied soft computing and intelligent techniques to achieve improved performance on clustering and CHS algorithms.[16–20] In Leu et al.,[19] the gravitational search algorithm (GSA) and PSO have been utilized that are dependent on the law of gravity and swarming nature, correspondingly. Both the algorithms are inflexible and highlight step-wise updating. Likewise, the harmony search algorithm[16] has been established to optimize the distribution of energy. This algorithm has updating performance in such an approach that local searching is thriving. In contrast, a fuzzy logic-based method has been detailed by Lee and Cheng[17]; however, the fuzzy inference system is straightforward, and it necessitates a priori information regarding the information. Yet, the a priori information from such dynamic networks is not practicable. Nevertheless, such information can be obtained from the networks, but it remains inaccurate, and therefore the consequential clustering effectiveness cannot be significant.

3. Objective model cluster head selection

The implemented model for selecting the CH estimate is based on three major properties, namely energy, distance, and delay, that is, the distance of the chosen CH to the nodes of the particular cluster has to be less. In addition, the distance of the CH to the sink must also be less. Likewise, the dissipation of energy owing to the delay and transmission of data must be reduced with suitable CHS. Taking into consideration these three constraints, the process to select the CH is derived as a reduction function, as given in Equation (1):

$$F = \beta f_2 + (1-\beta) f_1; 0 < \beta < 1 \tag{1}$$

where:

$$f_1 = \alpha_1 * f_i^{Dis} + \alpha_2 * f_i^{Energy} + \alpha_3 * f_i^{Delay} \tag{2}$$

$$f_2 = \frac{1}{n} \sum_{p=1}^{n} \left\| N_{nor}^{p} - n_s \right\| \tag{3}$$

In Equation (2) $\alpha_1, \alpha_2, \alpha_3$ are the distance, energy, and delay invariable parameters, respectively, and the addition of the entire parameters must be unity, that is, $\alpha_1 + \alpha_2 + \alpha_3 = 1$.

The fitness of distance factor is calculated by the Equation (4), where $f_{(1)}^{Dis}$ and $f_{(2)}^{Dis}$ are articulated as given in Equations (5) and (6):

$$f_i^{Dis} = \frac{f_{(1)}^{Dis}}{f_{(2)}^{Dis}} \tag{4}$$

$$f_{(1)}^{Dis} = \sum_{p=1}^{|c(q)|} \sum_{q=1}^{C_H^n} \left\| N_{NOR-q}^{p} - N_H^q \right\| + \left\| N_H^q - n_s \right\| \tag{5}$$

$$f_{(2)}^{Dis} = \sum_{\substack{p=1 \\ p \notin |c(q)|}}^{N} \sum_{q=1}^{N} \left\| N_{NOR-q}^{p} - N_H^q \right\| \tag{6}$$

In Equation (5), the numerator term sums up the two distance operator, in which N_{NOR-q}^{p} indicates the nodes that are normal in the qth cluster and in Equation (6), and the denominator term denotes the distance enclosed by the total number of nodes from one node to another, as a total. Moreover, the f_i^{Dis} value revolves to a large number, while the distance of the normal node to the CH is lengthier.

The estimation of the fitness of energy factor is given as in Equation (7):

$$f_i^{Energy} = \frac{f_{(1)}^{Energy}}{f_{(2)}^{Energy}} \tag{7}$$

In Equation (7), the value of f_i^{Energy} turns out to be greater than one, when the cumulative of the whole CH given by $f_{(1)}^{Energy}$ and $f_{(2)}^{Energy}$ takes the maximum energy value and the least CH count.

The cumulative energy of a cluster is provided in Equation (8), where the value of $nE_c(q)$ has to be less for the improved CH, as in Equation (9). For reducing the maximization measure, the energy of a node is deducted from the value of unity:

$$nE_c(q) = \sum_{\substack{p=1 \\ p \in q}}^{N} \left(1 - E(N_{NOR}^{P}) * E(N_H^{I})\right); 1 \leqslant q < C_H^n \tag{8}$$

$$f_{(1)}^{Energy} = \sum_{q=1}^{C_H^n} nE_c(q) \tag{9}$$

$$f_{(2)}^{Energy} = C_H^n * \underset{q=1}{\overset{C_H^n}{\mathrm{Max}}} \left(E(N_{NOR}^{q})\right) * \underset{q=1}{\overset{C_H^n}{\mathrm{Max}}} (E(N_H^q)) \tag{10}$$

In Equations (8) and (10), $E\left(N_{NOR}^{p}\right)$ indicates the energy related with the pth common node and $E(N_H^q)$ denotes the energy that is subjected to the qth common node. The consumption of energy should be sustained at a slighter value when any of the nodes in the WSN is taken in to account.

The value of fitness that is associated with the delay factor is calculated and is proportional to the number of members inhabited within a cluster. Hence, to eliminate delay, the CH should own few members as in Equation (11), where the numerator encloses the maximum number of cluster members, and the denominator comprises of the whole node count contained in a network. The fitness value can consider a value that belongs within one and zero. In addition, f_i^{Delay} has to consider a smaller value to obtain an improved selection of the CH:

$$f_i^{Delay} = \frac{\underset{q=1}{\overset{C_H^n}{\text{Max}}}\left(CH_N^q\right)}{N} \tag{11}$$

4. Network architecture and energy model

The process of selecting the CH is portrayed in Figure 1, in which the constraints of the network to be determined when choosing the CH are presented. Usually, the transfer of data related with the WSN takes place between the CH and the sensor node as well as the base station; therefore, the energy can be preserved, and the lifespan of the sensors can be conserved. The CH is implemented to be chosen depending on three parameter types, that is, energy, delay, and distance. On considering the transmission of data, the revealing distance representation performs the shortest path. The energy related with the CH is necessary to be huge enough, and an additional transfer of data takes place between the base station and the CH. Energy is assessed by the exploitation of the energy model. The delays should be fewer, and are described by delay representation. Once the CH is chosen, it begins to interact with the base station until it loses the entire energy and turns out to be dead nodes.

Assume a WSN comprised of N number of sensor nodes, possessing a particular base station or sink node, n_s. Every sensor node is distributed arbitrarily; however, within the highest radio range through the coordinate values of y_m and x_m. Here, N number of sensor nodes are fixed as C_H^n number of clusters and the CH for the nth cluster is indicated as N_H^n. Every sensor node utilizes the CH-dependent routing method to attain transfer of data to the base station. The distance of the pth normal nodes to the qth CH can be indicated as d_{pq}, whereas the distance of the qth CH to the sink node n_s can be represented as b_n. An uncomplicated WSN with five cluster nodes is revealed in Figure 2, where the base station n_s collects data from the nearer cluster nodes $N_H^1, N_H^2, N_H^3, N_H^4$, and N_H^5.

Assume that the node of a sensor has an initial energy of E_i that cannot go through recharging at a later moment. The loss of energy related with every packet that is conveyed from the pth normal node, N_{NOR}^p to q^{th} CH, N_H^q in a free space and the multi-path fading design, has a larger level of reliance over the distance that unites the transmitter to the receiver. The network approves the time-division multiple access (TDMA) protocol to carry out the transmission of data. Energy dissipation happens at the end of the transmitter, owing to the consumption of the power

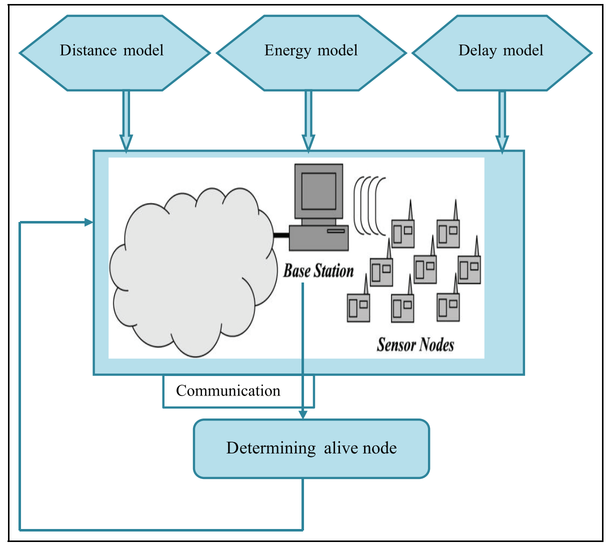

Figure 1. Overall cluster head selection architecture.

amplifier in addition to radio electronics. On the contrary, radio electronics alone is subject to the dissipation of energy at the end of the receiver. Depending on the distance in addition to the nature of the node as a usual node or a head node, the dissipation of energy for all packets abides by two different models that form the dissipated energy.

The energy dissipation focused with a usual node can be articulated as in Equation (12):

$$E_{dis}\left(N_{NOR}^p\right) = \left\{ \begin{array}{l} E_e * S_p + E_{pa} * \left\|N_{NOR}^p - N_H^q\right\|^4; \quad if \ \left\|N_{NOR}^p - N_H^q\right\| \geqslant d_i \\ E_e * S_p + E_{sf} * \left\|N_{NOR}^p - N_H^q\right\|^2; \quad if \ \left\|N_{NOR}^p - N_H^q\right\| < d_i \end{array} \right\} \tag{12}$$

In Equation (12) S_p is the packet size, E_{pa} indicates the energy usage of the power amplifier in the transmitter, $\left\|N_{NOR}^p - N_H^q\right\|$ denotes the distance between the normal node and CH, E_e is the electronic energy depending on the factor filtering, spreading, digital coding, amplifier, and modulation, and can be signified as $E_e = E_{Tx} + E_{da}$. Here, E_{Tx} is the energy used by the transmitter and E_{da} is the energy for data aggregation.

When the CH obtains S_p bytes of data, the receiver utilizes the energy as given in Equation (13) and the value energy of all nodes is updated another time after receiving or sending S_p bytes of data:

$$E_{dis}\left(N_H^p\right) = E_e * S_p \tag{13}$$

$$E_{t+1}\left(N_{NOR}^p\right) = E_t\left(N_{NOR}^p\right) - E_{dis}\left(N_{NOR}^p\right) \tag{14}$$

$$E_{t+1}\left(N_H^p\right) = E_t\left(N_H^p\right) - E_{dis}\left(N_H^p\right) \tag{15}$$

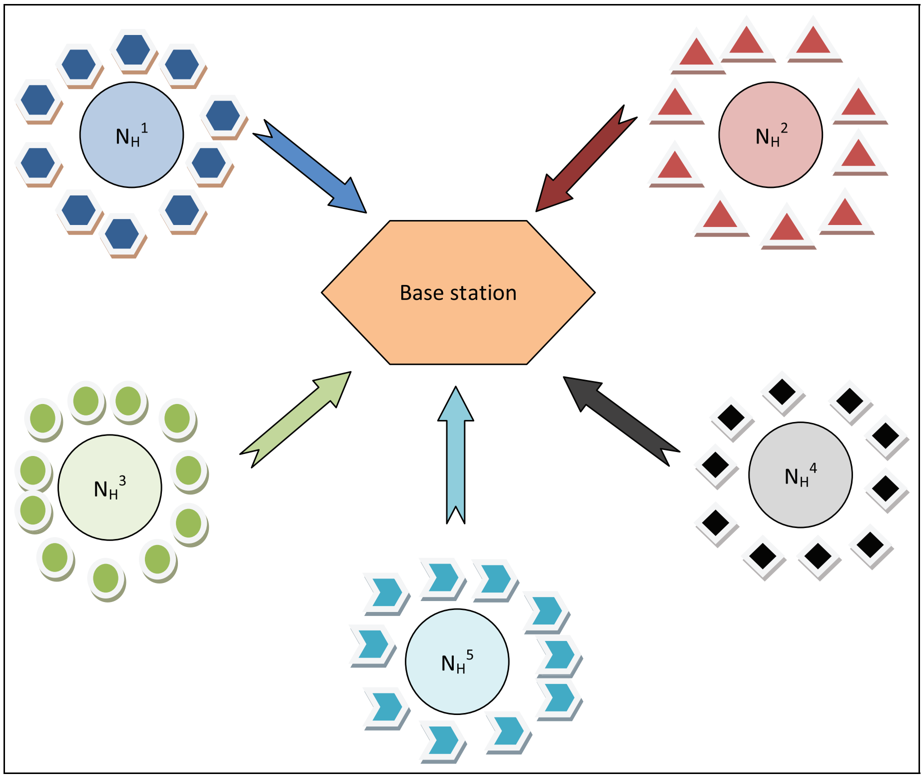

Figure 2. Simulated wireless sensor network.

In Equations (14) and (15), $E_t(N_H^p)$ and $E_t\left(N_{NOR}^p\right)$ are the previous energy of the cluster node and the normal node, respectively. At all tth time instants, the energy of all nodes reduces and finally reaches zero.

5. Optimal cluster head selection by Artificial Bee Colony-based Dynamic Scout bee algorithm

The Artificial Bee Colony (ABC) algorithm is condensed as the ABC-based CHS (ACHS) algorithm, and it was published by Dervis Karaboga. Of course, the honey bees take the liability of nectar discovery, along with sharing the particulars concerning the food source accessible to the bees living within the hive. A similar notion has been deployed in this algorithm. In the ACHS algorithm, the amount of nectar related with the solution is integrated with the value of fitness that corresponds to the solution and the position of food contribution points to the crisis. The employed bee count in and the food source count are generally similar.

The ACHS algorithm is accomplished with the subsequent primary steps.

1. Initialization.
2. Repeat.
3. *Employed bee phase*: at the initialization stage, the bees attain the sharing of information concerning the source of food with the bees in the dancing region. A bee waiting in the area of dancing for selecting the food source obtains its name as the onlooker, whereas the bee watching the food source is known as the employed bee. When the engaged bee visits the food that is previously visited throughout the previous cycle, it has the particulars in its memory. As a result, it goes on exploring a fresh food source and demonstrates its nectar amount. In this phase, the employed bees get situated over the food source.
4. *Onlooker bee phase*: based on the amount of nectar, the onlooker favors a food source. The probability related to the food source gets maximized, as the amount of nectar increases. Thus, the onlooker bees are positioned on the food source, depending on their quantity of nectar, in this phase. The possibility that an onlooker bee selects the food source is evaluated as given in Equation (16), where f_i signifies the fitness value related with a solution, and it demonstrates proportionality with the amount of nectar that the food source at location i includes. SB denotes the onlooker bees or the employed bee's own size:

PSEUDOCODE OF ADCHS ALGORITHM

Execute population initialization for the solution, Y_{ij}
Measure the population
cycle=1
Repeat
New solution is generated by means of Equation (17) and estimates them.
The employed bees are employed with the process of greedy selection.
The probability value $Prob_i$ that represents to the solution Y_i is intended by means of the Equation (16).
The new solution H_i has resulted from the solutions Y_i, associated with the value of $Prob_i$. The onlookers organize this new solution and consider them.
The onlookers are employed with the process of greedy selection.
The solution which is abandoned is revealed and a new randomly created solution X_i that employs on the scout is substituted by means of the Equation (18)
The position of the best food source position is remembered.
cycle=cycle + 1
until cycle= Maximum Cycle Number (MCN)

$$Prob_i = \frac{f_i}{\sum_{m=1}^{SB} f_m} \tag{16}$$

5. *Scout bee phase*: in this phase, the scout bees are passed to the exploration area to find out the new food source. Here, the scout bee tends to place a new food source in a random fashion, when the quantity of nectar gets exhausted.
6. Memorize the optimal solution.
7. Until (cycle = Maximum Cycle Number (MCN)): the three processes are performed repeatedly until the MCN is reached.

The location of food of a candidate is produced from the old one in recall by means of Equation (17), where in Equation (17) $k \in \{1, 2, \ldots\ldots, SB\}$ and $j \in \{1, 2, \ldots\ldots, D\}$, and D indicates the count of optimization factor that is selected randomly. ϕ_{ij} denotes a random number that belongs to the interval between $[-1, 1]$:

$$H_{ij} = Y_{ij} + \phi_{ij}(Y_{ij} - Y_{kj}) \tag{17}$$

The value that is subjected to the predestined number of cycles is expressed as the limit for abandonment. Assume that Y_i denotes the source that is abandoned and $j \in \{1, 2, \ldots\ldots.D\}$. In such a situation, the scout bee fixes Y_i in position of the new source, as explained in Equation (18):

$$Y_i^j = Y_{\min}^j + rand[0, 1](Y_{\max}^j - Y_{\min}^j) \tag{18}$$

A candidate source position is produced and measured with the ABC and distinguished against a formerly existing one. A new food source, on discovering it with a better nectar amount than the old one, will be reinstated instead of holding the preceding one in the holds of memory. The pseudo code that represents the ABC-based Dynamic Scout bee (ADCHS) algorithm is given below:

The main significance of the proposed ADCHS algorithm over the ACHS algorithm is that the scout bee is dynamic, and the results are the multiples of normal scout bee. In ADCHS algorithm, the produced scout bee is dynamic, and the resulting outcome is two times the usual scout bee, then the greedy selection method is employed for the scout bees, and then the most excellent solution is discovered. In this implemented ADCHS algorithm, the solution population is initialized and subsequently the population is estimated. As in the ACHS algorithm, the engaged bee is provided with a novel solution, as well as employing it with a process of greedy selection. Then the probability value that corresponds to the solution is measured by its value of fitness. In the phase onlooker bee, the novel solution for the onlooker is created upon the value of probability and then it employs greedy solution for the onlooker bee. Therefore, the abandoned solution that is associated to the scout is described. If an abandoned solution is recognized, the most excellent solution is remembered and the new solution for the scout bee is produced, and the created scout bee is dynamic and doubled. The process is repeated until it satisfies the condition for termination. The flow chart that illustrates the ADCHS algorithm is provided by Figure 3.

The ACHS algorithm is improved with mathematical expression in order to obtain the best solution. Assume a food source, Y_{ij}, that indicates an index that pertains to the nodes of the sensor. The CH count in addition to the length of food source is equal in this algorithm.

Encoding the food source of ACHS: primarily, food source Y_{ij} is produced randomly, where $i \in \{1, 2, \ldots\ldots\ldots, N_{COLONY}\}$ and $j \in \{1, 2, \ldots\ldots.D\}$, and D indicates the length related to the CH count or the source of food. The food source size is $Y_{ij} \times N_{COLONY}$, where the colony size is double the food source size, which is

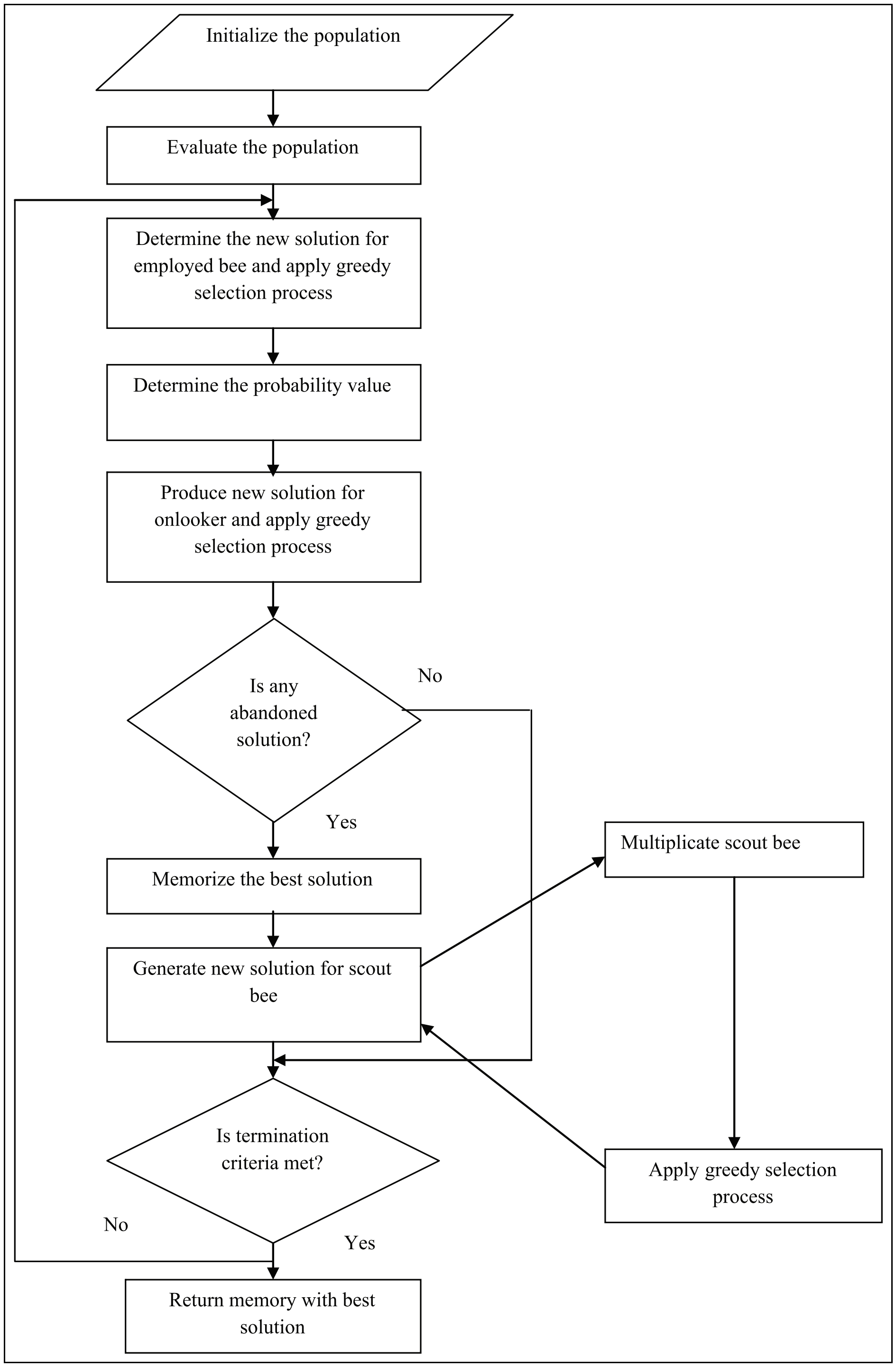

Figure 3. Steps of the Artificial Bee Colony-based Dynamic Scout bee algorithm.

provided as $2 * SB$, and it should satisfy the condition $Y_{ij} \neq Y_{ik}$.

Evaluation: the food source is calculated by means of the fitness function using Equation (1) in the bee phase that is employed. If the value of fitness is less when distinguished to the old food source, the new solution can be achieved.

Onlooker bee: it is the onlooker bee phase that updates the source of food that belongs to the half colony. The selection of the food source is established as per Equation (16). The onlooker tends to remember the source of food that happens newly in its path when the value of fitness of the earlier food source is behind the new one's fitness.

Scout bee: at the instant the abandoned solution is acknowledged in the ADCHS algorithm, the scout bee packs a source of fresh food in its position. The scout bee pursues the fitness function of Equation (19) to generate the new food source, where S_{ij}^* is a scout bee that is newly produced depending on the minimum fitness value of $S_{ij}^{(1)}$ and $S_{ij}^{(2)}$, where $S_{ij}^{(1)}, S_{ij}^{(2)} \in \{S_{ij}\}$:

$$S_{ij}^* = \underset{\{S_{ij}\}}{\arg\min} F(S_{ij}) \tag{19}$$

Thus, the proposed ADCHS algorithm produces two scout bee solutions $S_{ij}^{(1)}$ and $S_{ij}^{(2)}$ instead of the conventional FACHS algorithm, which produces only one scout bee. Subsequently, as the normal greedy selection method is engaged among the two scout functions, the new food source gets chosen that is associated with the best solution.

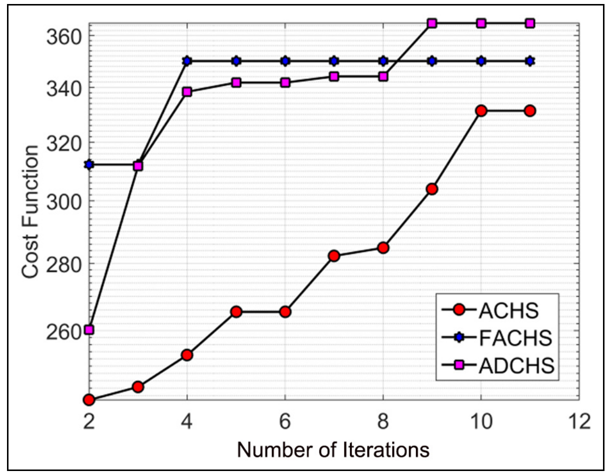

Figure 4. Convergence graph. ACHS: Artificial Bee Colony-based cluster head selection; FACHS: Fractional Artificial Bee Colony-based cluster head selection; ADCHS: Artificial Bee Colony-based Dynamic Scout bee.

6. Experimental results

The model for choosing the CH, subjected to the WSN and the performance of the recommended ADCHS algorithm, is attained in MATLAB R2015a. A WSN comprises the number of sensor nodes indicated by N that are available in a region, along with a base station in the core location. The model related with the WSN demonstrates the model plot for 0–2000 rounds, and it is carried out by fixing the values as in the conventional technique[21]; 50/100 amount of sensor nodes with an primary energy E_i, 0.5 and E_{fs} of 10pJ/bit/m^2. The transmitter (E_{pa}) energy that the power amplifier shows is 0.0013pJ/bit/m^2, the value of data aggregation energy E_{da} is 5nJ/bit/signal, and the transmitting energy E_{Tx} is 50nJ/bit/m^2 . Subsequent to these values, the model is implemented until it arrives at dead nodes.

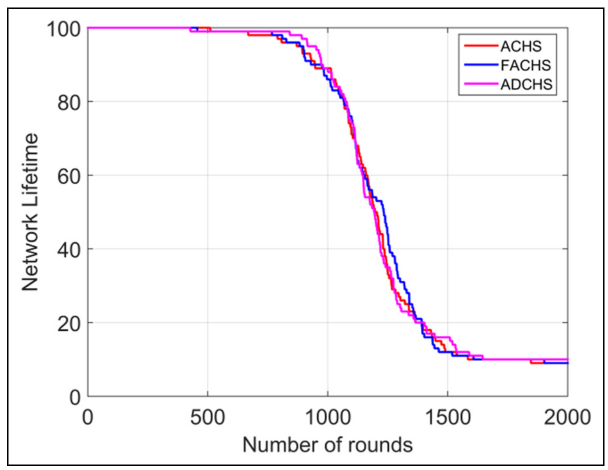

Figure 5. Statistical analysis regarding the alive node. ACHS: Artificial Bee Colony-based cluster head selection; FACHS: Fractional Artificial Bee Colony-based cluster head selection; ADCHS: Artificial Bee Colony-based Dynamic Scout bee.

6.1. Statistical analysis

In this section, the statistical analysis of the conventional and the implemented system is analyzed depending on the two factors, namely, energy and distance by means of the fitness parameter. Figure 4 demonstrates the convergence graph concerning the number of iterations. From Figure 4, the convergence analysis for the proposed ADCHS method concerning the number of iteration is 8.3% better than the ACHS method and 2.7% better than the FACHS method. Thus, the capability of the proposed ADCHS method is proved to be better when compared with the existing methods:

$$(\%) = \frac{\text{Cost function of the implemented technique} - \text{Cost function of the conventional technique}}{\text{Cost function of the conventional technique}} \tag{20}$$

The iteration is continued until it attains at the dead node. From Figure 5, the statistical analysis of the proposed ADCHS technique with respect to the number of nodes can be determined. From the analysis, it is known that the implemented method is 16.6% superior to the ACHS method and 22.2% superior to the FACHS technique. Hence, it is shown that the proposed ADCHS method offers an increased number of alive nodes with an

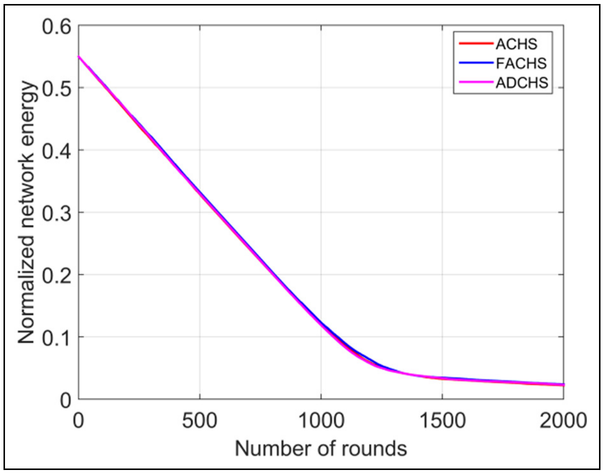

Figure 6. Statistical analysis regarding normalized energy. ACHS: Artificial Bee Colony-based cluster head selection; FACHS: Fractional Artificial Bee Colony-based cluster head selection; ADCHS: Artificial Bee Colony-based Dynamic Scout bee.

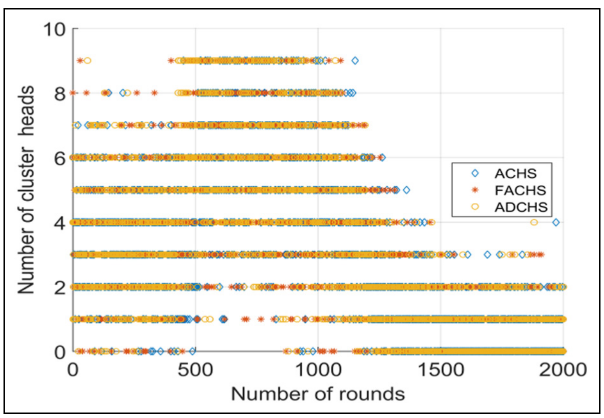

Figure 7. Statistical analysis of cluster head count. ACHS: Artificial Bee Colony-based cluster head selection; FACHS: Fractional Artificial Bee Colony-based cluster head selection; ADCHS: Artificial Bee Colony-based Dynamic Scout bee.

increase in the number of nodes. Similarly, from Figure 6, the normalized network energy in terms of the number of rounds is obtained. From the analysis, it is known that the implemented ADCHS technique is 20% better than both the ACHS and FACHS methods.

Figure 7 shows the statistical analysis of the implemented ADCHS algorithm and conventional ACHS and FACHS algorithms, by considering the CH count that is selected at each particular round. In the final round 2000, a sum of 10 CHs is selected in the implemented ADCHS algorithm. The figure legibly exposes the statement that the count of CHs that is chosen with the implemented ADCHS algorithm goes beyond the traditional ACHS and FACHS algorithms.

6.2 CHS performance

The bar chart for the contrast of the traditional FACHS and ACHS algorithms and the implemented ADCHS algorithm by means of the distance among CHs is revealed in Figure 8. A node is converted to a CH merely when the associates belonging to a certain cluster display the lowest distance with the CH. In the implemented ADCHS algorithm, the distance among the CHs is less than that of the traditional techniques. Figure 9 illustrates the distance among the alive nodes of the traditional and implemented methods. In the implemented technique, the quantity of alive nodes is increased in every round, and the distance among all the nodes is fewer when evaluated compared to the traditional methods. Figure 10 demonstrates the distance among the normalized energy of the network for the traditional and the implemented methods. In the recommended system, the usage of energy is less, and the distance is decreased when distinguished with other conventional algorithms. Table 1 shows the comparative analysis of the implemented and conventional techniques regarding the normalized energy for rounds from 0 to 2000. According to Table 1, the implemented technique provides, in general, a better presentation when compared with the traditional methods.

6.3 Parameter evaluation

The parameter evaluation for the network lifetime by varying the factors of the ABC is obtained from Figure 11. From Figure 11, it is known that limit 5 is 15.3% better than limit 3 and 17.3% better than limit 1. Thus, the lifetime of the network regarding colony size for varying limit size is verified. Similarly, from Figure 12, normalized network energy by varying parameters of the ABC is verified. From Figure 12, limit 5 is 27.2% superior to limit 1 and 50% superior to limit 3. Thus, the capability of the proposed method is verified.

Similarly, from Table 1, for limit 1, the alive node for the 600th iteration is 2% better than those for the 200th and 400th iterations. Similarly, the alive node for the 800th iteration is 12.6% lesser than those for the 200th, 400th, and 600th iterations. Also, the normalized network energy for limit 1 in the 0th iteration is 14.6% better than that for the 200th iteration; in the 400th iteration, it is 22.4% better than in the 600th iteration. Similarly, from Table 2, for limit 2, the alive node for the 800th iteration is 2% better than those for the 200th, 400th, and 600th iterations. Similarly, the alive node for the 1000th iteration is 18% lesser than those for the 200th, 400th, and 600th iterations. Also, the normalized network energy for limit 2 in the 0th iteration is 40% better than that for the 400th iteration and so on.

Also from Table 3, for limit 2, the alive node for the 600th iteration is 5% better than those for the 200th and

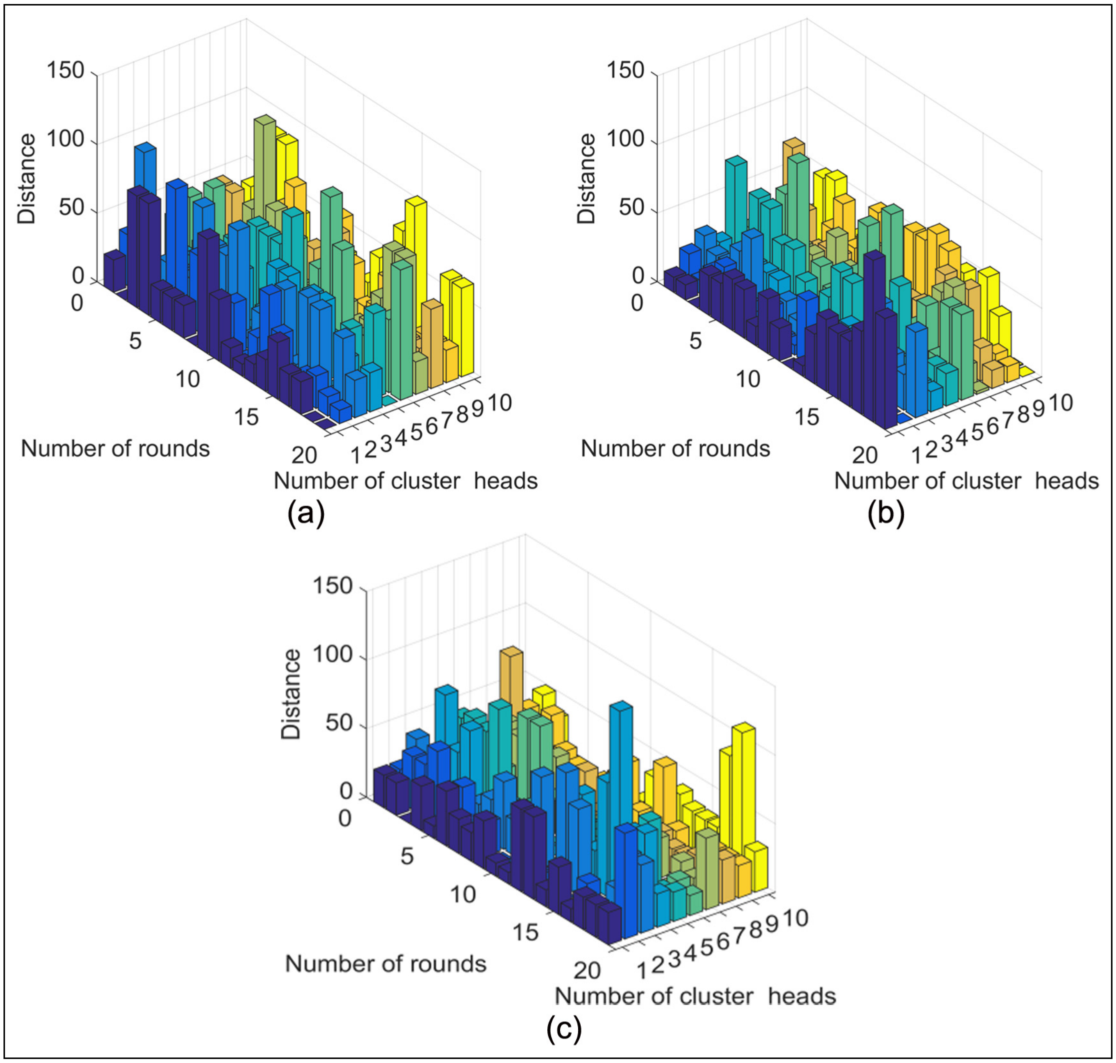

Figure 8. Cluster head of (a) Artificial Bee Colony-based cluster head selection, (b) Fractional Artificial Bee Colony-based cluster head selection, and (c) Artificial Bee Colony-based Dynamic Scout bee.

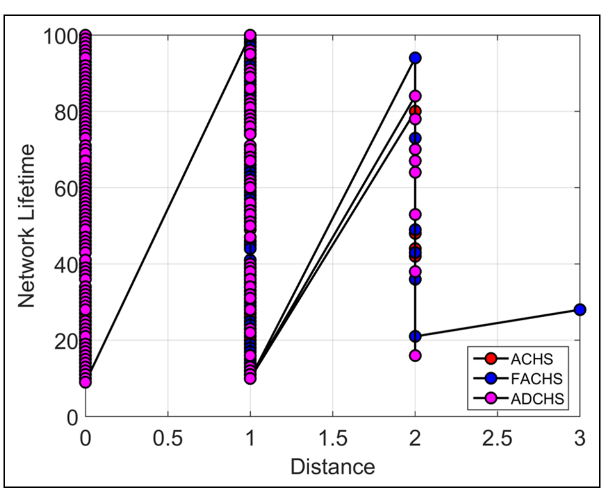

Figure 9. Alive nodes of Artificial Bee Colony-based cluster head selection (ACHS), Fractional Artificial Bee Colony-based cluster head selection (FACHS), and Artificial Bee Colony-based Dynamic Scout bee (ADCHS).

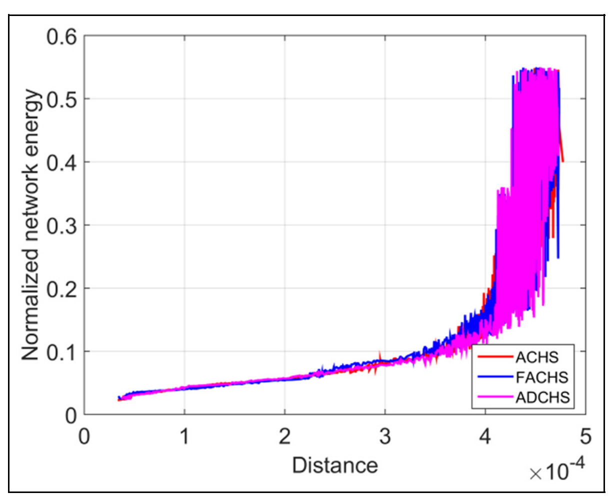

Figure 10. Normalized network energy of Artificial Bee Colony-based cluster head selection (ACHS), Fractional Artificial Bee Colony-based cluster head selection (FACHS), and Artificial Bee Colony-based Dynamic Scout bee (ADCHS).

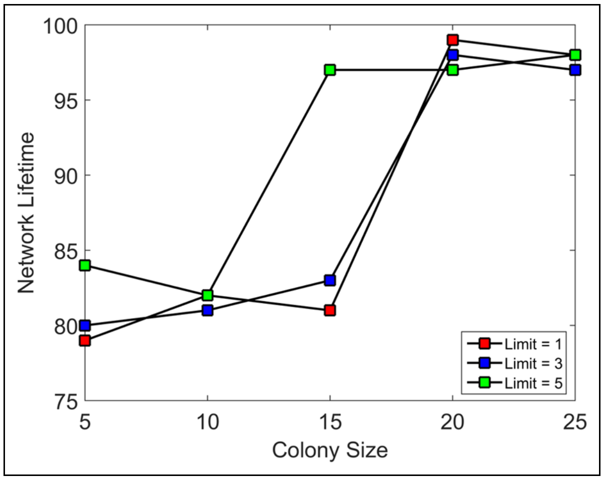

Figure 11. Network lifetime of the proposed method by varying the parameters of the Artificial Bee Colony (ABC).

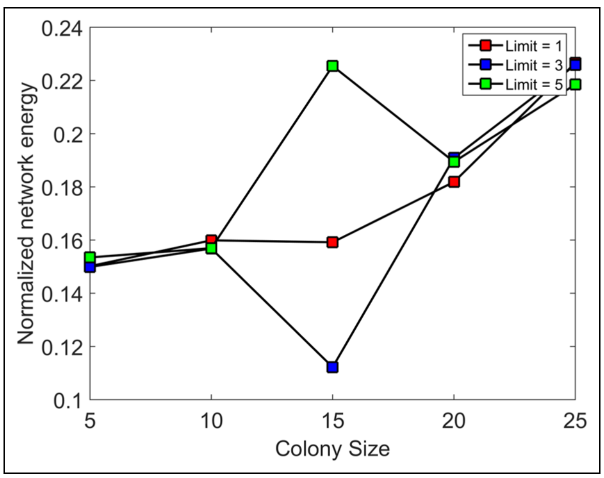

Figure 12. Normalized network energy proposed method by varying the parameters of the Artificial Bee Colony (ABC).

400th iterations. Similarly, the alive node for the 1000th iteration is 18% lesser than those for the 200th, 400th, and 600th iterations. Also, the normalized network energy for

Table 1. Comparison study of the existing and implemented technique in terms of the normalized energy.

Rounds	ACHS	FACHS	ADCHS
0	0.54956	0.54956	0.54956
225	0.44904	0.45097	0.45211
500	0.3286	0.32937	0.33184
725	0.23224	0.23282	0.23516
1000	0.12086	0.11857	0.1226
1225	0.054103	0.052985	0.058044
1500	0.032645	0.033615	0.034483
2000	0.022259	0.023083	0.023833

ACHS: Artificial Bee Colony-based cluster head selection; FACHS: Fractional Artificial Bee Colony-based cluster head selection; ADCHS: Artificial Bee Colony-based Dynamic Scout bee

limit 2 in the 0th iteration is 12.6% better than that for the 200th iteration and so on. Similarly, from Table 4, the alive node for limit 1 in the 0th and 100th iteration is 1% better than those for the 200th, 400th, and 600th iterations. Similarly, the alive node for the 1000th iteration is 18% lesser than those for the 200th, 400th, and 600th iterations. Also, the normalized network energy for limit 1 in the 400th iteration is 20% better than that for the 600th iteration and so on. Also from Table 5, the alive nodes for limit 2 in the 0th and 200th iterations are 2% better than those for the 400th and 600th iterations. Also, the alive nodes for limit 2 in the 0th and 200th iterations are 3% better than those for the 800th and 1000th iterations. Also, the normalized network energy for limit 2 in the 400th iteration is 17% better than that for the 600th iteration and so on. Thus, the capability of the proposed ADCHS algorithm is verified. Table 6 summarizes the analysis on alive nodes and normalized network energy by varying the limits of the scout bee size for population size 25.

7. Conclusion

In a WSN, choosing and optimally positioning the CH is the main feature. CH routing is executed between the base

Table 2. Comparative analysis on alive nodes and normalized network energy by varying the limits of the scout bee size for population size 5.

Rounds	Limit 1		Limit 2		Limit 3	
	Alive nodes	Normalized network energy	Alive nodes	Normalized network energy	Alive nodes	Normalized network energy
0	100	0.549569	100	0.549561	100	0.549555
200	100	0.469531	100	0.466844	100	0.466982
400	100	0.385355	100	0.383772	100	0.38681
600	98	0.299713	96	0.301448	97	0.305354
800	87	0.218282	90	0.221172	87	0.22779
1000	79	0.15018	80	0.149913	84	0.153461

Table 3. Comparative analysis on alive nodes and normalized network energy by varying the limits of the scout bee size for population size 10.

Rounds	Limit 1		Limit 2		Limit 3	
	Alive nodes	Normalized network energy	Alive nodes	Normalized network energy	Alive nodes	Normalized network energy
0	100	0.549555	100	0.549564	100	0.549566
200	100	0.471527	100	0.470262	100	0.470596
400	100	0.390679	100	0.387715	100	0.389277
600	95	0.30812	98	0.306027	97	0.306965
800	83	0.230599	86	0.228029	85	0.227912
1000	82	0.159895	81	0.156802	82	0.156951

Table 4. Comparative analysis on alive nodes and normalized network energy by varying the limits of the scout bee size for population size 15.

Rounds	Limit 1		Limit 2		Limit 3	
	Alive nodes	Normalized network energy	Alive nodes	Normalized network energy	Alive nodes	Normalized network energy
0	100	0.549558	100	0.549564	100	0.54953
200	100	0.468185	100	0.460355	100	0.523144
400	100	0.391067	100	0.371183	98	0.47002
600	95	0.309535	100	0.281616	98	0.392176
800	88	0.23197	98	0.193015	97	0.309544
1000	81	0.159169	83	0.112212	97	0.225438

Table 5. Comparative analysis on alive nodes and normalized network energy by varying the limits of the scout bee size for population size 20.

Rounds	Limit 1		Limit 2		Limit 3	
	Alive nodes	Normalized network energy	Alive nodes	Normalized network energy	Alive nodes	Normalized network energy
0	100	0.549531	100	0.549542	100	0.549541
200	100	0.504158	100	0.502235	100	0.506914
400	99	0.439251	99	0.447624	99	0.444571
600	99	0.353464	99	0.361638	99	0.358623
800	99	0.267947	99	0.275643	98	0.273288
1000	99	0.181848	98	0.190896	97	0.189409

Table 6. Comparative analysis on alive nodes and normalized network energy by varying the limits of the scout bee size for population size 25.

Rounds	Limit 1		Limit 2		Limit 3	
	Alive nodes	Normalized network energy	Alive nodes	Normalized network energy	Alive nodes	Normalized network energy
0	100	0.54953	100	0.54953	100	0.54953
200	100	0.52601	100	0.523614	100	0.524113
400	99	0.482207	98	0.470438	99	0.473873
600	98	0.396974	98	0.392587	98	0.388018
800	98	0.311739	97	0.309952	98	0.303006
1000	98	0.226638	97	0.225842	98	0.218476

station and the sensor node for data interaction. A principle dynamic scout bee (DS) has been incorporated along with the ACHS technique to produce several scout bee solutions for choosing the CH that signifies the WSN. The presentation demonstrated by the implemented ADCHS method has been verified with the two major factors of routing methods, energy and distance. The results acquired following the testing of the implemented ADCHS technique have been distinguished with the ACHS and FACHS techniques by means of the number of alive nodes and energy in network. The implemented ADCHS technique has been established to offer less consumption of energy, along with an increase in the number of alive nodes at every iteration compared with the conventional ACHS and FACHS algorithms.

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References

1. Chung WY, Lee BG and Yang CS. 3D virtual viewer on mobile device for wireless sensor network-based RSSI indoor tracking system. *Sens Actuat B Chem* 2009; 140: 35–42.
2. Li BL. High performance flexible sensor based on inorganic nanomaterials. *Discover Value* 2013; 176: 522–533.
3. Yu X, Li C and Low ZN. Wireless hydrogen sensor network using AlGaN/GaN high electron mobility transistor differential diode sensors. *Sens Actuat B Chem* 2008; 135: 188–194.
4. Javaid N, Waseem M and Khan ZA. ACH: away cluster heads scheme for energy efficient clustering protocols in WSNs. In: *Saudi international electronics, communications and photonics conference*, Fira, 8 July 2013, pp.1–4. Piscataway, NJ: IEEE.
5. Hosseinirad SM, Ali MN and Basu SK. LEACH routing algorithm optimization through imperialist approach. *Int J Eng Trans A Basics* 2014; 27: 39–50.
6. Poduri S and Sukhatme GS. Constrained coverage for mobile sensor networks. In: *proceedings of the IEEE international conference robotics and automation (ICRA'04)*, 26 April–1 May 2004, pp.165–172. Piscataway, NJ: IEEE.
7. Zou Y and Chakrabarty K. Sensor deployment and target localizations based on virtual forces. In: *proceedings of IEEE INFOCOM'03 Twenty-second annual joint conference of the IEEE computer and communications societies* (IEEE Cat. No.03CH37428, San Francisco, CA, 2003. Piscataway, NJ: IEEE.
8. Fotouhi H, Alves M and Zamalloa MZ. Reliable and fast hand-offs in low-power wireless networks. *IEEE Trans Mob Comput* 2014; 13: 2621–2633.
9. Tyagi S and Kumar N. A systematic review on clustering and routing techniques based upon LEACH protocol for wireless sensor networks. *J Network Comput Appl* 2013; 36: 623–645.
10. Geeta DD, Nalini N and Biradar RC. Fault tolerance in wireless sensor network using hand-off and dynamic power adjustment approach. *J Network Comput Appl* 2013; 36: 1174–1185.
11. Fan CS and Shuo C. Rich: region-based intelligent cluster-head selection and node deployment strategy in concentric-based WSNs. *Adv Electr Comput Eng* 2013; 13: 3–8.
12. Jia D, Zu H, Zou S, et al. Dynamic cluster head selection method for wireless sensor network. *IEEE Sens J* 2016; 16: 2746–2754.
13. Lin H, Wang L and Kong R. Energy efficient clustering protocol for large-scale sensor networks. *IEEE Sens J* 2015; 15: 7150–7160.
14. Ni Q, Pan Q, Du H, et al. A novel cluster head selection algorithm based on fuzzy clustering and particle swarm optimization. *IEEE/ACM Trans Comput Biol Bioinform* 2017; 14: 76–84.
15. Khan BM, Bilal R and Young R. Fuzzy-TOPSIS based cluster head selection in mobile wireless sensor networks. *J Electr Syst Inform Technol*. Epub ahead of print 4 January 2017. DOI: 10.1016/j.jesit.2016.12.004.
16. Hoang DC, Yadav P, Kumar R, et al. Real-time implementation of a harmony search algorithm-based clustering protocol for energy-efficient wireless sensor networks. *IEEE Trans Ind Inform* 2014; 10: 774–783.
17. Lee JS and Cheng WL. Fuzzy-logic-based clustering approach for wireless sensor networksusing energy predication. *IEEE Sens J* 2012; 12: 2891–2897.
18. Gautam N and Pyun JY. Distance aware intelligent clustering protocol for wireless sensor networks. *J Commun Networks* 2010; 12: 122–129.
19. Leu JS, Chiang TH, Yu MC, et al. Energy efficient clustering scheme for prolonging the lifetime of wireless sensor network with isolated nodes. *IEEE Commun Lett* 2015; 19: 259–262.
20. Parvin JR and Vasanthanayaki C. Particle swarm optimization-based clustering by preventing residual nodes in wireless sensor networks. *IEEE Sens J* 2015; 15: 4264–4274.
21. Kumar R and Kumar D. Multi-objective fractional artificial bee colony algorithm to energy aware routing protocol in wireless sensor network. *Wireless Networks* 2015; 22: 1461–1474.

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