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Improving the Lifetime of Clustering-Based Wireless Sensor Networks by Considering the Conditional Dependencies in Inter-Cluster Routing

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ABSTRACT

Considering the importance of energy consumption of cluster heads and the impact on the lifetime of cluster heads on the network lifetime, this paper addresses the issue of multi-hop inter-cluster routing. In the procedure proposed by the present study, first some analyses were done demonstrating that selecting the next hop for each cluster head is influenced by selecting the next hops for other cluster heads; therefore, to perform the inter-cluster routing, the dependency between the choices of next hops should be taken into consideration. Afterwards, we apply an evolutionary algorithm that is capable of taking these conditional dependencies into account in finding optimal routes between the cluster heads. In this evolutionary algorithm, the network lifetime is used as the fitness function for evaluating the solutions. The proposed method is evaluated using simulation and is compared to a classic routing method and two methods based on genetic algorithm (which lack the ability to take conditional dependencies into consideration). The results reveal that the proposed method improves the network lifetime.

Keywords: Wireless sensor networks, Inter-cluster routing, Conditional dependencies, Lifetime.

Mathematics Subject Classification: 90B18, 68M10, 60XX

Computing Classification System : I.2.8, F.1.2, C.2.2

1. INTRODUCTION

Wireless sensor networks are made up of a large number of sensor nodes with low processing power and low energy consumption. The sensors gather data from the environment and send the data toward the sink (Akyildiz, 2009; Nikzad, 2014; Arabi, 2016; MotahariNasab, 2016). Wireless sensor networks are limited in terms of energy (Barry 2009; MotahariNasab, 2016) because sensors work on small batteries and in many applications, if the sensor battery goes dead after the deployment of the sensors in the environment, it is impossible or very difficult to replace the sensors or their batteries (Giuseppe, 2009; Hajian, 2010A; Pratyay, 2013). For this reason, energy consumption is the greatest challenge in wireless sensors (8) and the energy consumption in the networks must be minimized so as to improve the network lifetime(Hajian, 2010B).

One of the most efficient ways to reduce energy consumption in the wireless sensors is to cluster the sensors (Pratyay, 2013; Palan, 2017; Liu, 2012; Suneet, 2013). In cluster-based routing, sensor nodes are divided into clusters each of which has a leader known as cluster head. The members of each cluster send the data they have gathered to the cluster head. The cluster head processes the data received and then forwards the data to the sink (Pratyay, 2013; Bari, 2009). In fact, since in every cluster only one node (i.e. the cluster head) is involved in the routing and transmission of data to the sink, clustering the sensors reduces energy consumption (Pratyay, 2013).

Various studies have addressed clustering in sensor networks. The first study in this field is LEACH (low-energy adaptive clustering hierarchy) algorithm. After the LEACH algorithm, other methods (Heinzelman, 2002; Bagci, 2013; Liao, 2013; Sanjuna, 2016; Younis, 2014; Boyinbode, 2010; Abbasi, 2007) have been introduced for clustering the sensors in wireless sensor networks.

There are three stages in cluster-based routing algorithms (MotahariNasab, 2016):

1. selecting the cluster heads from among the number of candidates so that a criterion such as the energy consumption of the nodes is optimized
2. cluster formation: (i.e. assigning the sensors to the cluster heads)
3. data transmission: Data transmission in the clustering-based sensor networks is done on two levels: from sensors to the cluster heads and from the cluster heads to the sink

The third stage, i.e. data transmission in the wireless sensor networks, consumes more energy than the other stages (Hajian, 2010; MotahariNasab, 2016) and this is addressed in the present study. This study focuses on the second level of data transmission, i.e. data transmission from the cluster heads to the sink.

The link between the cluster heads and the sink may be either single-hop or multi-hop (Bari 2009; Suneet, 2013). In the single-hop method, each cluster head gathers the data from its cluster members and, having processed the data, forwards them directly to the sink. In the multi-hop method, each cluster head forwards the data of its cluster members to the sink through other cluster heads. Considering that the increased distance between the source and destination increases the energy consumed for data transmission, use of the multi-hop method often reduces energy consumption and increase the network's lifetime (Bari 2009). Besides, for large-scale networks, the multi-hop transmission of data from the cluster heads to the sink is the only choice (Bari 2009).

The lifetime of cluster heads is very important because the lifetime of the sensor network is strongly dependent on the lifetime of the cluster heads. The lifetime of cluster heads is influenced by the method of data transmission from the cluster heads to the sink. If the multi-hop method is used to transmit the data from the cluster head to the sink, and assuming that each cluster head has d valid one-hop neighbors, for a network with n cluster heads, the number of routes from the cluster head to the sink is $O(d^n)$. To find a routing which is efficient in terms of energy consumption, such a broad search space must (particularly for large-scale networks) be searched within an acceptable time (Bari 2009; Suneet, 2013). For this reason, in addition to the conventional methods, heuristic and meta-heuristic methods are also used for this purpose (Bari 2009; Suneet, 2013, Ioannis, 2016). One group of the widely used and efficient meta heuristic methods to solve such problems is evolutionary algorithms, particularity the genetic algorithm (Kaedi, 2017, Shamaei and Kaedi, 2016). Section 2 reviews some studies of the use of evolutionary algorithms for routing and data transmission from the cluster heads to the sink.

In this paper, a method is developed to find the data transmission route from each cluster head to the sink, which, unlike our former proposed methods (Bohlooli and Jamshidi, 2014; Ghasemi, et al., 2015), considers the conditional dependencies between the cluster heads to design the appropriate route for forwarding the data from the cluster heads to the sink. This is done with the use of an evolutionary algorithm called 'Bayesian optimization algorithm'. The results of this method are compared to the traditional routing method MHRM and the two previous methods based on genetic algorithm (Bari 2009; Suneet, 2013) in terms of network lifetime.

In Section 2, the previous studies on the use of evolutionary algorithms for transmitting the data from the cluster heads to the sink in the wireless sensor networks are reviewed. Afterwards, in Section 3, the considered network model is developed. In Section 4, the proposed method is introduced based on Bayesian optimization algorithm. Section 5 evaluates the proposed method and, finally, Section 6 concludes the paper with a summary.

2. EVOLUTIONARY ALGORITHMS AND THEIR APPLICATION IN TRANSMITTING THE DATA FROM THE CLUSTER HEADS TO THE SINK

In this section, first the evolutionary algorithms, particularly the genetic algorithm, are briefly reviewed and afterwards, their use in transmitting the data from the cluster heads to the sink in wireless sensor networks is investigated.

2.1. Evolutionary algorithms and genetic algorithm

Evolutionary algorithms have been inspired by Darwin's theory of evolution and natural selection. They attempt to solve optimization problems by evolving a population of solutions (Kiran and Findik, 2015, Precup, 2011, Skrjanc, et al., 2005). The genetic algorithm (Goldberg, 1989; Holland, 1975; Mitchell, 1996) is one of the best-known and most widely used evolutionary algorithms. This algorithm starts by a population of candidate solutions often generated randomly. Each of the candidate solutions is called a chromosome and consists of an array of genes. A fitness function is used to evaluate the efficiency of each solution. The genetic algorithm uses random search to find the optimal solution. For this purpose, from among the population, pairs of chromosomes are selected as parent chromosomes based on one of the various selection methods, such that fitter solutions have a greater chance for being selected. Afterwards, some of the genes of the two chromosomes are interchanged by the crossover operator. Then, the mutation operator makes some minor random changes on some of the chromosome genes. The next generation of chromosomes are produced through these operations. These steps are repeated until reaching the termination condition of the algorithm.

In addition to the genetic algorithm, other optimization algorithms fall into the evolutionary algorithms category too. Those algorithms include the Bayesian optimization algorithm (Pelikan, 2002; Pelikan, 2005), differential evolution (Storn, 1997) and Evolutionary programming (Poli, 2014), each of which are appropriate for solving the optimization problems with certain characteristics.

2.2. A review of the use of evolutionary algorithms in the data transmission from the cluster heads to the sink

As mentioned, the three issues in the cluster-based sensor networks are the selection of the cluster heads, cluster formation, and data transmission. Some previous studies (Jin, 2003; AfrashtehMehr, 2011; Enan, 2011; Seo, 2009; Hussain, 2007; Youssef, 2007; Peiravi, 2013) have used the genetic algorithm to solve these problems. However, considering the issue addressed in this paper, later on in the rest of this section only some cases that use of the genetic algorithm in order to solve the problem of transmission of data from the cluster head to the sink are reviewed.

In (Bari, 2009), a sensor network is taken into account in which the cluster heads are determined based on the sensor node distributions (Bari, 2007) and the predetermined grid points (Bari, 2006B). Then the sensors are assigned to the cluster heads. Afterwards, the aim is to find an appropriate multi-hop route from the cluster heads to the sink. This is done by using the genetic algorithm and the proposed method is named EEGA (energy efficient genetic algorithm). Each chromosome is considered as an array of integers, the length of which is equal to the number of cluster heads. Each gene shows the next hop of a cluster head. Figure 1 displays an example of a chromosome and its corresponding route. In the initial population, the value of each gene is randomly selected from the neighbors existing in the transmission range of the cluster head. Thus, all the chromosomes of the initial population indicate valid routings and the aim is to find a routing which increases the network lifetime. The fitness of each chromosome is defined based on the network lifetime. Uniform and k-point crossover methods are used to exchange the genes of parent chromosomes, and the roulette wheel method is used to select the chromosomes. An example of the crossover operation is presented in Figure 2. It has been shown that this routing method increases the network lifetime by 200% in comparison to the minimum hop routing model (MHRM) (Gupta, 2003) and minimum transmission energy model (MTEM) (Heinzelman, 2000). The first draft of this study has been presented in (Wazed, 2007).

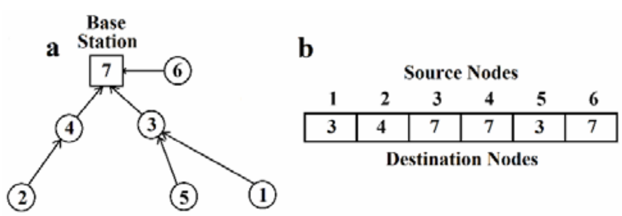


Figure 1. An example of a chromosome and its corresponding route (5)

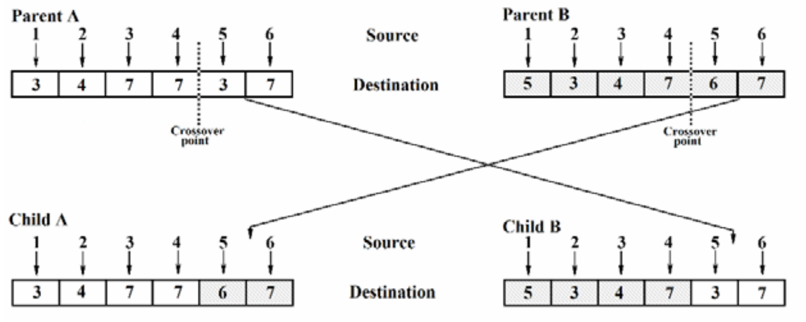


Figure 2. An example of chromosomes crossover (5)

In (Suneet, 2013), a method named genetic algorithm-based routing (GAR) has been introduced in which the network model and chromosome structure as well as the crossover operator are like as EEGA (Bari, 2009). One of the differences between the two methods is the definition of the fitness function. In GAR, the fitness function is defined as the reverse of total transmission distance in one round of data collection or data transmission to the sink. These two methods differ in the selection method and the detail of the mutation operator in genetic algorithm. It has been shown that the GAR method has been able to improve the network lifetime by 230% more than the MHRM (Gupta, 2003) method.

The studies reviewed had used the genetic algorithm to find the multi-hop route form the cluster heads to the sink. The genetic algorithm is one of the existing evolutionary algorithms and to the best of our knowledge, no other evolutionary algorithm has been used to solve this problem. However, when there are a conditional dependencies between the variables of the decision problem, the use of more advanced evolutionary algorithms that take into account the conditional dependencies is a more appropriate choice. In Section 4, it will be shown that there are conditional dependencies between the variables in the problem of multi-hop routing from the cluster heads to the sink and afterwards, a more appropriate evolutionary algorithm called 'Bayesian optimization algorithm' is used to solve this problem.

3. NETWORK MODEL

In this study, a network is assumed where a number of sensors are randomly distributed and the cluster heads are selected based on the sensor node distribution (Bari, 2007). The selection of cluster heads is centralized and is performed in the sink and is then broadcast to all the nodes. After the selection of the cluster heads, each sensor is assigned to one cluster head which is the nearest among the cluster heads existing in its transmission range. It is assumed that every sensor is at least in the transmission range of one cluster head and the sink is informed of the physical position of all the nodes by a device like GPS. Each sensor collects the data from the environment and forwards them directly to the related cluster head.

It has been assumed that the sink does not have energy limitation and the network structure is fixed, i.e. the position of sensors and cluster heads is fixed after they are deployed in the environment.

The problem is finding the optimal multi-hop route from the cluster heads to the sink, such that the network lifetime is maximized.

Each period of gathering data from all cluster heads and forwarding them to the sink is considered as one round (Heinzelman, 2000; Suneet, 2013; Bari, 2009) and the network life time is defined as the number of rounds until the first relay node runs out of power (Heinzelman, 2000; Suneet, 2013; Bari, 2009).

In each round, the energy consumed by each node i is modeled based on the first order radio model (13; 39) as:

$$E_i = E_{R_i} + E_{T_i} \tag{1}$$

where E_{R_i} is the energy consumed by node *i* for receiving data from node *j* and is calculated as:

$$E_{R_i} = \alpha_1 . b_1 \tag{2}$$

In (2), b_i is the number of bits received by the ith cluster head in a round, and a_1 is the receive energy coefficient. ET_i is the energy consumed by node *i* for forwarding the data to node *j* (node j can be another cluster head or sink) and is calculated as:

$$E_{T_i} = \alpha_2 . b + \beta . b_i . d_{i,j}^m \tag{3}$$

where $d_{i,j}^m$ is the Euclidean distance between node *i* and node *j* and α_2 is the transmit energy coefficient. *b* is the amplifier coefficient and *m* is the path loss exponent which is a value between 2 and 4.

4. PROPOSED PROCEDURE

This paper investigates the multi-hop routing of cluster heads to the sink. The aim is to improve the network lifetime. In multi-hop routing, the next hop of each cluster head to transmit the data to the sink is determined. Later on in this section, first, in Subsection 4.1, it is demonstrated that there are conditional dependencies between the selections of next hops and they may not be considered as independent decisions. Afterwards, in Subsection 4.2, the Bayesian optimization algorithm is introduced which is capable of taking into account these conditional dependencies during optimization procedure. In Subsection 4.3, the details of the application of Bayesian optimization algorithm for multi-hop routing from cluster heads to the sink are discussed.

4.1. Conditional dependency between the selections of next hops of cluster heads

As mentioned previously, in order to design the multi-hop routes from the cluster heads to the sinks, the next hop of each cluster head must be selected so that the routing tree can be designed based on next hops and the route from each cluster head to the sink be derived.

The problem raised here is that the selections of the next hops of cluster heads should not be considered as independent decision. This will be explained as follows:

The degree of appropriateness of ‘the selection of node j as the next hop of cluster head i’ is the dependent upon the other cluster heads that select cluster head j as their next hop. If other cluster heads with high total traffic use cluster j as the next hop, the use of cluster head j as the next hop of cluster head i increases the load of cluster head j and, consequently, increases its energy consumption. This causes cluster j to quickly run out of energy and break down. So, It can reduce the network lifetime.

Example: In this very simple example, we present conditions where there are dependencies between the selections of next hop for various cluster heads. Suppose there are six cluster heads in the wireless sensor networks, each of which collects data from the existing sensors in the related cluster heads and forwards the data to the sink in a multi-hop routing (i.e. through other cluster heads). In Figure 3.a, the cluster heads 1 and 2 are in transmission range of cluster head 3 and are considered neighbors of cluster head 3. Of these two cluster heads, the one which is more appropriate and improves the network lifetime should be selected as the next hop of cluster head 3. Suppose that, presently, cluster head 1 is selected as the next hop of cluster heads 5 and 6, and that cluster head 2 is selected as the next hop of cluster head 4; that is the routing tree and the next hops of cluster heads are similar to Figure 3.b. To simplify the equations, without losing the generality, two simplifying assumptions are used. Even though we use these assumptions to ease the explanations, these conditions can occur in practical applications.

Simplifying assumption 1: The number of bits that are collected by the cluster heads 1, 2, 3, 4, 5, and 6 from the sensors belonging to their clusters, and to be transmitted to the sink, are all equal; that is

$$b_1 = b_2 = b_3 = b_4 = b_5 = b_6 = b \tag{4}$$

Simplifying assumption 2: The distance from cluster head 1 to the sink is equal to the distance from cluster head 2 to the sink (S stands for sink); therefore,

$$b_{1,S} = b_{2,S} = d \tag{5}$$

According to the discussion in Section 3, energy consumption of cluster head 1 in Figure 3.b consists of two parts:

- The required energy for receiving data by cluster head 1, which is calculated according to (2), as follows,

$$E_{R_1} = \alpha_1(b_1 + b_5 + b_6) \tag{6}$$

That can be rewritten considering the first simplifying assumption, as follows:

$$E_{R_1} = 3.a_1.b \tag{7}$$

- The required energy for transmitting data from cluster head 2 to the sink (node S), which is calculated according to (3), as follows,

$$E_{T_1} = \alpha_2.(b_1 + b_5 + b_6) + \beta.(b_1 + b_5 + b_6).d_{1,S}^m \tag{8}$$

That can be rewritten by considering the first and second simplifying assumptions, as follows:

$$E_{T_1} = 3.\alpha_2.b + 3.\beta.b.d^m \tag{9}$$

Hence, according to the (1), the total energy consumed by cluster head 1 is calculated as follow:

$$E_1 = E_{R_1} + E_{T_1} = 3.(\alpha_1.b + \alpha_2.b + \beta.b.d^m) \tag{10}$$

Besides, accordingly, the energy consumption of cluster head 2 in Figure 3.b can be computed as follows:

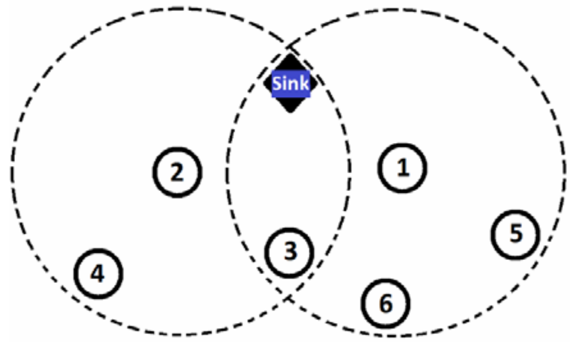
$$E_{R_2} = \alpha_1(b_2 + b_4) = 2.\alpha_1.b \tag{11}$$
$$E_{T_k} = \alpha_2(b_2 + b_4) + \beta(b_2 + b_4)d_{k,S}^m = 2.\alpha_2.b + 2.\beta.b.d^m \tag{12}$$
$$E_2 = E_{R_2} + E_{T_2} = 2.(\alpha_1 b + \alpha_2 b + \beta.b.d^m) \tag{13}$$

Therefore, if the selection of the next hop for other cluster heads are done as in Figure 3.b, the energy consumption of cluster head 2 is less than cluster head 1 and the selection of cluster head 2 as the next hop of cluster head 3 is more appropriate; since this choice makes energy consumption more balanced and may increases the network lifetime.

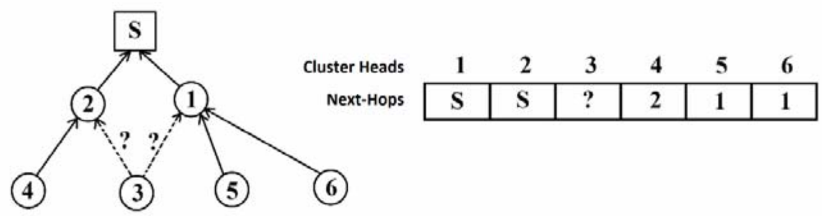
Now consider Figure 3.c. The energy consumption of cluster heads 1 and 2 in this figure would be as follows:

$$E_1 = E_{R_1} + E_{T_1} = 2.(\alpha_1 b + \alpha_2 b + \beta.b.d^m) \tag{14}$$
$$E_k = E_{R_2} + E_{T_2} = 3.(\alpha_1 b + \alpha_2 b + \beta.b.d^m) \tag{15}$$

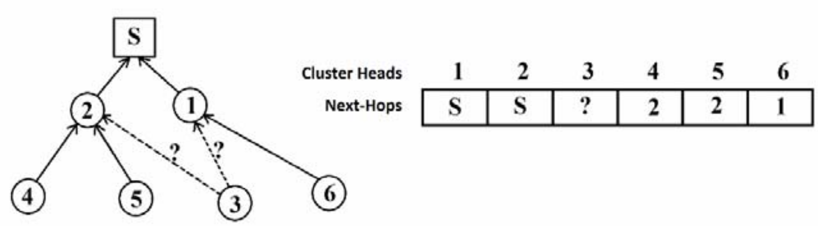
Hence, if the selection of the next hop for other cluster heads is done as in Figure 3.c, the energy consumption of cluster head 1 is less than that of cluster head 2, and the selection of cluster head 1 as the next hop of cluster head 3 is a more appropriate choice, because it increases the network lifetime.



An example of a wireless sensor network with six nodes



B. The first multi-hop routing tree



C. The second multi-hop routing tree

Figure 3. An example of the wireless sensor networks with six nodes and multi-hop inter-cluster routing tree

This example shows that the selection of the next hop for cluster head 3 is conditionally dependent upon the selection of the next hops for other cluster heads and cannot be decided independently without considering the other decisions (that is, the selection of next hops for other cluster heads). Therefore, to find the optimum routing from cluster heads to the sink, if a method is provided that considers these conditional dependencies between the selections, a more appropriate multi-hop route can be found which improve the network lifetime. A method like genetic algorithm which has been used in previous studies to solve this problem (see section 2) does not consider these dependencies between the choices. In genetic algorithm, by applying crossover operator, chromosomes that contain sub-solutions (i.e. choices on the next hops) break into parts and the sub-solutions are exchanged in two chromosomes. However, it is probable that the existence of these sub-solutions next to each other in a chromosome cause routing with a long lifetime (that is, a chromosome with high fitness) but exchanging and combining of the sub-solutions of the two chromosomes do not follow the conditional dependencies; therefore necessarily, two parent chromosomes with long lifetime would not produce two offspring chromosomes with long lifetime. Also, in greedy routing methods, such as Kruskal and prim's algorithms, decisions on the next hops of the nodes are taken locally and greedily, and the relationship between this decision and other decisions are not considered. Later on in this paper, the Bayesian optimization algorithm for routing from cluster heads to sink that has the potential to consider conditional dependencies between the sub-solutions will be used. Afterwards, the effect of considering these consider conditional dependencies will be evaluated in Section 5.

4.2. Bayesian optimization algorithm

Bayesian optimization algorithm (BOA) is a kind of evolutionary algorithm that develops a population of candidate solutions by building Bayesian networks and sampling them (Kaedi and Ahn 2017). In fact, the general procedure of this algorithm is similar to genetic algorithm, but instead of using standard operators of genetic algorithm (i.e. crossover and mutation operators), this algorithm constructs Bayesian networks and samples them to prevent the “building block” disruption (i.e. the interdependent sub-solutions whose juxtaposition increases the quality of solutions) which is a challenge and drawback in genetic algorithm.

A Bayesian network is a directed acyclic graph that represents probabilistic relationships among a set of variables. In this graph, each node corresponds to a variable and the edges correspond to conditional dependencies. Beside the directed acyclic graph, a set of conditional probability tables is used to represent the probability of conditional dependencies among the variables (24).

In the BOA algorithm, the initial population is produced randomly with a uniform distribution on all possible solutions. The population is then updated through several successive iterations. Every iteration consists of four steps. Firstly, the promising solutions are selected from the current population using one of the selection methods (such as those used in the genetic algorithm). In the second step, a Bayesian network compatible with promising solutions is built. Third, the new candidate solutions are produced through sampling the Bayesian networks. And in the fourth step, new candidate solutions join the previous solutions and replace all or some of them. These four steps are repeated until a termination condition is reached (Pelikan, 2002). In this paper, two termination conditions are considered: reaching a predefined number of iterations or reaching the algorithm convergence.

Thanks to the use of the Bayesian network, this algorithm is able to consider the multivariate interactions between variables (sub-solutions) (Pelikan, 2002) and has been deemed one of the most complete and useful evolutionary algorithms in recent years.

4.3. Multi-hop routing based on Bayesian optimization algorithm

In this section, the Bayesian optimization algorithm is used to find the multi-hop routes from cluster heads to sink to use the capability of this algorithm for considering the dependencies between the selections of the next hops of the cluster heads. In multi-hop routing, the next hop of each cluster head is determined. The determined next hops are broadcasted into the cluster heads. So, each cluster head knows to which of its neighbors it must transmit the aggregated data or the data received from other cluster heads. In this section, the details of applying the Bayesian optimization algorithm are discussed. The flowchart of the proposed method is presented in Figure 4.

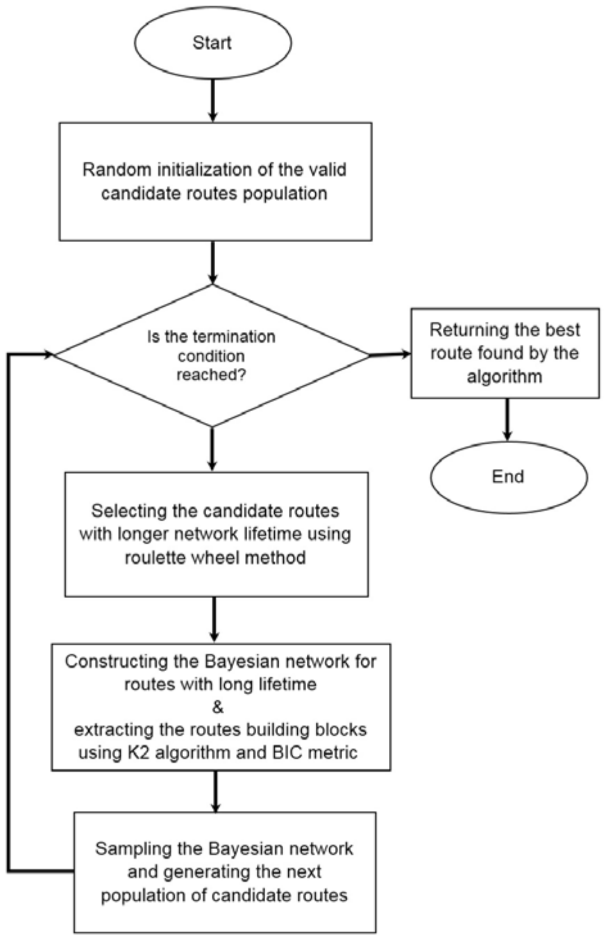


Figure 4. The flowchart of the proposed method.

4.3.1. The optimization problem definition

As mentioned earlier, the aim is to find a routing that improves the network lifetime and we determine the network life time as the number of the rounds of data collection, until the energy of the most energy consuming cluster head ends (Heinzelman, 2000; Suneet, 200; Bari, 2009). We use this criterion for calculation of the fitness of each solution. According to the considered definition, network lifetime is calculated according to the following equation (Bari, 2006A; Bari, 2009):

$$L_{net} = \frac{E_{initial}}{E_{\max}} \tag{16}$$

In this equation, $E_{initial}$ is the initial energy of the cluster heads (it is considered to be equal for all cluster heads) and $E_{\max}$ is the energy consumption of the cluster head that in a round of data collection, has the highest energy consumption. The energy consumption of each cluster head is calculated according to the first order radio model (Heinzelman, 2002; Heinzelman, 2000), which was introduced in Section 3. L_{net} shows the lifetime of the network.

According to the above descriptions, the optimization problem considered here is defined as a maximization problem, where the goal is to find a routing using which the network lifetime is maximized. This maximization problem is formulated as follows:

$$\underset{net}{Maximize}\, L(net) \tag{17}$$

where $L(net)$ is calculated as:

$$L(net) = \frac{E_{initial}}{E_{\max}} \tag{18}$$

and

$$E_{\max} = \max_k E_k = \max_k (\mathrm{E}_{R_k} + \mathrm{E}_{T_k}) \tag{19}$$

E_{R_k} and E_{T_k} in (19) are calculated from (2) and (3). This optimization problem is resolved in the rest of this section.

4.3.2. Solutions representation

As mentioned above, for routing, it is required that the next hop of each of the cluster heads be determined for data transmission. Therefore, we consider any candidate solution as an array, whose length is equal to the number of cluster heads. It is assumed that the network has n cluster heads and S stands for sink. The next-hop of a cluster head can be another cluster head or the cluster head can be directly connected to the sink.

4.3.3. The generation of the initial population

For generating of the initial population, a number of valid solutions are produced. By valid solution we mean a solution in which the next hop of each cluster head is in the transmission range of that cluster head and the next hop of at least one of the cluster heads is sink. To this end, the next hop for each cluster head is selected randomly with the uniform distribution from among the neighbors of that cluster head. In each solution, moreover, the existence of sink between the next hops is also controlled. In the next population of the algorithm, the values for the variables in these valid solutions are combined together and the new solutions are produced.

4.3.4. Fitness function

In this study, the routing problem is defined as a maximization problem and its objective is to maximize the network lifetime. On the other hand, as mentioned in Section 4.3.2, a candidate solution is an array demonstrating a routing between cluster heads. The fitness of a candidate solution is defined as the network lifetime achieved using the corresponding routing. As mentioned in Section 4.3.1, the network lifetime is calculated according to (16).

4.3.5. Application of the algorithm

As mentioned in Section 4.2, Bayesian optimization algorithm starts its task from an initial population. In the initial population, a number of initial valid solutions are produced. Each solution is an array that consists of a number of variables that represent the selected next hops for the cluster heads. As it is shown in Figure 4, during the application of the algorithm, by constructing the Bayesian network for the solutions with high fitness in every generation, the “routing building blocks” are discovered and extracted. By “routing building blocks”, we mean the decisions about next hops of the cluster heads, simultaneous existence of which in the routing, would lead to high fitness of the solutions (i.e. long network lifetime). We use the K2 algorithm (Cooper, 1992) and BIC (Bayesian information criterion) for making the Bayesian network. Then, by sampling the Bayesian network, it is tried to get these “routing building blocks” with higher probability and simultaneously in the production of the next generation solutions so as to achieve solutions with higher fitness. Construction of Bayesian network for solutions with high fitness and then sampling the Bayesian network are repeated from generation to generation up until the termination condition is reached. The algorithm terminates when no significant improvement is observed (i.e., the algorithm converges) or when the algorithm reaches a predefined number of iterations.

5. EXPERIMENT RESULTS

In Section 4, a method was proposed for multi-hop inter-cluster routing. As mentioned before, in the presented method the dependencies between the choices of next hops are taken into account in the evolutionary algorithm. In this section, this idea is evaluated. For this purpose, our proposed method is simulated and compared to a classic routing method and two methods based on genetic algorithm (which lack the ability to take conditional dependencies into consideration). The results demonstrate the effect of considering the conditional dependencies in multi-hop inter-cluster routing.

To evaluate the proposed procedure, first a network with 110 sensors and 4 cluster heads deployed in a 200×200 m^2 is considered. The position of cluster heads is determined based on the distribution of sensors and according to the procedure proposed in (Bari, 2007). The transmission range of each sensor is assumed to be 40 m and the transmission range of each cluster head is assumed to be 200 m. Afterwards, the number of cluster heads increases from 4 to 40, and, the number of sensors is raised to 900 and the area to 900×900 m^2. The first order radio model introduced in Section 3 is used.

In this radio model, α_1 and α_2 equals 50 nJ/bit and β equals 100 pJ/bit/m2 and the path loss exponent is set to 2. The rate of data production by each cluster is 1000 Bits/Round and the initial energy of each cluster head is considered to be 5 J. The three different conditions for the sink's position include: the center of square, the bottom left side, and the middle of the lower side. The algorithm parameters are presented in Table 1. In the Bayesian optimization algorithm, the size of the initial population is 300 chromosomes and the roulette wheel selection method with a rate of 70% is used. The Bayesian optimization algorithm is performed for 100 generations in each experiment. In case of the algorithm convergence, it may terminate before reaching the 100th iteration.

The algorithm has been implemented in MATLAB. For this purpose, the source codes of MATEDA toolbox (Santana, et al., 2009) have been applied for carrying out the Bayesian optimization algorithm.

Our simulations show that the algorithm converges before reaching the 100th iteration. The algorithm convergence diagrams for a network with 20 cluster heads and for different positions of sink are presented in Figures 5, 6, and 7.

Table 1: Parameter values for the proposed method

Parameter	Value
Selection method	roulette wheel selection
Selection rate	70%
Population size	300
Termination condition	Reaching the maximum number of generations/ reaching the algorithm convergence
Maximum number of generations	100
Bayesian network construction method	K2 algorithm
Model selection criterion	BIC

The proposed method is compared to two methods based on the genetic algorithm known as EEGA (Energy efficient GA) (5) and GAR (12) (discussed in Section 2) and a conventional routing method known as MHRM (Minimum Hop Routing Mode). In MHRM method, each cluster finds the route with minimum number of hops toward the sink (Gupta, 2003A; Gupta, 2003B).

The criterion for evaluation is network lifetime which is computed based on the definition introduced in Section 3. There are some random steps in the proposed method (e.g., chromosome selection, Bayesian network sampling, etc). To decrease the effect of these random steps, the simulation has repeated for 20 times and the results have been averaged. Network lifetime is illustrated in Figures 8, 9, and 10 for several numbers of cluster heads and for different positions of sink. The results have been obtained by averaging over 20 runs of simulation. Investigation of the results indicates that the proposed method, i.e. considering conditional dependencies between the selections of next hops of cluster heads has been conducive to finding multi-hop routes with lower energy consumption and, as a result, has improved the network lifetime.

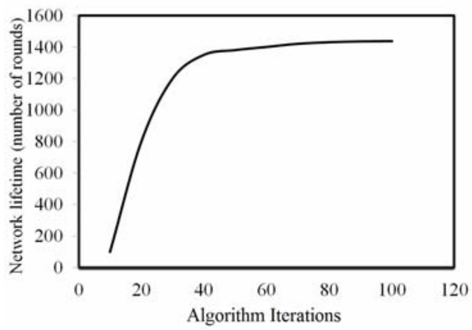


Figure 5. The algorithm convergence diagram for a network with 20 cluster heads when the sink is located at the center of square.

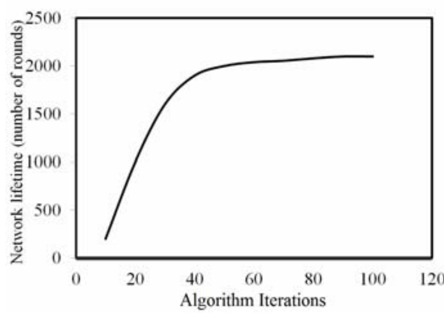


Figure 6. The algorithm convergence diagram for a network with 20 cluster heads when the sink is located at the bottom left side.

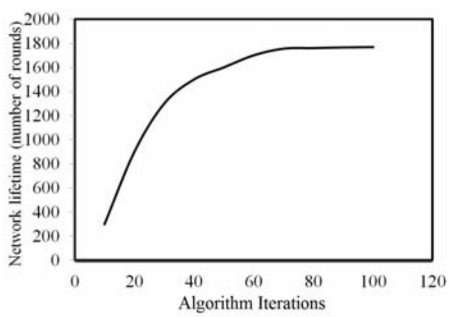


Figure 7. The algorithm convergence diagram for a network with 20 cluster heads when the sink is located at the middle of the lower side.

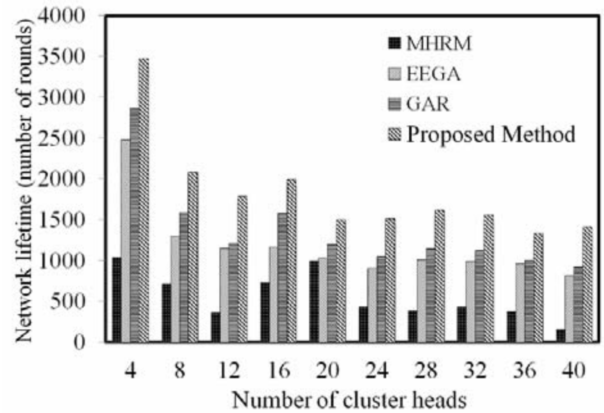


Figure 8. Network lifetime for several numbers of cluster heads when the sink is located at the center of square.

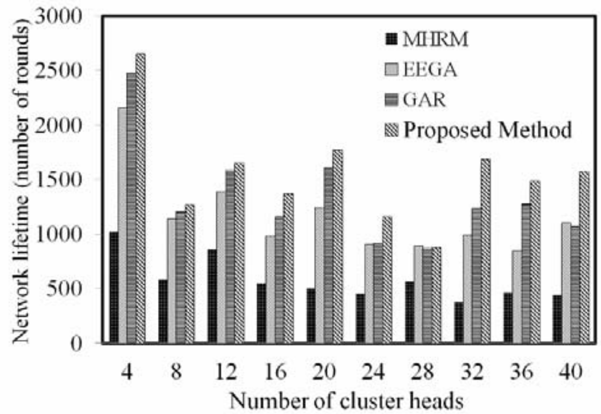


Figure 9. Network lifetime for several numbers of cluster heads when the sink is located at the bottom left side.

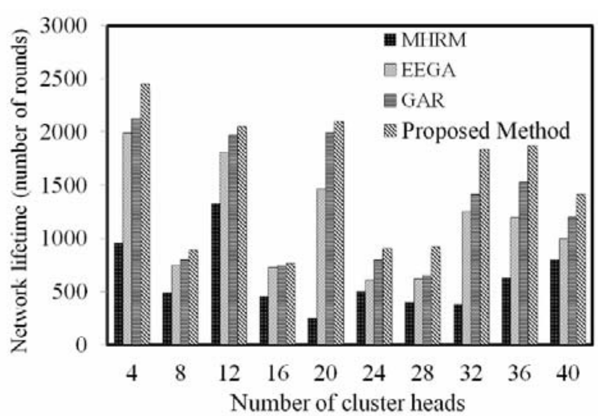


Figure 10. Network lifetime for several numbers of cluster heads when the sink is located at the middle of the lower side.

6. CONCLUSION AND FUTURE WORK

Cluster-based routing in wireless sensor networks reduces energy consumption in these networks. Various algorithms have been developed for multi-hop inter-cluster routing determining the next hop of each cluster head. In this paper we showed that if a cluster head is detected to be an appropriate next hop for a large number of cluster heads, its energy consumption will increase and it may soon become completely broken, which results in decreased network lifetime. Therefore, the selection of next hops for cluster heads is a decision with conditional dependency which should not be decided upon independently. This has not been addressed in the previous literature and this study attempted to address this issue. Afterwards, Bayesian optimization algorithm which is an evolutionary algorithm capable of taking conditional dependencies into account is used to find optimal routes between the cluster heads. The results of this method were compared to those of the previous methods. The evaluations revealed that considering conditional dependencies in choosing next hops can reduce energy consumption and increase the network life time.

Further research can be conducted for investigating the conditional dependencies between the decision variables in solving other problems of cluster based wireless sensor networks (e.g., cluster heads selection problem).

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