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ENERGY EFFICIENT DYNAMIC ADAPTIVE RECLUSTERING PROTOCOL FOR HETEROGENEOUS WIRELESS SENSOR NETWORKS

C. P. Subha[1] and S. Malarkkan[2]
[1]Department of Electronics and Communication Engineering, Sathyabama University, Chennai, India
[2]Manakula Vinayagar Institute of Technology, Puducherry, India
E-Mail: subhakarthikeyan38@yahoo.com

ABSTRACT

Wireless sensor networks are composed of a large number of sensor nodes with limited energy resources. One critical issue in wireless sensor networks is how to gather sensed information in an energy efficient way since the energy is limited. The clustering algorithm is a technique used to reduce energy consumption. It can improve the scalability and lifetime of wireless sensor network. In this paper, we introduce an adaptive clustering protocol for wireless sensor networks, which is called Adaptive Decentralized Re-Clustering Heterogeneous Protocol (ADRHP) for Wireless Sensor Networks. In ADRHP, the cluster heads and next heads are elected based on residual energy of each node and the average energy of each cluster. Clustering has been well received as an effective way to reduce the energy consumption of a wireless sensor network. Clustering is defined as the process of choosing a set of wireless sensor nodes to be cluster heads for a given wireless sensor network. Therefore, data traffic generated at each sensor node can be sent via cluster heads to the base station. The selection of cluster heads and next heads are weighted by the remaining energy of sensor nodes and the average energy of each cluster. ADRHP is an adaptive clustering protocol; cluster heads rotate over time to balance the energy dissipation of sensor nodes. The simulation results show that ADRHP achieves longer lifetime and more data message transmissions than current artificial neural network (ANN) based clustering protocol such as Residual Energy Based Clustering Self organizing map (R-EBCS) in wireless sensor networks.

Keywords: R-EBCS, Adaptive Decentralized Re-Clustering Heterogeneous Protocol (ADRHP), ANN.

1. INTRODUCTION

In wireless networks such as wireless sensor networks, nodes spend most of their power in communication, either sending their own data or relaying other nodes' data [5, 13, 14]. Therefore, designing power-efficient clustering algorithms and routing is one of the major concerns in wireless networks. Furthermore, the communication power can be reduced by jointly considering other layers' protocols, which make use of the broadcast nature of the wireless medium. Moreover, these algorithms should be implemented in a distributed way. Therefore, the main goal of this paper is to design a distributed minimum-power clustering algorithm for wireless networks.

The deployment of wireless sensor networks in many application areas, e.g., aggregation services, requires self-organization aggregation services, requires self-organization [7] of the network nodes into clusters. In these cases, sensors in different regions of the field can collaborate to aggregate the information they gathered. For instance, in habitat monitoring applications the sink may require the average of temperature; in military applications the existence or not of high levels of radiation may be the target information that is being sought. It is evident that by organizing the sensor nodes in groups i.e., clusters of nodes, we can reap significant network performance gains. Clustering not only allows aggregation, but limits data transmission primarily within the cluster, thereby reducing both the network traffic and the contention for the channel [7].

2. SOM BASED ROUTING PROTOCOLS

The Self-Organizing Map (SOM) is an unsupervised neural network structure consists of neurons organized on a regular low dimensional grid. Each 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 neighbourhood relation as shown in Figure-1. Every input vector activates a neuron in output layer (called winner neuron) based on its most similarity [8, 9].

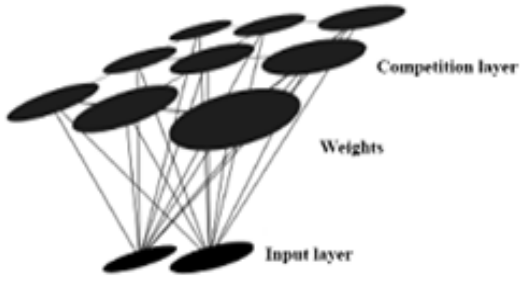

Figure-1. SOM topology.

There are different applications for SOM neural networks in WSNs routing protocols. These applications can be divided into three general groups: deciding optimal route, selection of cluster heads and clustering of nodes.

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3. RESIDUAL ENERGY BASED CLUSTERING SELF ORGANIZING MAP (R-EBCS)

In order to use the effectiveness of cluster-based routing algorithms in increasing of WSNs lifetime, Residual Energy Based Clustering Self organizing map (R-EBCS) is used. The classic idea for topological clustering and incorporate a topology-energy based clustering method in order to approach to our main goal in WSNs, extending life time of the network with enough network coverage. In our idea, energy based clustering can create clusters with equivalent energy levels. In this way, energy consumption would be better balanced in whole network.

a) Algorithm assumptions

The proposed algorithm (REBCS) is more like LEACH-C and LEA2C protocols for heterogeneous network. The operation of the algorithm is divided into rounds in a similar way to LEACH-C. Each round begins with a cluster setup phase, in which cluster organization takes place, followed by a data transmission phase, throughout which data from the simple nodes is transferred to the cluster heads. Each cluster head aggregates/fuses the data received from other nodes within its cluster and relays the packet to the base station. In every cluster setup phase, Base Station has to cluster the nodes and assign appropriate roles to them. 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, the node is a cluster head otherwise it is a normal node.

b) Cluster setup phase

The protocol uses a two phase clustering method SOM followed by K means algorithm which had been proposed in with an exact comparison between the results of direct clustering of data and clustering of the prototype vectors of the SOM [10]. We selected SOM for clustering because it is able to reduce dimensions of multi-dimensional input data and visualize the clusters into a map. In our application, dimensions of input data relates to the number of variables (parameters) that we need to consider for clustering. The reason for using SOM as preliminary phase is to make use of data pre-treatment (dimension reduction, regrouping, visualization) gained by SOM. Therefore the data set is first clustered using the SOM, and then, the SOM is clustered by k means. The variables that we want to consider as SOM input dataset is x and y coordination of every node in network space and the energy level of them. So we will have a D matrix with N-3 dimensions. Since we are applying two different type variables, first we have to normalize all values.

$$V' = \frac{v - \min_a}{(\max_a - \min_a)} \quad (1)$$

So by means of above equation, our dataset matrix would be

$$D = \begin{bmatrix} \frac{xd_1}{xd_{max}} & \frac{yd_1}{yd_{max}} & \frac{E_1}{E_{max}} \\ . & & \\ . & & \\ \frac{xd_n}{xd_{max}} & \frac{yd_1}{yd_{max}} & \frac{E_n}{E_{max}} \end{bmatrix} \quad (2)$$

Where D is the data sample matrix or input vectors of SOM, $XD=(xd_1...xd_n)$ are X coordinates, $YD=(yd_1. ..yd_n)$ are Y coordinates, $E=(E_1 ...E_n)$ are energy levels of all sensor nodes of the networks, xd_{max} is the maximum value for x coordinate of the network space, yd_{max} is the maximum value for Y coordinate of network space and E_{max} is the remain energy of maximum energy node of the network(at the beginning it is equal to E initial).In order to determine weight matrix, Base Station has to select m nodes with highest energy in the network. At the beginning, the nodes have equal energy level according to our assumptions. So we can partition the network space to m regions and select the nearest node to center of every region. However due to using two phase SOM-K means method, we usually need to consider a rather large value for m, especially in large WSNs. In this case we can choose the m nodes randomly. We need three variables of these selected (high energy) nodes to apply them as weight vectors of our SOM: their x coordinate, their y coordinate and their energy level. Therefore our weight matrix would be,

$$\mathbf{W} = \begin{bmatrix} \frac{\mathbf{xd_1}}{\mathbf{xd_{max}}} \dots\dots\dots \frac{\mathbf{xd_m}}{\mathbf{xd_{max}}} \\ \frac{\mathbf{yd_1}}{\mathbf{yd_{max}}} \dots\dots\dots \frac{\mathbf{yd_m}}{\mathbf{yd_{max}}} \\ 1 - \frac{\mathbf{E_1}}{\mathbf{E_{max}}} \dots\dots 1 - \frac{\mathbf{E_m}}{\mathbf{E_{max}}} \end{bmatrix} \quad (3)$$

W is the weight matrix of SOM, XD= (xd1..xdn) are x coordinates, YD= (yd1…ydn) are y coordinates and (1-E1/Emax…1-En/Emax) are consumed energy of m selected max energy sensor nodes. In this way we want to move the nodes with less energy towards max energy nodes in order to form balanced clusters. So the SOM topology structure would be as Figure-2.

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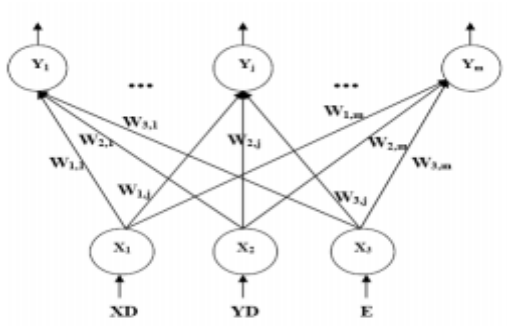

Figure-2. SOM topology structure.

In our application, learning is done by minimization of Euclidian distance between input samples and the map prototypes weighted by a neighborhood function h $_{i,j}$.So the criterion to be minimized is defined by,

$$\mathbf{E_{SOM}} = \frac{\mathbf{1}}{\mathbf{N}} \sum_{\mathbf{K=1}}^{\mathbf{N}} \sum_{\mathbf{j=1}}^{\mathbf{M}} \mathbf{h}_{\mathbf{j,N(X^{(K)}} \left\| \mathbf{w_{.j} - x^{(k)}} \right\|^2} \quad (4)$$

Where N is the number of data samples, M is the, number of map units; N(x ^{k})is the neuron having the closest referent to data sample N(x^{k})and his the Gaussian neighborhood function defined by:

$$\mathbf{h\,i.j(t)} = \mathbf{exp}\left(-\frac{\left\| \mathbf{r_{j-} r_j} \right\|^2}{2\sigma^2_{\mathbf{t}}} \right) \quad (5)$$

Where $\left\| \mathbf{r_j - r_j} \right\|^2$ the distance between map unit j and input sample i and t σ is the neighborhood radius at time t which is defined by:

$$\sigma(\mathbf{t}) = \sigma_{\mathbf{o}} \mathbf{exp}(-\frac{\mathbf{t}}{\mathbf{T}}) \quad (6)$$

Where t is the number of iteration, t is the maximum number of iteration or the training length. The distance between X $_{k}$ and weight vectors of all map neurons are computed. A neuron N(X$_k$) which has the minimum distance with input sample X $_{k}$, would win the competition phase:

$$\mathbf{N(X_K)} = \mathbf{arg}_{\mathbf{1<j\leq m}} \mathbf{min} \left\| \mathbf{W_{.J} - X_K} \right\|^2 \quad (7)$$

The neighborhood radius is a great value at the beginning and it will reduce with increasing of the time of the algorithm in every iteration. After competition phase, SOM should update the weight vector of the winner N(X$_k$)and all its neighbors which placed at the neighborhood radius of (R N(X$_k$)).

$$\mathbf{w_j(t+1)} = \mathbf{w_j}(t) + \alpha(t) \mathbf{h_{j,N(x_k)}(t_k)_k (x(t) - W_j(t))}$$

Else,

$$\mathbf{W_j(t+1) = w_{.j}(t)} \quad (8)$$

Where h$_{j,n(x(k)}$(x(t) is the neighborhood function at time *t* and a (*t*) is the linear learning factor at time *t* define by:

$$\alpha(\mathbf{t}) = \alpha_{\mathbf{0}}(1 - \mathbf{t}/\mathbf{T}) \quad (9)$$

Where 0 is the initial learning rate, *t* is the number of iteration and *T* is the maximum training length. The learning phase repeats until stabilization (no more change) of weight vectors. SOM clusters *n* data samples into *m* map units (clusters). Now the SOM should be given to K means algorithm as input. K-means, partitions the data set into *K* subsets (clusters) such that all objects in a given dataset are closest to the same centroid. K-means randomly selects *K* of objects as cluster centroids [11]. 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. The criterion to be minimized in K-means is defined by

$$\mathbf{E_{K-means}} = \frac{\mathbf{1}}{\mathbf{c}} \sum_{\mathbf{k=1}}^{\mathbf{c}} \sum_{\mathbf{x \in Q_K}} \left\| \mathbf{x - C_k} \right\|^2 \quad (10)$$

Where *C* is the number of clusters, *Q $_k$* is *Kth* cluster, *Ck is* the centroid of cluster *Q$_k$*. The best value for *K* (optimal number of clusters) can be determined with an index. We selected Davies-Bouldin index. DB index actually compute the ratio of intraclusters dispersion to inter-cluster distances by:

$$\mathbf{I_{DB}} = \frac{\mathbf{1}}{\mathbf{C}} \sum_{\mathbf{K=1}}^{\mathbf{C}} \mathbf{max} \left\{ \frac{\mathbf{S_c(Q_k) + S_c(Q_l)}}{\mathbf{d_{ce}(Q_k, Q_l)}} \right\} \quad (11)$$

$$\mathbf{s_c(Q_k)} = \frac{\sum_{\mathbf{i}} \left\| \mathbf{x_i - c_k} \right\|^2}{\left| \mathbf{Q_k} \right|} \quad (12)$$

$$\mathbf{d_{cl}(Q_k, Q_l)} = \left\| \mathbf{c_k - c_l} \right\|^2 \quad (13)$$

Where *C* is the number of clusters, *Sc* is the intra cluster dispersion and *dcl* is the distance between centroids of two clusters *k* and *l*. Small values of DB index correspond to clusters which are compact, and whose centers well separated from each other. Consequently, the number of clusters that minimizes DB index is taken as the optimal number of clusters. Now, Base station knows the optimal number of clusters and their member nodes. So the next step before going to transmission phase is selection of suitable cluster heads for each cluster and assigning appropriate roles to each node.

c) Cluster head selection phase

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Different parameters can be considered for selecting a CH in a formed cluster. In three criterions have been considered for CH selection:

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

When we select the nearest node to BS in a cluster as CH, we insure to consume least energy to transmit the messages to BS. Also the nearest sensor to gravity center (centroid) of the cluster insures least average energy consumption for intra cluster communications. Whereas, selecting nodes with maximum residual energy shows better results compared to the nearest node to base station and nearest node to centroid level.

d) Transmission phase

After formation of clusters and selecting their related cluster heads now it's time to send data packets sensed at normal nodes to their related cluster heads and after applying data aggregation functions to received packets by CHs, send messages on to the base station. The energy consumption of all nodes is computed.

$$\mathbf{E_{Tx}(k,d) = E_{Tx(l)} + E_{Tx-amp}(k,d)} \quad (14)$$

$$\mathbf{E_{Tx}(k,d)} = \begin{cases} \mathbf{kE_{elec}(k,d) + k\in_{friss} d^2 if, d < d_{crossover}} \\ \mathbf{kE_{elec}(k,d) + k\in_{tworayamp} d^4, else} \end{cases} \quad (15)$$

The energy consumption for receiving k bits of data is computed by:

$$\mathbf{E_{Rx}(k,d) = E_{Rx-else}(k) = k.E_{elec}} \quad (16)$$

Where Eelec is the energy of electronic transmission/reception, kis the size of message in bit, dis the distance between transmitter and receiver, E tx_amp is amplification energy, friss ε is amplification factor, d crossover is a threshold distance in which transmission factors change. Also energy consumption of data aggregation of CHs is:

$$\mathbf{E_{DA} = 5NJ / bit / msg} \quad (17)$$

After every transmission phase, we count a new round and would have a cluster head rotation (in the case of using maximum energy criterion) The best time for re-clustering can be when a relative reduction occurs in energy level of nodes. So the energy level of m selected highest energy nodes are checked regularly. 20 percent depletion of initial energy for first time re-clustering phase and 5 percent depletion for next times are used. When the re-clustering threshold is satisfied, BS sends a re-clustering message to whole network.

4. ADRHP

ADRHP (Adaptive Decentralized Re-clustering Heterogeneous Protocol) is a clustering protocol for wireless sensor networks. It is used to collect data from distributed sensor nodes and transmit data to a base station. Here heterogeneous network consists of three types of nodes i.e normal nodes, advanced nodes and super nodes. Clusters are formed with all the three types of nodes. The cluster head is selected based on the energy of the node. The super nodes have the greatest chance of becoming the cluster head in a cluster. ADRHP is designed to support periodic remote monitoring sensor networks. The network activity is organized into rounds, where each round has two phases: initial phase and cycle phase. The duration of the cycle phase is longer than the duration of the initial phase in order to minimize overhead. In this protocol, the sensor nodes periodically switch on their sensors and transmitters, sense the environment, and transmit the data[10].

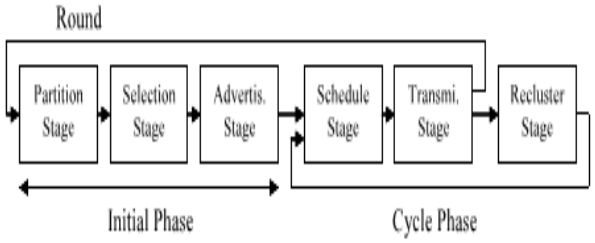


Figure-3. ADRP operations.

The wireless sensor network consists of N sensor nodes, and sensor nodes are deployed randomly in the sensing field. As shown in Figure-3, the base station splits the network into clusters and elects some sensor nodes as cluster heads, which collect sensor data from other nodes in the clusters and transfer the aggregated data to the base station.

Each cluster has one cluster head, next heads and set of sensor nodes. Since data transfers to the base station dissipate much energy, the nodes take turns with the transmission by rotating the cluster heads, which leads to balanced energy consumption of all nodes and hence to a longer lifetime of the network

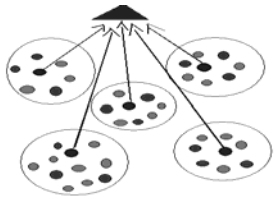
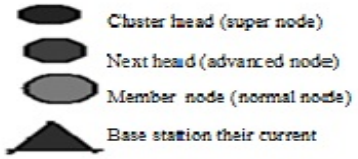


Figure-4. Clustering topology.



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In this proposed protocol, we consider the following assumptions:

1. There is a base station located far away from the square sensing field.
2. Each sensor node is assigned a unique identifier (ID)
3. Each sensor node has power control and the ability to transmit data to any other sensor node or directly to the base station.
4. Nodes are immobile.
5. All the sensor nodes are location aware. To get the information, sensor nodes can use GPS or other location detect scheme

A. ADRHP algorithm

1. Initial phase

During the initial phase, Base station receives information about current locations and remaining energy levels from sensor nodes. The base station uses the remaining energy level and locations to split the network into clusters and determine the cluster heads. Once the clusters are formed, the base station determines the next heads. In order to do this, the base station computes the average energy for each cluster in the network, and sensor nodes that have energy storage below this average cannot become next heads for this round. Once the cluster heads and next heads are determined, the base station broadcast the information including cluster heads and next heads to all sensor nodes. The initial phase consists
of three stages: partition stage, selection stage and advertisement stage**.**

a) Partition stage

During this stage, each sensor node transmits the data of its position and the amount of energy to the base station. The sensor nodes get their current location by using a global positioning system receiver that is activated at the beginning of each initial phase. On receiving the data, the base station calculates the energy value of all sensor nodes and then elects the cluster heads by minimizing the total sum of the distances between the cluster heads and sensor nodes. Furthermore, base station makes sure that only nodes with enough energy are participating in the cluster heads selection. ADRHP can distribute the energy between the sensor nodes by positioning cluster heads into the centre of clusters. At end of this stage, ADRHP partitions the nodes into set of clusters and each cluster is managed by a selected cluster head. There are three different kinds of nodes: Cluster head, member node and Next head are formed with the three types of nodes i.e, **nomal nodes, advanced nodes and super nodes** with different energy levels. The super nodes get elected as cluster heads.

b) Selection stage

Cluster head is responsible for receiving all the data from nodes within the cluster, aggregating this data and send the aggregate data to the base station. If this role was fixed, the cluster head would quickly drain its limited energy and die. Therefore, ADRHP includes rotation of this role among all the sensor nodes in the network to distribute the energy load. In this stage, ADRHP protocol requires a set of sensor nodes to be elected as next heads. Once the clusters have been formed, the ADRHP selects a set of sensor nodes as next heads. To do this, the ADRHP computes the threshold (average energy) for each cluster, and whichever nodes have energy above this threshold can be next heads for the current round.

The ADRHP repeats the following two steps for each cluster to select set of sensor nodes as next heads. ADHRP computes the threshold for each cluster j.

$$T_j = \frac{1}{m}\sum_{i=1}^{m} Ei(t) \tag{18}$$

where m is number of sensor nodes in cluster j. Ei(t) is the current energy of node i. The sensor nodes with higher energy are more likely to become next heads. If current energy of node i is greater than or equal toTj, the threshold of cluster j, the n node i is member of set NH j.

$$Ei(t) \geq T_{j,} \;\; i \in NH_j \tag{19}$$

Where NH j is the set of nodes that are eligible to be next heads in cluster j. The advanced nodes get more chance of becoming next heads than normal nodes. Once NHj sets have been created, the ADRHP elects group of next heads from the sets and specifies its member nodes.

At end of this stage, there are three different kinds of sensors:

1. Cluster heads collect sensor data from cluster members, aggregate the data and forward it to the base station.
2. Sensor nodes gather sensor data and forward the data to the cluster head.
3. Next heads act as sensor nodes but during the re-cluster stage each sensor node selects next head as new cluster head and switch to it.

The threshold value is checked by the base station after all the nodes that are in the set have been elected as cluster heads and are depleted of energy . The threshold is calculated for each of the existing number of nodes and the new set of cluster heads are selected.

c) Advertisement stage

During this stage, the base station sends a message containing the cluster head ID and next heads for each sensor node. If a node's cluster head ID matches its own ID, the node is a cluster head; otherwise, the node is a sensor node.

B. Cycle phase

During the cycle phase, each cluster head creates and distributes the TDMA schedule, which specifies the time slots allocated for each member of the cluster. The cluster head advertises the schedule to its cluster members

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through broadcasting. Each node is assigned a unique time slot during which it can transmit its data to the cluster head. Upon receiving data packets from its cluster nodes, the cluster head aggregates the data before sending them to the base station. At end of this phase each node selects next head as new cluster head and switch to it. The advanced nodes become the next cluster head. The nodes join the next cluster head and become cluster members in order to complete clusters forming. The cycle phase consists of three stages: Schedule stage, Transmission stage and Re-cluster stage.

a) Schedule stage

Once clusters have been formed, the sensor nodes must send their data to the cluster head. ADRHP uses TDMA, which allows the sensor nodes to enter a sleep mode when they are not transmitting data to the cluster head. Also, using a TDMA approach in intra cluster communication ensures there are no collisions of data within the cluster. Based on the number of nodes in the cluster, the cluster head node creates a TDMA schedule telling each node when it can transmit. The TDMA schedule divides time into a set of slots, the number of slots being equal to the number of nodes in the cluster. Each node is assigned a unique time slot during which it can transmit its data to the cluster head.

b) Transmission stage

The data transmission stage consists of three major activities:

- Data gathering.
- Data aggregation.
- Data sending.

At each sensing period, all sensor nodes send their data to their cluster heads and check the contents of incoming data and then combine them by eliminating redundant data. Then, the cluster heads transmit the aggregated data to the base station using a CSMA MAC protocol. The data aggregation is to minimize traffic load by eliminating redundancy.

c) Re-cluster stage

The ADRHP periodically re-clusters the network in order to distribute the energy consumption among all sensor nodes in a wireless sensor network. In the initial phase the base station sends messages containing the cluster head ID and next heads for each sensor node in the network. So, the sensor nodes can switch directly to the next heads without communicate with the base station. Thus, the ADRP protocol forms new clusters each cycle phase.

5. NETWORK LIFETIME

Network lifetime is the time span from the deployment to the instant when the network is considered nonfunctional. When a network should be considered nonfunctional is, however, application-specific. It can be, for example, the instant when the first sensor dies, a percentage of sensors die, the network partitions, or the loss of coverage occurs.

In this paper the lifetime of the Residual Energy based self organizing map protocol is analyzed in the three conditions i.e when cluster head is selected 1. Nearest to base station 2. Nearest to centroid 3. Based on residual energy. And the network lifetime for the ADRHP protocol has been analyzed.

6. SIMULATION RESULTS

The simulation is done in NS2 SOFTWARE. The network simulator ns2 is used to simulate the algorithm. The list of parameters are the radio propagation mode is Two Ray Ground, the channel type is wireless channel, antenna type is Omni antenna, maximum number of packet is 50, number of nodes used are 25, routing protocol is DSDV & AODV, the interface queue type is Drop Tail, the network interface type is phy/wireless, the MAC type is 802-11.The size of the network is 500*500m. The maximum simulation time is 100 minutes.

Table-1. Simulation parameters.

Type	REBCS	ADRHP
Channel	Wireless channel	Wireless channel
Radio Propagation model	Propagation /Two ray ground	Propagation /Two ray ground
Network Interface type	Phy/Wireless Phy	Phy/Wireless Phy
Mac type	MAC 802.11	MAC 802.11
Link layer type	LL	LL
Antenna	Omni	Omni
Max packets	50	50
Routing Protocol	AODV	DSDV
Interface Queue type	Queue/Drop tail/PriQueue	Queue/Drop tail/PriQueue
Size of NW	500*500	500*500
No of nodes	25	25
Simulation time	70min	100min

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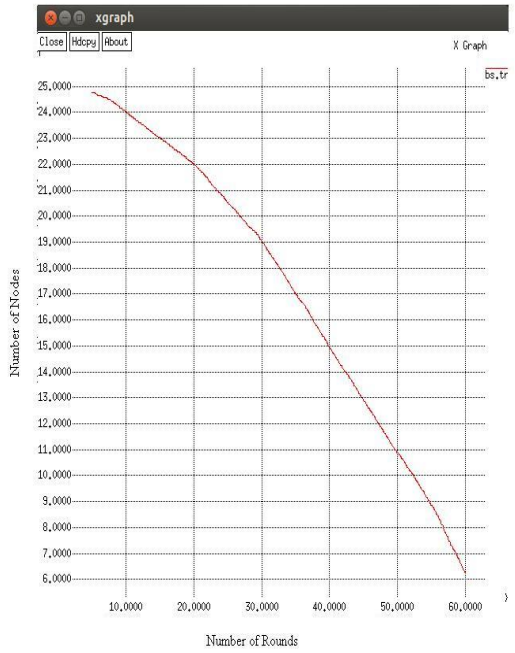

Figure-5. Lifetime (Rounds) in CH selection(BS).

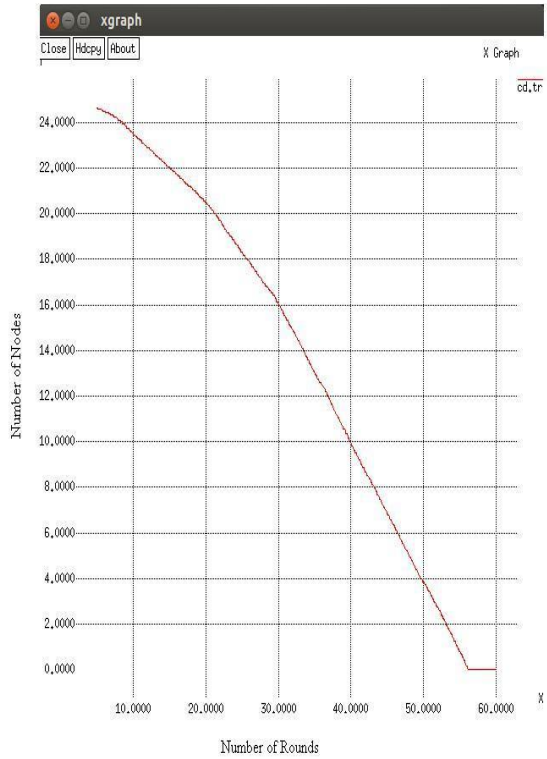

Figure-6. 5 Lifetime (Rounds) in CH selection (Centroid).

From the simulation results it is inferred that the network life time has been increased when the cluster head selection is made based on residual energy of the nodes to 70 rounds as in Figure-7 compared to other two methods. The network lifetime is 60rounds when cluster head selection is based on nearest to a base station and 60 rounds when cluster head selection is done based on centroid as in Figure-6 and Figure-7. But the number of rounds is extended to 100 rounds in ADRHP as in Figure-8. m The network lifetime has been improved considerably in ADRHP protocol compared to REBCS protocol.

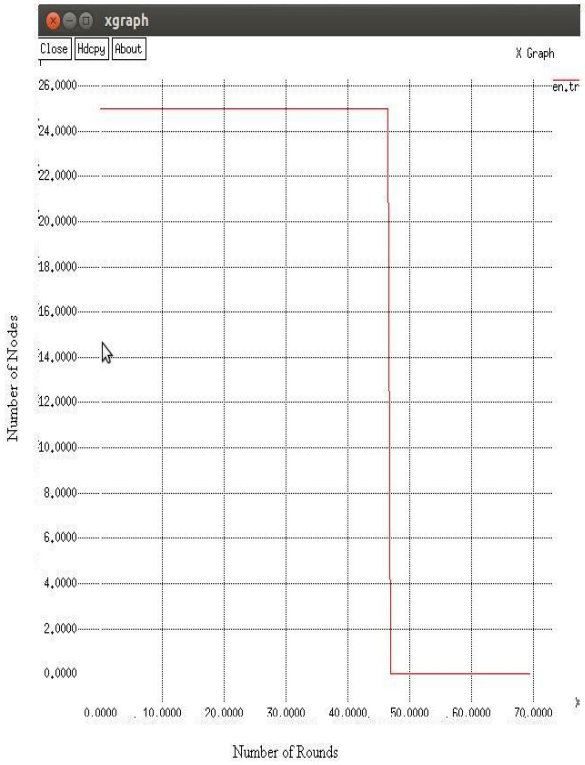

Figure-7. 5 Lifetime (Rounds) in CH selection (Residual Energy).

6. CONCLUSIONS

ADRHP protocol has been proved to be more efficient for electing cluster heads and next heads in wireless sensor networks and improving in the network lifetime. The selection of cluster heads and next heads are weighted by the remaining energy of sensor nodes and the average energy of each cluster. The sensor nodes with the highest energy in the clusters can be a cluster heads at different cycles of time. By means of the former, the role of cluster heads can be switched dynamically. Simulations results show that ADRHP has extended the lifetime of the network and reduced the communication overhead. Hence, the performance of the proposed protocol is better in terms of lifetime, data delivery and communication overhead, when compared with REBCS. ADRHP protocol has extended the lifetime of the network by 30% as compared to the existing protocol. From the analysis done so far it has been proved that the heterogeneous network based clustering protocols increases the life time of the network. So future work can be done by analyzing various

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heterogeneous networks with different clustering algorithms to enhance the lifetime.

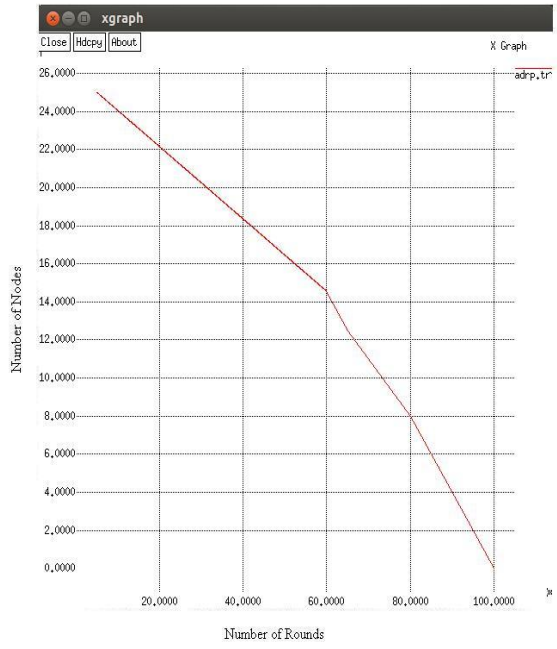

Figure-8. Lifetime (Rounds) in ADRHP.

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