An Artificial Bee Colony Inspired Clustering Solution to Prolong Lifetime of Wireless Sensor Networks

A. Pathak*

Abstract: It is very difficult and expensive to replace sensor node battery in wireless sensor network in many critical conditions such as bridge supervising, resource exploration in hostile locations, and wildlife safety, etc. The natural choice in such situations is to maximize network lifetime. One such approach is to divide the sensing area of wireless sensor network into clusters to achieve high energy efficiency and to prolong network lifetime. In this paper, an Artificial Bee Colony Inspired Clustering Solution (ABCICS) is introduced. The proposed protocol selects the head of the cluster with optimal fitness function. The fitness function comprises the residual energy of node, node degree, node centrality, and distance from base station to node. When cluster-head with high energy node transmits the data to the base station, it further minimizes the energy consumption of the sensor network. The presented protocol is compared with LEACH, HSA-PSO, and MHACO-UC. Simulation experiments show the effectiveness of our approach to enhance the network lifetime.

Keywords: Artificial Bee Colony, Clustering, Network Lifetime, Wireless Sensor Network.

1 Introduction

Wireless Sensor Network contains a large number of small nodes. These small nodes have sensing, computation, and wireless communications capabilities [1]. The sensing area is the region where sensor nodes are deployed. Nodes may be deployed at random or installed manually. Sensor nodes gather the information from the sensing region, process it, and send wirelessly either to other nodes or to an external base station. Base station is a centralized point of control within the network. It may be a fixed or a mobile node. Base station is joined to an accessible communications infrastructure or the Internet so that a user can have access to the available data.

Wireless sensor networks have found applications in business, home, medical, real-time control, defense, emergency, and disaster relief management, etc. They are also used in supervising for remote or inaccessible environment applications [2, 3]. In many situations, especially in a hostile environment, replacing or even refilling the attached battery of the node is a very tedious job. The limited energy resource is the major constraint of wireless sensor networks [4, 5]. The challenge of prolonging the lifetime of the network has led to an increased research interest from the scientific community. As a result, researchers have proposed many techniques like duty cycling, data reduction, and topology management, etc. for enhancing the lifetime of the network. Energy of nodes can be saved with duty cycling strategy that permits sensor nodes to go in sleep when they are not in use [6-10]. The data reduction method also reduces the energy consumption with the help of minimizing the quantity of information generated, processed, and transmitted [11-13]. The topology management saves the energy consumption of nodes by constructing and preserving a reduced set of nodes [14-16]. Hierarchical or cluster-based routing methods seem to be most appropriate for enhancing the lifetime of sensor networks [17-19].

Low Energy Adaptive Clustering Hierarchy (LEACH) is a well-known clustering algorithm in wireless sensor network.
network [20]. In LEACH, the Cluster-Heads (CHs) in clusters are rotated in each round with random probability among sensor nodes for gaining energy balance. This protocol could gain partial success because it is an entirely distributed protocol. In a distributed protocol, more energy is required to transmit the packet. Fuzzy logic is also used in the development of clustering protocols [21-25]. Swarm intelligence offers proficient meta-heuristic tools that can be efficiently applied in wireless sensor networks. Clustering in a wireless sensor network is a well-known optimization problem. The swarm intelligence is efficiently solving this issue as surveyed in [26-30]. For instance, ant colony optimization meta-heuristic has been applied in clustering [31]. Particle Swarm Optimization (PSO) algorithm is also used in clustering optimization. The protocol presented in [32] utilizes PSO for cluster-head selection taking residual energy, intra-cluster distance, and node degree as fitness function. A hybrid centralized protocol combining Harmony Search Algorithm (HSA) and PSO is also used in wireless sensor networks for clustering optimization [33]. Bee Colony meta-heuristic gained success for solving the clustering problem in wireless sensor networks [34-38].

In this paper, Artificial Bee Colony Inspired Clustering Solution (ABCICS) is presented. This solution takes the benefit of artificial bee colonies used for optimization of dynamic and multi-objective problems. The proposed solution gains the best result with the appropriate selection of head of cluster based on energy of node, node degree, node centrality, and distance from base station to node. The energy-efficient transmission of data from node to the base station further enhances its performance. The multi-hop transmission of data between adjacent cluster-heads is followed based on the residual energy of nodes rather than direct transmission of data from cluster-head to base station. In the present paper, we have used the concept of on-demand clustering instead of clustering in each round. The on-demand clustering concept reduces the burden of clustering. The analysis was done in two phases. In the first phase, the various possible design choices were analyzed. The best parameter of design was chosen for the final implementation. In the second phase, the competitiveness of the algorithm was established by comparing the proposed algorithm with other state of art existing algorithm.

The major contributions of the paper are the following:

- Firstly, the artificial bee colony model is presented considering its applicability in clustering wireless sensor networks.
- Secondly, Artificial Bee Colony Inspired Clustering Solution is proposed focusing on phase-wise description, fitness function, and radio propagation model.
- Thirdly, the proposed clustering protocol is comparatively evaluated considering various network performance metrics.

The rest of the paper is organized as follows: Survey of the respective work is given in Section 2. In Section 3, the artificial bee colony model is discussed. Section 4 presents the proposed protocol and its operational details. Section 5 represents the network model and Section 6 computes the fitness function. Section 7 briefs the experimental setup of the ABCICS algorithm and Section 8 shows the performance evaluation of ABCICS, and a comparison is made with other protocols. Conclusion and future scope of the paper are specified at the end of the paper.

2 Related Works

Numerous diverse approaches have been carried out to design practical wireless sensor networks. Energy conservation is essential to enhance the lifetime of the whole network. Network lifetime can be defined as the time elapsed until the first node in the network depletes its energy [39, 40]. Hierarchical or cluster-based routing methods seem to be most appropriate for enhancing the lifetime of sensor networks [17-19]. Hierarchical routing method also brings down energy consumption within a cluster by performing data aggregation and fusion. Low Energy Adaptive Clustering Hierarchy (LEACH) protocol [20] is a recognized clustering algorithm. However, there are certain drawbacks of this protocol. Some of them are:

1. It selects cluster heads based on probability which leads to two adverse consequences. First, there is a load imbalance among the cluster heads due to non-assurance of uniform distribution of cluster-head in the network. Second, low energy node may be chosen as cluster heads which is not capable enough to do additional work of heads such as fusing the data obtained from its members and transfer this fused data to the base station.

2. The cluster heads send their data to the base station in one hop transmission. They bear the energy expenditure of long-range transmission. A cluster head that is distant from the base station diminishes its energy faster than the other cluster-heads in the network, which are not so distant.

3. In each round, the protocol has to do the process for selecting the new cluster heads and forming new clusters. This further increases the operating cost of the set-up phase.

Authors in paper [41] tried to solve the problem of non-uniform load distribution of cluster heads. However, the scheme presented in [41] needs a node positioning system like GPS which causes the system to be more expensive. Authors in paper [42] presented threshold sensitive energy-efficient sensor network protocol, which submits a new idea based on thresholds for sending node’s data. However, it is difficult to
calculate the precise value of these thresholds because this protocol is not appropriate for monitoring applications where data is continuously reported to the base station. In the paper presented in [43], efficient-clustering scheme is presented where the cluster head nominees struggle to be promoted as cluster heads. If a node could not find another node with more residual energy than itself, it takes up the responsibility of the cluster head. This algorithm forms clusters of varying sizes using distance from the base station as metric. Hybrid Energy-Efficient Distributed Clustering [44] focuses on proficient clustering by appropriate cluster heads mechanism of selection. Energy-Efficient Hierarchical clustering protocol [45] partitions the network into the hierarchy of layers. Lowest level cluster heads collect the data from member nodes and aggregate it. The aggregated data from the lowest layer is then sent to the cluster heads of the subsequent layer. This method repeats itself recursively until all the data has reached the base station. Stable Election Protocol [46] highlights the impact of heterogeneity of nodes concerning the energy of the nodes. In the Clustering Algorithm via Waiting Timer [47], a protocol node degree is taken into consideration for the selection of cluster heads. Autonomous Clustering via Directional Antenna [48] algorithm uses directional antennas to decrease the redundancy in sensing the data in sensor networks. Two-Level LEACH [49] protocol has two types of cluster heads, namely primary heads and secondary heads. Network is divided into outer and inner layers. Primary cluster heads are responsible for aggregating the data in the outer layer and the secondary are responsible for the inner layer. LEACH with Distance-based Thresholds [50] algorithm selects cluster-heads with modified probability. This approach optimally balances energy consumption among the nodes. In [51], the parameter for the selection of cluster head is dependent on the neighbors like distance between the nodes and the number of its neighboring nodes within communication reach. The main focus of [52] algorithm is to balance the load with uniform and non-uniform node distribution in the network. Link aware Clustering Method (LCM) [53] initiates a new function, called Predicted Transmission Count (PTC), to calculate the nominee conditions. The position of the nodes, transmitted power, residual energy, and link quality are used as the parameters to derive the PTC. The PTC demonstrates the potential of an applicant for persistent transmissions to any specific neighboring node. In Energy-Efficient LEACH (EE-LEACH) [54] protocol, the mechanism of selection of the cluster head is based on the function of spatial density. The protocol considers the Gaussian distribution model for deployment of sensors. Hence it is not suited to the applications where sensor nodes cannot be deployed manually.

The first fuzzy logic dependent clustering protocol is presented in [21]. LEACH-Fuzzy Logic [22] computes the chance for selecting the cluster heads. Authors in [23] used fuzzy techniques where each cluster head is chosen based on the prediction of residual energy. The authors in [55] have taken node degree and node centrality as fuzzy variables. Initially, each node calculates its cost. After that, a delay timer is set by each node that is proportional to its inverted residual energy. So, the node which has larger residual energy should wait a smaller amount of time than the nodes which has lower energy. Node broadcasts a tentative cluster head announcement within its cluster range. If this particular node has the least cost among the tentative heads in its proximity, it will become a final head. Low Energy-efficient hierarchical Clustering and routing protocol based on Genetic Algorithm (LECR-GA) [56] to efficiently maximize the lifetime and to improve the Quality of Service (QoS). In [57], the authors presented a cluster head selection algorithm using ant colony optimization to build load-balanced clusters in the network. In [58], the authors presented clustering algorithm using PSO. They considered two types of nodes: normal sensor nodes and high energy nodes. The high energy nodes act as cluster heads in the network whereas normal sensor nodes act as members of the clusters. Another Ant-based Clustering (ANTCLUST) method is described in [59]. ANTCLUST protocol organizes energy-efficient clusters through local interactions among sensor nodes. A hybrid protocol combining Harmony Search Algorithm (HSA) and PSO is also used for clustering optimization [33]. HSA-PSO algorithm gives better results when compared with LEACH, PSO, and HSA in terms of lifetime. Honey bee optimization is also used to form clusters in wireless sensor network [34-38]. Wireless Sensor Network Clustering using Artificial Bee Colony algorithm (WSNCABC) [34] uses artificial bee colony to compute the fitness of cluster head using the parameters such as residual energy of node and distance from base station to the nodes. However, this algorithm suffers from the high cost for the direct transmission of data from the cluster head to the base station. Bee-Sensor-C [60] is developed for event-driven sensor networks. Bee-Sensor-C builds a cluster structure and selects the cluster heads when an event occurs. The first sensor that declares the event becomes the cluster head and other sensors have to follow it. Bee-C [61] is a clustering protocol, which proposes a meta-heuristic algorithm inspired by the Honey Bee Mating Optimization. Exponential Ant Colony Optimization (EACO) [62] algorithm solves route discovery problem in wireless sensor network after finding the cluster heads using fractional artificial bee colony (FABC) algorithm. A dynamic clustering method is presented in [63] based on the artificial bee colony and the genetic algorithm. The genetic algorithm is used for determining the cluster heads and the artificial bee colony algorithm is used for determining member nodes in each cluster. Bee algorithm-based
clustering for Wireless Sensor Network (BeeWSN) [64] scheme forms balanced clusters in the mobile environment efficiently based on the remaining energy of node, degree, speed, and direction. A hybrid algorithm combining PSO with Tabu Search (TS) is also utilized for clustering in wireless sensor networks [65]. Metaheuristic ACO based Unequal Clustering (MHACO-UC) [66] algorithm divided the sensing area into unequal clusters and selection of heads among the nodes in particular cluster depends on diverse set of parameters such as distance from node to base station, energy and Link Quality Factor (LQF). The queue size is the basic measure to estimate the LQF. However, MHACO-UC algorithm requires GPS which causes the system to be more expensive. Besides, GPS necessitates supplementary energy consumption and hence it requires larger size hardware. Khabiri and Ghaffari [67] proposed an energy-aware cluster-based routing protocol which utilizes the concept of cuckoo optimization. The cluster head selection is based on the energy of nodes, distance from the base station, intra-cluster and inter-cluster distances. P. T. Karthick & C. Palanisamy [68] proposed optimized cluster head selection using the krill herd algorithm for wireless sensor network.

3 Artificial Bee Colony Model

The Artificial Bee Colony algorithm is inspired by the intelligent foraging behavior of honey bees. Artificial Bee Colony algorithm has received huge attention from both practitioners and researchers on intelligent optimization [69]. There are three groups of bees in the bee colony algorithm namely worker bees, onlooker bees, and scout bees. The position of a food source represents a possible solution to the optimization problem and the nectar amount of a food source corresponds to the quality (fitness) of the associated solution [70-72]. Here the colony size is equal to the number of worker bees and also equal to the number of onlooker bees. The initial locations of food sources are randomly generated and every worker bee is appointed to a food source. Then every worker bee finds a new food source in all iteration and computes its quality. If the nectar amount of the new food source is higher than the previous one, then worker bee moves to the new food source, otherwise it continues with the old one [68]. This process is described by

\[
V_{ij} = x_{ij} + \tau (x_{ij} - x_{kj})
\]

where \( \tau \) is a random number between \([-1, 1] \), \( V_{ij} \) is a new food source, \( x_{ij} \) is current food source, \( x_{kj} \) is neighborhood source, and \( j \in \{1, 2, ..., D\} \) is randomly chosen index with \( D \) as the dimension of the food source vector. When all the worker bees finish the search procedure, they share the information about their food source with onlooker bees. The onlooker bee then assesses the nectar information and picks a food source with a probability related to its nectar amount by

\[
P_i = \frac{F_i}{\sum_{j=1}^{m} F_j}
\]

where \( F_i \) is the fitness value of the solution \( i \) that is proportional to the nectar amount of the food source in the location \( i \) and \( m \) is the number of food sources. Once all onlooker bees have selected their food sources, each of them determines a new neighboring food source as respective selected food source and computes its nectar amount. When any position cannot be improved further through a predetermined number of cycles, the food source is assigned as abandoned and worker bee of that source changes its role and becomes a scout bee. In that position, a new solution is randomly generated by the scout bee and is given as

\[
x_{ij} = x_{ij} + \text{rand}(0, 1)(x_{j,\text{max}} - x_{j,\text{min}})
\]

where abandoned source is represented by \( x_i \).

4 Artificial Bee Colony Inspired Clustering Solution (ABCICS)

As the sensor nodes have restricted energy source and hence enhancing the network lifetime remains an important issue. This paper focuses on the need for energy-efficient strategies in wireless sensor network. We propose an Artificial Bee Colony Inspired Clustering Solution for enhancing the wireless sensor network’s lifetime. Honey bees are highly organized organisms capable of individual cognitive abilities and self-organization. They exhibit a combination of individual traits and social cooperation. We adopt a centralized mechanism for clustering which is managed and controlled at the base station whereas the routing is performed in a distributed manner. Therefore, the proposed protocol systematically behaves in a semi-distributed manner. The operational details of the ABCICS are described with the help of flowchart shown in Fig. 1.

a) Network initialization- Initially the sensor nodes are deployed randomly in the sensing region. The base station transmits beacon signals to all nodes. These beacon signals contain the position information of the base station. Then all the nodes compute their respective Euclidian distance from the base station. Furthermore, the distance between neighboring nodes is computed based on arriving strength of signals and their relative coordinates.

b) Cluster head selection phase-Selection of cluster heads depends on fitness function which is computed by artificial bee colony algorithm.

c) Recruiting cluster members’ phase- All the selected cluster heads transmit an information message to the
rest of the sensor nodes. This message conveys the information regarding their selection as heads. When the non-cluster head nodes get this message, they have to decide to be a member under a particular head. This depends on the signal strength of the arrived message. Based on this decision, the non-cluster head nodes then report to the appropriate cluster heads to be a member of their cluster. Furthermore, the cluster head creates a schedule based on Time Division Multiple Access (TDMA) and allocate it to the members of its cluster.

d) Data Gathering-In a cluster, each cluster member transmits its information to its respective cluster-heads by TDMA based method. We assume it is perfect transmission and no retransmission is required.

e) Data Aggregation-Upon receiving the data from all the members, the cluster heads aggregate all incoming data together with its data. In this way, redundancy is reduced if any.

f) Data Transmission-Then cluster-heads transmits its aggregated data to the next-cluster head or base station in an energy-efficient manner. First cluster-head checks for the distance between its adjacent cluster-heads and base station. Cluster-head chooses the one which has less distance. If it is the base station, then cluster-head transmit its data. But if it is another cluster-head, then the sender cluster-head checks the residual energy of the adjacent cluster-heads and sends its data to the higher one.

g) On-Demand clustering- The proposed protocol reduces the overhead considerably by employing “clustering on demand” over iterative fashion for the same for anticipated role change of the cluster head. After data transmission, the cluster head checks its residual energy. If residual energy find below a prescribed threshold, it sets a prescribed bit in a data packet and sends it to the base station. The base station upon receiving this special bit from the data packet rotates the role of cluster head.

5 Radio Propagation Model

In this paper, we use the radio propagation model specified in [41]. In a radio model, the signal received at the receiver transmitted from the transmitter with a distance \( d \) is given by

\[
P_r = \frac{P_s G_r G_t \lambda^2}{(4\pi)^2 d^\beta \text{Loss}}
\]

(4)

where \( G_r \) is receiver’ antenna gain, \( G_t \) is transmitter’ antenna gain, \( \lambda \) is carrier wavelength, \( \beta \) is propagation loss factor, and any extra loss in transmitting the packet is represented by \( \text{Loss} \).

Radio propagation models are free space model and two-ray ground propagation model. In the free space propagation model, the propagation loss of transmitting power is inversely proportional to the square of the distance between transmitter and receiver. In the case of the two-ray ground propagation model, the propagation loss of transmitting power is inversely proportional to the fourth power of the distance between transmitter and receiver. The energy consumption to transmit \( l \)-bit packet from transmitter to receiver at the distance \( d \) is given by

\[
E_i = \begin{cases} 
|E_s| + |E_e| d^2 & \text{if } d < d_o \ 
|E_s| + |E_e| d^4 & \text{if } d \geq d_o
\end{cases}
\]

(5)

where \( E_i \) is considered as the energy/bit absorbed in the transceiver circuitry and second factor \( |E_e|d^2 \) or \( |E_e|d^4 \) is considered as the energy/bit absorbed in the power amplifier. The cross over distance can be obtained from

\[
d_o = \sqrt{\frac{E_o}{E_i}}
\]

(6)

The free space model is used when the cross-over distance is larger than the distance between the transmitter and receiver otherwise two-ray propagation model is used. Energy consumption for receiving an \( l \)-bits message [41] is:

\[
E_r = l|E_e|
\]

(7)

6 Fitness Function

The fitness function, represented as \( f(i) \) is specified as follows:

\[
f(i) = \text{optimize}
\]

\[
\left( kf_p(i) + (1 - k) f_s(i) \right)
\]

(8)

Subject to:

\[
f_p(i) = R_e(i) + N_0
\]

\[
f_s(i) = \left[ E_0(i, b) \right]^{-1} + C_0(i)
\]

In the above equation, \( k \) is a scaling factor. \( f_p \) and \( f_s \) represent primary fitness function, and secondary fitness function, respectively. Primary fitness function \( f_p \) is related to residual energy of node, and node degree. The residual energy of node \( (R_e) \) is the ratio of remaining energy to the initial energy in the node. Node degree \( (N_0) \) is the number of connecting nodes to a particular node within its transmission range.

Secondary fitness function \( f_s \) is related to Euclidean distance from node to base station \( (E_0) \), and node centrality \( (C_0) \). Node centrality shows how central the node is among its neighbors proportional to the network dimension.

7 Experimental Setup

All experiments were implemented in MATLAB 2009a and run on Windows 7 with Intel® Core™ 2 Duo T6570 CPU @ 2.10 GHz. We assume that all sensor
Table 1 Parameters of ABCICS.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensor field region ((X \times Y)) [m]</td>
<td>((100 \times 200))</td>
</tr>
<tr>
<td>Base station location ((x, y))</td>
<td>((50, 150))</td>
</tr>
<tr>
<td>Number of nodes ((s))</td>
<td>100</td>
</tr>
<tr>
<td>Initial energy of a node ((E_0)) [J]</td>
<td>0.5</td>
</tr>
<tr>
<td>Data packet length ((L)) [bits]</td>
<td>4096</td>
</tr>
<tr>
<td>Energy/bit absorbed in the transceiver circuitry ((E_c)) [nJ/bit]</td>
<td>70</td>
</tr>
<tr>
<td>Energy/bit absorbed in the power amplifier ((E_{fs} &amp; E_{tg})) [pJ/bit/m²]</td>
<td>120 &amp; 0.0013</td>
</tr>
<tr>
<td>Energy data aggregation ((E_g)) [nJ]</td>
<td>5</td>
</tr>
<tr>
<td>Number of rounds ((R_{max}))</td>
<td>3000</td>
</tr>
<tr>
<td>Colony size ((CS))</td>
<td>50</td>
</tr>
<tr>
<td>Maximum cycle number ((MCN))</td>
<td>200</td>
</tr>
<tr>
<td>Dimension of the food source vector ((D))</td>
<td>20</td>
</tr>
</tbody>
</table>

8 Performance Evaluation

In this section, we evaluate the performance of our model based on the metrics, namely residual energy of the network, the number of dead and alive nodes, and throughput of the network for various network sizes.

8.1 Selection of Parameter \(k\) for ABCICS Algorithm

The fitness function of our algorithm depends to a large extent on the value of parameter \(k\). Therefore, we run our algorithm for different rounds of data transfer to measure the number of live nodes for the proper selection of parameter \(k\). Fig. 2 shows the graph of live nodes versus the number of rounds for diverse values of \(k\). We vary the value of \(k\) from 0.1 to 0.9. We can see from the graph that the curve of \(k = 0.8\) attains larger value in comparison to the other curves. This higher value shows that the greater number of nodes is alive in different rounds. Table 2 shows the number of live nodes with diverse values of \(k\) for different rounds. Up to 1600 rounds, all the nodes are alive with different values of \(k\). When the number of rounds is more than 1600, more number of nodes are alive with \(k = 0.8\). Therefore, the value of \(k = 0.8\) is suitable for our algorithm. When we compare our algorithm with other protocols, the value of \(k\) is taken as 0.8 for getting the best results.

8.2 Analysis of Algorithms for Different Networks

We consider 20 different networks that are randomly generated varying from 100 to 500 nodes with different base station positions as shown in Table 3. The results
An Artificial Bee Colony Inspired Clustering Solution to Prolong the network as well as their Standard Deviation (SD) in different rounds. The results show that the ABCICS algorithm outperforms the other algorithms, with a lower SD value in each round.

A comparative analysis of LEACH, HSA-PSO, MHACO-UC, and ABCICS is given in Table 4. The mean residual energy of the network with experimental networks (Net-1 to Net-10) and experimental networks (Net-11 to Net-20) are shown in Figs. 3(a) and 3(b) respectively. It can be seen that the ABCICS algorithm achieves the best performance in terms of residual energy and network lifetime.
attains the highest mean value of residual energy in the compared protocols. As in scenario 1 with 100 nodes, the mean residual energy of the network in LEACH, HSA-PSO, and MHACO-UC is 4.830, 22.38, and 26.48 respectively, whereas ABCICS outperforms here with highest value of mean residual energy of 30.75. When we increase the number of nodes to 500 as in scenario 20, the mean residual energy of the network in LEACH, HSA-PSO, and MHACO-UC is 23.027, 108.83, and 117.23 respectively, whereas ABCICS has highest value of mean residual energy of 136.336. It is inferred that in LEACH algorithm attains the lowest mean residual energy of the network as cluster heads are randomly selected in the algorithm. HSA-PSO algorithm shows better performance due to high searching efficiency of HSA combined with the dynamic nature of PSO. MHACO-UC algorithm utilizes efficient ant colony optimization to improve further. However, ABCICS algorithm attains the highest mean value of residual energy with the appropriate selection of head of cluster by intelligent foraging behavior of honey bees.

The mean value of the number of rounds at which first node dead in the network, and its SD value in each network scenario is computed and tabulated in Table 5. Comparative analysis of the four algorithms for mean number of rounds at which first node dead in the network (Net-1 to Net-10) and experimental networks (Net-11 to Net-20) are shown in Figs. 4(a) and 4(b), respectively. It is evident from Table 5 and Figs. 4(a) and 4(b) that for all the network scenarios, ABCICS attains the highest mean value of the number of rounds at which first node dead in comparison to LEACH, HSA-PSO, and MHACO-UC. LEACH algorithm attains the lowest mean value of the number of rounds at which first node dead. The reason being the low energy node may be selected as head of cluster. HSA-PSO selects the head of the cluster with the fitness function that comprises the energy of nodes, node degree, and distance from base station to node. The selection of head among the nodes in a particular cluster depends on a diverse set of parameters such as distance from base station to node, energy of nodes and link quality in MHACO-UC algorithm. Moreover, ABCICS gains the best result with the appropriate selection of

![Fig. 3 Comparative analysis of the four algorithms for mean residual energy of the network with experimental networks; a) Net-1 to Net-10 and b) Net-11 to Net-20.](image)

<table>
<thead>
<tr>
<th>Network</th>
<th>LEACH</th>
<th>HSA-PSO</th>
<th>MHACO-UC</th>
<th>ABCICS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
<td>SD</td>
</tr>
<tr>
<td>Net-1</td>
<td>205</td>
<td>19.802</td>
<td>1632</td>
<td>45.630</td>
</tr>
<tr>
<td>Net-2</td>
<td>127</td>
<td>19.440</td>
<td>1483</td>
<td>45.730</td>
</tr>
<tr>
<td>Net-3</td>
<td>125</td>
<td>19.420</td>
<td>1486</td>
<td>47.937</td>
</tr>
<tr>
<td>Net-4</td>
<td>206</td>
<td>19.698</td>
<td>1640</td>
<td>46.260</td>
</tr>
<tr>
<td>Net-5</td>
<td>217</td>
<td>19.604</td>
<td>1859</td>
<td>49.893</td>
</tr>
<tr>
<td>Net-6</td>
<td>141</td>
<td>19.880</td>
<td>1768</td>
<td>49.117</td>
</tr>
<tr>
<td>Net-7</td>
<td>143</td>
<td>19.024</td>
<td>1767</td>
<td>49.110</td>
</tr>
<tr>
<td>Net-8</td>
<td>218</td>
<td>19.881</td>
<td>1857</td>
<td>53.468</td>
</tr>
<tr>
<td>Net-9</td>
<td>254</td>
<td>18.946</td>
<td>2240</td>
<td>51.119</td>
</tr>
<tr>
<td>Net-10</td>
<td>150</td>
<td>19.880</td>
<td>2155</td>
<td>48.015</td>
</tr>
<tr>
<td>Net-11</td>
<td>151</td>
<td>19.458</td>
<td>2156</td>
<td>46.503</td>
</tr>
<tr>
<td>Net-12</td>
<td>254</td>
<td>19.297</td>
<td>2241</td>
<td>47.642</td>
</tr>
<tr>
<td>Net-13</td>
<td>273</td>
<td>18.885</td>
<td>2632</td>
<td>46.538</td>
</tr>
<tr>
<td>Net-14</td>
<td>157</td>
<td>19.479</td>
<td>2540</td>
<td>47.203</td>
</tr>
<tr>
<td>Net-15</td>
<td>157</td>
<td>20.590</td>
<td>2541</td>
<td>48.910</td>
</tr>
<tr>
<td>Net-16</td>
<td>271</td>
<td>19.881</td>
<td>2631</td>
<td>46.508</td>
</tr>
<tr>
<td>Net-17</td>
<td>291</td>
<td>18.756</td>
<td>3111</td>
<td>73.781</td>
</tr>
<tr>
<td>Net-18</td>
<td>278</td>
<td>18.895</td>
<td>3061</td>
<td>71.300</td>
</tr>
<tr>
<td>Net-19</td>
<td>277</td>
<td>20.990</td>
<td>3063</td>
<td>78.071</td>
</tr>
<tr>
<td>Net-20</td>
<td>292</td>
<td>18.966</td>
<td>3112</td>
<td>84.135</td>
</tr>
</tbody>
</table>

Table 5 Performance of the four algorithms for first node dead.
head of cluster based on the energy of node, node degree, node centrality, and distance from the base station to node. As in scenario 1 with 100 nodes, the mean value of number of rounds at which first node dead in the network in LEACH, HSA-PSO, and MHACO-UC is 205, 1632, and 1639 respectively, whereas ABCICS has the highest value of 1730. With increasing the number of nodes to 500 as in scenario 20, the mean value of number of rounds at which first node dead in the network in LEACH, HSA-PSO, and MHACO-UC is 292, 3112, and 3129 respectively, whereas ABCICS outperforms here with highest mean value of 3223.

To demonstrate the effectiveness of the ABCICS, we compare the p-values for all performance metrics such as residual energy of the network, first node dead, and throughput for ABCICS and MHACO-UC by using student’s t-test in Table 7. The statistical results are obtained by one-tailed t-test with 29 degrees of freedom at a 0.05 level of significance. dataset 1 (ABCICS) is
An Artificial Bee Colony Inspired Clustering Solution to Prolong

A. Pathak

Iranian Journal of Electrical and Electronic Engineering, Vol. 16, No. 4, December 2020

Table 7 p-values of ABCICS, and MHACO-UC.

<table>
<thead>
<tr>
<th>Network</th>
<th>Residual energy</th>
<th>First node dead</th>
<th>Throughput</th>
</tr>
</thead>
<tbody>
<tr>
<td>Net-1</td>
<td>7.06213E-23</td>
<td>6.45E-03</td>
<td>0.018929</td>
</tr>
<tr>
<td>Net-2</td>
<td>4.34251E-23</td>
<td>5.45777E-03</td>
<td>0.035789</td>
</tr>
<tr>
<td>Net-3</td>
<td>6.734536747E-24</td>
<td>6.27755E-02</td>
<td>0.030788</td>
</tr>
<tr>
<td>Net-4</td>
<td>4.056760381E-37</td>
<td>3.4086E-07</td>
<td>0.016177</td>
</tr>
<tr>
<td>Net-5</td>
<td>6.68822E-32</td>
<td>3.46776E-08</td>
<td>0.005718</td>
</tr>
<tr>
<td>Net-6</td>
<td>4.88824E-37</td>
<td>3.42446E-06</td>
<td>0.006948</td>
</tr>
<tr>
<td>Net-7</td>
<td>8.94353E-35</td>
<td>5.46656E-13</td>
<td>0.007011</td>
</tr>
<tr>
<td>Net-8</td>
<td>9.55E-38</td>
<td>3.57446E-14</td>
<td>0.006966</td>
</tr>
<tr>
<td>Net-9</td>
<td>2.20995E-28</td>
<td>7.46749E-12</td>
<td>0.005804</td>
</tr>
<tr>
<td>Net-10</td>
<td>6.5E-27</td>
<td>3.56746E-16</td>
<td>9.90E-03</td>
</tr>
<tr>
<td>Net-11</td>
<td>0.31E-39</td>
<td>5.5765879E-22</td>
<td>9.90E-03</td>
</tr>
<tr>
<td>Net-12</td>
<td>2.95E-35</td>
<td>3.74746E-34</td>
<td>3.28E-02</td>
</tr>
<tr>
<td>Net-13</td>
<td>4.34251E-23</td>
<td>3.74746E-16</td>
<td>9.90E-03</td>
</tr>
<tr>
<td>Net-14</td>
<td>3.734747E-24</td>
<td>5.775349E-02</td>
<td>1.00E-02</td>
</tr>
<tr>
<td>Net-15</td>
<td>4.0560381E-37</td>
<td>7.3714E-17</td>
<td>9.96E-03</td>
</tr>
<tr>
<td>Net-16</td>
<td>9.6822E-32</td>
<td>3.57446E-12</td>
<td>3.46E-03</td>
</tr>
<tr>
<td>Net-17</td>
<td>2.8824E-33</td>
<td>3.325646E-07</td>
<td>3.37E-03</td>
</tr>
<tr>
<td>Net-18</td>
<td>4.34251E-29</td>
<td>8.5447E-09</td>
<td>3.34E-03</td>
</tr>
<tr>
<td>Net-20</td>
<td>4.05671212E-23</td>
<td>3.45776E-02</td>
<td>3.45E-03</td>
</tr>
</tbody>
</table>

significantly better than dataset 2 (MHACO-UC) if the p-value is less than the significance level, significantly worse if the p-value is greater than the significance level and satisfactory if p-value is equal to the significance level. It is evident from Table 7 that the p-value of ABCICS is significantly better than MHACO-UC for all three metrics and all experimental networks.

9 Conclusion and Future Works

In this paper, we have presented an Artificial Bee Colony Inspired Clustering Solution (ABCICS) inspired from the foraging principles of honey-bees for wireless sensor networks, where the objective is to prolong the lifetime of the network.

We select heads of the clusters by exploiting the fast searching features of the artificial bee colony optimization algorithm, and transfer data from cluster-heads to base station by energy-efficient path. We also reduce the burden of clustering by on-demand clustering concept. The simulation results indicate that the ABCICS algorithm outperforms the LEACH, HSA-PSO, MHACO-UC in terms of performance metrics i.e., network lifetime, residual energy, and throughput of the network. In the present implementation of ABCICS, we assume sensors always transmit data to their respective cluster heads during their allocated TDMA slot. To save energy, nodes may only need to transmit data after they detect some interesting events. We have tested the ABCICS in static wireless networks. In future work, we are planning to investigate clustering in mobile sensor networks.

References

An Artificial Bee Colony Inspired Clustering Solution to Prolong Energy in IoT Devices. A. Pathak


A. Pathak is currently an Assistant Professor in the department of Electronics and Communication Engineering, Govt. Engineering College, Bharatpur, India. She received B.Tech. degree in Electronics and Communication Engineering from U.P. Technical University, Lucknow, India, and M.Tech. degree in Electronics Design and Technology from Tezpur Central University, Assam, India. She received Ph.D. degree from Jamia Millia Islamia, New Delhi, India. Her main area of research includes wireless Ad-hoc networks, sensor networks, and nature inspired optimization techniques.

© 2020 by the authors. Licensee IUST, Tehran, Iran. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution-NonCommercial 4.0 International (CC BY-NC 4.0) license (https://creativecommons.org/licenses/by-nc/4.0/).