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Research Paper

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

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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

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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 inversed 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

$$V_{ij} = x_{ij} + \tau\left(x_{ij} - x_{kj}\right) \tag{1}$$

where τ is a random number between [–1, 1], V_i is a new food source, x_i is current food source, x_k is neighborhood source, and $j \in \{1, 2, \ldots, D\}$ 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

$$P_i = \frac{F_i}{\sum_{l=1}^{m} F_l} \tag{2}$$

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

$$x_{ij} = x_{ij} + \mathrm{rand}(0,1)\left(x_{j\max} - x_{j\min}\right) \tag{3}$$

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 their 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 recovering 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

$$P_r = \frac{P_t G_t G_r \lambda^2}{(4\pi)^2 d^{\beta} Loss} \tag{4}$$

where G_r is receiver’ antenna gain, G_t is transmitter’ antenna gain, λ is carrier wavelength, β is propagation loss factor, and any extra loss in transmitting the packet is represented by *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

$$E_T = \begin{cases} lE_e + lE_{fs} d^2 & \text{if } d < d_o \\ lE_e + lE_{tg} d^4 & \text{if } d \geq d_o \end{cases} \tag{5}$$

where E_e is considered as the energy/bit absorbed in the transceiver circuitry and second factor $lE_{fs}d^2$ or $lE_{fs}d^4$ is considered as the energy/bit absorbed in the power amplifier. The cross over distance can be obtained from

$$d_o = \sqrt{E_{fs} / E_{tg}} \tag{6}$$

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

$$E_R = lEe \tag{7}$$

6 Fitness Function

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

$$f(i) = \text{optimize}\left(kf_p(i) + (1-k)f_s(i)\right) \tag{8}$$

Subject to:

$$f_P(i) = R_e(i) + N_D(i)$$
$$f_s(i) = [E_u(i,b)]^{-1} + C_n(i)$$

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_D) 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_u), and node centrality (C_n). 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.

Parameter	Value
Sensor field region (X×Y) [m]	(100×200)
Base station location (x, y)	(50,150)
Number of nodes (s)	100
Initial energy of a node (E_{int}) [J]	0.5
Data packet length (L) [bits]	4096
Energy/bit absorbed in the transceiver circuitry (E_e) [nJ/bit]	70
Energy/bit absorbed in the power amplifier (E_{fs} & E_{tg}) [pJ/bit/m^2]	120 &0.0013
Energy data aggregation (E_g) [nJ]	5
Number of rounds ($R_{\max}$)	3000
Colony size (CS)	50
Maximum cycle number (MCN)	200
Dimension of the food source vector (D)	20

nodes have the same initial energy and the capabilities of all nodes such as processing and communicating are similar. They are not equipped with a global positioning system, i.e. do not have capable antennae with moving capabilities. We also assume that the base station is fixed and not limited in terms of energy, memory, and computational power. The required simulation parameters for various algorithms are shown in Table 1.

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

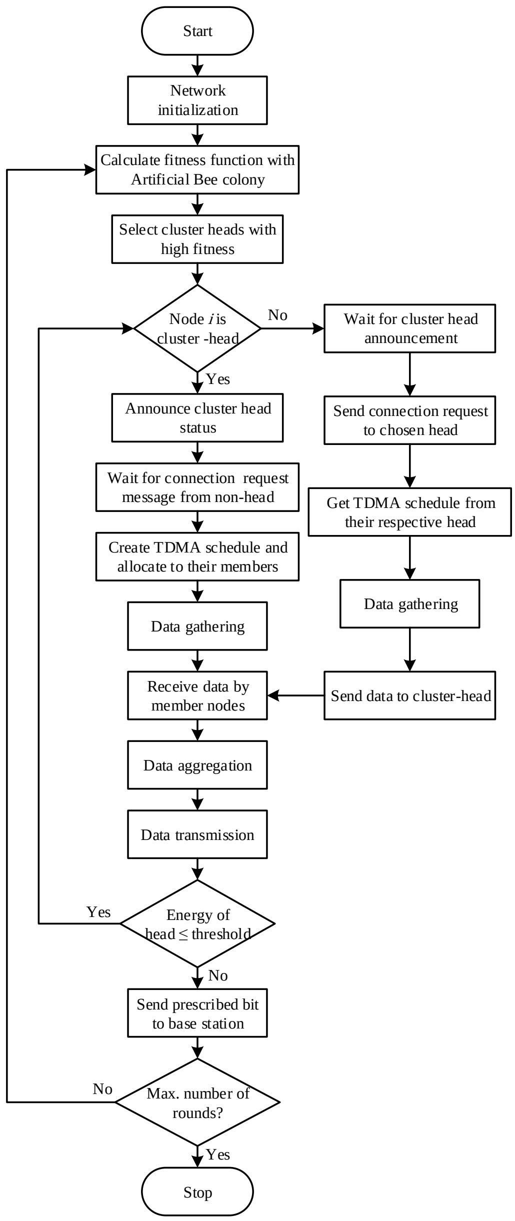


Fig. 1 Flowchart of artificial bee colony inspired clustering solution.

Table 2 Number of live nodes with different values of k for different rounds.

Rounds	1600	1700	1800	1900	2000	2100	2200	2300	2400	2500	3000
$k = 0.1$	100	100	30	25	22	18	10	5	0	0	0
$k = 0.2$	100	100	29	24	21	19	10	4	0	0	0
$k = 0.3$	100	97	42	38	25	22	12	5	0	0	0
$k = 0.4$	100	96	41	38	25	21	11	5	0	0	0
$k = 0.5$	100	99	34	20	22	21	12	9	0	0	0
$k = 0.6$	100	100	35	30	23	21	12	10	0	0	0
$k = 0.7$	100	94	39	34	17	9	8	5	0	0	0
$k = 0.8$	100	100	50	40	25	22	18	11	5	2	0
$k = 0.9$	100	95	40	35	18	10	8	5	0	0	0

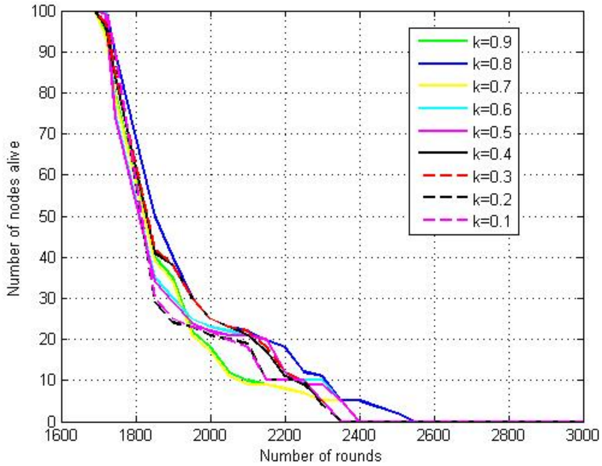


Fig. 2 Number of alive nodes with different values of k.

Table 3 Experimental networks.

Network	No. of nodes	Base station positions
Net-1	100	50-150
Net-2	100	100-200
Net-3	100	0-0
Net-4	100	50-50
Net-5	200	50-150
Net-6	200	100-200
Net-7	200	0-0
Net-8	200	50-50
Net-9	300	50-150
Net-10	300	100-200
Net-11	300	0-0
Net-12	300	50-50
Net-13	400	50-150
Net-14	400	100-200
Net-15	400	0-0
Net-16	400	50-50
Net-17	500	50-150
Net-18	500	100-200
Net-19	500	0-0
Net-20	500	50-50

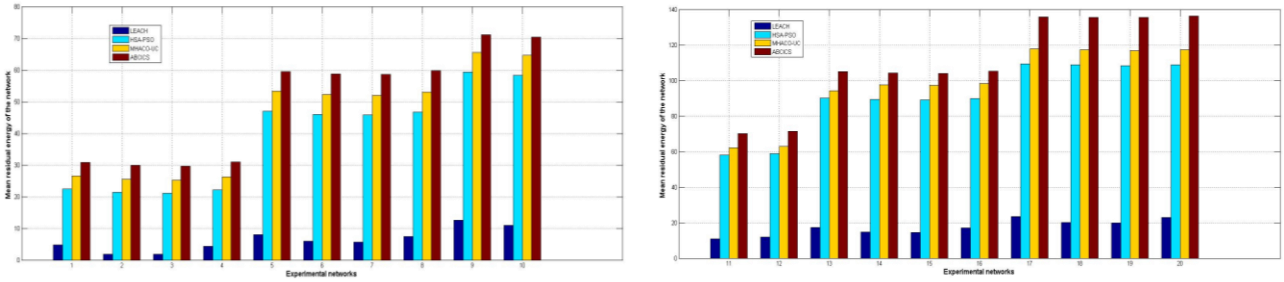
Table 4 Performance of the four algorithms for residual energy.

Network	LEACH		HSA-PSO		MHACO-UC		ABCICS	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Net-1	4.830	0.93395	22.38	0.91892	26.48	0.68892	30.75	0.51243
Net-2	1.897	0.97749	21.42	0.93528	25.52	0.70528	29.8933	0.54893
Net-3	1.847	1.01782	21.1566	0.93206	25.2566	0.70206	29.7033	0.51694
Net-4	4.347	0.99042	22.1666	0.92711	26.2666	0.69711	30.9533	0.52832
Net-5	7.994	0.89500	47.0066	1.03488	53.3066	0.80488	59.45	1.31588
Net-6	5.924	0.92795	46.0066	0.96737	52.3066	0.73737	58.75	1.27001
Net-7	5.617	0.91395	45.75	0.97794	52.05	0.74794	58.5566	1.41657
Net-8	7.474	0.93434	46.68	1.07555	52.98	0.84555	59.8066	1.28839
Net-9	12.637	0.97978	59.2733	1.12676	65.5733	0.89676	71.0966	1.62957
Net-10	11.027	1.02187	58.3	1.22896	64.6	0.99896	70.33	1.59917
Net-11	10.830	1.03652	58.0933	1.17764	62.1933	0.94764	70.1233	1.52013
Net-12	11.837	1.08962	58.8433	1.14430	62.9433	0.9143	71.4566	1.81215
Net-13	17.417	1.21658	90.1566	2.14936	94.2566	1.91936	104.996	2.83506
Net-14	14.777	1.27116	89.29	2.13789	97.69	1.90789	104.276	2.98267
Net-15	14.510	1.26637	88.9966	2.16308	97.3966	1.93308	104.03	3.02747
Net-16	17.154	1.23049	89.9233	2.16184	98.3233	2.49184	105.25	2.78985
Net-17	23.567	1.43655	109.396	2.08003	117.796	2.41003	135.836	3.46633
Net-18	20.100	1.26933	108.806	2.00257	117.206	2.33257	135.55	3.64935
Net-19	19.790	1.27869	108.386	2.00305	116.786	2.33305	135.423	3.82691
Net-20	23.027	1.41563	108.83	2.08080	117.23	2.4108	136.336	3.46633

of the experiments are taken as an average of 30 independent runs.

A comparative analysis of LEACH, HSA-PSO, MHACO-UC, and ABCICS is given in Tables 4, 5, and 6. In each network scenario, the mean residual energy of the network as well as their Standard Deviation (SD) in each case is computed and highlighted in Table 4. Comparative analysis of the four algorithms for 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 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 value of 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

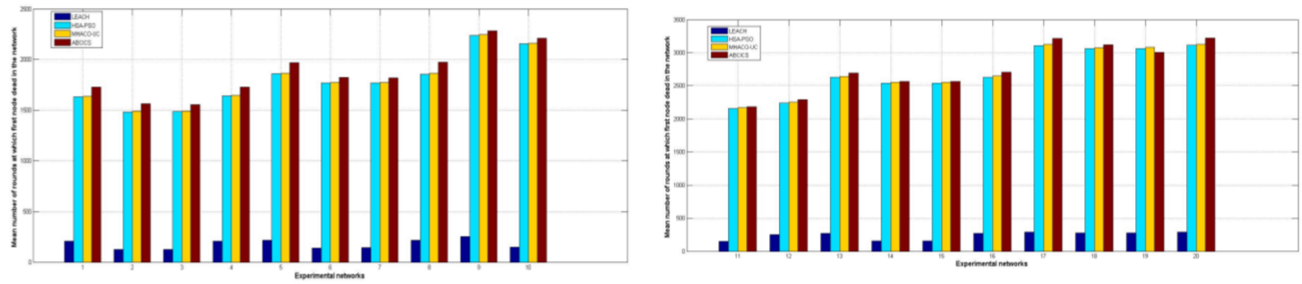


(a) (b)

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.

Table 5 Performance of the four algorithms for first node dead.

Network	LEACH		HSA-PSO		MHACO-UC		ABCICS	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Net-1	205	19.802	1632	45.630	1639	45.2	1730	44.34
Net-2	127	19.440	1483	45.730	1490	45.3	1565	44.58
Net-3	125	19.420	1486	47.937	1493	47.507	1557	46.45
Net-4	206	19.698	1640	46.260	1647	45.83	1729	47.581
Net-5	217	19.604	1859	49.893	1866	49.463	1971	45.445
Net-6	141	19.880	1768	49.117	1775	48.687	1823	46.837
Net-7	143	19.024	1767	49.110	1774	48.68	1819	50.250
Net-8	218	19.881	1857	53.468	1864	53.038	1975	44.617
Net-9	254	18.946	2240	51.119	2247	50.689	2284	46.272
Net-10	150	19.880	2155	48.015	2162	47.585	2212	46.272
Net-11	151	19.458	2156	46.503	2168	46.133	2181	46.354
Net-12	254	19.297	2241	47.642	2253	47.272	2291	46.871
Net-13	273	18.885	2632	46.538	2644	46.168	2696	47.586
Net-14	157	19.479	2540	47.203	2552	46.833	2564	45.470
Net-15	157	20.590	2541	48.910	2553	48.54	2563	45.138
Net-16	271	19.881	2631	46.508	2648	46.138	2706	43.330
Net-17	291	18.756	3111	73.781	3128	55.411	3216	46.291
Net-18	278	18.895	3061	71.300	3078	66.93	3122	46.291
Net-19	277	20.990	3063	78.071	3080	67.701	3006	54.368
Net-20	292	18.966	3112	84.135	3129	73.765	3223	44.528

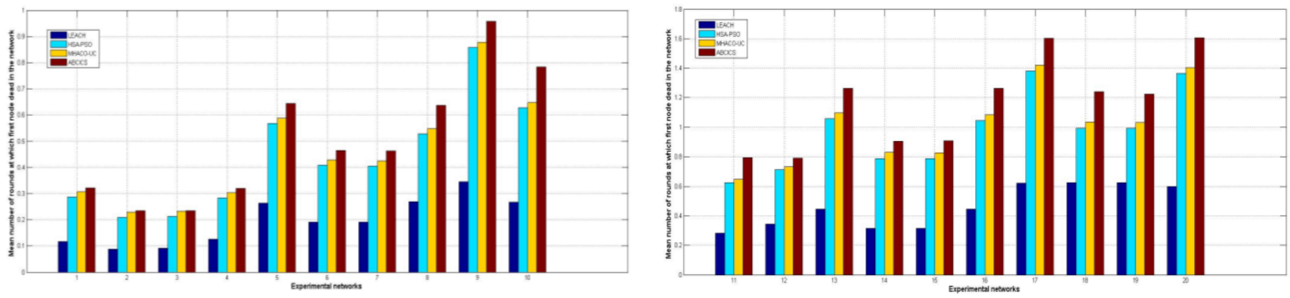


(a) (b)

Fig. 4 Comparative analysis of the four algorithms for mean value of number of rounds at which first node dead in the network with experimental networks; a) Net-1 to Net-10 and b) Net-11 to Net-20.

Table 6 Performance of the four algorithms for throughput of network.

Network	LEACH		HSA-PSO		MHACO-UC		ABCICS	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Net-1	0.116333	0.063923	0.286667	0.070139	0.306667	0.058844	0.322333	0.048968
Net-2	0.088533	0.063167	0.21	0.068229	0.23	0.059543	0.234333	0.049667
Net-3	0.091133	0.062912	0.212333	0.07098	0.232333	0.059431	0.234333	0.049555
Net-4	0.126333	0.062725	0.283333	0.066609	0.303333	0.06056	0.319667	0.050684
Net-5	0.2630	0.077333	0.568	6.270139	0.588	0.073107	0.644667	0.063231
Net-6	0.190933	0.076236	0.408	0.077966	0.428	0.069283	0.464667	0.059407
Net-7	0.19078	0.076767	0.405	0.08055	0.425	0.067495	0.462	0.057619
Net-8	0.2695	0.082152	0.528	0.141869	0.548	0.066098	0.636667	0.056222
Net-9	0.345	0.086573	0.857667	0.119933	0.877667	0.074701	0.956667	0.064825
Net-10	0.267	0.080222	0.627667	0.116017	0.647667	0.086635	0.784	0.076759
Net-11	0.282833	0.078636	0.625667	0.114918	0.645667	0.074342	0.794667	0.064466
Net-12	0.343	0.093556	0.711	0.13535	0.731	0.490364	0.79	0.480488
Net-13	0.446	0.095758	1.058	0.329933	1.098	0.076177	1.262	0.066301
Net-14	0.315	0.099551	0.789	0.145965	0.829	0.066664	0.904	0.056788
Net-15	0.315	0.123674	0.7874	0.142017	0.8274	0.071821	0.908	0.061945
Net-16	0.444133	0.106953	1.044	0.128348	1.084	0.080606	1.262	0.07073
Net-17	0.62	0.080772	1.380333	0.151281	1.420333	0.127852	1.603	0.117976
Net-18	0.6242	0.079044	0.994333	0.149935	1.034333	0.137489	1.241	0.127613
Net-19	0.6254	0.075846	0.993533	0.149746	1.033533	0.130213	1.225	0.120337
Net-20	0.597333	0.230231	1.363667	0.145234	1.403667	0.140597	1.605	0.130721



(a) (b)

Fig. 5 Comparative analysis of the four algorithms for throughput of the network with experimental networks; a) Net-1 to Net-10 and b) Net-11 to Net-20.

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

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

Network	*p*-value		
	Residual energy	First node dead	Throuhput
Net-1	7.06213E-23	6.45E-03	0.018929
Net-2	4.34251E-23	5.45777E-03	0.035789
Net-3	6.734536747E-24	6.27755E-02	0.030788
Net-4	4.056760381E-37	3.4086E-07	0.016177
Net-5	6.68822E-32	3.46776E-08	0.005718
Net-6	4.88824E-37	3.42446E-06	0.006948
Net-7	8.94353E-35	5.46656E-13	0.007011
Net-8	9.55E-38	3.57446E-14	0.006966
Net-9	2.20995E-28	7.46749E-12	0.005804
Net-10	6.5E-27	3.56746E-16	9.90E-03
Net-11	0.31E-39	5.5765879E-22	9.90E-03
Net-12	2.95E-35	3.74746E-34	3.28E-02
Net-13	4.34251E-23	3.74746E-16	9.90E-03
Net-14	3.734747E-24	5.775349E-02	1.00E-02
Net-15	4.0560381E-37	7.3714E-17	9.96E-03
Net-16	9.6822E-32	3.57446E-12	3.46E-03
Net-17	2.8824E-33	3.325646E-07	3.37E-03
Net-18	4.34251E-29	8.5447E-09	3.34E-03
Net-19	6.7536747E-28	6.2411155E-08	3.24E-03
Net-20	4.0567121E-23	3.45776E-02	3.45E-03

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

[1] I. F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "Wireless sensor networks: A survey," *Computer Networks*, Vol. 38, No. 4, pp. 393–422, 2002.

[2] D. K. Lobiyal and A. Pathak, "Energy-aware bee colony approach to extend lifespan of wireless sensor network," *Australian Journal of Multi-Disciplinary Engineering*, Vol. 13, No. 1, pp. 29–46, 2017.

[3] A. A. A. Ari, A. Gueroui, N. Labraoui, and B. O. Yenke, "Concepts and evolution of research in the field of wireless sensor networks," *International Journal on Computational Networks and Communication*, Vol. 7, No. 1, pp. 81–98, 2015.

[4] A. Pathak and D. K. Lobiyal, Maximization the lifetime of wireless sensor network by minimizing energy hole problem with exponential node distribution and hybrid routing," in *Proceedings of IEEE Students Conference on Engineering and Systems*, Allahabad, India, pp. 1–5, Mar. 2012.

[5] C. Titouna, M. Aliouat, and M. Gueroui, "FDS: Fault detection scheme for wireless sensor networks," *Wireless Personal Communication*, Vol. 86, No. 2, pp. 549–562, 2016.

[6] H. Liu, G. Yao, J. Wu, and L. Shi, "An adaptive energy-efficient and low-latency MAC protocol for wireless sensor networks," *Journal of Communications and Networks*, Vol. 12, No. 5, pp. 510–517, 2010.

[7] A. Khasawneh, M. Latiff, O. Kaiwartya, and H. Chizari, “A reliable energy-efficient pressure-based routing protocol for underwater wireless sensor network,” *Wireless Networks*, Vol. 24, No. 6, pp. 2061–2075, 2018.

[8] H. Liu, G. Yao, J. Wu, and L. Shi, “An adaptive energy-efficient and low-latency MACprotocol for wireless sensor networks,” *Journal of Communications and Networks*, Vol. 12, No. 5, pp. 510–517, 2010.

[9] G. Lu, B. Krishnamachari, and C. S. Raghavendra, “An adaptive energy efficient and low-latency Mac for data gathering in wireless sensor networks,” in *Proceedings of IEEE Parallel and Distributed Processing Symposium*, New Mexico, USA, pp. 224–230, 2004.

[10] M. M. Alam, E. B. Hamida, O. Berder, D. Menard, and O. Sentieys, “A heuristic self-adaptive medium access control for resource-constrained WBAN systems,” IEEE Access, Vol. 4, pp. 1287–1300, 2016.

[11] R. Willett, A. Martin, and R. Nowak, “Back casting: adaptive sampling for sensor networks,” in *Proceedings of IEEE International Symposium on Information Processing in Sensor Networks*, California, USA, pp. 124–133, Apr. 2004.

[12] L. Tan and M. Wu, “Data reduction in wireless sensor networks: A Hierarchical LMS prediction approach,” *IEEE Sensors Journal*, Vol. 16, No. 6, pp. 1708–1715, 2016.

[13] N. Kimura, S. Latifi, “A survey on data compression in wireless sensor networks,” in *Proceedings of IEEE International Conference on Information Technology: Coding and Computing*, Nevada, USA, pp. 8–13, Apr. 2005.

[14] Y. Liu, Q. Zhang, and L. Ni, “Opportunity-based topology control in wireless sensor networks,” *IEEE Transactions on Parallel and Distributed Systems*, Vol. 21, No. 3, pp. 405–416, 2010.

[15] R. Zhang and M. A, Labrador, “Energy-aware topology control in heterogeneous wireless multi-hop networks”, in *Proceedings of IEEE International Symposium on Wireless Pervasive Computing*, Puerto Rico, pp. 1–5, Feb. 2007.

[16] F. Ingelrest, D. Simplot-Ryl, and I. Stojmenovic, “Optimal transmission radius for energy efficient broadcasting protocols in Ad Hoc networks,” *IEEE Transactions on Parallel and Distributed Systems*, Vol. 17, No. 6, pp. 536–547, 2006.

[17] X. Liu, “A survey on clustering routing protocols in wireless sensor networks,” *Sensors Journal*, Vol. 12, No. 8, pp. 11113–11153, 2012.

[18] A. Pathak and M. Tiwari, “Clustering in wireless sensor networks based on soft computing: A literature survey,” in *Proceedings of IEEE Conference on Automation and Computational Engineering (ICACE)*, Greater Noida, India, pp. 29–33, Oct. 2018.

[19] M. M. Afsar and M. H. Tayarani, “Clustering in sensor networks: A literature survey,” *Journal of Network and Computer Applications*, Vol. 46, pp. 198–226, 2014.

[20] W. R. Heinzelman, A. Chandrakasan, and H. Balakrishnan, “Energy-efficient communication protocol for wireless microsensor networks,” in *Proceedings of IEEE International Conference on System Sciences*, Maui, Hawaii, USA, pp. 10–20, Jan. 2000.

[21] I. Gupta, D. Riordan, and S. Sampalli, “Cluster-head election using fuzzy logic for wireless sensor networks”, in *Proceedings of IEEE International conference on communication networks and services research (CNSR)*, Halifax, Novia Scotia, Canada, pp. 255–260, May 2005.

[22] G. Ran, H. Zhang, and S. Gong, “Improving on leach protocol of wireless sensor networks using fuzzy logic,” *Journal of Information Computational Science*, Vol. 7, No. 1, pp. 767–775, 2010.

[23] J. Lee and W. Cheng, “Fuzzy-logic-based clustering approach for wireless sensor networks using energy predication,” *IEEE Sensors Journal*, Vol. 12, No. 9, pp. 2891–2897, 2012.

[24] N. Nokhanji, Z. M. Hanapi, S. Subramaniam, and M. A. Mohamed, “An energy aware distributed clustering algorithm using fuzzy logic for wireless sensor networks with non-uniform node distribution,” *Wireless Personal Communications*, Vol. 84, No. 1, pp. 395–419, 2015.

[25] P. Nayak, “A fuzzy logic-based clustering algorithm for WSN to extend the network lifetime,” *IEEE Sensors Journal*, Vol. 16, No. 1, pp. 137–144, 2016.

[26] M. Mavrovouniotis, C. Li, S. Yang, “A survey of swarm intelligence for dynamic optimization: Algorithms and applications,” *Swarm and Evolutionary Computation*, Vol. 33, pp. 1–17, 2017.

[27] A. Pathak, “A Bee colony inspired clustering protocol for wireless sensor networks,” in *Proceedings of IEEE Conference on Computing, Communication and Automation (ICCCA)*, Greater Noida, India, pp. 570–575, May 2017.

[28] S. J. Nanda and G. Panda, “A survey on nature inspired meta-heuristic algorithms for partitioned clustering,” *Swarm and Evolutionary Computation*, Vol. 16, pp. 1–18, 2014.

[29] D. Karaboga, B. Gorkemli, C. Ozturk, and N. Karaboga, "A comprehensive survey: artificial bee colony (ABC) algorithm and applications," *Artificial Intelligent Review*, Vol. 42, No. 1, pp. 21–57, 2014.

[30] M. Saleem, G. A. Di Caro, and M. Farooq, "Swarm intelligence based routing protocol for wireless sensor networks: Survey and future directions," *Information Science*, Vol. 181, No. 20, pp. 4597–4624, 2011.

[31] J. Wang, J. Cao, B. Li, S. Lee, and R. S. Sherratt, "Bio-inspired ant colony optimization based clustering algorithm with mobile sinks for applications in consumer home automation networks," *IEEE Transactions on Consumer Electronics*, Vol. 61, No. 4, pp. 438–444, 2015.

[32] B. Singh and D. K. Lobiyal, "A novel energy-aware cluster head selection based on PSO for WSN," *Human Centric Computing and Information Science*, Vol. 13, No. 2, pp. 6–18, 2012.

[33] T. Shankar, S. Shanmugavel, and A. Rajesh, "Hybrid HSA and PSO algorithm for energy efficient cluster head selection in wireless sensor networks," *Swarm and Evolutionary Computation*, Vol. 30, pp. 1–10, 2016.

[34] S. Okdem, D. Karaboga, and C. Ozturk, "An application of wireless sensor network routing based on artificial bee colony algorithm," in *Proceedings of IEEE Conference on Evolutionary Computation*, New Orleans, LA, USA, pp. 326–330, Jun. 2011.

[35] D. Karaboga, S. Okdem, and C. Ozturk, "Cluster based wireless sensor network routing using artificial bee colony algorithm," *Wireless Networks*, Vol. 18, No. 7, pp. 847–860, 2012.

[36] R. Kumar and D. Kumar, "Multi-objective fractional artificial bee colony algorithm to energy aware routing protocol in wireless sensor network," *Wireless Networks*, Vol. 22, No. 5, pp. 1461–1474, 2016.

[37] A. A. A. Ari, B. O. Yenke, N. Labraoui, I. Damakoa, and A. Gueroui, "A power efficient cluster-based routing algorithm for wireless sensor networks: Honey bees swarm intelligence based approach," *Network and Computer Applications*, Vol. 1, pp. 6977–6997, 2016.

[38] C. Ozturk, E. Hancer, and D. Karaboga, "Dynamic clustering with improved binary artificial bee colony algorithm," *Applied Soft Computing*, Vol. 2, pp. 69–80, 2015.

[39] R. Madan and S. Lall, "Distributed algorithms for maximum lifetime routing in wireless sensor networks," *IEEE Transactions on Wireless Communications*, Vol. 5, No. 8, pp. 2185–2193, 2006.

[40] L. C. Wang, C. W. Wang, and C. M. Liu, "Optimal number of clusters in dense wireless sensor networks: A cross-layer approach," *IEEE Transactions on Vehicular Technology*, Vol. 58, No. 2, pp. 966–976, 2009.

[41] W. B. Heinzelman, A. P. Chandrakasan, and H. Balakrishnan, "An application-specific protocol architecture for wireless microsensor networks," *IEEE Transactions on Wireless Communications*, Vol. 1, No. 4, pp. 660–670, 2002.

[42] A. Manjeshwar and D. Agrawal, "Teen: A routing protocol for enhanced efficiency in wireless sensor networks," in *Proceedings of International IEEE Parallel and Distributed Processing Symposium (IPDPS)*, San Francisco, USA, pp. 2009–2015, Apr. 2001.

[43] M. J. Handy, M. Haase, and D. Timmermann, "Low energy adaptive clustering hierarchy with deterministic cluster head selection," in *Proceedings of IEEE International Conference on Mobile and Wireless Communications Networks (MWCN)*, Stockholm, Sweden, September 9-11, pp. 368–72, 2002.

[44] O. Younis and S. Fahmy, "Heed: A hybrid, energy-efficient, distributed clustering approach for Ad Hoc sensor networks," *IEEE Transaction on Mobile Computing*, Vol. 3, No. 4, pp. 366–379, 2004.

[45] S. Bandyopadhyaya and E. Coyle, "An energy efficient hierarchical clustering algorithm for wireless sensor networks," in *Proceedings of IEEE International Conference on Communications (INFOCOM)*, California, USA, pp. 1713–1723, 2003.

[46] G. Smaragdakis, I. Matta, and A. Bestavros, "SEP: A stable election protocol for clustered heterogeneous wireless sensor networks," in *Proceedings of International Conference on Sensor and Actor Network Protocols and Applications (SANPA)*, Boston, USA, pp. 5–31, Aug. 2004.

[47] C. Wen and W. Sethares, "Automatic decentralized clustering for wireless sensor networks," *EURASIP Journal on Wireless Communication and Networking*, Vol. 5, No. 1, pp. 686–697, 2005.

[48] Y. C. Chen and C. Y. Wen, "Distributed clustering with directional antennas for wireless sensor networks," *IEEE Sensors Journal*, Vol. 13, No. 6, pp. 2166–2180, 2013.

[49] V. Loscri, G. Morabito, and S. Marano, "A two-level hierarchy for low-energy adaptive clustering hierarchy," in *Proceedings of IEEE Vehicular Technology Conference (VTC)*, Dallas, TX, USA, pp. 1809–1813, Sep. 2005.

[50] S. H. Kang and T. Nguyen, "Distance based thresholds for cluster head selection in wireless sensor networks," *IEEE Communications Letters*, Vol. 16, No. 9, pp. 1396–1399, 2012.

[51] W. Zhuo, "Energy efficient clustering algorithm based on neighbors for wireless sensor networks," *Journal of Shanghai University (English Edition)*,Vol. 15, No. 2, pp. 150–153, 2011.

[52] L. Ying, H. Qi, and W. Li, "Load-balanced clustering algorithm with distributed self-organization for wireless sensor networks," *IEEE Sensor Journal*, Vol. 13, No. 5, pp. 1498–506, 2013.

[53] S. S. Wang and Z. Chen, "LCM: A link-aware clustering mechanism for energy-efficient routing in wireless sensor networks," *IEEE Sensor Journal*, Vol. 13, No. 2, pp. 728–736, 2013.

[54] S. A. Gopi and T. Ponnuchamy, "EE-LEACH: development of energy-efficient LEACH Protocol for data gathering in WSN," *EURASIP Journal on Wireless Communications and Networking*, Vol. 1, No. 1, pp. 1–9, 2015.

[55] H. Taheri, P. Neamatollahi, O. Younis, S. Naghibzadeh, and M. Yaghmaee, "An energy-aware distributed clustering protocol in wireless sensor networks using fuzzy logic," *Ad Hoc Networks*, Vol. 10, pp. 1469–1481, 2012.

[56] R. Hamidouche, Z. Aliouat, A. M. Gueroui, "Genetic algorithm for improving the lifetime and QoS of wireless sensor networks," *Wireless Personal Communication*, Vol. 101, No.4, pp. 2313–2348, 2018.

[57] C. K. Ho and H. T. Ewe, "A hybrid ant colony optimization approach for constructing load–balanced clusters," in *Proceedings of IEEE International Conference on Congress on Evolutionary Computation (CEC 2005)*, Edinburgh, United Kingdom, pp. 2010–2017, Sep. 2005.

[58] M. Azharuddin and P. K. Jana, "Particle swarm optimization for maximizing lifetime of wireless sensor networks," *Computers and Electrical Engineering*, Vol. 51, pp. 26–42, 2016.

[59] J. Kamimura, N. Wakamiya, and M. Murata, "A distributed clustering method for energy-efficient data gathering in sensor networks," *International Journal Wireless Mobile Computing*, Vol. 1, No. 2, pp. 113–120, 2006.

[60] X. Cai, Y. Duan, Y. He, J. Yang, and L. Changle, "Bee-Sensor-C: An energy-efficient and scalable multipath routing protocol for wireless sensor networks," *International Journal on Distributed Sensor Networks*, Vol. 11, No. 3, pp. 1–14, 2015.

[61] M. Fathian, B. Amiri, and A. Maroosi, "Application of honey-bee mating optimization algorithm on clustering," *Applied Mathematics and Computation*, Vol. 190, No. 2, pp. 1502–1513, 2007.

[62] R. Kumar, D. Kumar, and D. Kumar, "EACO and FABC to multi-path data transmission in wireless sensor networks," *IET Communications*, Vol. 11, No. 4, pp. 522–530, 2017.

[63] M. Asadi Zangeneh and M. Ghazvini, "An energy-based clustering method for WSNs using artificial bee colony and genetic algorithm," in *Proceedings of IEEE Conference on Swarm Intelligence and Evolutionary Computation*, Kerman, Iran, pp. 35–41, Mar. 2017.

[64] M. Ahmad, A. A. Ikram, and I. Wahid, "A bio-inspired clustering scheme in wireless sensor networks: BeeWSN," *Procedia Computer Science*, Vol. 130, pp. 206–213, 2018.

[65] K. Vijayalakshmi and P. Anandan, "A multi objective Tabu particle swarm optimization for effective cluster head selection in WSN," *Cluster Computing*, pp. 1–8, 2018.

[66] K. Guleria and A. Kumar Verma, "Meta-heuristic ant colony optimization based unequal clustering for wireless sensor network," *Wireless Personal Communications*, Vol. 105, No. 3, pp. 891–911, 2019.

[67] M. Khabiri and A. Ghaffari, "Energy-aware clustering-based routing in wireless sensor networks using cuckoo optimization algorithm," *Wireless Personal Communications*, Vol. 98, No. 3, pp. 2473–2495, 2018.

[68] P. T. Karthick and C. Palanisamy, "Optimized cluster head selection using krill herd algorithm for wireless sensor network," *Journal for Control, Measurement, Electronics, Computing and Communications*, Vol. 60, No. 3, pp. 340–348, 2019.

[69] C. Ozturk, E. Hancer, and D. Karaboga, "Dynamic clustering with improved binary artificial bee colony algorithm," *Applied Soft Computing*, Vol. 28, No. 1, pp. 69–80, 2015.

[70] Y. Wang, C. Li, Y. Duan, J. Yang, and X. Cheng, "An energy-efficient and swarm intelligence-based routing protocol for next-generation sensor networks," *IEEE Intelligent Systems*, Vol. 29, No. 5, pp. 74–77, 2014.

[71] D. Karaboga, *An idea based on honey bee swarm for numerical optimization*. Technical Report-TR06, Erciyes University, Engineering Faculty, Computer Engineering Department, 2005.

[72] D. Karaboga and B. Basturk, "On the performance of artificial bee colony (ABC) algorithm," *Applied Soft Computing*, Vol. 8, pp. 687–697, 2008.

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