IOSR Journal of Computer Engineering (IOSR-JCE)
e-ISSN: 2278-0661,p-ISSN: 2278-8727, Volume 20, Issue 3, Ver. I (May. - June. 2018), PP 39-43
www.iosrjournals.org

Improvement of Cluster Heads Selection in Hierarchy Sensor Networks Using Bayesian Networks

Farzad Kiani[1]
[1]*(Department of Computer Engineering, Engineering and Natural Sciences Faculty, Istanbul Sabahttin Zaim University, 340303, Kucukcekmece, Istanbul/Turkey)*

Abstract: *One of the basic and challenging issues in the wireless sensor networks is energy consumption. They are consist of many small size sensor nodes that have limited memory and battery. The most of the node energy is used in during the transmit data in the network. Therefore, power consumption management in the sensor nodes is very important and has a big role in the network lifetime. The consumed energy to transmit data in sensor networks can be decreased by different techniques so one of the most effective method is organizing nodes in the form of clusters and selection of appropriate cluster heads. In this paper, the Bayesian method is used to select the cluster heads. Selection of nodes using the proposed method reduces the energy loss of nodes in data transmission and increasing network lifetime.*

Keywords – *Bayesian networks, sensor networks, hierarchical routing, network lifetime*

Date of Submission: 11-05-2018 Date of acceptance: 28-05-2018

I. Introduction

Sensor networks consist of a large number of small size, low cost, low memory, and limited energy sensor nodes. The application of these networks are in many various fields such as security, medicine, environmental monitoring, fire detection in forests, and so on. Nowadays, we hear them as Internet of Things (IoT). Due to its diverse applications, the use of these networks is increasing day by day. One of the main issue in these networks is energy efficiency. By discharging the energy in the network nodes, the nodes and the resulting network can be lost [1, 2]. Energy in sensor nodes is used in sensing of the environment, processing and data transferring. Transmission of data in the network consumes more energy than the other two. To prevent node energy loss, used protocols in sensor networks should use properly the available energy of nodes. Since most of the energy in the network nodes is used to transmit data, then the transmission of additional data in the network should be avoided as much as possible. For this purpose, the use of proper routing protocols for transmitting data between nodes in the network is investigated [1, 2, 3]. The data transmission in these networks is based on flat, hierarchical or locational approaches. Hierarchy methods have better performance on energy generally. One of the famous protocol in hierarchical based approach is LEACH [3]. It is most basic and powerful routing methods, so, dozens of protocols to this protocol have been proposed such as [4, 5]. In this protocol, time is divided into parts of equal length called round. Each round is also divided into deployment phase and the sustainability phase. The deployment phase is the selection of the cluster heads and formation of clusters phase. In the second phase, the network data is transmitted to the central station. The method for choosing cluster heads is a random manner. How to select cluster heads in sensor networks is effective over network lifetime. In this paper, the selection of nodes as nodes in the network is carried out based on the Bayesian method. The use of the Bayesian method to select the cluster heads in the sensor networks reduces the energy loss of the nodes in the routing and increases the network lifetime.

The Bayesian network is a directional, non-rotational and one-part graph. It serves as a tool for modeling knowledge that is uncertain. One of the most important benefits of these networks is the use of a graphical model that facilitates easy understanding of the problem and simplicity in modeling knowledge. The Bayesian network consists of two main parameters. The first is the effective factors associated with the problem called random variables. The problem variables are the network nodes. The second parameter is the communication that in the network represents the causal relationship between the random variables. If a random variable is the cause for another random variable, we connect one edge from the first to the second variable. The first variable is the parent and the child's second variable. In other words, the edges in a network represent conditional dependencies [6].

Random variables in a Bayesian network can be two types depending on the problem's requirements. These are discrete and continuous types. In a discrete state, each random variable has a number of states and it can be in three forms, a binary, an ordered sum, or a subset of the integers. Each random variable has a conditional probability table and the values in the tables in the table indicate the probability of a state of the variable being provided by the parent of that node. If the network variables are continuously random, we will have a continuous probability distribution function for each random variable and the probability values of these random variables are determined based on the continuous distribution function.

The likelihood of using the Bayesian network is different from the classical probability. The classical probability is based on probability rules. For example, when throwing a coin, the probability of earning each side is equal to one second and this value is fixed for all coincidental random experiments. Bayesian probability can reflect the belief of one person [7]. For example, to throw a coin, one might claim that the probability of a tail up is three tenths and this is the degree of belief of him/her. In the Bayesian network, one can deduce any kind of deduction using the probability distribution, which is the probability distribution equal $p(x,y)=p(x|y).p(y)$ to the two random variables (x and y) and the order of this distribution is 2 to power 2. In general, if the network has a random variable, the probability distribution will be related to the variable of order 2 to power n, so, the time to execute the deduction algorithm will be long using this distribution model. One of the solutions to reduce computing is to use the concept of conditional independence, which simplifies the inference and reduction of operations. If two random variables are independent of each other, then we will have $p(h)=p(h|e)$ [7].

Designing a suitable Bayesian network is one of the most important issues for creating a network in relation to the problem. Because, creating an optimal Bayesian network will increase network efficiency and increase the inference speed and simplicity of the network. Finding an optimal network for a given problem is one of the NP-hard issues [8]. Therefore, it can be a new research topic independent of each subsection. There are several algorithms for building a Bayesian network that one of them is the pearl's algorithm [8].

After constructing the Bayesian network, we can deduce on this network inference that there are different methods for deducing the Bayesian network (ex: a concise conclusion and a rough conclusion). The exact inference method is used on networks that are not complicated by their structure and the calculations are performed on the network at a desirable speed. While the Bayesian network is complex, exact inference on the relevant network is difficult and in some cases not possible. In this case, we approximate the inference using the exact inference instead of approximate inference [9, 10]. The complex Bayesian network means that the network has many nodes and that the network is almost entirely a graph.

As stated above, the transmission of data in sensor networks is a challenge due to the specific limitations of sensor networks. In designing and implementing routing protocols in sensor networks, efforts are being made to reduce energy wasting in data transmission by balancing the energy consumption in network nodes to increase overall network lifetime. In general, nodes selected in the same round as the cluster head consume more energy than nodes. As a result, in the next rounds, it is better not to select nodes as head nodes that were previously cluster head. Other parameters in the network design are scalability, reliability, fault tolerance, trust data and security. Lifetime and scalability criteria in sensor networks have a higher priority than other criteria generally. Of course, the priority of design parameters of network are related with application types and their requirements. In these networks, the data will be sent to the base station after the nodes have collected and processed the relevant data. Different methods are used to send node data to the base station. For this purpose, there are different protocols for routing the data in the sensor network. Each of these protocols uses special routing techniques. These protocols should properly use the energy in the nodes to prevent the loss of energy due to the transfer of data in an inappropriate manner [1, 3, 10]. Figure 1 is an example of hierarchy topologies so the nodes collaborate together distributary. In general, cluster management in these protocols is local and does not require any central controller.

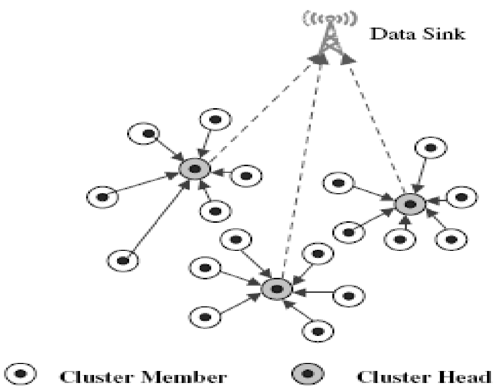

Fig. 1. An example of hierarchy topologies

In the deployment phase, two major operations are carried out, which include forming clusters and choosing head of clusters. After this phase, the structure of the network and the relationship between the nodes are specified and the data is sent to the base station in the network. In the method of selecting the cluster heads, each node first produces a random number between zero and one, and if this value is less than the threshold value, it is selected as the head. Other parameters can be effective in the election process of cluster heads as remained energy of nodes, distance to neighbor nodes and base station. The formation of clusters in general is in two types of approaches. In one of them, the clusters take place after the distribution of the nodes, and then CH is selected for each cluster. In the other category, after distribution of the nodes, the CHs are selected for the entire network, and then the nodes decide which CHs they are connected to clusters. In this method, after selecting the node as the cluster header, the ADV message is sent to the other nodes in their neighbors. Each node measures the distance from the sender to ninety by receiving the message and its intensity. The nodes that are not selected as cluster headers select a nearest cluster head and become a member of him by receiving the intensity of the signals transmitted from the cluster heads. In the phase of stability, instead of nodes sending their data directly to the base station, they send them to their cluster heads. The cluster head compresses receiving signals from its members and produces a single then send it to base station. To reduce the overhead due to the first phase, the duration of the second phase of the first phase is greater.

II. Bayesian Network Model to Cluster Head Selectıon

To design a Bayesian network for selecting cluster heads in sensor networks, we define the effective novel parameters in related with the problem. The factors that can be used to select a node as a cluster head are the number of clusters, energy of nodes, round number and random number generated per network round. After determining the factors affecting the selection of clusters, the Bayesian network relates to the problem with considering the relationship between random variables and the previous probabilities associated with each of the variables. The values of CPT tables related to the variables are determined according to the parameters in the proposed protocol. In this paper, we implemented the proposed method on the famous LEACH protocol. In figure 2 is shown the proposed Bayesian Network model. In this article, the basic concepts of bayesian networks are used as mentioned in [6, 7].

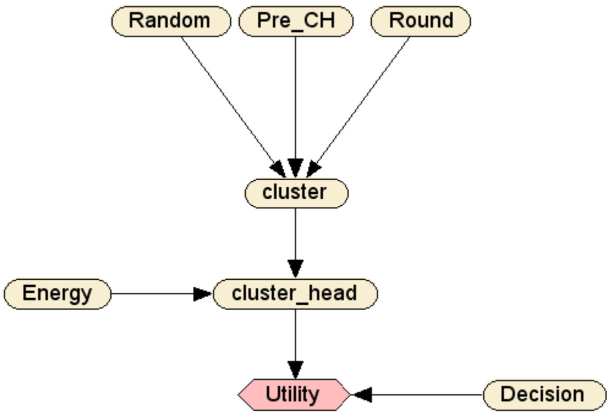

Fig. 2. Bayesian network designed for selection of cluster heads

The earlier the variables' exact values are accurate; the created expert system will have more efficiency. As a result, the nodes that are selected as cluster heads transfer the data properly in the network and prevent the energy dissipation. This will improve the lifetime of the sensor network. In this paper, the selection of cluster heads in the sensor network is distributed based architecture based on Bayesian network method. Given the proposed Bayesian network for the problem, each network node can be selected as a cluster head in one round based on the values of each of the variables and observations. In the proposed method, a node with more energy and high probability value in its *Cluster* variable is selected as the cluster head. The values of the *Cluster* variable are determined by the *Random*, *Pre_CH*, and *Round* variables. In each round, each node generates a random value between zero and one in selection process of cluster head. Based on the generated number, the value of the variable *Random* is specified. If the generated value is high, the probability of choosing this variable as cluster head is more. The *Pre_CH* variable prevents the repeat selection of a node as a cluster header. This causes the nodes to be selected equally as a cluster over the lifetime of the network. As a result, energy in the network nodes is consumed almost equally and prevents overhead on some nodes and early failure of these nodes due to high-energy consumption. The *Round* variable specifies the number of network periods. If a node is not selected as a cluster head in the network, with the round number increasing, the node selection increases as the cluster head. Given the three variables *Random*, *Pre_CH* and *Round*, the value of the probability of the *Cluster* variable is determined. The *Cluster* variable is the probability of selecting a node as a cluster head without considering the energy factor. Then the probability of selecting a node as a cluster head is determined by given the values of the variable *Cluster* and *Energy*. The remaining energy in a node has a direct effect on the selection of a node as a cluster head. After all the variables in the network have been selected as cluster heads, the values for the *Pre_CH* and *Round* variables are returned to the original values. In a simple test of the proposed method in LEACH protocol, a network with 100 nodes in about 20 rounds of the network, all nodes will once be selected as the cluster head node. This value is 10 rounds in the basic LEACH protocol. Also, it is 17 in the improved last version of LEACH protocol. On other the hand, these results show the proposed method has a good performance in the energy consumption in the networks that are in a hierarchical structures.

III. Implementatıon of Proposed Method

The implementation of the proposed method is in the MATLAB [11] software program that is written in figure 3. In this code, a random number is selected for each random variable. In this method, for all relevant variables, a number is assigned, and then the problem graph is implemented using the neighborhood matrix. Using the *mk_bnet* command, the network is created in the BNT packet [12], and then, the conditional probability tables for each variable are specified using the *bnet.cpt* command. By specifying relevant views with the *enter_evidence* command, the probability of choosing and not choosing the cluster head is determined. By obtaining this probability, an appropriate decision can be made to deploy the target groups to reduce energy consumption.

```
N = 20;
dag = zeros(N,N);
a = 1; t = 2; s = 3; w = 4; r = 5; c = 6; h = 7; j = 8;
k = 9; l =10; x = 11; y = 12; z = 13; u = 14; v = 15;
o = 16; p = 17; q = 18; m = 19; n = 20;
dag ([j ,k, l],s) = 1; dag([x ,y ,z],c) = 1;
dag ([u ,v],t) = 1; dag([o ,p, q, m ,n],r) = 1;
dag ([s ,c, h, t ,w ,r],a) = 1;
ns = [2 2 2 3 2 2 3 2 2 2 2 2 2 2 4 2 2 2 2 2];
bnet = mk_bnet(dag, ns);
draw_graph (bnet.dag);
bnet.CPD {a} =tabular_CPD (bnet, a, [0.001 …0.11]);
bnet.CPD {t} = tabular_CPD (bnet, t, [0.93 …0.95]);
bnet.CPD{s} = tabular_CPD (bnet, s, [0.77 …0.02]);
bnet.CPD {w} =tabular_CPD (bnet, w, [0.8 0.1 0.1]);
bnet.CPD{r} = tabular_CPD (bnet, r, [0.03 …0.15]);
bnet.CPD{c} =tabular_CPD (bnet, c, [0.85 0.9999]);
Bnet.CPD {h} =tabular_CPD (bnet, h, [0.08….0.02]);
bnet.CPD {j} = tabular_CPD (bnet, j, [0.3 0.7]);
bnet.CPD {k} = tabular_CPD (bnet, k, [0.15 0.85]);
bnet.CPD {l} = tabular_CPD (bnet, l, [0.3 0.7]);
bnet.CPD{x} = tabular_CPD (bnet, x, [0.92 0.08]);
bnet.CPD{y} =tabular_CPD (bnet, y, [0.998  0.002]);
bnet.CPD {z} = tabular_CPD (bnet, z, [0.7    0.3]);
bnet.CPD {u} = tabular_CPD (bnet, u, [0.73   0.27]);
bnet.CPD {v} = tabular_CPD (bnet, v, [0.07   0.48]);
bnet.CPD {o} = tabular_CPD (bnet, o, [0.05   0.95]);
bnet.CPD {p} = tabular_CPD (bnet, p, [0.02   0.98]);
bnet.CPD {q} = tabular_CPD (bnet, q, [0.13   0.87]);
bnet.CPD {m} =tabular_CPD (bnet, m, [0.05   0.95]);
bnet.CPD {n} = tabular_CPD (bnet, n, [0.15   0.85]);
Engine = jtree_inf_engine (bnet);
ev = cell(1,N);  ev{J} = 1;
engine = enter_evidence (engine, ev);
mA = marginal_nodes(engine, a);
fprintf ('P(A|J)=%5.3f, mA.T(1));
```

Fig. 3. An algorithm for selecting the cluster head based on the proposed Bayesian network

The output of this program is a number that shows the amount of the profit and loss so in this project is used nodes of decision making and useful nodes. Given the effective factors and the observation of the observations, the probability of selecting the node as the cluster head is calculated. Moreover, decision nodes show the amount of profit and loss that can be achieved. The goal of this project is to maximize profits, which results in lower network energy consumption.

IV. Conclusion

In this paper, a new method for selection of clusters in sensor networks for the transmission of data to the base station was presented. This algorithm improves important network factors such as node energy consumption, network lifetime, and latency of data sent to the base station. In this paper, the proposed method is implemented on the some LEACH protocol versions that the results are shown the proposed method has a better performance in the energy consumption in whole of the network. In additional, the proposed method is observed that more balance is used in resources.

References

[1] F. Kiani, E. Amiri, M. Zamani, T. Khodadi, AA. Manaf, Efficient intelligent energy routing protocol in wireless sensor networks. *International Journal of Distributed Sensor Networks*, 2015, 1-13.

[2] A. Anwar, D. Sridharan, A Survey on Routing Protocols for Wireless Sensor Networks in Various Environments, *International Journal of Computer Applications*, 112(5), 2015, 13-29.

[3] W. Heinzelman, A. Chandrakasan and H. Balakrishnan, Energy-Efficient Communication Protocol for Wireless Microsensor Networks, *Proceedings of the 33rd Hawaii International Conference on System Sciences*, 2000, 1-10.

[4] P. radhakrishnan, *Enhanced routing protocol for graceful degradation in wireless sensor networks during attacks*, bachelor of Engineering, University of madras, Chennai, 2003.

[5] A. Sarkar, T. Murugan, Routing protocols for wireless sensor networks: What the literature says?, *Alexandria Engineering Journal*, 55(4), 2016, 3173-3183.

[6] F. Leopoldo, *Bayesian Inference in Probabilistic Graphical models*, Universitetsservice US-AB, Stockholm, 2017.

[7] A. Darwiche, *A Differential Approach to Inference in Bayesian Networks*, 2018, 1-20, http://web.cs.iastate.edu/~jtian/cs673/cs673_spring03/Adnan_diff.pdf

[8] S. J. Russell and P. Norvig, *Artificial Intelligence: A Modern Approach* (Prentice Hall, 3nd edition, 2018).

[9] N. Peyrard et al., Exact or approximate inference in graphical models: why the choice is dictated by the treewidth, and how variable elimination can be exploited, *arXiv:1506.08544v2 [stat.ML]*, 2018, 1-47.

[10] K. Sohraby, D. Minoli, T. Znati, *Wireless Sensor Networks, Technology, Protocols, and Applications*, Wiley Online Library Books, 2006.

[11] https://www.mathworks.com/downloads/

[12] https://github.com/bayesnet/bnt

Farzad Kiani "Improvement of Cluster Heads Selection in Hierarchy Sensor Networks Using Bayesian Networks." IOSR Journal of Computer Engineering (IOSR-JCE) 20.3 (2018): 39-43.