Enthralment of Received Signal Strength Vaticinate of Cluster Head and Number of Rounds

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Abstract: The dispersed nature and vibrant topology of wireless sensor network have some basic requirements that include reduced energy utilization and extended network's lifetime. In this paper, we have focused on hierarchical protocols. In such protocol the nodes are arranged in clusters. To synchronize action and route data, cluster head are selected one per cluster. We have introduced a new approach in wireless sensor network for selecting the cluster-head by making use of artificial neural network in order to increase network's lifetime. We have used residual energy as a factor to make cluster-head. Radial basis function network model is used for cluster-head selection problem. The simulation results provide network's performance on the basis of some factors including number of dead nodes, total energy consumption, cluster head formation, number of nodes dying and the number of packets transferred to base station and cluster head. The performance of the proposed algorithm is compared with LEACH and LEACH-C based on energy efficiency and improved network lifetime

I INTRODUCTION

Wireless Sensor Networks (WSN) that on sensor, battery, processor and communication unit which is to collect data from the environment they have created networks of small nodes. Wireless Sensor Networks aim of Madiran delivered to the collection point of data collected from the environment. The studies in the literature on this topic can be collected in the localization and energy efficiency, data routing. One of the important work areas in WSN is to select a cluster head (CH) in self-organized clusters create their own clusters and each cluster can send the data. Clustering algorithms basic principle, the energy of the nodes in the network to select a CH in order to use the highest efficiency and the data are included in the set is based on its submission to him. If the selected cluster head transmits data from the central node.

Cluster head (CH) selection on the calculated energy to generate a random number with the participation threshold of parameters such as the number of nodes in the CH node or that the network is based on a high. But choosing themselves a CH node of a clustering algorithm clusters close to each other based on the distance from the node would lead to less energy will be more accurate than logically. When analyzed studies on the subject, which appears to be related to the selection algorithm Leach per cluster. LEACH algorithm was developed in 2002 by Heinzelman and CH selection was built. In another study that was made by Heinzelman in the same year, due to the not to be homogeneous distance between CH and nodes in cluster, the CH of the energy efficiency of the nodes has been mentioned is low. There are studies about the measurement of the battery capacity with distance information and the distance estimation between nodes and determine the position of movable objects in confined spaces with RSSI.

The rest of the paper is organized as follows. Section II gives a brief overview of work related method. Section III and IV describes the preliminaries and the proposed methodology. Section V presents the experimental results obtained from the proposed method and comparison with existing work. The paper is Conclusion in section VI respectively.

II RELATED WORKS

Mengying Ren et al [1] proposes a unified framework of clustering approach (UFC), composed of three important parts: 1) neighbor sampling; 2) backoff-based cluster head selection; and 3) backup cluster head based cluster maintenance.

Qingjian Ni et al [2] proposed a solution based on fuzzy clustering preprocessing and particle swarm optimization. More specifically, first, fuzzy clustering algorithm is used to initial clustering for sensor nodes according to geographical locations, where a sensor node belongs to a cluster with a determined probability, and the number of initial clusters is analyzed and discussed.

Miao Zhao et al [3] proposed a three-layer framework for mobile data collection in wireless sensor networks, which includes the sensor layer, cluster head layer, and mobile collector (called SenCar) layer.

Mee Hong Ling et al [4] investigated the effectiveness of trust and reputation model (TRM) in clustering as an approach to achieve higher network performance in cognitive radio (CR) networks. Reinforcement learning (RL) based TRM has been adopted as an appropriate tool to increase the efficacy of TRM.

Degan Zhang et al [5] proposed a novel passive multi-hop clustering algorithm (PMC) to solve these problems. The PMC algorithm is based on the idea of a multi-hop clustering algorithm that ensures the coverage and stability of cluster.

III PRELIMINARIES

Hemavathi et al [6] developed the influence of an obstacle can be realized through Received Signal Strength Indicator. Hence, the proposal incorporates Received Signal Strength Indicator as one of the parameters in Cluster Head Selection. The fuzzy logic is employed to predict the Cluster Head. Then, based on the energy consumption of Cluster Head, the number of rounds for the node to continue as CH is predicted using threshold. The proposal is simulated in MATLAB and implemented in hardware using Zigbee and AtMega controller. The results confirm the impact of Received Signal Strength on Cluster Head selection and the number of rounds prediction. Further, to overcome the shortfall of existing first order radio model, linear regression based energy prediction model is proposed.

The RSSI based CH selection scheme (RSSI-LEACH) incorporates Received Signal Strength Indicator in addition to Residual Power of Sensor Node, Distance of the Node from Base Station for CH selection. The fuzzy logic is used to predict the CH selection. Further, the energy consumed by the member node and CH in the presence and absence of obstacle is observed. Based on these values, the number of rounds a node can act as CH or reclustering interval can be estimated. RSSI based CH selection scheme is elaborated in the following sub-section.

a) Fuzzy based CH and Number of Rounds Prediction

The flowchart of the proposal is depicted. The nodes are randomly located. Based on their positions, DNBS is computed. The RSSI of the nodes is measured through XCTU and then the path loss is arrived. XCTU is a graphical interface used to configure the Zigbee either as BS or CH or member node and also to view the network along with the network parameters [30]. Further, RPSN of the nodes is also observed in the presence and absence of obstacle. In the absence of hardware, the energy consumed by the node can be computed using proposed linear regression based energy prediction model. If the energy of the nodes is above the live threshold, then nodes are said to be alive. If the node possesses energy higher than CH_Threshold, then the node is declared as eligible node for CH selection. Fuzzy logic based CH selection probability and the number of rounds of communication prediction is invoked. The node with the highest probability will be selected as CH. When, the energy is below CH_Threshold, CH reselection occurs.

The linear regression based energy prediction model is detailed in the subsequent sub-section.

b) Linear Regression Based Energy Prediction Model

Linear regression based energy prediction model is proposed and is portrayed in Fig. 3. In this, two different intercepts PL(d0_LOS) and PL(d0_MP) correspond to the path loss in the absence and presence of obstacle are considered.

Therefore, the energy consumption of a node at a distance „d" is obtained as follows:

$$y1 = mx+c1$$
$$y2 = mx+c2$$

where

$$m = \frac{\sum (x - x)(y - y)}{\sum (x - \bar{x})^2}, \quad c = (\bar{y} - m\bar{x})$$

where x is the path loss of the node (in dB), y1 and y2 are the energy consumption of a node without obstacle (in J) and with obstacle (in J). Here,x' and y' are the mean of x, y for (both y1 and y2). Furthermore, „m" is the slope of the line whereas „c" is the y intercept of the line (c1 for y1 and c2 for y2) respectively.

The energy consumption of a node in the absence and presence of obstacle can be estimated. With this energy consumption, the RPSN of the nodes can be computed and fed as one of the input to fuzzy based CH selection scheme.

IV PROPOSED SCHEME

In this section, a neural network based clustering and energy efficient routing is proposed in WSN with the objective of maximizing the network lifetime. In the proposed scheme, the problem is formulated as linear programming (LP) with specified constraints. Cluster head selection is done using adaptive learning in neural networks followed by routing and data transmission. The simulation results show that the proposed scheme can be used in wide area of applications in WSNs.

The solution for the energy aware routing problem is proposed using an LP formulation. The objective of the LP is to select a number of nodes with higher levels of residual energy to form an optimal route, while minimizing the total routing cost. Let us label the basestation as node 0 and label the CH nodes as nodes 1 to n, where n is the total number of CH sensor nodes. So the problem reduces to

$$\textbf{Minimize} \sum_{1 \le i \le n} R\_C \quad \text{---------------(1)}$$

Subject to following constraints

$$\sum_{1 \le j \le n} D_{ij} - \sum_{1 \le j \le n} D_{ji} = b_i \quad \text{------------(2)}$$

$$D_{ij} \ge 0 \;, 1 \le j \le n \quad \text{------------(3)}$$

$$E \le P_{\max imum} \quad \text{------------(4)}$$

Constraint (4) specifies the amount of data transmitted *bi* between two nodes *Si* and *S j* Constraint (5) specifies amount of data to be transmitted from two nodes *Si* and *S j* , Constraints (6) guarantees a minimum node lifetime and limits the maximum power consumption of any node in the network. The proposed protocol is divided into two phases namely as: setting up phase and energy aware routing and data transmission phase.

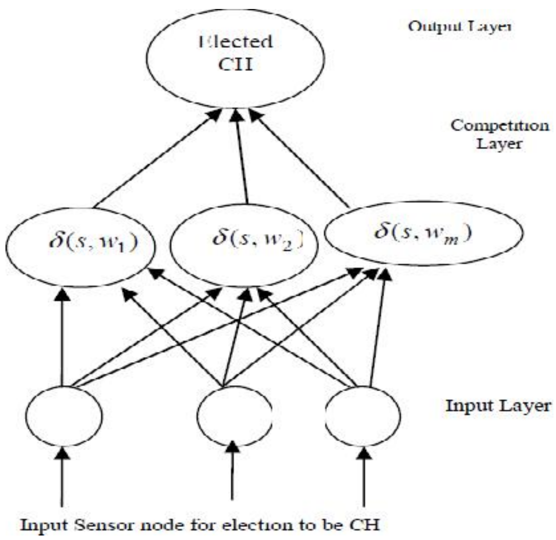


Fig 4.1 Selection of CH

Setup Phase

In this part, the initial cluster head selection and cluster formation algorithm are introduced , followed by the energy aware routing.

Cluster Head Election

To ensure balanced energy consumption among the cluster head nodes throughout the network lifetime, many clustering protocols favor uniformly distributed clusters with stable average cluster sizes. But we propose a new neural network based coverage aware clustering algorithm. The set of cluster head nodes can be selected based on the cost metric defined in equation 3. The densely populated parts of the network will be overcrowded with cluster head nodes, while the scarcely covered areas will be left without any cluster head nodes.

In such a situation, it is likely that the high cost sensors from poorly covered areas will have to perform expensive data transmissions to distant cluster head nodes, further reducing their lifetime. There are three layers in the proposed neural network: Input layer, Competition layer and Output Layer. Neural networks have solved a wide range of problems and have good learning capabilities. Their strengths include adaptation, ease of implementation, parallelization, speed, and flexibility. A two - layer feed forward neural network that implements the idea of competitive learning is depicted in Figure 2 above. The nodes in the input layer admit input patterns of sensor nodes competing for CH and are fully connected to the output nodes in the competitive layer. Each output node corresponds to a cluster and is associated with weight Wj , j = 1,2,....,m , where m is the number of clusters.

The neurons in the competitive layer then compete with each other, and only the one with the smallest D Ei value becomes activated or fired. Each neuron in the proposed algorithm for CH selection has an adaptive learning. The learning rate μ determines the adaptation of the vector towards the input pattern and is directly related to the convergence. If μ equals zero, there is no learning. If μ is set to one, it will result in fast learning, and the prototype vector is directly pointed to the input pattern. For the other choices ofμ , the new position of the vector will be on the line between the old vector value and the input pattern. Generally, the learning rate could take a constant value or vary over time.

Algorithm1: Proposed algorithm

1. Initialize the Vector $S = \{S_1, S_2, ..., S_m\}$ of sensor nodes competing for Cluster head. //Processing at Input Layer
2. Choose a winner k from sensor nodes as CH whose E_i^D is minimum as follows
   $k = \arg\min\{E_i^D\}$ // Competition Layer
3. Also E_i^D smallest Euclidean distance to BS i.e. $E_i^D = k \sum_{i=1,2,...m} |S_i - BS|$, where k is proponality constant
4. Update the value of weight vector as follows:
   $w_j(new) = w_j(old) + \mu(S_i - w_j(old))$, where μ is learning rate of the neurons. $0 \le \mu \le 1$
5. Repeat Steps (2-4) iteratively.
6. Neuron with smallest value of E_i^D is winner.// Output Layer

V SIMULATION RESULTS

In this section, the simulation results are implemented using MATLAB2014 which is figured in 5.1- 5.7 and the performance graphs are figured in 5.7 - 5.8 respectively.

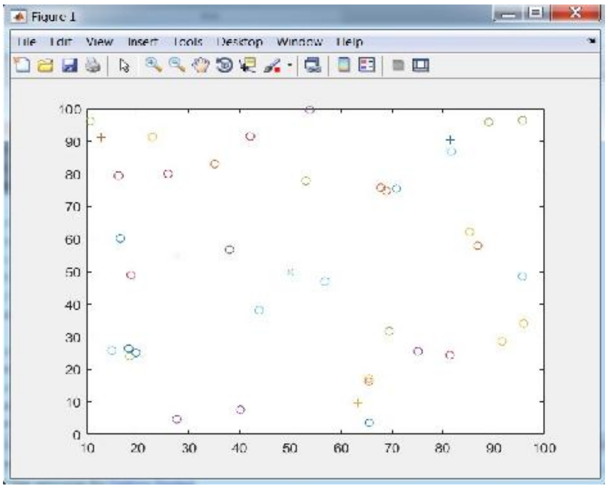
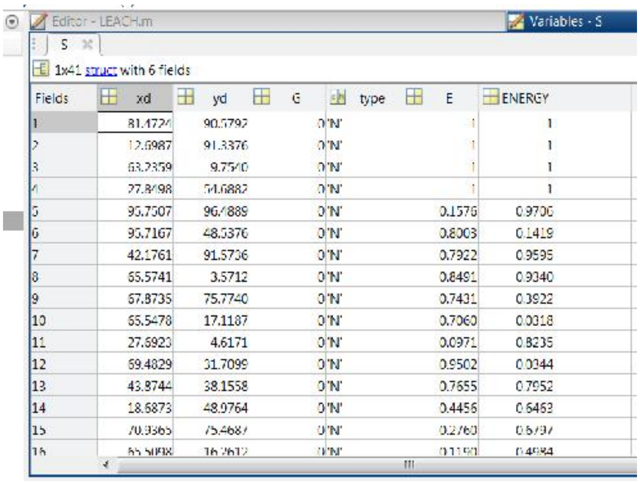


Fig 5.1Node initialization



Editor - LEACH.m | Variables - S

1x41 struct with 6 fields

Fields	xd	yd	G	type	E	ENERGY
1	81.4724	90.5792	0	'N'	1	1
2	12.6987	91.3376	0	'N'	1	1
3	63.2359	9.7540	0	'N'	1	1
4	27.8498	54.6882	0	'N'	1	1
5	95.7507	96.4889	0	'N'	0.1576	0.9706
6	95.7167	48.5376	0	'N'	0.8003	0.1419
7	42.1761	91.5736	0	'N'	0.7922	0.9595
8	65.5741	3.5712	0	'N'	0.8491	0.9340
9	67.8735	75.7740	0	'N'	0.7431	0.3922
10	65.5478	17.1187	0	'N'	0.7060	0.0318
11	27.6923	4.6171	0	'N'	0.0971	0.8235
12	69.4829	31.7099	0	'N'	0.9502	0.0344
13	43.8744	38.1558	0	'N'	0.7655	0.7952
14	18.6873	48.9764	0	'N'	0.4456	0.6463
15	70.9365	75.4687	0	'N'	0.2760	0.6797
16	65.5098	16.2612	0	'N'	0.1190	0.4984

Fig 5.2 LEACH operation

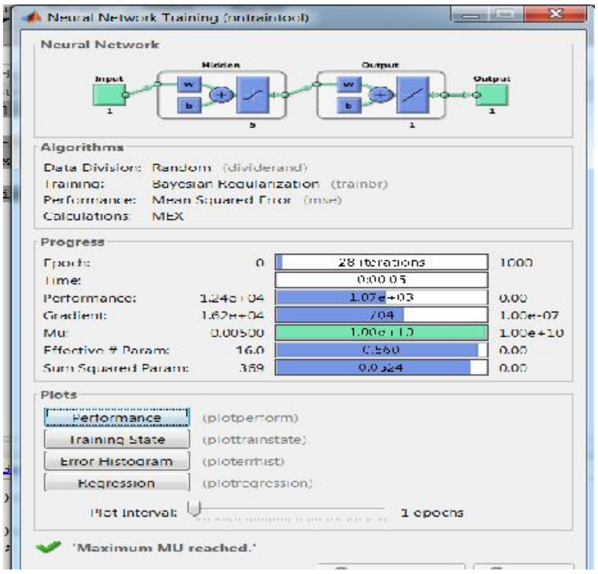


Fig 5.3 ANN training

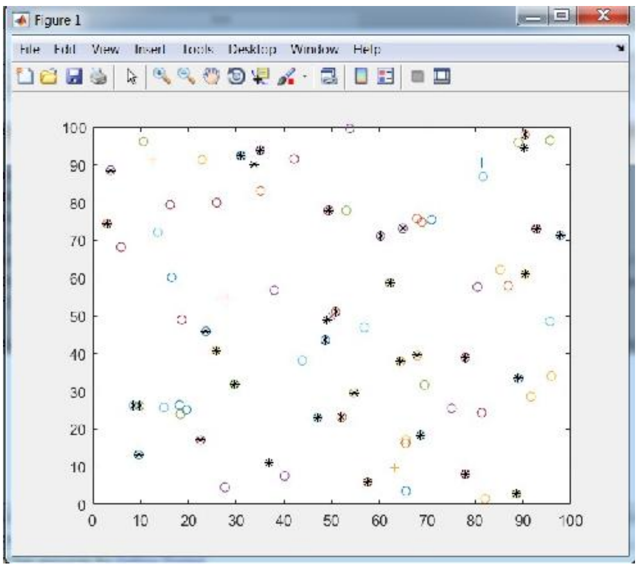
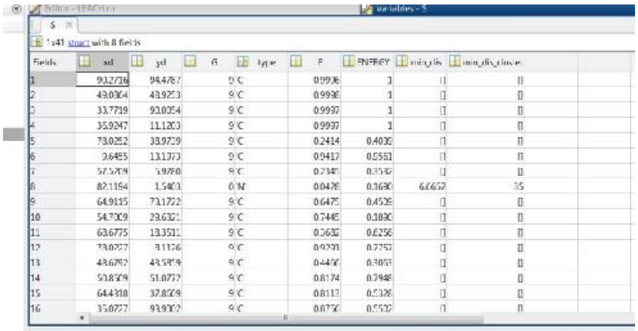


Fig 5.4 CH selection



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1x41 struct with 8 fields

Fields	xd	yd	G	type	E	ENERGY	min_dis	min_dis_cluster
1	93.2736	94.4787	9	'C'	0.9936	1	[]	[]
2	49.0364	43.9253	9	'C'	0.9998	1	[]	[]
3	33.7719	90.0054	9	'C'	0.9997	1	[]	[]
4	35.9247	11.1203	9	'C'	0.9997	1	[]	[]
5	73.0252	38.9739	9	'C'	0.2414	0.4039	[]	[]
6	9.6455	13.1373	9	'C'	0.9417	0.5551	[]	[]
7	57.5709	5.9780	9	'C'	[illegible]	[illegible]	[]	[]
8	82.1154	1.5403	0	'N'	0.0478	0.1690	6.6652	35
9	64.9115	73.1722	9	'C'	0.6475	0.4529	[]	[]
10	54.7009	29.6321	9	'C'	0.7445	0.1890	[]	[]
11	63.6775	13.3511	9	'C'	0.3682	0.6256	[]	[]
12	[illegible]	[illegible]	9	'C'	[illegible]	[illegible]	[]	[]
13	[illegible]	[illegible]	9	'C'	[illegible]	[illegible]	[]	[]
14	50.8509	51.0772	9	'C'	0.8174	0.7948	[]	[]
15	64.4318	37.8009	9	'C'	0.8113	0.5328	[]	[]
16	35.0727	93.9002	9	'C'	[illegible]	[illegible]	[]	[]

Fig 5.5 energy results of individual nodes

PERFORMANCE RESULTS:

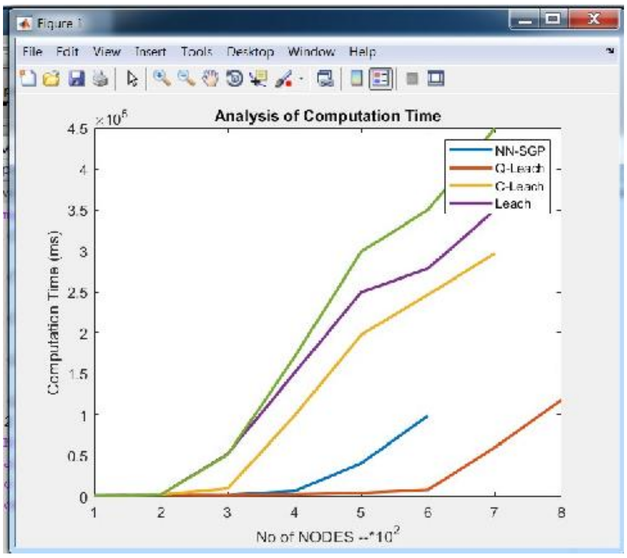

Fig 5.6 comparison graph of computation time

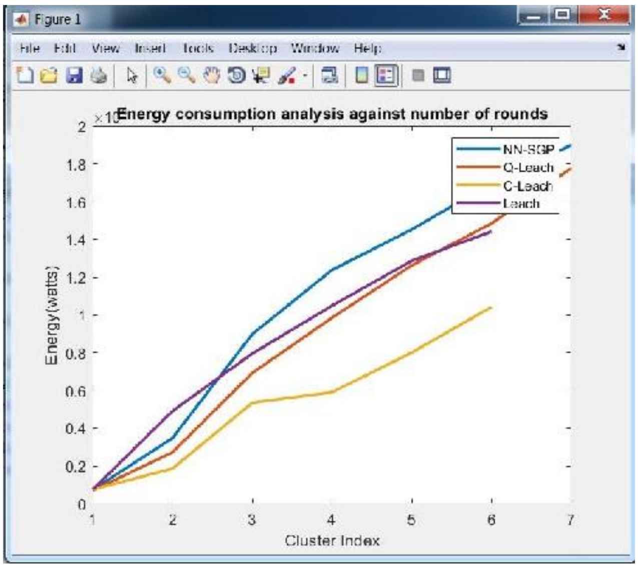

Fig 5.7 comparison graph of energy computation

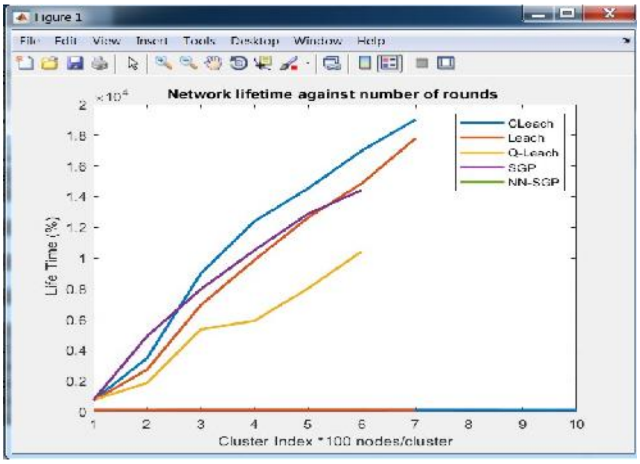

Fig 5.8 comparison graph of Network lifetime

VI CONCLUSION

This paper has proposed a neural network based energy efficient routing and clustering protocol for WSNs. The selection of CH is done using adaptive learning mechanism. Simulations results show that it performs better than existing routing protocol PEACH in terms of residual energy and .number of alive nodes. So the proposed scheme can be used in wide areas of sensor networks where energy efficiency is a critical issue.

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