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Multi-layer Clustering Topology Design in Densely Deployed Wireless Sensor Network using Evolutionary Algorithms

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Abstract
Due to the resource constraint and dynamic parameters, reducing energy consumption has become the most important issue of the wireless sensor network (WSN) topology design. All the proposed hierarchy methods cluster a WSN in different cluster layers in one step of evolutionary algorithm usage with complicated parameters, which may lead to reduction in efficiency and performance. In fact, in the WSN topology, increasing a cluster layer is a trade-off between time complexity and energy efficiency. In this work, regarding the most important WSN design parameters, a novel dynamic multi-layer hierarchy clustering approach is proposed using evolutionary algorithms for densely deployed WSNs. Different evolutionary algorithms such as genetic algorithm, imperialist competitive algorithm, and Particle Swarm Optimization (PSO) are used to find an efficient evolutionary algorithm for implementation of the proposed clustering method. The results obtained demonstrate the PSO performance, which is more efficient compared to the other algorithms in order to provide a maximum network coverage, an efficient cluster formation, and a network traffic reduction. The simulation results of the multi-layer WSN clustering design through PSO algorithm show that this novel approach reduces the energy communication significantly and increases the lifetime of network up to 2.29 times with providing full network coverage (100%) till 350 rounds (56% of network lifetime) compared to the WEEC and LEACH-ICA clustering.

Keywords: *Wireless Sensor Networks, Cluster Head, Genetic Algorithm, Imperialist Competitive Algorithm, Network Lifetime*.

1. Introduction

A collection of tiny and smart wireless sensors creates a powerful network named wireless sensor network (WSN) [1, 2]. A WSN consists of four different units including the sensing, computing, power, and transmission units. The sensing unit includes some sensors to guarantee the interaction with the surroundings. The sensing radius clarifies the sensing coverage and deployment density of the network. The micro-processor is responsible for the overall node controlling. Mostly, power is supplied with a mini, fixed, and irreplaceable battery. Lack of power resources leads to the drainage and death of the sensor node. The radio unit includes a short range radio transmitter for data link connection creation [3]. Depending on the sensor hardware boundaries, the radio radius determines the radius of clusters that affects the network connectivity and coverage [5].

Mostly, geographical positions of sensor nodes are not pre-determined. Sensors are deployed randomly or in grid form inside or very close to occurrence of a physical phenomenon in a hazardous environment where the risk of human monitoring for data collection and controlling particular purposes is high. In grid deployment, sensors are deployed in equal distances from each other, while in random deployment, sensor formation is not predictable [6].

WSNs are utilized in many agricultural, industrial, environmental, health-care, and military applications such as data collection, security monitoring, and tracking objects [7, 8]. After a WSN is constructed, sensors start to sense and gather data from the situation of physical phenomena continually. They capture the events in the area and transmit the collected data to the base station (BS) directly or via other intermediate nodes for further analysis and decision-making [9]. BS is stationary, and is established in a far distance from a WSN. The end user makes decisions based on the results obtained from the analysis of the collected data. Although compared to the other types of networks WSNs are cheaper, their capabilities and resources are more limited. Sensors rely on small and low-powered batteries. Recharging or exchanging these batteries is very difficult or even impossible. Due to the power resource constraints, energy consumption is an important issue in a WSN topology design. In addition to energy limitation, network coverage, type of deployment, localization, secure localization, routing, robust, and secure routing, data fusion and synchronization are some of the other WSN issues [10].

Nodes operate continuously and remain active as long as energy is available, and when the battery is drained, the node dies. In far and wild environments, to increase network lifespan, sensors are deployed densely. If a sensor dies, the nearest neighbor node can operate to prevent any network failure. On the other hand, without applying data fusion algorithms, dense sensor deployment may lead to redundancy in data collection. Most of the energy in WSNs is consumed for data transmission. Therefore, using a suitable network topology and architecture leads to an efficient energy conservation. One of the most efficient network architectures is hierarchy topology, which increases network lifetime as long as months or even years [11].

Applying clustering routing protocols leads to optimization of energy consumption of the network. Sensors are grouped in some clusters based on the hierarchy routing protocols. In this approach, different operations are assigned to every node throughout network lifetime for data collection and enhancement of energy efficiency based on the aim of network scalability. Ordinary sensors send their collected data to their own cluster heads (CHs) continually. Sending data to BS can be carried out directly or through some intermediate CHs. CHs forward the collected data to BS after applying some special duties such as local analysis and data fusion [12].

In other words, CHs act like gateways between ordinary sensors and a BS. CHs consume more communication energy, as they send data over longer distances compared to the ordinary sensors. Thus rotation of CH duty continually among all sensor nodes and selection of new CHs in every round can balance energy consumption of WSNs.

To put it mildly, clustering sensor nodes reduces network energy consumption efficiently. Most of the clustering algorithms construct a network using single-hop transmission based on a two-layer architecture. The communication energy consumption proportions with the distance of two nodes. Therefore, based on the network situation, sometimes multi-hop transmission in short distances may lead to a reduction in energy consumption compared to long-distant transmissions [6].

In order to design an optimal hierarchy WSN topology, in addition to energy consumption, some other important issues such as coverage, connectivity, and data fusion should be taken into account. Therefore, minimizing or maximizing these parameters converts a topology design to a discrete NP-hard problem. Evolutionary algorithms are capable of finding optimal solutions for most NP-hard problems [13].

Recently, different evolutionary algorithms such as GA, ACO, and ICA have been used to optimize different WSN parameters to design a high performance network topology. One of the most common meta-heuristic methods for discrete NP-problems is the particle swarm optimization (PSO). The important advantage of PSO over other methods is that it provides a powerful exploration and exploitation in a complex space with less computational complexity [14]. In this paper, after considering two-layer and three-tire communication clustering patterns, a hybrid method, multi-layer clustering topology (MCT) of WSNs, for the network clustering through multi-layer programming approach, has been proposed.

In other proposed methods, the WSN multi-layer clustering is designed in one layer, while in the proposed method, every layer clustering is designed in one layer based on the important parameters of WSN clustering. The contribution of this proposed method is to the network lifetime extension up to three times with a minimum number of clusters, a maximum value of coverage, and connectivity without any sensor node out of range and memberless cluster.

In this paper, the most import clustering parameters are studied. After categorizing the clustering algorithm from different approaches, some important algorithms are investigated. WSN clustering using evolutionary algorithms is based upon some important parameters that are discussed completely.

This paper involves Section 2 that reviews the related works, Section 3 that reviews the evolutionary algorithms, Section 4 that describes the evaluation function, Section 5 that discusses the proposed WSN model, Section 6 that includes the results and discussion, and section 7 that concludes the paper.

2. Review of related works

In the WSN design and implementation, there are many special issues. The main objectives of the WSN design are to extend the network lifetime and to optimize energy consumption. In order to reduce the energy consumption of a WSN design, hierarchy architecture including different routing algorithms is an effective method with fusing and combining data in all clusters to reduce the number of transmitted messages to BS. The hierarchy clustering is a more effective method when an application requires hundreds or even thousands of sensor nodes. To form clusters, CH selection algorithms should create the best possible clusters along with a low number of transmission massages and guarantee to keep a fixed value of time complexity, if possible [15]. The clustering and routing protocols should find a high level of priorities and be able to adapt with application-related requirements. Like in traditional networks, data security is also very important. Providing a secure connection gets more emphasis when a WSN is designed for military applications.

Clustering algorithms conserve bandwidth because they limit interaction domain and prevent data redundancy. In addition, clustering establishes the network topology in sensor layers to reduce the network maintenance cost. It means that the ordinary sensors are maintained while connected to CHs, and they are not influenced by network changes during the CH selection phase. Also in two-layer WSNs, gateways may be overloaded when the density of sensors is increased. It may cause communication delay and failure in object tracking. In addition, the two-tire WSN design is not suitable for the large collection of sensors that cover a large application area [16,17].

In all clustering algorithms, some important parameters should be introduced. Based on the resource limitations including low power computation, limited memory, and battery power, a CH can provide clustering services only for a limited number of sensors. Therefore, the number of CHs influences the network performance. A large number of CHs leads to increment of network energy consumption, and a low number CHs extremely damages the network connectivity and coverage [18]. In most random or probabilistic clustering algorithms, CH selection and cluster formation creates different clusters in every round. In a pre-determined clustering algorithm, for CH selection, clustering algorithms have some special criteria, and cluster forming is based upon proximate nodes, connectivity, degree, etc., while in the probabilistic methods, every node uses a probability value for CH selection. However, it is assumed that the relation of CHs and their members is done through single-hop connection, while in most applications, multiple inter-connections are required when the connection range of sensors is limited or the number of CHs is too large compared with the ordinary sensors [19].

Depending on the type and capability of sensors, WSNs may be categorized into the heterogeneous and homogenous networks. Heterogeneous WSNs contain two types of sensors; one group of sensors are equipped with higher processing and hardware capabilities, which are pre-selected to act as CHs. Another group is the ordinary sensors with lower capabilities that are used to capture and monitor the physical phenomena. Against the heterogeneous WSNs, in the homogenous WSNs, hardware capabilities and resources of all sensor nodes are equal, and every node is able to act as CH.

Centroid and distributed clustering algorithms are the other WSN clustering classifications. Centroid algorithms are based upon characteristics and functions of sensor nodes in the clusters, while distributed algorithms emphasize on the methods used for cluster formation. Some coordinating sensors and BS are responsible for determining functions of the network members and controlling members of clusters. However, these networks are not recommended for too large-scale WSNs. They are suitable only for WSNs with a high quality of connections. In fact, the performance of distributed clustering algorithms is better compared with the algorithms in too large scale WSNs [20].

In distributed clustering approaches, every sensor node decides to act as a CH by executing its own algorithm, while in central approach, BS or the coordinating node selects a group of sensor nodes to act as CHs. Sometimes a combination of both approaches in a few algorithms is desired. In the cluster-forming phase, a packet is broadcast to all nodes inside the radio range. In single-hop transmissions, cluster members send the collected data to their CHs, while in multi-hop transmission, nodes communicate with CHs through proximate nodes [21].

In most of the proposed methods, a time-division multiple access (TDMA) protocol is used for data transmission. Therefore, every sensor is able to schedule the sleeping time frequently to save more energy. Therefore, in these types of mechanisms, synchronization is very important. Also data fusion reduces the energy consumption of every node. It is one of the main WSN design issues in most proposed methods. However, the implementation of data fusion in most applications is not possible, and regarding the application type, it should be optimized.

Some classic paternalistic algorithms have been proposed to cluster homogeneous sensors. Mostly, in these algorithms, CHs are selected only based upon the local parameters. In order to design optimized clustering topology, the classic algorithms such as the Low-energy Adaptive Clustering Hierarchy (LEACH), LEACH-C, and Hybrid Energy-Efficient Distributed (HEED) algorithms are not able to take all the WSNs parameters into account.

The Low-energy adaptive clustering hierarchy (LEACH) protocol has been introduced for WSNs clustering [21]. The main goal of the LEACH protocol is to minimize the total sensor energy consumption to extend the lifetime of WSNs. LEACH is a TDMA-based MAC protocol, i.e. the distributed algorithm that integrates two-tire clustering with a simple routing (single-hop). The sensors are grouped in some random clusters that are randomly created in every round. The task of CH rotates through all sensor nodes based on a probability value that is assigned to every sensor in every round. It causes that the total number of CHs becomes dynamic in every round. When a node is selected to operate as a CH, the residual energy of node is not taken into consideration. CHs are not distributed uniformly over the application area, and the number of CHs is not minimized. Therefore, useless or overloaded clusters and lack of coverage and connectivity are avoidable [22].

An energy efficient LEACH-C protocol uses the centralized approach for clustering a WSN. The total number of clusters is bound, and CHs are randomly selected. The basic information of sensors including location and residual energy is transmitted to BS for the CH selection and cluster-forming phase. The residual energyless node will not find any chance to act as a CH. Regarding the WSNs design criteria, the task of CH is rotated among all sensor nodes during the network lifespan. Transmitting the node situation to BS in far distances is very difficult. As a result, this protocol is not suitable for large-size networks. It may lead to increase the delay and idle times of nodes [23].

Node degree or deployment density are the two main parameters to balance cluster energy in the cluster-forming phase. A hybrid, energy-efficient, distributed clustering (HEED) algorithm is a distributed method that improves the LEACH algorithm. It selects CHs based on the residual energy of every node. Reducing energy consumption of nodes, making cluster distributions uniform, terminating clustering with a fixed number of rounds, and increasing network lifetime through uniform distribution of energy consumption are some important variables in the HEED algorithm [24].

A weighted energy efficient clustering (WEEC) is another WSN clustering algorithm. Regarding the distance of the node and BS, a weight is assigned to every node. An optimum range of cluster number is calculated based on the closest and farthest nodes. When a cluster becomes closer to BS, a small size cluster is desirable. The results of this algorithm show the significant reduction of energy consumption and the increment of the network lifetime [25].

In all the proposed methods, WSNs are clustered in different cluster layers in one step of evolutionary algorithm usage with complicated parameters, which may lead to reduce the efficiency and performance of the WSN clustering design. Adding a cluster layer is a trade-off between time complexity and energy efficiency. There is a lack of any previous work that clusters a WSN in different layers using different parameters for different layers [26].

In a WSN topology design through evolutionary algorithms, different algorithms are applied to improve different clustering algorithms. GA is used to adapt and optimize LEACH, HEED, and WEEC. Moreover, it is used to design a hierarchy topology regarding the most important clustering parameters with different network sizes and types of network deployments, grid or random. Mostly, the data is transferred using single-hop transmission. The topology generated using GA reduces communication energy consumption and the number of active nodes along the network lifetime increment. Consequently, the network connectivity becomes satisfactory [27].

In another proposed method, the imperialist competition algorithm (ICA) is used to optimize the created clusters by the LEACH algorithm. In the initialization phase, ICA uses the LEACH output for its initialization phase of imperialists with different types of deployments and network sizes. The proposed method extends the network lifetime favorably. Additionally, it finds out the adequate position of CHs inside every cluster. The results obtained demonstrate that the proposed method is performed efficiently compared to the traditional cluster-based protocols. Clusters formation and management through an intelligent method creates more energy-efficient clusters. Applying data diffusion to energy efficient clusters leads to save more energy and extend lifespan. High-energy nodes are selected to act as CHs and create clusters that are evenly positioned over the desired field [28].

Our proposed method periodically selects CHs among nodes based on the most important WSN characteristics such as sensor residual energy, intra-communication cost of clusters, connectivity and coverage of the network, memberless clusters, and out of range sensors in every layer. In order to optimize these parameters, different evolutionary algorithms such as GA, ACO, and ICA are used to design the high performance WSN topology. The WSN topology design is a discrete problem to which only a few algorithms are able to find an optimal solution. Therefore, cost/fitness function plays an important role in convergence of the algorithms.

3. Evolutionary algorithms (EAs)

EAs inspire different biological evolution mechanisms such as natural selection, reproduction, mutation, and symbiosis to search and find an optimal solution in the solution domain scope. As they are non-compatible, other creatures are eliminated even though they might be very good. Self-repetition or the desire for immortality is the main motivation inside all creatures. Mutation occurs due to some random or non-random parameters causing non-programed changes. Mostly, the result of these non-programed changes is unpleasant but sometimes a few percent of mutation results are desirable. Symbiosis may improve the generation of creatures like dogs and cats. They are cleverer compared to other biotypes since they are living with humans [29].

In order to solve a problem through such algorithms, simple repetition mechanisms are used. By inspiring different natural phenomena, many evolutionary algorithms such as genetic algorithm (GA), ant colony optimization algorithm (ACO), imperialist competition algorithm, artificial bee colony algorithm (ABC), and particle swarm optimization (PSO) have been introduced. Originally, most EAs are designed to solve continuous and a few algorithms are able to solve discrete or integer problems. With some manipulations, a continuous algorithm is able to solve an integer or discrete problem [30].

3.1 Genetic algorithm (GA)

A special EA named GA was introduced in 1970s. In order to optimize any problem using GA, it should be encoded with the genes. Binary strings of 0's and 1's are one of the most common encoding methods. In this research work, chromosomes are presented with an array of binary numbers of genes. Every gene represents a role of sensor node. When the value is 1, the sensor node functions as a CH; and when the value is 0, it functions as an ordinary sensor node. A chromosome with 7 genes representing seven sensors in the network is shown in figure 1.

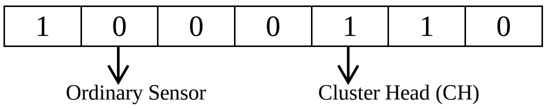

Figure 1. A schematic view of a chromosome with 7 genes.

In the first step of GA, an initial population of chromosomes is produced, which is evaluated using a cost or fitness function. After the evaluation, the population is sorted based on a rank value number that is assigned to every chromosome in the evaluation phase. In the selection step, a pair of chromosomes will be selected through some random selection methods such as the elitist, tournament, and roulette wheel. In this work, the tournament method was used to select a pair of chromosomes [31].

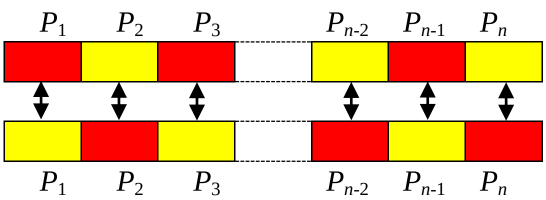

Figure 2. A schematic representation of uniform cross-over.

The cross-over is one of the most important operators in GA. The cross-over operation in GA leads to a rise in the GA diversity. Having selected a pair of chromosomes, the cross-over operator will be applied to create new chromosomes from the selected chromosomes. The pair chromosomes named parents exchange their genes and create two children as new members. There are numerous types of cross-over such as the single-point (one-point cross-over), two-point cross-over, cut and splice, and uniform cross-over methods. In this work, the uniform was selected among different methods. In this way, n random points, p_1 to p_n between 1 and the length of chromosome (N), will be generated randomly. The children will be generated as follow: every portion of the first child in all genes is exchanged

with the corresponding portion on the second child, and vice versa (Figure 2) [32].
Another GA operator is mutation, which produces other possible solutions from the domain solution space. It increases exploration in the search space domain. At first, a subset of chromosomes of the population is randomly selected. Inside a chromosome, a gene will be randomly mutated with a specific defined mutation probability rate. Thus in the mutation phase, the role of some sensors may change from a CH to an ordinary sensor, and vice versa. The fixed mutation rate is not recommended. To increase GA convergence, it is recommended that the mutation probability rate be decreased as the generation value increases. The new generated population is merged with the old generation and ranked after the evaluation of every chromosome. Therefore, the new generation of population is selected based on the best chromosomes. GA is terminated when conditions are satisfied; otherwise, GA is repeated from the selection step.

3.2 Imperialist competition algorithm (ICA)

ICA, introduced in 2007, is a new paradigm in the optimization algorithms and intelligence systems. Using social, political, and cultural processes to create an optimization algorithm is unique. In ICA, first a population of countries with different characteristics are created. Those countries that have better qualities and more power decide to colonize other weaker countries to establish an imperialism. In fact, intra-empire competitions cause to improve problem solution, while the main competition occurs among different imperialists. The assimilation and revolution are two important concepts. In the colonialism process, an imperialist imposes a set of policies on the colonized society with some changes to assimilate the target society to the dominant culture. Those policies are named assimilation policies.

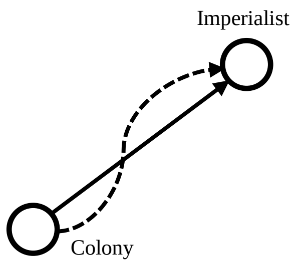

Figure 3. Movement of a colony toward its imperialist.

Based on the same manner, every colony moves toward its empire, which is shown in figure 3. The colony movement may be done in one or two directions. The direct movement is not desirable though [33]. Sometimes colonized countries are not satisfied with their situations, and they decide to experiment a completely different policy. Therefore, they go through fundamental changes or a revolution. In other words, the revolution, which is similar to mutation in GA, takes place in some countries' dimensions randomly. The target of revolution is to increase the search power of the algorithm to create new solutions in domain scope, as the empire might be located in an undesirable position of domain scope [34].
Comparing colonies with their corresponding imperialists, imperialists' evaluation is based on an objective function, eliminating the weakest colony from the weakest imperialist and assigning it to any other imperialist randomly, converting the colony-less imperialist to a colony, assigning it to any other imperialist randomly, and reporting the best imperialist are some other ICA steps [35].

3.3 Particle swarm optimization (PSO)

PSO was defined to solve continuous problems but with some algorithm modifications, it can be used for discrete problems. It has been proposed to create some living creatures, named particles, and distribute them across the search space. In PSO, every particle has five characteristics such as position, objective function, velocity, the best experienced position, and the objective function value of the best experienced position. Every particle calculates the value of the objective function regarding its own position in the search space. It selects a movement direction based on a combination of the present local and the best previous positions of itself in addition to the information of the best global position of particles.
The velocity vector is tangent to the movement vector. After a collective movement of particles, one step of PSO is done. The algorithm steps will repeat until it meets a termination condition [36].
Creating and evaluating the initial population, finding and recording the best local and global experienced positions, updating the velocity, and position of particles, the exiting algorithm if the termination algorithm is met; otherwise, repeating from step two are different steps of a PSO algorithm.

4. Evaluation function

In this section, we describe the sensor characteristics used in this work. Regarding the sensor resource constrains, every cluster can provide clustering services for a limited number of members. Therefore, the maximum number of members inside a cluster is an important WSN topology design. It examines the efficiency of every cluster. Therefore, with the reduction of living nodes during the network lifespan, the total number of clusters will also be reduced.

Clustering living active sensors with an optimum number of clusters leads to the increment of the network lifetime and algorithm efficiency. Data loss is an important measurement to evaluate the robustness of WSN topology. The ordinary sensor duty is to collect data from the covering environment and transmit it to BS via CHs. Through measuring the data loss parameter continually over the network lifespan, the data connectivity links, and the coverage of network is controlled. The routing algorithm is more robust when the data lost is very low. The data transfer rate is important as well.

The most important part of an optimization problem is the evaluation function obtained from the conversion of objective parameters, which are supposed to be optimized. The fitness function evaluates every chromosome by a numeric value that specifies its quality. As the quality of chromosomes (as the answer to the problem) goes higher, the chance of chromosomes to be selected in the next generation will also increase.

In this work, we did a comprehensive study and divided the objective function into six factors, φ_1 to φ_6, which are considered as the following parameters. This function is a weighted summation of these five factors, and considered as the cost function. If a SN cannot access its CH within its radio coverage, it is disconnected from the network. This sensor becomes out of range, and is represented by SN_{out}. The total number of out of range sensors, φ_1, is obtained by (1).

$$\varphi_1 = \begin{cases} \sum N_{SN_{out}} & \text{if } N_{SN_{out}} > 0 \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

Every Cluster should have some nodes belonging to the cluster; otherwise, it becomes a cluster without any member, and is denoted by $CH_{memberless}$, where the total number of memberless clusters, φ_2, is calculated through (2).

$$\varphi_2 = \begin{cases} \sum N_{CH_{member\text{-}less}} & \text{if } N_{CH_{member\text{-}less}} > 0 \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

For every cluster, a pre-defined number of nodes is allocated depending on the hardware and communication capabilities of the nodes. If a cluster provides services for more than the maximum number of members, it is called an overloaded cluster and represented by $CH_{overload}$, where the total number of overloaded clusters, φ_3, is calculated through (3).

$$\varphi_3 = \begin{cases} \sum N_{CH_{overload}} & \text{if } N_{CH_{overload}} > 0 \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

It is also assumed that in the proposed model, every cluster can provide services for five CHs or SNs maximum. In the first part of the work, a random number between 0 to 1, *J* is assigned to every sensor's battery, while in the second part, the battery charge of all sensors is 0.5 *J*. When a sensor acts as a cluster head, it loses more energy. Thus sensors with a higher residual battery charge should be selected to act as the cluster heads. As a result, the role of cluster heads should uniformly rotate among sensor nodes and increase network lifespan. φ_4 represents the rate of average CH batteries to SN batteries (4).

$$\varphi_4 = \frac{\sum CH_{Batteries}}{\sum SN_{Batteries}} \quad (4)$$

The unified sensor distribution among clusters can prevent cluster overloading and wastage of resources defined by φ_5. In clustering, it is very important that the members are distributed in the clusters evenly. φ_5 represents uniform member distribution among clusters that leads to balance the network communication energy (5).

$$\varphi_5 = \text{Avg}\left(\sum N_{CH\text{-}members} - \left\lceil \frac{N_{SNs}}{N_{CHs}} \right\rceil \right) \quad (5)$$

where, N_{SNs} represents the total number of living sensors and N_{CHs} is the total number of CHs in every round. If we assume that the maximum number of cluster members is NCH_{max}, clusters with the highest number of members are desirable. We define a variable; φ_6 that shows the total number of the clusters that contain less than $\frac{1}{2} \times NCH_{max}$ members should be minimized (6). In every optimization, algorithms may fall in local optimum trap. This parameter avoids the local optimum loop trap and small cluster formation.

$$\varphi_6 = \sum N_{CH\text{-}members} < \frac{1}{2} \times CH\max \quad (6)$$

As already mentioned, the main issue in WSN is energy limitation. To increase the WSN lifetime, in addition to the value of energy consumption, the number of sensors that cannot access any cluster, clusters overlapping, number of memberless clusters, cluster overload, evenly distribution of members in clusters, and total number of clusters with lower number of members than $\frac{1}{2} \times NCH_{max}$ are some parameters that are effective in WSN optimization.

Also in the WSN design, some parameters such as sensor energy consumption, uniform distribution of clusters, network coverage, network connectivity, and rooting should be taken into account. In the WSN optimization, which is a multi-objective optimization, to increase the WSN lifespan, in addition to the value of energy consumption, residual batteries, network coverage, connectivity, cluster overlapping, and cluster overload are the parameters involved. Our multi-objective optimization was formulated and presented by (7).

$$\text{Cost Function}=\min\left\{\sum_{i=1}^{6} w_i \times \varphi_i\right\} \tag{7}$$

where, φ_1 represents the number of sensors that cannot access any CH, φ_2 represents memberless clusters representing overloaded clusters, φ_3 represents the sum of overloaded clusters, φ_4 represents the rate of average CH batteries to SN batteries, φ_5 represents variance of cluster member distribution, and φ_6 represents clusters with low members.

Table 1. Different weight values of cost function for GA, ICA, and PSO.

	w_1	w_2	w_3	w_4	w_5	w_6	w_7
GA	10^4	10^2	1	10	10	10^2	10
ICA	10^3	10^3	1	10	10	10^2	10^2
PSO	10^4	10^3	1	10	10^2	10^2	10^2

where, the w_i presents the weight of each parameter in the cost function. This form of formulation is suitable for a numeric evaluation function called cost function, which specifies the quality of every possible solution in a population, and it is meant to minimize costs. By tuning these weights in GA, ICA, and PSO, the optimum value for the parameters can be manually obtained. Table 1 shows the different weight values of cost function for GA, ICA, and PSO obtained. After the results were generated, the better probabilities and methods were selected, and the rest of the work by using those probability values and methods were continued. Also it should be mentioned that in this work, all values and methods are related to the problem's criteria. If the problem's criteria change, the proposed values and methods might not be optimized. To cover and solve this problem, different optimization methods were tried including GA, ICA, and PSO.

5. Proposed WSN model

In a simulation of any WSN, essentially, a model should be represented. The model involves energy consumption, collected data, radio communication, sensor placement, and topology aspects. This section describes the WSN model studied and used in the rest of the work. As already mentioned, in the proposed model, all sensors and base station are stationary and homogeneous.

In the WSN design, some parameters such as energy consumption, clusters' uniform distribution, coverage, connectivity, and rooting should be taken into account. It is assumed that all the sensor nodes are stationary and identical in capabilities. A sensor node can function in three modes: (i) as a super cluster head (SCH), (ii) as a cluster head (CH), and (ii) as an ordinary sensor (SN), depending on the role assigned to a sensor dynamically. Every sensor has a sensing coverage radius (R_{sen}) and a radio communication radius (R_{rx}) associated with it.

A cluster-based topology with single-hop transmission in every layer was used in this research work. It was assumed that the remote BS could always communicate with all the sensor nodes directly. SCHs and CHs are required to communicate over relatively longer distances; therefore, their batteries drain more quickly than those of the other sensor nodes. SCHs and CHs have to gather the sensed data from the members of the corresponding clusters, pre-process the gathered data, and forward it to BS after data fusion. The main issues in WSNs are to reduce the network energy consumption [28], optimize the deployment of sensors, and enhance the network coverage and connectivity.

The radio communication and sensing coverage areas of the sensors are in a circular shape. The overlapping of sensing areas/inter-section of clusters/overlapping of coverage of two sensors can be obtained by (8).

$$A = 2R^2\cos^{-1}\left(\frac{d}{2R}\right)-\frac{1}{2}d\sqrt{4R^2-d^2} \tag{8}$$

where, R represents the clusters/sensing/radio communication radii and d is the Euclidean distance between two sensors. Sensors consume energy for sensing, processing, and radio transmission. A major part of energy is used for radio communication. In the first radio model [21], it is assumed that the radio channel is symmetric such that the energy required to transmit a message from node A to node B is the same as the energy required to transmit a message from node B to node A. Data transmission energy consists of transmission (E_{Tx}) and receiving (E_{Rx}) energies. Thus the total consumed energy to transfer a k-bit message over a distance d using the first radio model may be given by (9).

$$E_{Tx}(k,d) = E_{Tx-elec}(k) + E_{Tx-amp}(k,d) \Rightarrow$$
$$E_{Tx}(k,d) = \begin{cases} k \times E_{elec} + k \times \varepsilon_{fs} \times d^2 & d < d_0 \\ k \times E_{elec} + k \times \varepsilon_{amp} \times d^4 & d \geq d_0 \end{cases} \quad (9)$$

where, d_0 is a threshold distance defined as $d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}}$, $E_{Tx\text{-}elec}$ is the energy spent by the transmit circuit, $E_{Tx\text{-}amp}$ is the energy-cost of the transmission amplifying circuit, $E_{Rx\text{-}elec}$ signifies the energy-cost of the receiving circuit, and E_{elec} is the energy expense to transmit or receive 1-bit message by the transmitting or the receiving circuit. The energy spent in receiving data can be obtained by (10).

$$E_{Rx}(k,d) = (E_{Rx} + E_{BF}) \times k \quad (10)$$

where, E_{BF} is the beam forming energy. One has to minimize not only the transmit distances but also the number of transmit and receive operations for each message. The energy consumption for data fusion is represented by (11).

$$E_{da-fus}(k,d) = k \times E_{da} \quad (11)$$

The total communication energy for a sensor node ($E_{CE\text{-}Sen}$) may be represented by (12).

$$E_{CE-Sen}(k,d) = E_{Tx}(k,d) + E_{Rx}(k,d) + E_{da-fus}(k,d) \quad (12)$$

Therefore, the total communication energy (CE) for the whole network communication can be represented by (13).

$$CE = \sum_{i=1}^{n} E_{CE-Sen_i}(k,d_i) \quad (13)$$

6. Results and discussions

In this section, we describe the initialization of different parameters of the proposed WSN model and discuss the results obtained. The following values were used to initialize the GA, ICA, and PSO parameters from optimum average values of 50 repetitions of algorithms with 200 iterations. The size of population (*nPop*)/swarm size was 50 and the number of genomes/countries/particles was 200.

In GA, the selection probability (p_s) was 0.3, the mutation percentage (p_m) was 0.08, the number of mutants (N_m) = $\lceil p_m \times nPop \rceil$ was 4, the mutation rate (p_{mu}) was 0.02, the cross-over probability (p_{cr}) was 0.8, and the selection pressure (β) was 8.

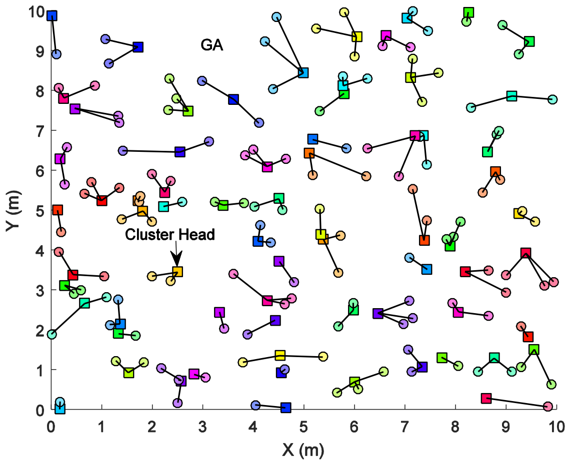

Figure 4. Final WSN design using GA.

The roulette wheel selection for the selection method and the uniform cross-over for the cross-over method were used. In the ICA parameters, the number of empires or imperialists (*nEmp*) was 50, the selection pressure (α) was 1, the assimilation coefficient (β) was 8, the probability of revolution (p_{re}) was 0.1, the revolution rate (μ) was 0.05, and the colonies mean cost coefficient (ξ) was 0.1.

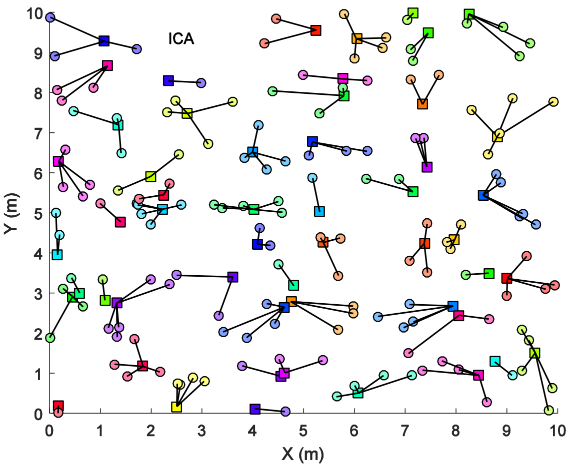

Figure 5. Final WSN design using ICA.

The PSO parameters were as what follow. The acceleration factors (φ_1, φ_2) were 2, the total acceleration factor, inertia weight (w) = $2/(\varphi - 2 + \sqrt{(\varphi^2 - 4\times\varphi)})$, inertia weight damping ratio (w_{damp}) was 1, personal learning coefficient (c_1) = $w\times\varphi_1$, and global learning coefficient (c_2) = $w \times \varphi_2$. The size of the monitoring area was $10m\times10m$. GA, ICA, and PSO were coded in MATLAB, version 9, on Intel(R) Core *i*7-4500U CPU @ 1.8GHz 2.4 GHz running Windows 8 professional.

The initial values for the sensor nodes were mentioned as what follow. The transmission energy (E_{Tx}) was 50 *nJ/bit*, the receiving energy

(E_{Rx}) was 50 *nJ/bit*, the beam forming energy (*EB*) was 5 *nJ/bit*, the energy consumption for data fusion (E_{da}) was 5 *pJ/bit*, the transmitter amplifier energy (ε_{amp}) was 100 *pJ/bit*, the transmitting amplifying energy in free space model (ε_{fs}) was 10 $pJ/bit/m^2$, the multi-path fading model (ε_{mp}) was 0.0013 *pJ/bit/m2*, the value of radio communication radius (R_{rx}) was 4 *m*, the sensing radius (R_{sen}) was 1 *m*, and 200 sensors were deployed randomly in the field.

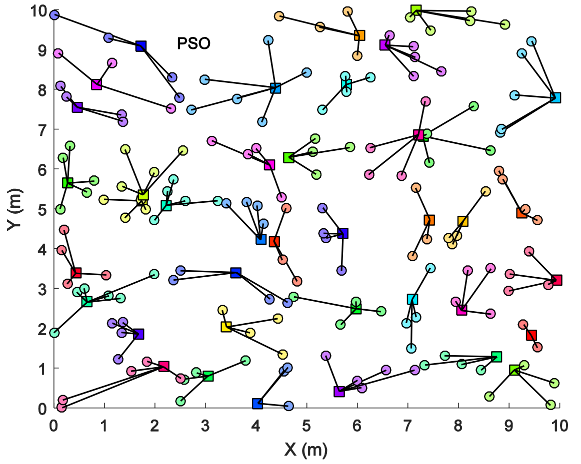

Figure 6. Final WSN design using PSO.

In the first part of this work, to design the first clustering layer, GA, ICA, and PSO were applied to find out a more efficient evolutionary algorithm for the proposed method. In the next step of this work, the proposed method was implemented through using a more efficient evolutionary algorithm to design and study three-layer clustering. Figures 4, 5, and 6 show the output of the proposed algorithm using GA, ICA, and PSO. The proposed clustering algorithm was applied on 200 random deployed sensors through GA, ICA, and PSO over 200 generations. In every generation, the cost function evaluated the population and assigned a value to every member. The output results of the optimization algorithms are listed in table 2. Clustering with an optimum number of clusters without any memberless cluster and out of range ordinary sensor was desirable. The results obtained demonstrate that the proposed clustered network of PSO was more efficient compared to the other algorithms.

Table 2. WSN parameters.

Algorithm	SN	CH	CHLE	CHDI	CH BA	SN BA
GA	131	69	57	31%	50.83×10^{-2}	46.75×10^{-2}
ICA	147	53	24	60%	42.19×10^{-2}	50.31×10^{-2}
PSO	161	39	1	17%	52.28×10^{-2}	47.16×10^{-2}

It clusters the sensor nodes with 39 CHs, while GA clusters all the ordinary sensors with 69 CHs and ICA with 53 CHs. Therefore, the proposed WSN topology of PSO uses fewer CHs to transmit all the collected data to BS. Thus it results in consuming a lower amount of batteries' energy and increasing the WNS lifespan.

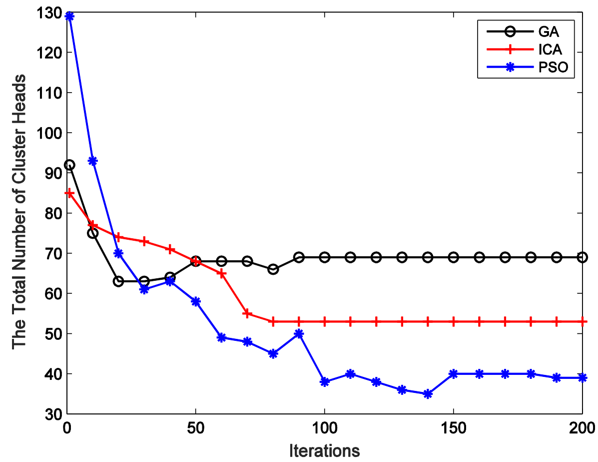

Figure 7. Total number of CHS per iterations.

Also CHML of the PSO algorithm contains only one cluster, while in GA, there are 57 clusters, and in ICA, 24 clusters. The total number of CHs plays an important role in the performance of the designed topology because a lower number of CHs leads to overloaded CHs or out of range ordinary sensors, and some part of the collected data is lost. In addition, a higher number of CHs may lead to a memberless cluster or clusters with members lower than ½×NCH_{max}. Therefore, it increases the total energy consumption of the network. The output results illustrate that although PSO starts with a maximum and ICA with a minimum number of CHs, after 200 generations, PSO could cluster all the living sensor nodes with a minimum number of CHs without any overloaded clusters or out of range ordinary sensors. Therefore, in CH optimization, the performance of PSO is more efficient compared to the other algorithms (figure 7).

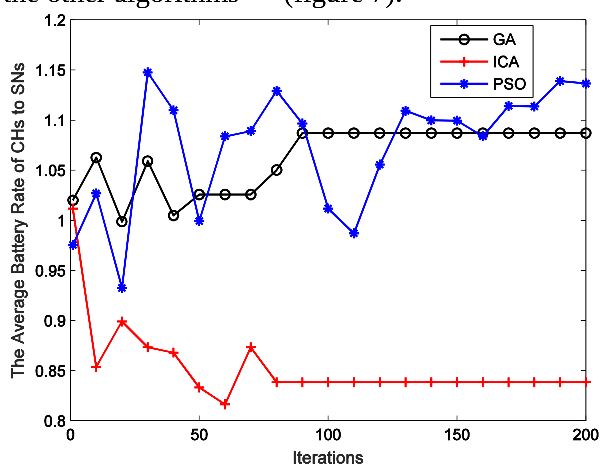

Figure 8. Average battery rate of CHs to SNs.

The network coverage, connectivity, and robust routing have a close relation with the residual energy of sensor nodes. To do cluster head functions, CHs consume more energy compared with ordinary sensors. Selecting CHs with a lower amount of residual battery may lead to the death of some intermediate nodes and disconnection of some sensor nodes. Therefore, selecting CHs with a higher amount of residual battery increases the network robustness, connectivity, and coverage. As shown in figure 8, the design topology through the PSO algorithm could find out CHs with the highest amounts of residual battery around 1.13, while GA optimizes with lower than 1.1, and ICA selects CHs with less than 0.65. Therefore, using the PSO algorithm to design a WSN topology leads to an increase in the network robustness and reliability. A uniform cluster deployment has a direct effect on all the network parameters such as energy consumption, coverage, and connectivity.

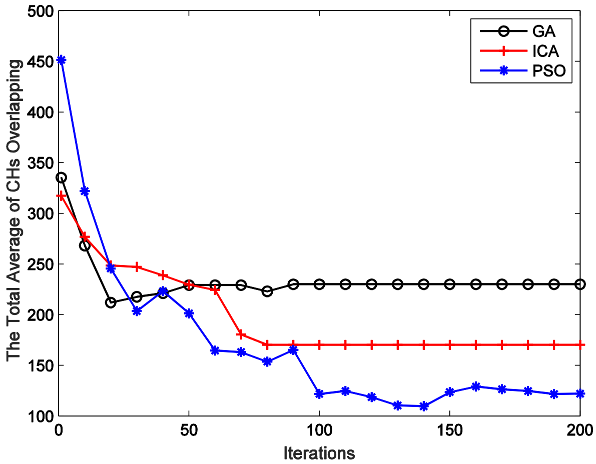

Figure 9. Total average of CH overlapping.

Most distributed clustering algorithms select CHs randomly based on the local sensor information regardless of the total network performance. Sometimes the selected CHs aggregate in a part of application area, while in other parts of the network, some CHs overload or do not even exist. Using cluster overlapping leads to measuring cluster uniformity. The results shown in figure 9 demonstrate that the proposed CHs by PSO for the network topology converge after 100 generations with the lowest amount of overlapping, while in primary generations, the PSO CHs find out the highest amount of overlapping. Due to a limited energy resource, reducing energy consumption is one of the main WSN design objectives. In addition to optimizing the total number of clusters, equal load balancing of sensors inside all clusters leads to a decrease in the energy consumption efficiently. As already discussed, every CH can provide clustering services for a limited number of members, which is shown by NCH_{max}. Therefore, the designed topology with a lower value of φ_6 is favorable.

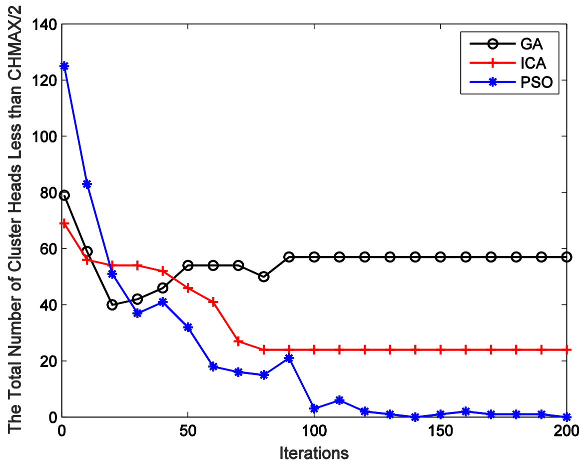

Figure 10. Total number of CHs less than ½×CH_{max}.

The output results, shown in figure 10, demonstrate that although in the primary iteration PSO starts with the highest value, it converges after 100 decades with the lowest value of φ_6. It proposes the best topology compared with other algorithms based on the φ_6 parameters with the lowest value of φ_6 (around 0). In the second part of this work, regarding the results obtained, the PSO algorithm was selected to be used for a three-layer hierarchy topology design. After designing the first layer, in the second layer clustering, some super clusters (SCHs) among cluster heads (CHs) were selected to act as gateways via CHs and BS.

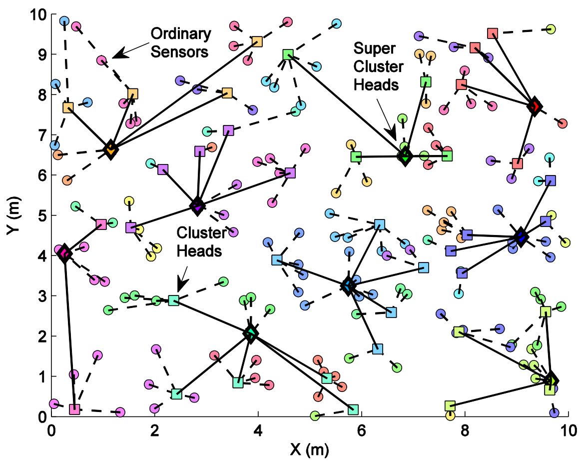

Figure 11. First output of proposed method.

Figure 11 shows the output of the first iteration for the proposed method, MCT that clusters the cluster heads of the first layer and selects some SCHs among CHs to design the second clustering layer. The results obtained were compared with WEEC and LEACH-ICA, disussed in the review of the related works.

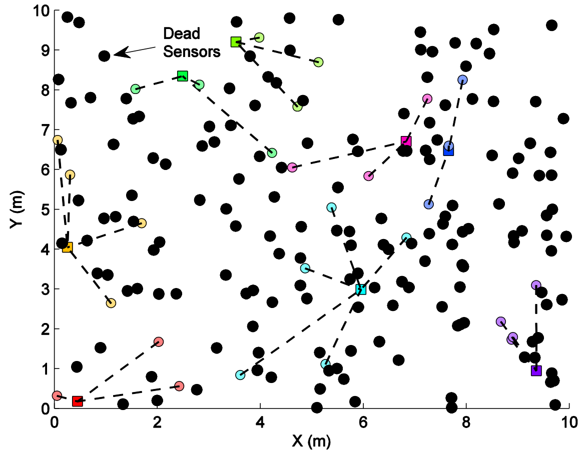

Figure 12. Last output of proposed method.

At the end of every generation, sensor batteries were updated based on the energy consumption, which was formulated in Equations 8-13. Through the proposed method, a dynamic MCT clustering was generated, which extended the network lifetime up to 620 rounds. Every evolutionary algorithm was stopped when the termination conditions were satisfied. In this scenario, when the total coverage of network became lower than 20%, the network was terminated. Figure 12 shows the final output of the last iteration (620 rounds) of WSN.

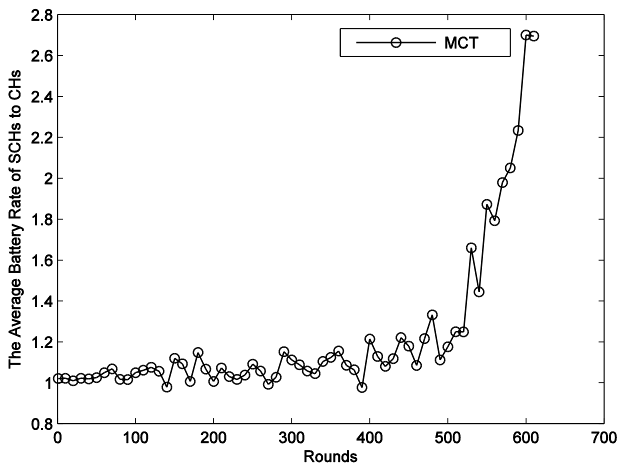

Figure 13. Average battery rate of SCHs to CHs.

In the second layer, similar to the first step, a set of sensor out of CHs should be selected to act as SCHs based on the different parameters. Given the significance of energy consumption, those CHs with the highest residual battery or battery in charge were eligible to act with the SCHs roles. Figure 13 shows the ratio of CHs to SCHs. Mostly, those CHs with a ratio more than 1 were selected to do the SCHs duties. After 400 rounds, the network resource crisis was seen, and the ratio moved upward sharply. Therefore, the proposed method always finds out the best set of CHs for the SCH duties.

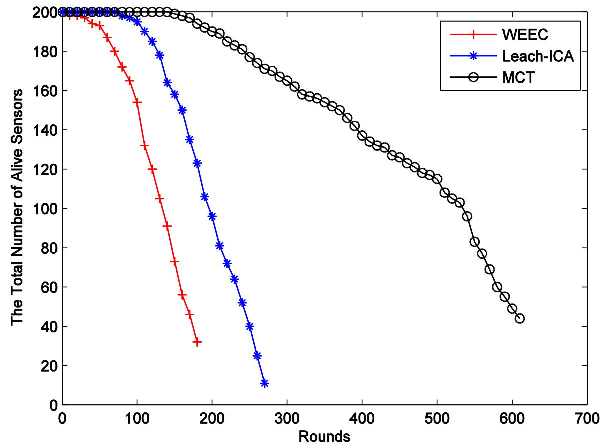

Figure 14. Total number of alive sensors.

As already discussed, resource limitation is the most important issue in WSNs. Different algorithms and protocols are implemented to balance the network load and reduce the energy consumption and extend the network lifetime satisfactorily. With inefficient energy consumption contorlling, the network performance, lifetime, coverage, connectivity, etc. are damaged seriously. With counting the total number of living sesnors in every round and calculating the rate of sensor death, the proposed method performance in terms of load balancimg and energy consumption controlling are obtained. In figure 14, the WEEC clustering upto 80 and in LEACH-ICA upto 150 rounds all sensor nodes are alive but after 110 rounds (WEEC) and 120 rounds (LEACH-ICA), only 30 nodes (WEEC) and 20 sensor nodes (LEACH-ICA) remain alive and sensors die quickly, while in MCT reduce the death of the sensor slope fevorably. It leads to extending the network lifespan up to two times compared to LEACH-ICA and three times compared with the WEEC clustering.

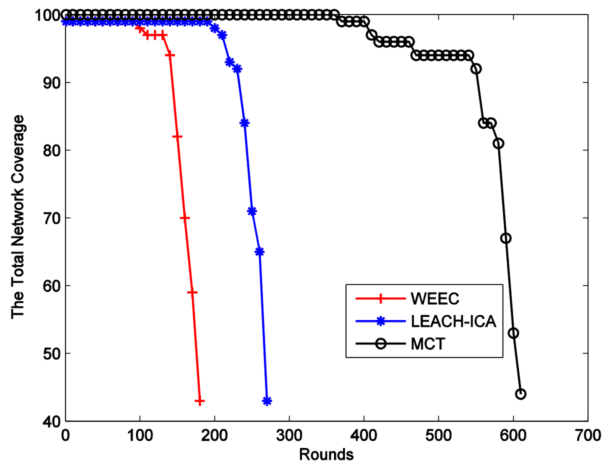

Figure 15. Total network coverage.

It clarifies that the MCT clustering has a better efficiency in load balancing and energy consumption controlling. The main duty of a WSN is to monitor and capture different physical phenomena over the network lifetime. WSN should cover the whole application area. To measure the network coverage, a set of grid points based on the sensor density, which is defined for the network as event points, is created. A minimum number of sensor nodes should report those event to BS. Via counting the total reported of grid points, the network coverage is calculated. As shown in figure 15, the coverage performance of WEEC, the proposed method, MCT, and LEACH-ICA is satisfactory. Over time, some sensors die due to the lack of energy, and the total number of living sensors is reduced. It results in the reduction of the network coverage gradually. Inside every node, the most amount of energy is consumed for data transmision. The sensors consume the same amount for sending and receiving data packets.

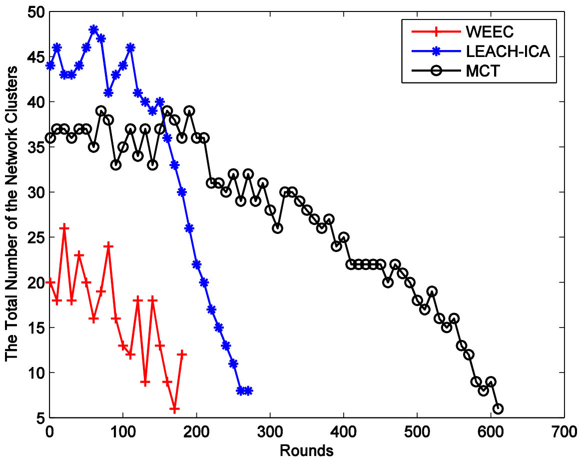

Figure 16. Total number of network clusters.

Also the communication energy depends on the distnace. In short distance communications, the sensor consumes square and in long distance communications, it consumes biquadratic of distance. Suppose that node A is located $2d$ distance of node C, and node B is located in the middle of them (distance from A and B is d) . If node A decides to send a packet to node C, $4d^2$ units of energy are consumed approximately. If node A sends the same packet to node C via node B, the d^2+d^2 ($2d^2$) units of energy will be consumed.

Every CH can provide the clustering services for a limited number of members. The MCT and LEACH-ICA algorithms prevent CH overloading through uniform CH deployment (Figure 16) and cluster the ordinary sensors with optimum number of non-overloaded clusters (Figure 17). Also a uniform deployment of CHs leads to reduce the short range communication cost (Figure 18), while in the WEEC algorithm, due to the lack of any mecanisim to prevent cluster overloading, some CHs become overloaded in every round (Figure 17).

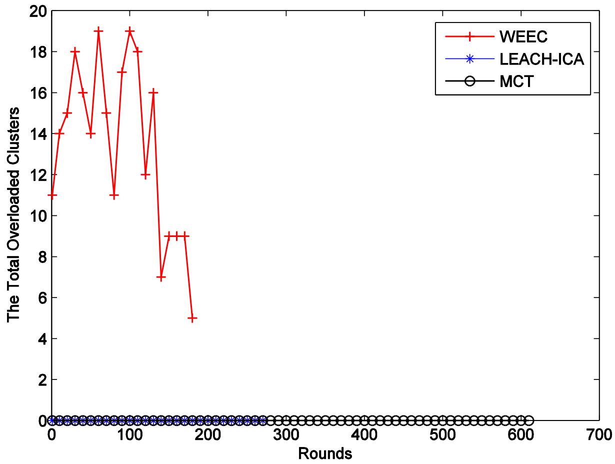

Figure 17. Total number of overloaded clusters.

As a result, addition to reducing the WEEC algorithm reliablity, the CHs overloading affects the inter-cluster and intera-cluster communication energy strongly.

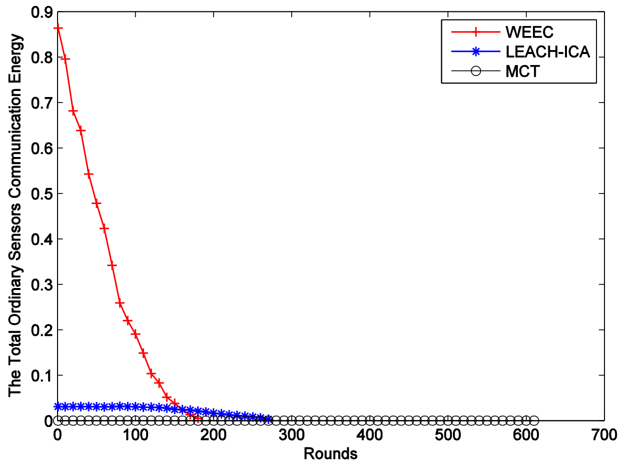

Figure 18. Total communication energy of ordinary sensors.

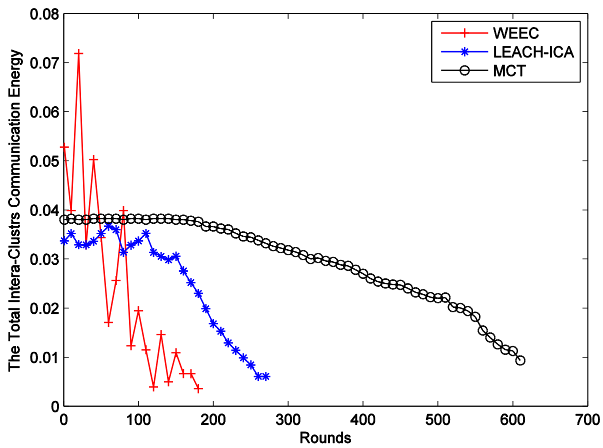

Figure 19. Total intera-cluster communication energy.

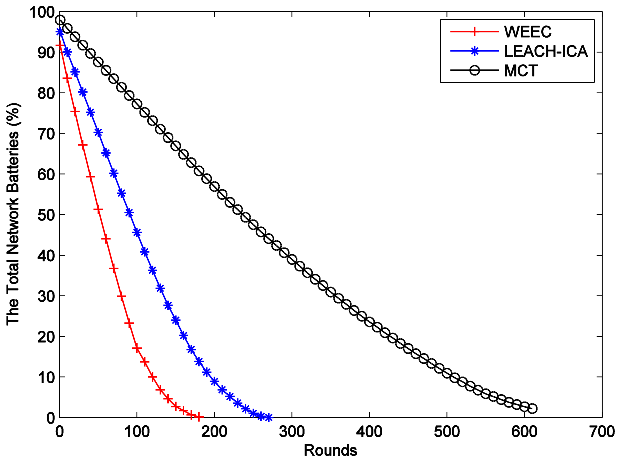

Figure 20. Total battery of network per rounds.

Figure 18 demonestarates that regarding the total number of CHs, the consumed intera-cluster communication energy of MCT is more wisely compared to the LEACH-ICA and WEEC protocols because MCT selects the best located sensors to act as a CH or SCH in every round. Moreover, an optimized communication energy in MCT leads to network liftime faverably. Therefore, using a more amount of communication energy in the WEEC and LEACH-ICA algorithms leads to drain the battteries more quickly, the death of living nodes, and the reduction of network lifesapn (Figure 20), while by reducing the communcation energy and efficient load balancing among all sensor nodes in the MCT algorithm, the sensor could conserve more energy and live for more rounds.

7. Conclusion

Due to the energy constraints, the WSN topology design becomes an open issue problem. In this work, a multi-layer clustering topology (MCT) using evolutionary algorithm for densely-deployed WSN through layer programming approach based on the most important WSN parameters including a number of living sensors, clusters, and sensor residual battery charge was proposed. The simulation results show that after deploying 200 sensors randomly and applying GA, ICA, and PSO to the proposed clustering algorithm for 200 iterations, the performance of PSO is better compared to others for some important parameters such as providing maximum network coverage, efficient cluster formation, and network traffic reduction. The results obtained demonstrate that the MCT hierarchy topology extends the lifetime of networks (by a factor of three approximately) and keeps full network coverage (100%) till 350 rounds (56% of network lifetime). The intera- and inter-communication energy in MCT clustering is lower compared to the WEEC and LEACH-ICA clusterings. In this work, the sleep scheduling was not taken into account, which will be undertaken in the future work.

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نشریه هوش مصنوعی و داده کاوی

طراحی توپولوژی خوشه‌بندی چندلایه در شبکه‌های حسگر بی‌سیم چگال با استفاده از الگوریتم‌های فراابتکاری

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چکیده:

با توجه به محدودیت منابع و پارامترهای پویا، کاهش مصرف انرژی مهمترین چالش در طراحی توپولوژی در شبکه‌های حسگر بی‌سیم می‌باشد. تمامی روشهای سلسله مراتبی پیشنهادی، یک شبکه حسگر با پارامترهای پیچیده و لایه‌های مختلف را در یک مرحله استفاده از الگوریتم‌های تکاملی خوشه‌بندی می‌کنند که این روش ممکن است منجر به کاهش کارایی و بازدهی الگوریتم طراحی توپولوژی خوشه‌بندی شود. در حقیقت، در یک توپولوژی شبکه حسگر، افزایش یک لایه خوشه، مصالحه‌ای میان پیچیدگی زمان و بهره‌وری انرژی است. در این مقاله، با توجه به مهمترین پارامترهای طراحی شبکه‌های حسگر، یک رویکرد جدید خوشه‌بندی سلسله مراتبی چند لایه با استفاده از الگوریتم‌های فرابتکاری برای شبکه‌های حسگر پیشنهاد شده است. الگوریتم‌های تکاملی مختلفی مانند الگوریتم ژنتیک، الگوریتم رقابت استعماری و بهینه‌سازی ذرات برای یافتن یک الگوریتم فراابتکاری کارآمد برای پیاده‌سازی روش خوشه‌بندی پیشنهادی مورد استفاده قرار گرفته‌اند. نتایج به دست آمده نشان می‌دهد که در روش پیشنهادی عملکرد الگوریتم بهینه‌سازی ذرات در مقایسه با سایر الگوریتم‌ها دیگر بهتر بوده و این الگوریتم توانسته است حداکثر میزان پوشش شبکه، شکل‌دهی موثر خوشه‌ها و کاهش مطلوب ترافیک شبکه را فراهم نماید. نتایج شبیه‌سازی الگوریتم خوشه‌بندی چند لایه شبکه‌های حسگر با استفاده از الگوریتم بهینه‌سازی ذرات نشان می‌دهد که این رویکرد جدید، توانسته است میزان انرژی ارتباطی را به طور قابل توجهی کاهش و طول عمر شبکه را به میزان ۲/۹۲ بار افزایش داده و پوشش کامل شبکه (۱۰۰٪) را تا ۳۵۰ دوره زمانی از طول عمر شبکه (۵۶٪ طول عمر شبکه) نسبت به سایر الگوریتم‌های خوشه‌بندی WEEC و LEACH-ICA فراهم می‌کند.

کلمات کلیدی: شبکه‌های حسگر بی‌سیم، سرخوشه، الگوریتم ژنتیک، الگوریتم رقابت استعماری، طول عمر شبکه.