Egyptian Computer Science Journal (ISSN-1110-2586)
Volume 40 – Issue1 January 2016

Improving Wireless Sensor Networks Life Time Using Neural Network

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Abstract

The use of wireless sensor networks (WSNs) has grown very fast in the last decade. The main concern in wireless Sensor Network is how to keep the network working in spite of sensors limited energy resource case the performance of that Network depends on their lifetime. Maximizing network lifetime in Wireless Sensor Networks (WSNs) was done by controlling total energy consumed along the network and trying to minimize it. To support high scalability and better data aggregation, sensor nodes are often grouped into disjoint, non overlapping subsets called clusters. Today Cluster based routing protocol are well known approach for extending Wireless Sensor Networks. In this work we merge the idea of cluster with neural network and measure the effect of changing the number of cluster on the number of live node and reserved energy. Experimental results end up with the proposed methodology gives lifetime than old ones, such as (LEACH, and LEA2C). While it can ensure more network coverage in it's lifetime through distributed death of nodes in network space.

Keywords: *Clustering, Self Organizing Map (SOM), Neural Networks, and Wireless Sensor Network (WSNs).*

1. Introduction

A wireless sensor network (WSN) is a wireless network consisting of spatially distributed devices using sensors to cooperatively monitor physical or environmental conditions such as temperature, sound, vibration, pressure at different locations. These tiny sensor nodes can easily deployed into a designated area to form a wireless network and perform specific functions. Each node in a sensor network is typically equipped with a radio transceiver or other wireless communications device, a small microcontroller and an energy source, usually a battery. The main and most important reason of Wireless Sensor Network (WSNs) creation was continuous monitoring of environments where are too hard or impossible for human to access or stay. So there is often low possibility to replace or recharge the dead nodes as well. The other important requirement is that we need a continuous monitoring so the lifetime and network coverage of these networks are our great concerns. Balanced distribution of energy in whole network will lead to balanced death of nodes in all regions preventing from lacking network coverage [1]. In many applications therefore, power conservation is a key aim; however, increasing the power dedicated to radio transmission and reception can broaden the radio range improving connectivity and boosting network functionality [2].

To maximize network lifetime in Wireless Sensor Networks (WSNs) the paths for data transfer are selected in such a way that the total energy consumed along the path is minimize and it named as Routing protocols. In this paper we present a new way to improving the (WSN) life time through using of Self organizing map neural networks. Our work is closely related to LEACH-Centralized that the Base Station has the control in cluster formation method which requires global knowledge about all nodes energy and positions. Also our protocol related to LEA2C protocol which is SOM-based clustering protocol. LEA2C handled the optimal number of clusters by a two-phase method; SOM followed by K-means and it shows a considerable profit compared with another LEACH like protocol. Also our work is closely related to (EBC-S) protocol [3], which is able to form the cluster not only based on nodes topological closeness (coordinates) but also based on their energy levels in each set-up phase by using SOM capability on multi dimensional data classification. The difference of our proposed methodology with previous one is that it is able to control the number of cluster in k-mean phase therefore be able to extend the lifetime of the network in the terms of first dead time and ensures more network coverage during network life time. Simulation results show the profit of our protocol over old ones, such as (LEACH, and LEA2C).

2. Wireless Sensor Networks

Many research studies focused on energy efficient routing protocols to address this problem. Routing in WSNs is challenging due to the specific characteristics that distinguish WSNs from other wireless networks such as wireless ad hoc networks or cellular networks [4]. Routing protocols can be divided based on different considerations like application, protocol operation, or network structure which is usually divide them into three general categories [5]: flat, hierarchical (cluster based) and location-based routings. In flat networks, each sensor node plays the same role and sends their data to sink node directly which always results in excessive data redundancy and faster energy consumption. In location based routing, sensor nodes are addressed by means of their locations. The sensing area is divided into small virtual grids. All nodes in same virtual grid are equivalent for routing and only one node need to be active at a time. In hierarchical routing as described in figure 1, sensor nodes are often grouped into disjoint, non overlapping subsets called clusters [6, 7]. Each cluster consists of some source nodes and a cluster head. Sensor nodes can gather information from the monitoring region and send the sensing information to their corresponding cluster head. The cluster head is elected from all the sensor nodes in a cluster according to some criteria, and is responsible for collecting sensing data from source nods. After receiving data from Sensor nodes, the cluster head also performs data aggregation to reduce the data size before sending data to the sink.

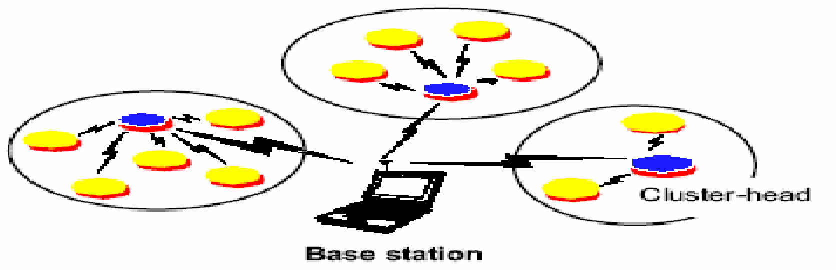

Figure 1. Hierarchical (cluster based) Routing

3. Clustering

Hierarchical or Cluster based routing protocols, the most energy efficient organization, have shown wide application in the past few years and numerous clustering algorithms have been proposed for energy conservation such as:

LEACH, HEED, LEACH-C and LEA2C etc.

Low Energy Adaptive Clustering Hierarchy (LEACH) [8] is the most famous clustering protocol which had been a basis for many further clustering protocols. The most important goal of LEACH is to have (Cluster Heads) to reduce the energy cost of transmitting data from normal nodes to a sink. In LEACH, nodes organize themselves into clusters; each cluster has one node acting as cluster head. All non-cluster head nodes (normal nodes) transmit their data to the cluster heads. The cluster-head is responsible for: 1) coordination among the cluster nodes and aggregation of their data, and 2) transmission of the aggregated data to the BS, directly or via multi-hop transmission. But the hot spots problem in multi-hop wireless sensor networks, When cluster heads cooperate with each other to forward their data to the base station, the cluster heads closer to the base station are burdened with heavy relay traffic and tend to die early, leaving areas of the network uncovered and causing network partition. So in Leach process each CH will transmit their data to sink directly. The operation of LEACH is divided into rounds. Each round begins with a set-up (clustering) phase when clusters are organized, followed by a steady- state (transmission) phase when data packets are transferred from normal nodes to cluster heads. After data aggregation, cluster heads will transmit the messages to the Base Station. The election of cluster head is done with a probability function: each node decides whether to become a CH for the current round, this decision is based on a predetermined fraction of nodes and the threshold *T(n)* [9], each node selects a random number between 0 and 1 and if the number is less than *T(n)*, the node is elected as a cluster head for current round:

$$T(n) = \begin{Bmatrix} \frac{p}{1-p\langle r \bmod \frac{1}{p}\rangle} & if\ n \in G \\ 0 & otherwise \end{Bmatrix} \qquad (2)$$

Where, P is the cluster head probability, r is the number of current round and G is the set of nodes that have not been cluster-heads in last 1/P round. The strength of LEACH is in its CH rotation mechanism and data aggregation.

Hybrid Energy-Efficient Distributed Clustering (HEED) [10], Unlike LEACH, it does not select cell-head nodes randomly. Only sensors that have a high residual energy can become cell-head nodes. HEED has three main characteristics:

- The probability that two nodes within each other's transmission range becoming CHs is small. Unlike LEACH, this means that CHs are well distributed in the network.
- Energy consumption is not assumed to be uniform for all the nodes.
- For a given sensor's transmission range, the probability of CH selection can be adjusted to ensure inter-CH connectivity.

In HEED, each node is mapped to exactly one cluster and can directly communicate with its CH. The algorithm is divided into three phases:

Initialization phase: The algorithm first sets an initial percentage of CHs among all sensors. Each sensor sets its probability of becoming a cluster-head, CHprob, as follows:

$$CHprob = Cprob * Eresidual/Emax \qquad (1)$$

Where Cprob is initial percentage of CHs among all sensors Eresidual is the current energy in the sensor, and Emax is the maximum energy, which corresponds to a fully charged battery.

Repetition phase: every sensor goes through several iterations until it finds the CH that it can transmit to with the least transmission power otherwise the sensor elects itself to be a CH. sensor doubles its CHprob value and goes to the next iteration of this phase. Until the sensor becomes a tentative CH if it's CHprob is less than 1. It can change its status to a regular node at a later iteration if it finds a lower cost CH or the sensor permanently becomes a CH if its CHprob has reached 1.

Finalization phase: each sensor makes a final decision on its status. It either picks the least cost CH or pronounces itself as CH.

LEACH-Centralized (LEACH-C) [11], is a Base Station cluster formation algorithm. It uses the same steady state protocol as LEACH. During the steady state phase, each node sends information about its current position and energy level to BS. The assumption usually is that each node has a GPS receiver. The BS have to insure the evenly distribution of energy among nodes. So it determines a threshold for energy level and selects the nodes (with higher energy than this threshold) as possible cluster heads. After determining the cluster heads of current round, BS sends a message containing cluster head ID for each node. If a node's cluster head ID matches its own ID, the node is a cluster head; otherwise it's a normal node and can go to sleep until data transmission phase. LEACH-C always insures the existence of K optimal number of cluster heads in every set-up phase while LEACH cannot ensure that.

Low Energy Adaptive Connectionist Clustering (LEA2C) [11], uses a two phase clustering method, SOM followed by K-means. LEA2C apply the connectionist learning by the minimization of the distance between the input samples (sensor nodes coordinates) and the map prototypes (referents) weighted by an especial neighborhood function. After set-up phase, the cluster heads of every cluster are selected according to one of the three criterions, max energy node, nearest node to BS and nearest node to gravity center of each cluster. The transmission phase continues until the occurrence of first dead in the network. After that, the reclustering (set-up) phase will repeat.

4. Self-Organizing Maps

The Self-Organizing Map (SOM) [12] is an unsupervised neural network structure that combines entities into separate groups, fines the prototypes and saves them into connection weights between competition layer and input layer. In unsupervised learning, the training of the network is entirely data-driven and no target results for the input data vectors are provided.

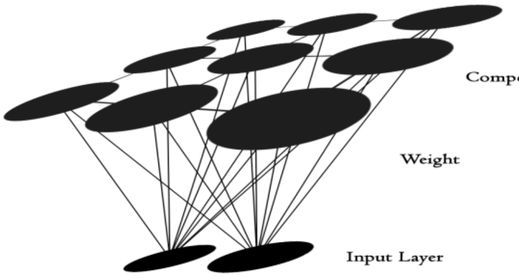

Figure 2. SOM topology structure

Each input node (neuron) is presented by an n- dimensional weight vector where n is equal to the dimensions of input vectors. Weight vectors (or synapses) connect the input layer to output layer which is called map or competitive layer. The neurons connect to each other with a neighborhood relation as shown in figure 2. Every input vector activates a neuron in output layer (called winner neuron) whose weight vector has the greatest similarity with the input sample. The similarity is usually measured by Euclidian distance of two vectors. The learning algorithm of SOM with N attributes of entities, M nodes in competition layer is described below:

Step 1: *Initialize weight vectors of competition layer*.

The weights may or may be not, initialized randomly. In some cases they are initialized around the mean of the inputs.

Step 2: *Determine the winner nodes*.

For each node j of competition layer, compute the distance between the weight vector of the node and the input vector by the following equation.

$$D_j = \sum_{i=1}^{n} \left\| W_{i,j} - X_i \right\|^2 \qquad (3)$$

Where *xi* is the input vector, *Wi,j* is the weight vector connecting input *i* to output neuron *j* and *Dj* is the sum of Euclidian distance between input sample *xi* and its connecting weight vector to *j*th output neuron.

Step 3*: Modify weight vectors.*

Modify the weight vectors of winner node and nodes within the neighbor range

$$W\ (new) = W\ (old) + h\ (t)\ (X - W\ (old)) \qquad (4)$$

h is the Gaussian neighborhood, X is input vector.

Step 4: *Exit or continue*

If every weight vector changes by only tiny amount stop the iteration (learning is completed).
Otherwise, go on to step2.

5. Proposed Algorithm

The operation of proposed algorithm is divided into group of successive rounds. Each group begins with a cluster setup phase followed by a data transmission phase. Each node on the same cluster transfers its data to the cluster head of that cluster. Then each cluster head aggregates the data received from other nodes within its cluster and relays them to the base station (BS). Assuming that BS has total knowledge about the energy level and position of all nodes of the network. The anther important assumption is that the sensor nodes are homogenous, means they have the same processing and communication capabilities also they have in the beginning the same amount of energy. A little information about each phase is described as follows:

Cluster Setup phase:

Two phases clustering method SOM followed by K-means are used. The selection SOM for clustering is done because it is able to reduce dimensions of multi-dimensional input data and visualize the clusters into a map [1]. The inputs variables to the SOM is x and y coordination of every node in topology and associate with the energy level of them. Since using two different type variables, so it must be normalized first.

So the input matrix to SOM will be as follows:

$$D = \begin{bmatrix} \frac{xd_1}{xd_{max}} & \frac{yd_1}{yd_{max}} & \frac{E_1}{E_{max}} \\ & \vdots & \\ \frac{xd_n}{xd_{max}} & \frac{yd_n}{yd_{max}} & \frac{E_n}{E_{max}} \end{bmatrix} \qquad (5)$$

The next step is defining the weight matrix. In order to determine weight matrix, Base Station has to select m nodes with highest energy in the network, which is equal in all nodes in beginning. So the weight matrix is:

$$W = \begin{bmatrix} \frac{xd_1}{xd_{max}} & & \frac{xd_m}{xd_{max}} \\ \frac{yd_1}{yd_{max}} & \cdots & \frac{yd_m}{yd_{max}} \\ \frac{E_1}{E_{max}} & & \frac{E_m}{E_{max}} \end{bmatrix} \qquad (6)$$

The learning is done by minimization of Euclidian distance which is explained in previous part. Now SOM clusters n data samples into m map units clusters) which will be the input to the next step which is k-means [13, 14]. K-means randomly selects K of objects as cluster centroids. Then other objects are assigned to these clusters based on minimum Euclidean distance to their centroids. The mean of every cluster is recomputed as new centroids and the operation will continue until the cluster centers do not change anymore [3]. At the end of this phase the Base station knows the optimal number of clusters and their member nodes. The next step is selection of suitable cluster heads for each cluster that's responsible for receiving data from other node, aggregate it and transmit it to Base station.

Cluster Head selection phase:

Three criterions have been considered for CH selection [15, 16]:

1- The sensor having the maximum energy level
2- The nearest sensor to the BS
3- The nearest sensor to gravity center (centroid) of the cluster.

The results from LEA2C show that the selecting nodes with maximum energy level (first factor) as cluster head, gives the best results [17] because in other two selections (nearest sensor to BS or cluster centroid) the selected CHs stay fixed during the transmission phase until next reclustering phase which may last for several rounds, that is lead to fast energy consumption to that node (cluster head) [18].

Transmission phase:

After formatting clusters and selecting their related cluster heads, it's ready to send data packets from normal nodes to their related cluster heads and after that the CH applying data aggregation functions to that received packets then send messages to the base station.
As in leach approach [7, 19] the energy consumed for transmission of k bits of data over a d distance is computed by:

$$E_T(k,d) = \begin{Bmatrix} k(E_{elec} + \epsilon_{fs}\ d^2\ \ for\ d \leq d_0 \\ k(E_{elec} + \epsilon_{mp}\ d^4\ \ for\ d > d_0 \end{Bmatrix} \quad (7)$$

where $E_{elec}$is the electronics energy, and ϵ_{fs} and $\epsilon_{mp}$are the amplifier energy factors for free space and multipath fading channel models, respectively and The reception of a k-bit message consumes $E_R(k)$ of energy

$$E_R(k) = kE_{elec} \quad (8)$$

Also energy consumption of data aggregation of CHs is:

$$E_{DA} = 5\text{nJ/bit/msg} \quad (9)$$

After every transmission phase, we count a new round and would have a cluster head rotation. But how often should we have a reclustering phase? Since our goal is to create clusters with equal energy levels, we should have a threshold for reclustering phase according to variation of energy level of the nodes. So the best time for reclustering can be when total energy of CH nodes reduced by level or percent less than the threshold that we chosen. This threshold energy level is defined experimentally. In this work, 20 percent depletion of initial energy for first time reclustering phase and 5 percent depletion for next times are used.

6. Simulations and Results

The proposed algorithm has been simulated and examined using MATLAB environment. We implement a homogenous WSN deployment squared range area (100 x 100 m^2). The base station is fixed motionless and stationary central device that is located far outside the WSN deployment sensing region. The parameter which is used in proposed work is shown in following table 1.

Table 1. Parameters of simulation

parameter	data
N	100
Area	100m x 100m
BS	50m x 175m
d_0	87m
Initial Energy	0.5J
E_{elec}	50nJ/bit
ϵ_{fs}	10pJ/bit/m^2
ϵ_{mp}	0.0013pJ/bit/m^4
Packet size	4000bits

Table 2. Reserved Energy and life nodes versus time

Round #	Total Reserved Energy			Number of Life Nodes		
	10 Cluster	20 Cluster	Leach	10 Cluster	20 Cluster	Leach
100	46.2900	46.2999	41.9166	100	100	100
400	35.1599	35.1997	18.5512	100	100	81
700	24.7263	24.7595	8.1544	90	80	50
1000	16.0384	18.2435	3.3599	90	80	28
1300	7.3504	12.1598	1.2185	90	80	11

From the table 2, the total reserved energy in the proposed model with 20 clusters is always higher than the proposed one with 10 clusters. In the meanwhile number of dead nodes in the proposed model with 20 clusters is higher. The reason behind this is the energy consumed in case of using 10 clusters more than in 20 cluster cases due to the distance factor between nodes and CH in each cluster so the total energy will decrees but the number of live nodes is more than those when using 20 clusters and that will be shown in figure 3.

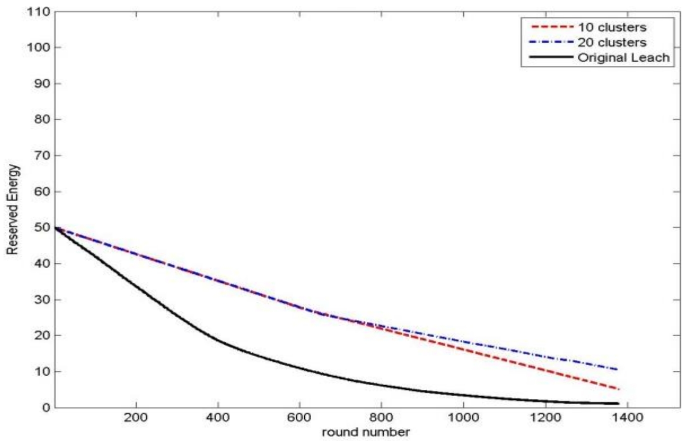

Figure 3. Reserved Energy versus Number of rounds

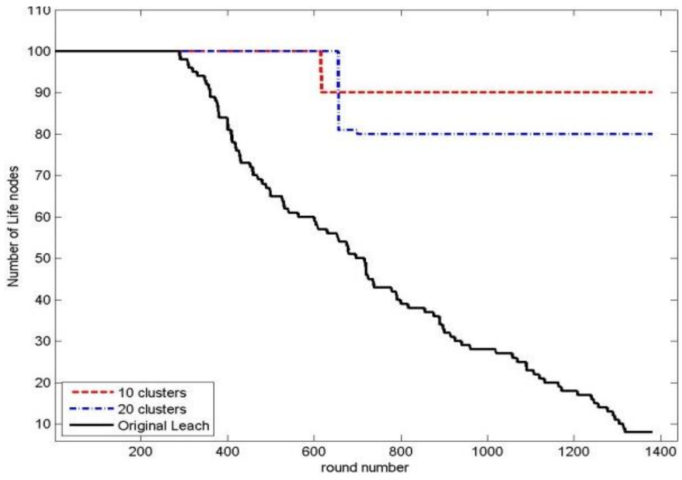

Figure 4. Number of a live nodes VS time

Figure 3 illustrate the advantages of the proposed protocol compared to LEACH according to the total reserved energy in network. It also shows that no big different between choosing different number of cluster in k-mean phase (10 or 20 clusters).

In the meanwhile figure 4 describe the different between the proposed protocol and LEACH according to the number of live nodes. It also gives more live when choosing less number of clusters on k-mean phase. In same time changing the number of nodes is direct proportion to live nodes and that is described in figure 5 which it shows changing number of nodes to 100, 200 and 300 is giving more live nodes but it approximately equal in reserved energy which is shown in figure 6.

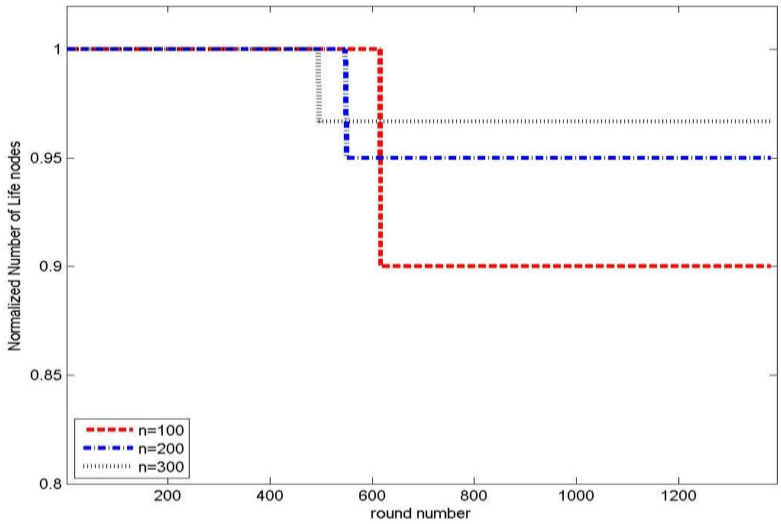

Figure 5. Live nodes with different node number

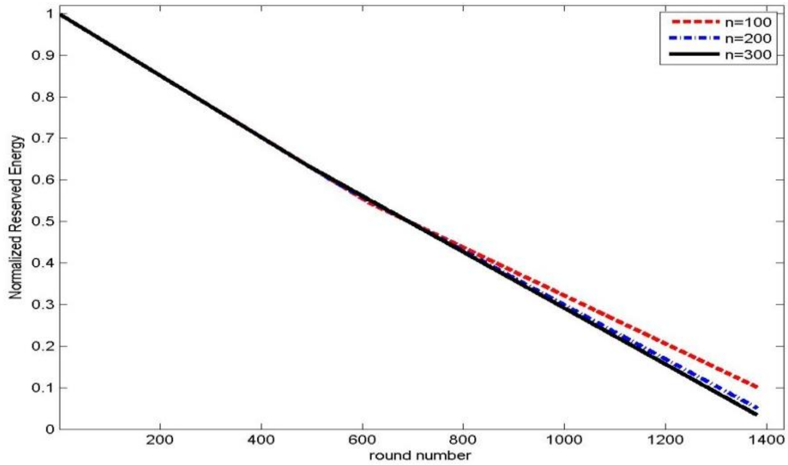

Figure 6. Reserved energy with different node number

The following figures 7 and 8 describe the different between original Leach and proposed algorithm using 100 and 300 nodes with respect to live node and figures 9, 10 with respect to reserved energy.

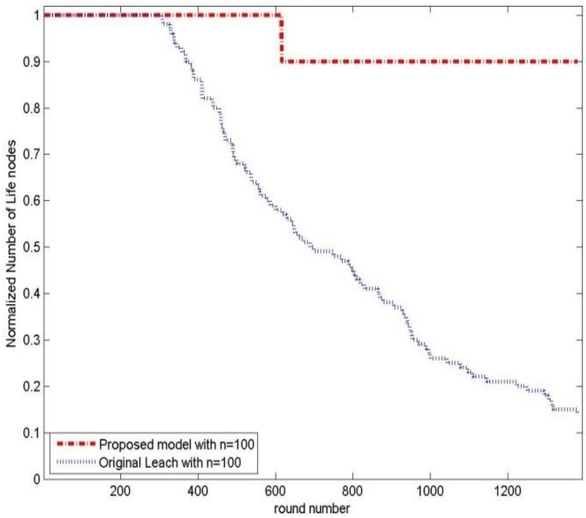

Figure 7. Live nodes VS time at n=100

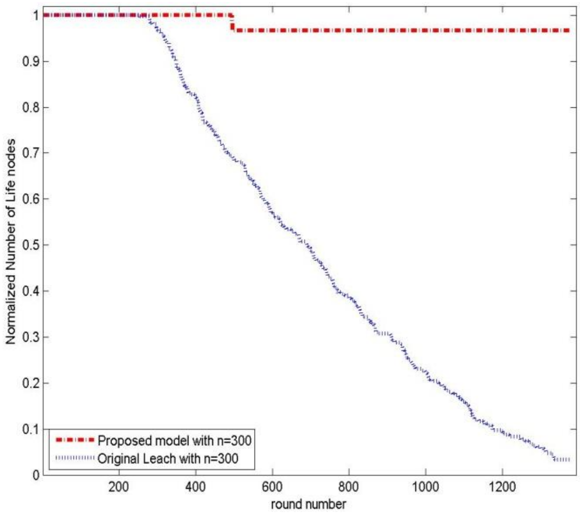

Figure 8. Live nodes VS time at n=300

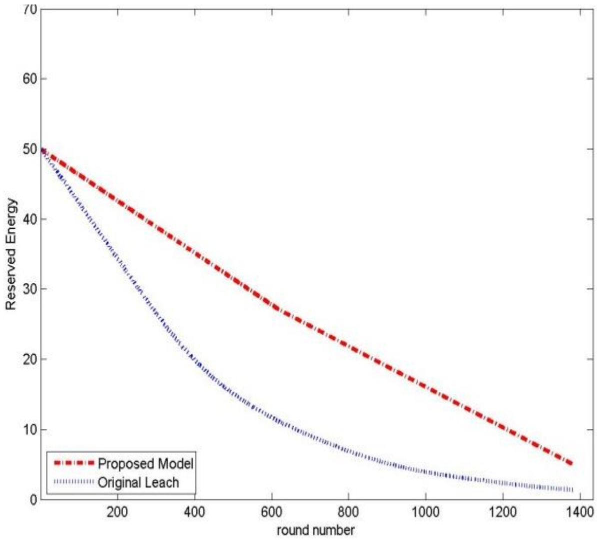

Figure 9. Reserved energy VS time at n=100

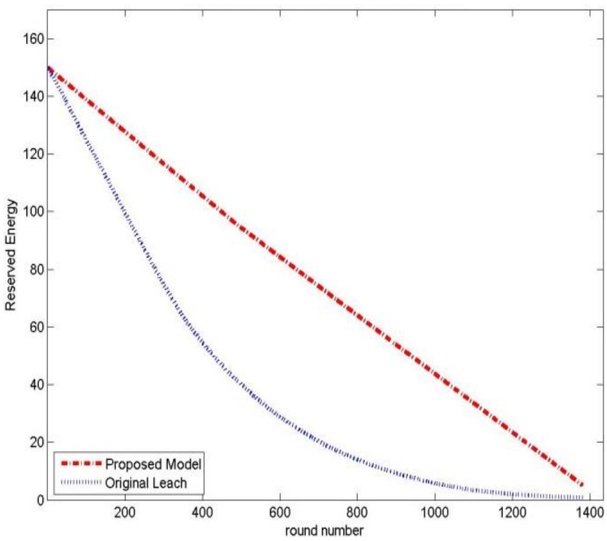

Figure 10. Reserved energy VS time at n=300

7. Conclusion

In this work we proposed Energy control protocol through SOM neural networks. This protocol applies energy levels and coordinates of nodes as clustering input parameters. It uses some nodes with maximum energy levels as weight vectors of SOM map units. The clustering phase is performed by a two phases namely, SOM, and K-means clustering method. Also in the proposed model changing the number of cluster in final phase (k-mean phase) has a great influence on the result, in another words chose 20 clusters which is close to LEA2C and 10 clusters selection are proposed. The simulation results show 45% Profit of our algorithm over LEACH in the terms of increasing first dead time and also using 10 clusters gives 10% profit over using 20 clusters and also simulation results show the profit over LEACH in the terms of reserved energy in network then changing the number of nodes is direct proportion to number of live nodes.

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