Research Article

IMPROVING THE CLUSTER HEAD SELECTION METHOD BETWEEN CLUSTERS USING GENETIC ALGORITHMS AND ANT COLONIES FOR THE PURPOSE OF ENERGY EFFICIENCY IN WSN

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Article History: Received: 14 June 2021; Accepted: 12October 2021; Published online: 25 October 2021

Abstract: A state-of-the-art debate around the world, which has received a lot of attention is the Wireless Sensor Networks (WSN). It is a combination of many sensor nodes with a small size and limited telecommunication and computation capabilities to collect and transfer information from one environment to the user or the base station. The present study aims to improve the efficiency of WSNs. In the suggested genetic algorithm, the meta-innovative method for problem-solving and selection of cluster heads was devised. To optimize the place of cluster heads and to receive the data of each cluster, a path with the lowest amount of energy consumption should be found for this purpose the ant colony algorithm was considered. The results of the study show that the offered algorithms reduced the consumed energy of the transmission by shortening data transmission. The reason the transmission length was regarded as the cost function is the same transmission cost as the cluster heads.

Keywords: wireless sensor network, genetic algorithm, ant colony algorithm, cluster head, energy efficiency.

Introduction

WSN is one of the new technologies among today's advanced technologies. It paves the way for designing and making sensors with a low consumption power, small size, and a suitable price. These sensors are able to perform a number of tasks, such as receiving the various information of the process environment and transferring the information. Internet of Things (IoT) is the ecosystem of the devices and connected objects via the internet, which enables transmission and reception of the data. IoT provides instant access to the information relevant to each device with high efficiency and effectiveness. So far 5 billion smart devices are connected and until 2020 about 50 billion devices will be connected. It would result in a huge traffic in data transmission [1]. In fact, IoT's design should regard the challenging issues related to connection and communication. WSN are crucial to observation of IoT. They act like a digital skin and perform a virtual layer, where information related to physical world could be read by the computational system. WSNs are comprised of distributed spatial sensors that can collect environmental data independently [2]. WSNs are an ordinary ad-hoc wireless network that could collect, integrate or transfer the data autonomously. This is a fast-access technology to information in order to integrate the recent technological achievements (e.g. microelectronic, network and communication); thereby changing it into fundamental elements in different regions (e.g. army, monitoring the environment, controlling the industry and urban

transportation) [3]. In general, most sensor nodes are powered by battery. In other words, their energy source is limited. Moreover, the majority of WSNs are usually placed in a region far from human access. Therefore, charging them is costly or impractical. Also, the "hot spot problem" refers to the fact that the nodes near the sink perish faster than the nodes located on the edge. The lifespan of WSNs is terminated when one or more key node(s) consume their energy because of limited budget, as well as hot spot problem. So, increasing the lifespan is one of the main challenges for WSN with the lack of the equipment needed for each energy cultivation. Recently, plans aiming at extending the lifespan of WSNs have attracted a lot of attention. Since energy supply is limited, improving energy efficiency is an appropriate way for extending their lifespan [4].

With this in mind, clustering the data has many functions in WSNs. The importance of clustering in various sciences, type of the used data, speed of clustering, precision, and other parameters led to the introduction of different methods and algorithms in data clustering. Clustering is a categorization technique without monitoring, in which the set of data (usually vectors in multi-dimensional spaces) are classified into a certain number of clusters according to similarity/ dissimilarity criterion. In case the number of clusters is equal to k and there are n number of m dimension, the cluster algorithm would allocate each data to one of the clusters , due to do the fact that the allocated data to each cluster is more similar than the data in other clusters. In this study, taking into account the limitations in the WSNs and its vast use in IoT a solution will be proposed to enhance energy efficiency of these networks.

History and significance of the study

One of the main challenges in WSNs is energy efficiency. A data collection plan with energy efficiency in the cluster WSN (EEDAC-WSN) was provided. These intra-core communications can reduce the small-size control frames and therefore detailed frames of the selected nodes using the cluster head node [5]. Sariga and posola's study investigated unequal clustering protocols in WSN. They mentioned that WSN is a key technology for living everywhere, due to its vast spectrum of plans. Clustering has various advantages, such as energy efficiency, lifespan, scalability, and less delay, but could result in the hotspot problem. Hence, to avoid this problem unequal clustering was suggested [6]. Mani-Kantan and Padmapria (2019) performed selection and path-finding of the efficient cluster in the mobile WSN. In their study an efficient protocol was created, which is comprised of a mobile communication network based on the network, selection of the cluster head, and communication. Multi-step verification is performed to ensure the security from the source node to the destination node to transfer data. It was found that the suggested system is better than other extant methods in case of package delivery and energy use [7]. In Remika et al.'s study (2019) it is claimed that the optimal selection of cluster head results in the longer lifespan of the network and moderate energy consumption during its lifespan. The suggested protocol selected the optimal head cluster and demonstrated that it is more efficient than the hierarchy adapted to the available low-energy [8]. Ashena et al. (2019) stated that the huge amount of the energy produced (flexible hardware and software frameworks) could perform the calculations using some services. The aim was to restart for or against the accepted technology [9]. Beshkani and Azami (2019) offered a new energy-based intensive clustering protocol using a self-organizing neural network map for WSN, able to cluster network nodes according to the energy level and node coordinates [10]. Tayebi Ghasbe et al. (2019) introduced important clustering techniques for energy efficiency [11]. Akhlaghi (2019) investigated fuzzy logic algorithms based on dynamic energy-conscious clustering, which increase the network lifespan considering LND. The main advantage of these protocols is that the number of optimal cluster, formed in each round, is almost impossible in Low-Energy Adaptive Clustering Hierarchy

(LEACH) [12]. Abdan (2019) stated that the improved ant colony algorithms prevent high energy consumption of one local node. This prompts a more consistent energy consumption in each node [13]. An advanced optimization energy algorithm based on PSO (EPSO-CEO)[1] was offered for WSN, in which clustering and cluster head selection using Particle Swarm Optimization (PSO)algorithm is done according to minimization of energy consumption in WSN [14]. In addition, non-intensive operation for optimization of green energy in EH-WSN was investigated. Optimization is obtained by two dimensions: dynamic mode adaptation (activation) at the temporal dimension and energy balance at spatial dimension. Considering the interactions between autonomous distributed sensors, game theory for non-intensive optimization based on the local information of the problem of spatial energy balance was devised. In addition, reinforcement learning techniques were provided for temporal mode adaptation in a dynamic and unknown setting [15].

Research method

In the present study, a genetic algorithm was used for optimization. Due to suitability of this method in analysis, it was identified as a better method. Some of the main characteristic of the genetic algorithm is its multi-dimensionality and overall search, while maintaining the population from one generation to the other. In general, in every genetic cycle the following steps should be observed: production of the primary population, omission of the submitted population, regeneration of dominated population (various methods for selection of the parents and crossover of the chromosomes is required at this stage), and mutation followed by the control of the exit condition from the algorithm.

In the present study the length of the designed chromosome depends on the number of cluster heads. The designed chromosome contains the coordinates of the node locations. At first, the primary population is created randomly according to the number of the intended cluster heads and includes node coordinates. The designed chromosome is depicted in Figure 1.

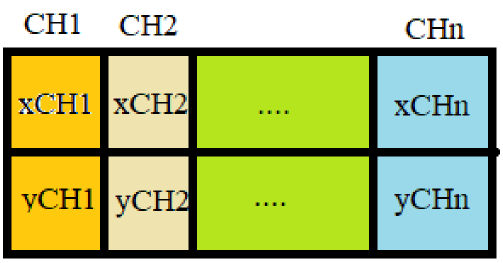


Figure1: the chromosome outline

The above chromosome has a two-line entry. The first line indicates the place of the sensor in the network in x coordinate and the second line indicates the coordinates of the sensors in the network's y direction. Moreover, CH is the node of the cluster head. In case there are 10 cluster heads, this chromosome has 10 columns which show the coordinates of 10 hypothetical cluster heads.

The Cost Function

[1]Enhanced PSO-Based Clustering Energy Optimization

In order to investigate the convergence of the optimization and observe the limitations of the problems, there is a need for a cost function (cost function). In this study aimed at discovering the minimum energy of data transfer, considering the fact that the amount of consumed energy relies on the data transfer distance, the amount of energy consumption is reduced by selecting the transfer distance as the cost function. For this purpose, at first a proximity matrix is produced for all ordinary nodes. The number of the lines of this matrix equals the number of the cluster heads and the number of columns equals the number of ordinary nodes. For every node, the distance from the node to all cluster heads is measured. Clustering operation is done according to the Euclidian distance of the nodes to the cluster heads.

$$CF = \sum_{i=1}^{CH} \sum_{j=1}^{node_{CH_i}} \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \qquad \text{Eq. } 1$$

In Equation 1, CH and node represent cluster head and sensor nodes and x is the distance of nodes from each other. The included indices are cluster head and simple node, respectively. Based on the above matrix the cost function defined in this study is:

Selection

Selection is done based on an order from the dominated to the subordinate. In this way, the two first parents would produce the first and second offspring and the second parents would produce the third and fourth offspring.

Crossover

In order to combine the populations, the percentage method was used. The two parents had two offspring. The first off spring had 75% of the genes first parent and 25% of the genes of the second parent. The offspring is depicted in Figure 2.

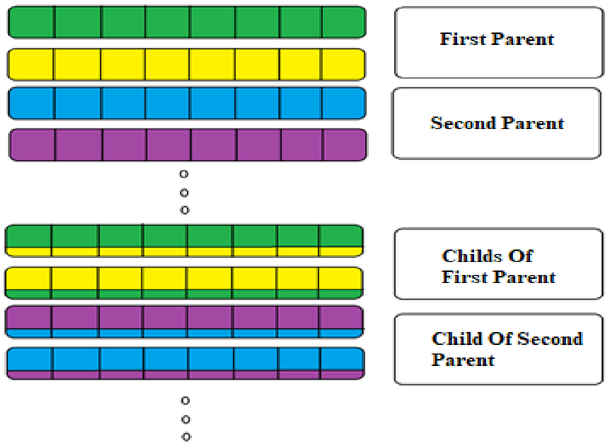


Figure 2: the offspring produced from crossover

In the above figure it is shown that each offspring is divided into two parts. This division is three fourth of each gene. According to the color of the parents, in every offspring the division of 75 to 25 is identified.

Mutation

In order to have mutations in this study, 5% of the population and 2% of genes would mutate. According to the following equation, the number of mutations is given. In this investigation, mutation means that based on the obtained mutations the same number of cluster heads transfer to other locations.

$$\text{Random selection of population} = 5\% \times \text{Number of population} \quad \text{Eq. 2}$$

$$\text{Number of Mutation} = \lceil 2\% \times \text{Random Selection Population} \rceil \quad \text{Eq. 3}$$

Using the above equations, the number of cluster heads that need to be relocated is obtained.

In order to optimize energy, the shortest path was selected. The reason for it is that the rate of transmission in the nodes was constant. This algorithm which performs optimization in a number of steps, uses the following new methods and ideas discussed separately:

Input: in this algorithm the input includes the sensor coordinates in the network, the place of the sink node, amount of the initial pheromone, and other necessary characteristics of the analysis.

Ant colony parameters: ant colony parameters (i.e. the number of ants, repetition, etc.) were included in the algorithm at this stage.

Examination of the sensors: at this stage it should be clarified that the sensors whose data is sent to the sink node is not sent any longer. In fact, by probing this condition the algorithm would not fall prey to repetitive calculations. However, it should be taken into account that this is useful in the movement of the second ant onward.

Offering a new assistant section to the algorithm: in the ant algorithm two possibilities influence path selection. The first one is the possibility based on pheromone and the other is the possibility achieved by the ant's personal choice. There is no intervention in the pheromone section, but in the other section by giving a direction, the ant's choice is given a proper range. Also, the randomness of this section is reduced. To do so, the following steps should be observed:

1) insertion of the nodes on the path: since all the information should be sent to the sink node, for this purpose the number of the nodes and the closest path from each node to the sink should be selected. Moreover, various nodes would be placed on the path.

2) calculation of the distance from the path to the first node: this could be calculated using the following equations:

$$dis_n = \min\left(\sqrt{(x_i - x_s)^2 + (y_i - y_s)^2}\right) \quad \begin{array}{l} i = 1, 2, ..., numnode \\ s \rightarrow startnode \end{array} \quad \text{Eq. 4}$$

In the above equation dis shows the distance and x and y are the coordinates of the location of the network nodes, so that the identified indices are distinguished.

Investigating the allowed nodes: at this stage the nodes placed in the transmission board of every sensor are considered as the allowed node and the nodes placed on the path are omitted:

$$n_{allowed} = n_{d<r} - n_{select} \quad \text{Eq. 5}$$

In Equation 5 $n_{allowed}$ indicates the allowed nodes and $n_{d<r}$ indicates all allowed nodes (selectable and non-selectable). n_{select} are sensors along the path and should be omitted from the list of allowed nodes.

Assigning a random weight to the ant's personal choice section: in this section, a personal possibility should be offered for every node. The nature of this part should be completely random so that all possible and rational paths have a chance to be selected. In this part, the aim was to give ants the far and uneconomical spots through a simple equation. Yet, there is a chance of selection for all nodes. In this equation attempt has been made to pass shorter paths and avoid going through the far paths to transfer data. This was achieved in Equation 6:

$$g_i = \frac{random(1 \sim 10)}{dis_i} \qquad i = 1,2,...,n_{allowed} \qquad \text{Eq. 6}$$

The numerator in Equation 6 maintains the random nature of the selection possibility and the denominator makes the selection range more rational to multiply the optimization speed.

Inserting the second controlling section (i.e., the distance of observing the second possibility according to the distance) means the normalized distance of every allowed node to the sensor node is achieved in this equation–represented as g_d– then, the possibility of the final personal choice of the ant is given.

Ant's final personal probability: the final probability is a combination of g_i and g_d obtained from Equation 7.

$$P_{ant_i} = \left(\frac{g_i}{\sum_{i=1}^{n_{allowed}} g_i} \times \frac{\sum_{d=1}^{n_{allowed}} g_d}{g_d} \right) \qquad \begin{matrix} i = 1,2,...,n_{allowed} \\ d = 1,2,...,n_{allowed} \end{matrix} \qquad \text{Eq. 7}$$

The above equation provides a probability based on the ant's personal choice. With a combination of this probability and the amount of pheromone (discussed in the next section), the final selection is done. According to the output of the equation the ant's willingness to move to one allowed destination is given without paying attention to the resultant pheromone. Due to inclusion of random selection in the analysis and in order to save the algorithm from the local optimal spots it was considered in the analysis.

The probability of the combination of pheromone and the ant's selection: by combination of the personal probability and pheromone in Equation 9 the ant's next destination is determined:

$$Pt_i = \frac{P_{ant_i} \times P_{Phromon_i}}{\sum_{i=1}^{n_{mojaz}} P_{ant_i} \times P_{Phromon_i}} \qquad i = 1,2,...,n_{allowed} \qquad \text{Eq. 8}$$

Where P_{ant_i} indicates the probability of the random selection of the destination node by the i^{th} ant and the probability of selection based on the pheromone of i^{th} ant.

Inclusion of energy in the probabilities: in order to take into account, the energy for controlling the heat of the sensor nodes, the amount of the remaining energy of the allowed nodes in the normalized way are multiplied by the probability. Then, the highest amount is selected as the next node.

$$W_{normal_i} = \frac{E_i}{\sum_{j=1}^{n_{allowed}} E_j} \qquad i = 1,2,3,\ldots,n_{allowed} \qquad \text{Eq. 9}$$

At first, in Equation 9 the normalized weight of each node is obtained.

$$P_{Total_i} = P_{t_i} \times W_{normal} \qquad i = 1,2,3,\ldots,n_{allowed} \qquad \text{Eq. 10}$$

The given probability of every node in multiplied by the normal weight in Equation 10. After calculation of the final probability, there is a final selection, in which the maximum of the given probability, would be the ant's selection of the next path.

$$n_{select} = Max(P_{Total_i}) \qquad \text{Eq. 11}$$

In Equation 11, n_{select} is the final selection node based on the combination of all probabilities in the study.

The cost function will be checked in the following.

Pheromone is calculated and updated after determining the ant's path.

$$Phromon_i = \frac{1}{L_{path}} + Phromon_i \qquad i = selected \quad node \qquad \text{Eq. 12}$$

In Equation 12, L_{path} is the length of the ant's selected path. In fact, the shorter the length of the selected path, the lower the cost is. Also, a stronger pheromone is put in the algorithm.

Based on the pheromone's natural structure it is diminished after a while. When 10 ants cross the paths, the selected nodes before the 10th cycle are recalled again and the resulting pheromone by their selection is removed.

$$Phromon_i = Phromon_i - \frac{1}{L_{path_i}} \qquad \begin{matrix} i = z - 10 \\ z > 10 \,\&\, z = iteration \end{matrix} \qquad \text{Eq. 13}$$

In case of convergence of the answers that result from the repetition of 50 complete cycles without the intended optimization, the optimization stops; or else, the algorithm returns to the section of examination of the sensors. This continues until the convergence condition is fulfilled. In other words, repetition of the cost function implies that ants find the best path and no other ant has found a better path. A better path is shorter and a path with a shorter length is the same path with lower required energy. So, parallel to the convergence condition, the amount of energy would be optimized, as well.

Results and analysis

In this section, the quality of the algorithm is probed. Afterwards, a case analysis is provided to assess and evaluate the findings. Therefore, in the first step, the problem is stated. Then, the cluster heads are found. In the next step, the optimal transfer path is sought.

variables	The amount
Network length	200
Network width	100
place of sink node	(100, 50)
number of nodes	2752
Number of cluster heads	100
Number of clusters	100
The number of the primary population in genetic	100
Percentage of mutations in populations	5%
Exit condition of optimization of the place of cluster	20 repetitions
Exit condition of the optimization of the transfer path to	20 repetitions
Clustering method	Fuzzy clustering
Cluster head locating method	Genetic algorithm
Path-finding to send data	Ant colony algorithm

In the next step using the fuzzy clustering algorithm fed into the algorithm, clustering of the network was done.

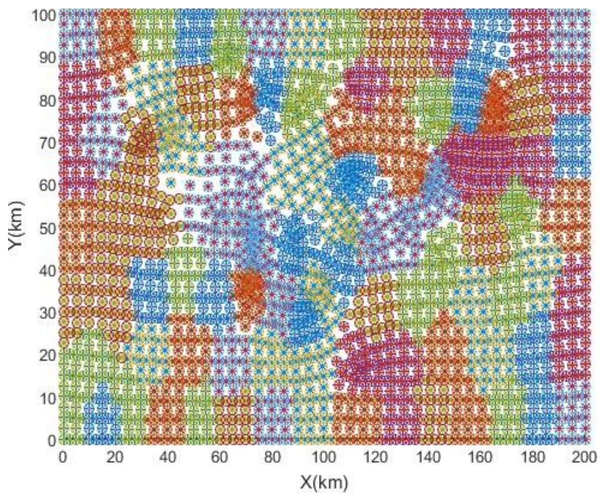
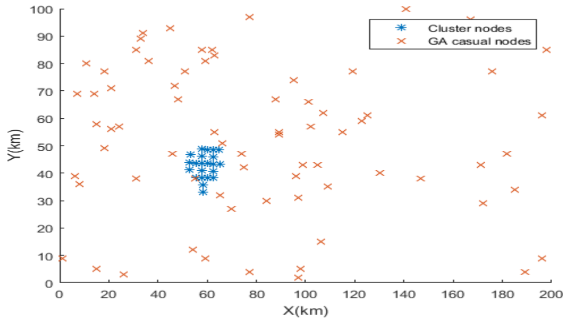


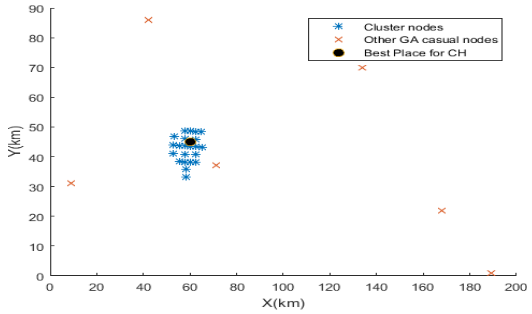
Figure 3: fuzzy clustering of the network

Next, for each observed cluster in this numeral example a cluster head should be found. It was done through the genetic algorithm and will be discussed later. For this purpose, the genetic algorithm is repeated 100 times for every cluster to find the best place of the cluster head of each cluster in the network. To do so, in each cluster 100 random nodes were placed in the given network, so in each cycle of the program 100 analyses take place. In fact, the number 100 is not the optimization cycles. It is only intra-circle repetitions or the primary populations for optimization available to the genetic algorithm to select the best location regarding the appropriateness of this spots.

The path to the optimal place for cluster head is given in Figure 4. At first the distribution of these spots was high. The reason for this was the initial random nature of the primary populations. With some investigations, it moves to the optimal spot (as shown in Figure 4b). It is shown in Figure 4c that all populations converge to the optimal spot. Only the nodes caused by mutations (inserted to reach the optimal location) put in the algorithm for random movement, were outside the specific range.



a



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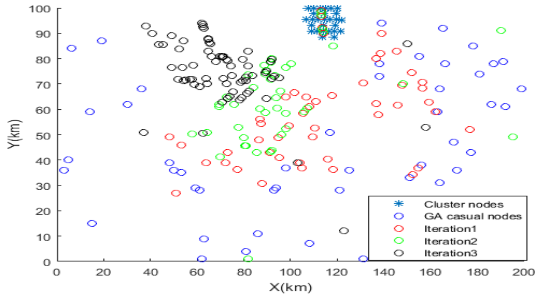

c

Figure 4. Convergence in cycles

What was mentioned in this section was intended only for one cluster head. Later, the changes in cost function in a number of cluster heads will be depicted. Four clusters were selected randomly and the changes in the efficiency and cost function were illustrated.

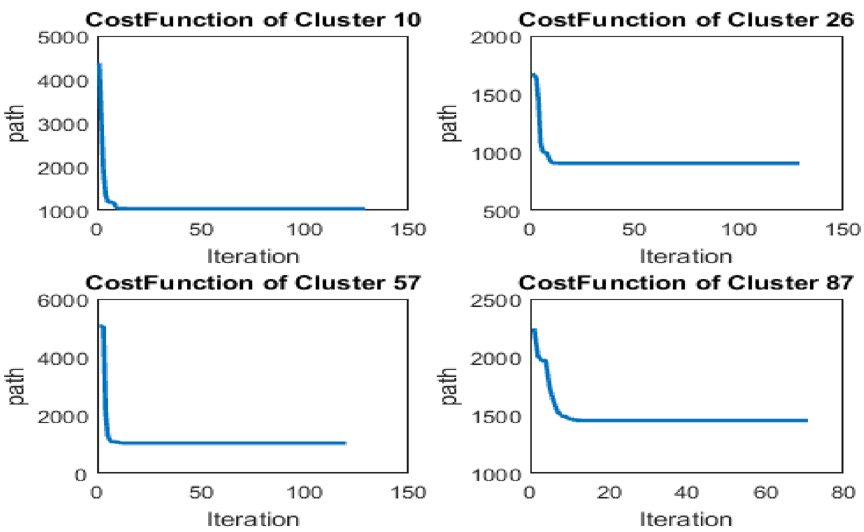

Figure 5: changes in cost function in the four random clusters

It is shown in Figure 5 that the changes in the cost function were similar and caused by the probable space. It should be kept in mind that the probable space in the mathematical problems are understandable and observable. However, considering meta-innovative problems this probable space was not observable. In fact, it is an environment with limitations and cost function of the algorithm. The vertical axis of Figure 6 is the path length, which is the basis of the cost function. So, a reduction in this amount leads to the fulfillment of goals.

By optimizing and locating all cluster head nodes in the following figure, the place of each cluster head could be seen. A suitable path to transfer data from every cluster head to the sink node at the center of the network should be found. It is discussed in the following.

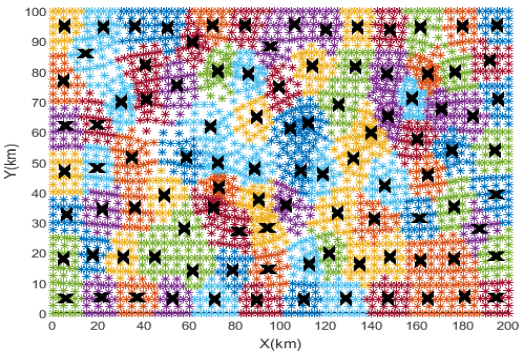

Figure 6: the place of cluster heads in every hundreds cluster

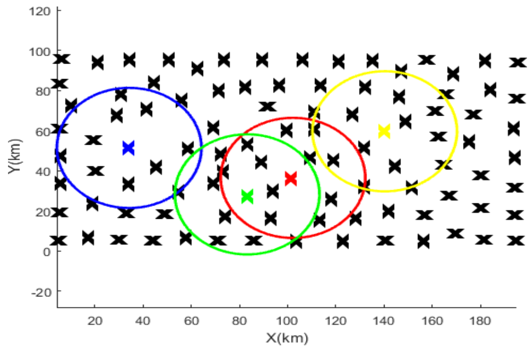

Figure 7: efficient range graph of every cluster and discovering the initial allowed nodes for path-finding

At this stage other nodes are excluded from ant colony analysis and only cluster heads transmit data via other cluster head notes or directly transmits data to the sink nodes. The suitable range of the node was about 30 meters in this study.

It is evident in Figure 7 that each sensor is able to send to a limited number of sensors at its efficient range. For example, four sensors were selected in this study and their efficient range is illustrated in a circle. The nodes located at this range are able to receive data from the sensors (i.e. the allowed nodes).

After path-finding the changes in cost function, together with the path could be observed. For this purpose, the shortest path was chosen as the basis of transmission, since in order to transmit data energy consumption entirely depends on the length of transmission. Paths with a lower energy also have the shortest length in the networks with the same transmission rate.

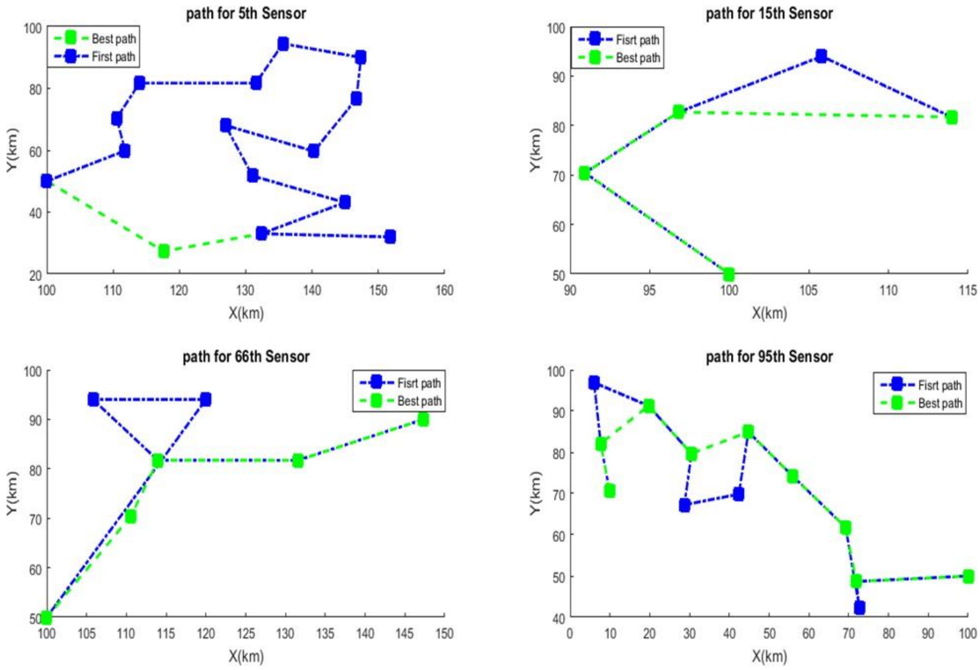

Figure 8: the optimal path in four random clusters

It was shown that the first ants crossed many paths. But on the final path– where it is optimal– some of the nodes that were longer were removed and the path was shorter. It is noteworthy that throughout sensor 5, the first ant was the so-called missed ant. The reason is that the difference between the optimal path and the initial path is noticeable. It shows that the offered algorithm is capable of returning the wrong paths by the ants. The results are acceptable based on the length of the optimal path.

Conclusion

Based on the available models a number of noteworthy results was achieved. These models are discussed in the following.

According to the results in the finding and optimization section of cluster head location, finding the center of the density could be very useful; since the aim was set based on the distance of the transfer. As a result, the best place for a cluster is where all nodes are close to each other. This is achieved by the square of the distance between the selected place in each optimization step and all cluster head nodes. Also, in a regular shape the best place for observing in a density center is the surface center that could be found easily. However, in complex shapes, which offers the most optimal algorithm, this place is hard to find. In ant colony algorithms attention to the simultaneous probability of the ant's personal probability, along with pheromone stops the ants from following the lost ants. In case the personal probability of the ant is not deemed, if an ant is lost in the first cycle other ants will follow it based on enhanced pheromone. With consideration and inclusion of this probability in the analysis, it was shown that even if the first ant is lost, other ants will find the right path and the lost ant returns to the path. Measuring the energy in this path was based on the path length, since energy consumption was based on the efficient range and the distance the data is transferred. The optimization is also according to the shortest path. It is noteworthy that in every optimization, only the nodes that have the remaining energy and are effective in the range are selected and placed on the allowed nodes list. With an increase in the efficient range of the sensors, the number of nodes on the path decreases. However, direct transmission of data to sink depletes the energy of cluster heads. In this way energy is gradually used for transfer from other nodes. Furthermore, energy consumption is distributed in the network nodes and the network's average energy shows a longer lifespan. Separating the list of the allowed nodes for transmission and also the target nodes at the beginning of the ant colony optimization accelerates the optimization. In the present study using the two types of nodes reduced the number of the lost ants and accelerated the transfer of the data to the sink.

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