Selection of Cluster Heads in Wireless Sensor Networks Using Bayesian Network

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***Abstract*—Wireless sensor networks consist of low powered tiny sensing nodes scattered in a wide uninhabited area without having any infrastructure. The structure of wireless sensor network can be flat, location based or hierarchical. Employing hierarchical routing in Wireless Sensor Network results in significant energy saving and prolonging the overall life of sensor network. One of the most critical steps in this routing scheme is the selection of cluster heads. Low-Energy Adaptive Cluster Hierarchy (LEACH) is one of the most popular hierarchical sensor network protocols. Due to random selection of cluster heads, however, it results in non-optimal utilization of resources. In this paper a Bayesian network based approach is used to select cluster heads. The approach incorporates energy level and signal strength of each sensor node. Experiments have been conducted to compare the performance of the proposed approach and LEACH Deterministic Cluster Head Selection and the results shows that the Bayesian network based approach performs better than LEACH Deterministic Cluster Head Selection and Chain-Based LEACH.**

Key words- Sensor Networks, Bayesian Network, Energy Efficiency, Clustering, LEACH,

I. INTRODUCTION

Recent advancement in micro-electronics and telecommunication technologies has resulted in design of tiny sensing nodes that are capable of sensing measureable changes in the surroundings. The measurements activity could be vibration, temperature, sound, pollution, pressure, habitat monitoring, video images, security, surveillance, health care, inventory management, factory automation and military applications [1]. These sensing nodes not only detect the phenomenon, but they also collect the data process and transmit it to the outside world for further processing [2]. These sensing nodes require careful resource management as they are tightly constrained in terms of battery power, transmission power, processing capacity and storage capability. Large number of such tiny sensing devices can be scattered in an area to form a decentralized and structure less network called wireless sensor network. The data being sensed by each node must ultimately be transferred to a nearby control center, called sink or base station. The communication is expensive in terms of energy usage between sensor nodes and base station [3]. Redundant data could be sent to the base station if two adjacent nodes are quite close to each other. Cluster-based routing has been proved to be more energy efficient as compare to other routing techniques [4], therefore the selection of cluster head is pivotal to the longevity of the sensor network.

The architecture of wireless sensor networks can be divided broadly in to three groups, namely, flat, hierarchical and location based. This paper focuses on hierarchical base wireless network. Wireless sensor network which can vary in size from tens to thousands of sensing nodes is divided in clusters. A cluster head is selected in each cluster to communicate with the base station on behalf of sensor in the respective cluster. Non cluster head sensors (leaf nodes) in each cluster send sensed data to the cluster head periodically. The cluster head aggregates and compress the incoming data and then sends it to the sink node [5].

Once a node is selected a cluster head, its overall energy consumption increases significantly as it has to communicate with all leaf nodes within the cluster as well with the base station. Therefore the process continues periodically and in each round different cluster head is selected to balance the energy consumption throughout the wireless sensor network. The algorithms designed for such network must provide a balance between network lifetime by compromising energy cost on the one hand and providing good quality of sensed data on the other hand.

Cluster head selection is an important procedural step due to the exact location of sensor node. If the selected cluster head is located closer to most of the nodes within the cluster, the cost of communication between cluster head and leaf nodes will be minimal. On the other hand if cluster head is located far away from majority of the leaf nodes then the transmission cost from leaf nodes to cluster head will be higher and the leaf nodes will consume more energy as stronger signal will be required to communicate.

Yu have proposed the EECH protocol (Energy Efficient Clustering Hierarchy) in 2009 [10], the protocol is further extension of LEACH. EECH algorithm incorporates residual energy of each node with respect to the overall aggregate energy remaining in the network before making the decision to become cluster head. EECH does not take the location of each node in to consideration during the cluster head selection process. Nam in 2008 [11] proposed E-ACHS (Extended Adaptive Cluster Head Selection) protocol, E-ACHS is a centralized protocol and the formation of cluster head is the responsibility of sink node. Sink node must know the exact location information of each node in the WSN before making cluster heads. ACHS divides unequal size clusters in to uniform cluster sizes to make it more energy efficient. Knowing exact location information requires either triangulation techniques or GPS to be integrated in to the WSN resulting in increased processing. Fazackerley proposed RSSI (Receive Signal Strength Indicator) algorithm for cluster-head selection process [5]. The algorithm evaluates the RF signal strength of neighboring nodes to decide which cluster-head to join. The RSSI algorithm outperforms LEACH by around 20%.

This paper uses Bayesian Networks to select a cluster head. The probability of each sensor node becoming a cluster head based on its probabilistic distance from remaining nodes is computed and the one with the highest probability is selected as the cluster head. Since the exact location which is required for cluster head selection is not known, therefore each node calculates the distance probabilistically. The distance depends upon the information a node receives from all other node in the cluster. This information comprises of the signal strength and battery power. Bayesian network is used to calculate the probabilistic distance between each pair of nodes. The probabilistic distance together with residual energy of each node enables the Bayesian network to find the most probable candidate to become a cluster head. The whole process is repeated to obtain new cluster head after each round and the residual energy is adjusted accordingly after every round.

The rest if the paper is organized as follow. Section II highlights the previous work done in cluster head selection process and compares a number of protocols by highlighting their benefits and drawbacks. Section III provides an overview of Bayesian networks. Section IV explains the proposed approach for the selection head process. The approach is based on residual energy and distances among sensor nodes. Finally Section V describes the experimental and simulation design as well as the results obtained through the proposed approach and LEACH Deterministic approach. Section VI highlights the conclusions and provides future research directions.

II. PRIOR WORK

The first hierarchical routing protocol introduced in the year 2000 is LEACH (Low-Energy Adaptive Clustering Hierarchy) [3]. In wireless sensor networks, the nodes working as cluster heads consumes more power as compare to leaf nodes due to long transmission ranges to remote base station and the additional processing needed for data aggregation and compression. LEACH solves this problem by dividing the operation of sensor networks in to periods or rounds, each node becomes cluster head randomly and energy consumption is spread uniformly among all the nodes in the network. The cluster head selection process in LEACH is random which results in less optimal selection of cluster heads. The overall longevity of the entire wireless sensor network depends upon the efficient power management of every sensing node since battery power is scarce. LEACH assumes that all nodes in the network are immobile, homogenous and energy constrained and the base station is located far away from the cluster. The inherent problem with LEACH is that, due to its stochastic nature, cluster head selection process is not optimal. Overall life of the sensor network can be enhanced by including residual energy and location of each node in the cluster head selection process, which is currently not the case with LEACH. Since LEACH has no location information and the cluster head selection process is random therefore adjacent nodes have potential to become cluster heads resulting in asymmetric cluster formation. Several LEACH enhancements were proposed which appears to solve some of the shortcomings of LEACH by using different methodologies and algorithms [6]. Low Energy Adaptive Clustering Hierarchy with Deterministic Cluster-Head Selection is one of the examples, and is proposed by Handy Haase and Timmermann [1]. For simplicity we call it LEACH Deterministic. It uses the same assumption about nodes and base station as LEACH does. However, it lessens pure stochastic nature LEACH by introducing a factor representing residual energy of each node. The result shows that LEACH Deterministic works better than LEACH, as it adds the residual energy of each node in the algorithm. Since it still does not make use the location information of individual sensor nodes, further room of improvement is obvious.

III. BAYESIAN NETWORK

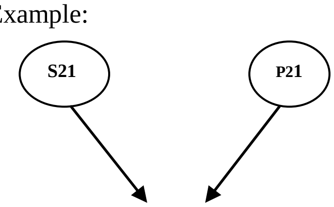
Bayesian network can be defined as graphical model representing conditional independences between a set of random variables. The graph representing different variables have edges that represent relationship among random variable that are often (but not always) causal. Bayesian network consists of a set of variable and a set of directed edges between variables, each variable has finite set of mutually exclusive states, variables together with the edges forms a directed acyclic graph (DAG), the graph must be acyclic means there must not be any feedback link or loop [8].

Let BN be a Bayesian Network over $u = \{A1,\ldots,An\}$. Bayesian network specifies a unique probability distribution $P(u)$ given by the product of all conditional probability tables specified in BN. The equation below represents the chain rule of BN.

$$P(u) = \prod_{i=1}^{n} P(Ai \mid \mathrm{pa}(Ai)),$$

Where $\mathrm{pa}(Ai)$ are the parents of Ai in BN and $P(u)$ reflects the properties of BN [9].

Bayesian Network Example:



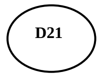


Figure 1, three nodes Bayesian Network

Figure1shown above is a small three node Bayesian Network, the network consists of three variables, two of the variable have directed edges to the third one. S_{21} which represents the signal strength from node 2 to node 1 has a direct influence on variable D_{21}. Similarly variable P_{21} which represents the power level from node 2 to node 1 also has direct influence on variable D_{21}. Variable D_{21} represents probabilistic distance form node 2 to node 1. Variables S_{21} & P_{21} are parents of D_{12}. These variables have finite set of mutually exclusive states. Any change of state of parent node will directly affect the child node. For example if evidence is received at S_{21}, this new evidence will change the probability at D_{21}. In the event that node 2 is very close to node, the probability can be expressed as;

$$P\ (D_{21}=Near|S_{21}=High,\ P_{21}=High) = 0.9$$

$$P\ (D_{21}=Near|S_{21}=Low,\ P_{21}=Low) = 0.05$$

IV. SIMULATIONS

Since a wireless sensor can possibly consists of from tens to thousands of nodes, size of cluster depends upon type of application where the network is employed. In our research as we are focusing only on the cluster head selection process, a small size cluster is used that consist of five nodes scattered randomly in an area. Figure 2 below show the scenario used in the simulation. The figure shows a scenario where five nodes are located in a cluster and are scattered randomly. From the figure 2 it is evident that node number 5 is located far from the rest of the four other nodes. Node 1, 2 and 3 are closed to each other and node 4 not far from node 2 and 3. In our research since location of sensing nodes are not known to the system, therefore we have employed Bayesian Network to find the probabilistic distance among the nodes in the cluster.

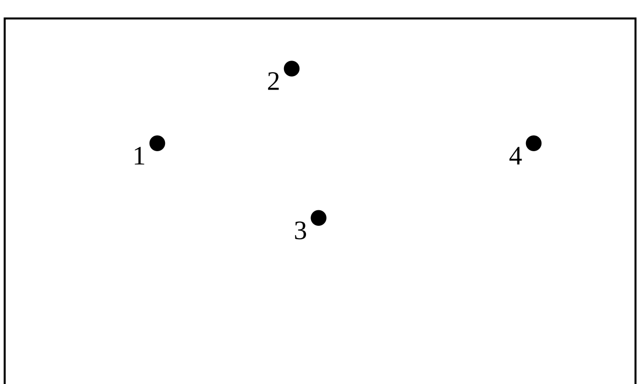


Figure 2, Sensor nodes scattered randomly in a cluster

At the start of each round, each node can potentially becomes a cluster head, the selection depends upon the location of the node with respect to rest of the nodes in the cluster and the residual energy level. Therefore at the start of each round each node will calculate its distance probabilistically from all other node in the cluster, the distance depends upon signal strength and power level. As every node in the cluster can become a cluster head therefore Bayesian Network must be built for every node considering it to be a candidate for cluster head. An example of such network for node #1 is shown in figure 3 below;

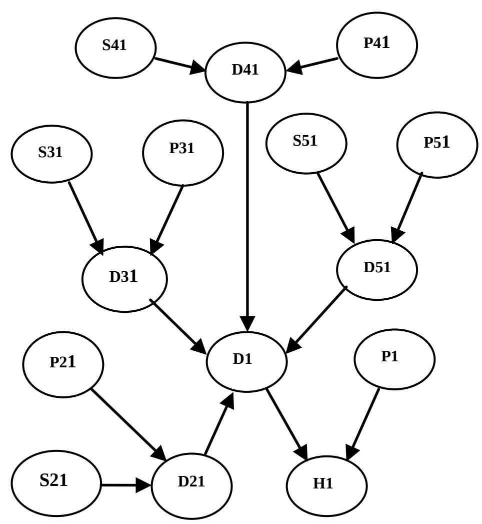


Figure 3, Bayesian Network for Node 1.

Figure 4 above shows that how node 1 sees the nodes in the cluster from its own perspective. H1 is the probability of node# 1 to become a cluster head, this probability is calculated by running the simulation using GeNie [7]. D1 is the probabilistic distance that shows how close node N1 is from all other nodes within the cluster. D21 is the distance from node 2 to 1, D31 is the distance from node 3 to node 1 and so on. S21 is the signal strength received by node 1. P1 is the power level of node 1. P21 is the power level of node 2 received by node 1, P31 is the power level of node 3 and so on. Probabilistic calculation of D21 is base on the signal strength S21 and power level P21. The same model is repeated for every node in the cluster. Individual nodes will receive probabilistic distance from every other node and then calculates the overall aggregate distance from itself to all other node in the cluster.

Figure 5 below shows the result of simulation for node 1, it can be seen from above that in the present scenario with the available signal strength and power level, node 1 has 86% probability of becoming a cluster for the present round. In the same way each node will calculate its own probability of becoming a cluster head, node showing highest probability will become cluster head for the current round.

In our simulation following assumptions have been made;

- Clusters are already formed before the cluster head selection process and the cluster could be of different size
- The Base station is located far from the cluster
- All sensing nodes are immobile
- All sensing nodes are homogenous, and are energy constrained
- Nodes have no location information
- After every round each leaf node will consume 2% energy
- Every cluster head after each round will consume 5% of energy
- Node 5 in the present scenario is located comparatively far from the rest of the nodes therefore it consume more energy, 3% of energy will be consumed by node 5 after each round.

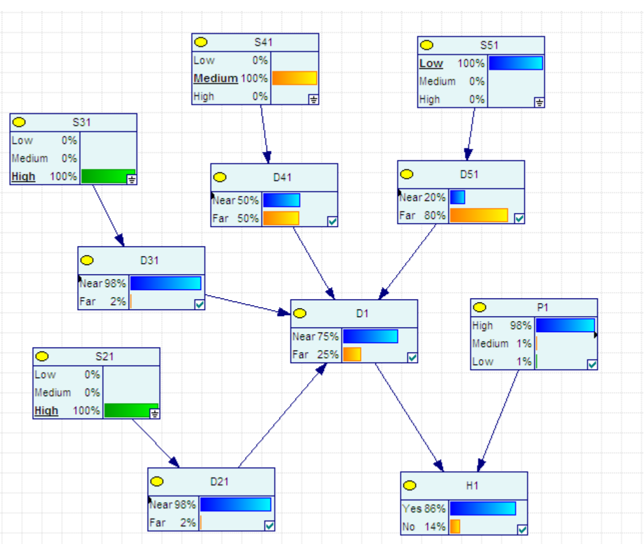


Figure 4, Simulation result from GeNie showing probability of node 1(H1)

There are five different types of variables and each variable have number of different states, Signal Strength has three states, Low, Medium and High that represents the strength of the signal received by a node. Power level also has three variables, Low, Medium and High that represents how much power level is left. The simulation is started by assuming that each node has maximum power (98%). Distance variable have two states, Near and Far, that represents probabilistically how far a node is from any other node. Another distance variable, D1 which gives aggregate distance from one node to all other node in the cluster also has two states, Near and Far. Finally the probability of a node of becoming a cluster head has two states, Yes or No. As shown in figure 4 that Node 1 has a probability of 86% of becoming a cluster head. At the end of each round the node showing the highest probability among the five sensor nodes will become a cluster head for that particular round. Table 1 below shows the simulation results, at the start of round 1, each node carries 98% energy, from P1 to P5. The probability of each node is listed from H1 to H5. At the end of each round, new T(n) value is calculated for next round, reduced power level is recorded and new cluster head is selected accordingly. As can be seen from the entry in the table that for round 1, node H3 has the highest probability among the five nodes and hence selected as cluster head for round 1.

Rounds	P1	P2	P3	P4	P5	H1	H2	H3	H4	H5	CLUSTER HEAD	Dispersion
1	0.98	0.98	0.98	0.98	0.98	0.86	0.89	0.9	0.86	0.73	H3	0%
2	0.96	0.96	0.93	0.96	0.95	0.85	0.88	0.88	0.85	0.72	H2	1%
3	0.94	0.91	0.91	0.94	0.92	0.84	0.85	0.87	0.84	0.7	H3	2%
4	0.92	0.89	0.86	0.92	0.89	0.83	0.84	0.84	0.83	0.69	H2	3%
5	0.9	0.84	0.84	0.9	0.86	0.82	0.81	0.83	0.82	0.68	H3	3%
6	0.88	0.82	0.79	0.88	0.83	0.81	0.8	0.8	0.81	0.66	H1	5%
7	0.83	0.8	0.77	0.86	0.8	0.79	0.79	0.79	0.8	0.65	H4	4%
8	0.81	0.78	0.75	0.81	0.77	0.78	0.78	0.78	0.78	0.64	H1	3%
9	0.76	0.76	0.73	0.79	0.74	0.75	0.77	0.77	0.77	0.62	H4	3%
10	0.74	0.74	0.71	0.75	0.71	0.74	0.76	0.76	0.75	0.61	H2	3%
11	0.72	0.69	0.69	0.73	0.68	0.73	0.73	0.75	0.74	0.6	H3	3%
12	0.7	0.67	0.64	0.71	0.65	0.72	0.72	0.72	0.72	0.59	H4	5%
13	0.68	0.65	0.62	0.66	0.62	0.71	0.71	0.71	0.7	0.57	H1	4%
14	0.63	0.63	0.6	0.64	0.59	0.68	0.7	0.69	0.69	0.56	H2	4%
15	0.61	0.58	0.58	0.62	0.56	0.67	0.68	0.69	0.68	0.55	H3	4%
16	0.59	0.56	0.53	0.6	0.53	0.66	0.67	0.66	0.67	0.54	H4	6%
17	0.57	0.54	0.51	0.55	0.5	0.66	0.65	0.65	0.64	0.53	H1	5%
18	0.52	0.52	0.49	0.53	0.47	0.64	0.65	0.65	0.63	0.51	H2	5%
19	0.5	0.47	0.47	0.51	0.44	0.63	0.62	0.64	0.62	0.5	H3	6%
20	0.48	0.45	0.42	0.49	0.41	0.62	0.61	0.61	0.62	0.49	H4	8%
21	0.46	0.43	0.4	0.44	0.38	0.61	0.61	0.6	0.6	0.48	H1	8%
22	0.41	0.41	0.38	0.42	0.35	0.58	0.6	0.59	0.59	0.46	H2	7%
23	0.39	0.36	0.36	0.4	0.32	0.57	0.57	0.58	0.58	0.45	H4	9%
24	0.37	0.34	0.34	0.35	0.29	0.56	0.55	0.57	0.54	0.44	H3	9%
25	0.35	0.32	0.29	0.33	0.26	0.54	0.54	0.54	0.53	0.42	H1	11%

Table 1, Simulation results from GeNie using Bayesian Network Approach

Node H3 consumes 5% energy the highest among the group, leaf nodes all consumes 2% energy node N5 which is located relatively at a distance from the rest of the four nodes consumes 3% energy in each round. The simulation was done up to 25 rounds and the power level decremented accordingly. The second last column list the selected cluster heads for each round and the last column lists energy the dispersion after each round. The scope of this research is to compare our proposed solution with the already established protocol, namely LEACH Deterministic. In LEACH Deterministic, exactly same power levels are used to run the simulation to analyze the sequence of selection of cluster heads. LEACH Deterministic is an extension of LEACH, LEACH calculates a threshold value which is based on probability and specific round number, this threshold value is then compared with random number generated by each node, if the random number is smaller than the threshold value, the node becomes cluster head. In our simulation for LEACH Deterministic, if there is more than one node capable of becoming of cluster head, the node with smallest random number is selected. Although this behavior is somewhat different from the original simulation.

Table 2 below shows all the simulation steps. Initially the Threshold value T(n) is computed with maximum power available (98%) and for round # 1, cluster head is selected after comparing which ever node has lowest random number as compare to the T(n) value of that round.

$$T(n) = \frac{P}{1 - P*\{r \bmod \frac{1}{P}\}}$$

The whole process is repeated for 25 rounds and at the end of each round, the node satisfied predefined conditions is selected as cluster head.

	N1	N2	N3	N4	N5	N1	N2	N3	N4	N5	N1	N2	N3	N4	N5		
Round #	Rand#N1	Rand#N2	Rand#N3	Rand#N4	Rand#N5	Tn*N1	Tn*N2	Tn*N3	Tn*N4	Tn*N5	P1	P2	P3	P4	P5	ClusterHead	Dispersion
1	0.7769724	0.2395242	0.4579052	0.522021103	0.7559512	0.245	0.245	0.245	0.245	0.245	0.98	0.98	0.98	0.98	0.98	H2	0%
2	0.5068357	0.0520371	0.0092058	0.253851926	0.9644694	0.32	0.31	0.32	0.32	0.31667	0.96	0.93	0.96	0.96	0.95	H3	1%
3	0.6034552	0.2253817	0.7430343	0.879895976	0.152077	0.47	0.455	0.455	0.47	0.46	0.94	0.91	0.91	0.94	0.92	H5	2%
4	0.5664414	0.9073358	0.4368135	0.123657463	0.7519694	0.92	0.89	0.89	0.92	0.87	0.92	0.89	0.89	0.92	0.87	H4	2%
5	0.9302412	0.0478935	0.1429543	0.880549552	0.9692851	0.18	0.174	0.174	0.174	0.168	0.9	0.87	0.87	0.87	0.84	H2	2%
6	0.5550981	0.1392567	0.1531593	0.235854627	0.0759358	0.22	0.205	0.2125	0.2125	0.2025	0.88	0.82	0.85	0.85	0.81	H5	3%
7	0.9012994	0.6891275	0.4107437	0.057276197	0.7077632	0.28667	0.26667	0.27667	0.27667	0.25333	0.86	0.8	0.83	0.83	0.76	H4	5%
8	0.2437535	0.8976929	0.3204478	0.779502928	0.1233101	0.42	0.39	0.405	0.39	0.365	0.84	0.78	0.81	0.78	0.73	H5	5%
9	0.5995576	0.9326523	0.4329137	0.656990117	0.6021326	0.82	0.76	0.79	0.76	0.7	0.82	0.76	0.79	0.76	0.7	H3	6%
10	0.9860356	0.8999144	0.9960755	0.031954682	0.8396527	0.16	0.148	0.148	0.148	0.126	0.8	0.74	0.74	0.74	0.63	H4	8%
11	0.0310374	0.7818968	0.9298688	0.86683224	0.0217119	0.195	0.18	0.18	0.1725	0.15	0.78	0.72	0.72	0.69	0.6	H5	9%
12	0.6460545	0.8542799	0.859727	0.921251787	0.6960456	0.25333	0.23333	0.23333	0.22333	0.19	0.76	0.7	0.7	0.67	0.57	H1	10%
13	0.9803054	0.4328582	0.7083235	0.267391529	0.1832002	0.355	0.34	0.34	0.325	0.27	0.71	0.68	0.68	0.65	0.54	H5	10%
14	0.5070571	0.8132062	0.4701106	0.450278353	0.5426368	0.69	0.66	0.66	0.62	0.49	0.69	0.66	0.66	0.62	0.49	H3	13%
15	0.0010456	0.4072015	0.2621399	0.574467396	0.7906343	0.134	0.128	0.122	0.12	0.092	0.67	0.64	0.61	0.6	0.46	H1	14%
16	0.9665466	0.6427562	0.5597604	0.190602252	0.987806	0.155	0.155	0.1475	0.145	0.1075	0.62	0.62	0.59	0.58	0.43	H4	14%
17	0.4970224	0.9559891	0.9582214	0.525981021	0.6862434	0.2	0.2	0.19	0.17667	0.13333	0.6	0.6	0.57	0.53	0.4	H1	15%
18	0.8951986	0.8466645	0.0070199	0.333717627	0.6753746	0.275	0.29	0.275	0.255	0.185	0.55	0.58	0.55	0.51	0.37	H3	16%
19	0.2845445	0.8382659	0.5659542	0.350026114	0.828883	0.53	0.55	0.51	0.49	0.34	0.53	0.55	0.51	0.49	0.34	H1	17%
20	0.7112042	0.8394874	0.7108844	0.467105796	0.6562671	0.096	0.106	0.098	0.094	0.062	0.48	0.53	0.49	0.47	0.31	H4	19%
21	0.5834027	0.7729637	0.4023188	0.699557595	0.6023322	0.115	0.1275	0.1175	0.105	0.07	0.46	0.51	0.47	0.42	0.28	H1	21%
22	0.0424689	0.801808	0.6172267	0.240038345	0.8806344	0.13667	0.16333	0.15	0.13333	0.08333	0.41	0.49	0.45	0.4	0.25	H4	23%
23	0.4820763	0.7890212	0.8199907	0.595053125	0.4584715	0.195	0.235	0.215	0.175	0.11	0.39	0.47	0.43	0.35	0.22	H5	26%
24	0.7645648	0.2372729	0.1740365	0.300631272	0.2329736	0.37	0.45	0.41	0.33	0.17	0.37	0.45	0.41	0.33	0.17	H3	31%
25	0.309456	0.7916047	0.1756512	0.824632153	0.8222167	0.07	0.084	0.072	0.062	0.028	0.35	0.42	0.36	0.31	0.14	H1	34%

Table 2, Simulation done using LEACH Deterministic algorithm

Second last column shows the selected cluster heads and the last column shows the energy dispersion at the end of each round.

V. RESULTS

In this paper only one scenario consisting of five nodes, shown in Figure 2 is evaluated for two different types of simulation methodologies, Two different simulations are run for same scenario and with same number of rounds, firstly the results for Bayesian Network approach are shown below,

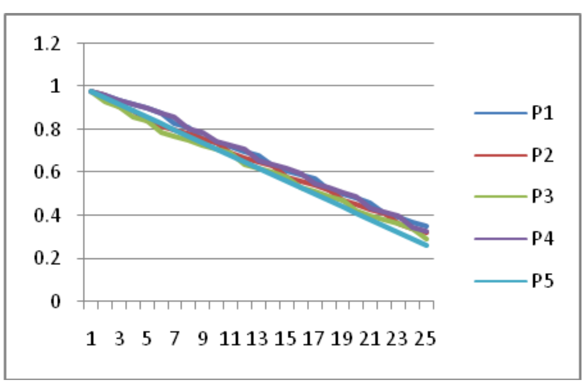


Figure 5, Power levels (y-axis) Vs number of rounds (x-axis)

Figure 5 shows the power consumption of each of the five sensor nodes, it is evident from the graph that all the five nodes are consuming power uniformly and equally, this trend of power consumption increases the life time of wireless network. Figure 6 shows the dispersion in power level that can be defined as ratio of standard deviation and average power. Figure 6 above compares the dispersion in power levels in bothe of the approaces, for BN power level is less than 12% at the end of round 25. The fact is evident from

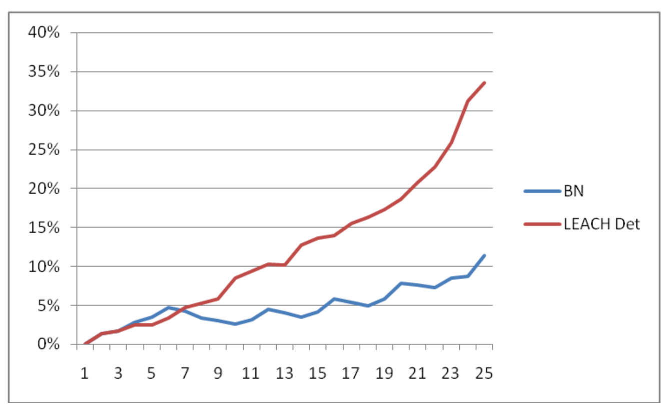


Figure 6, Dispersion of residual power with Bayesian Network and LEACH Determistic

entries of power level in Table 1, power consumption is uniform and equally spread among the five nodes. If the simulation is to continues beyond round 25, then it can be said intuitively that almost all the nodes will eventually die at the same round. Resulting in maximizing life time of the wireless sensor network.

The simulation results obtained for the LEACH Deterministic algorithm are some what different from that of Bayesian Network approach. LEACH Deterministic approach manages to reduce some level of randomness from the original LEACH, but as can be seen from the table above that some level of random is still present in this approach. This approach consider residual power in the cluster head selection process but altogther neglects the location of each sensing node. Figure 7 below shows the power levels from round 1 to round 25 of each of the five nodes.

It can be seen from Table 1 and Table 2 that the power level of node 5 after 25 rounds are different in the two different approaches, in Bayesian network approach the power level of node 5 is at 0.26 where as for the same node at the same round, the power level is at 0.14 for LEACH Deterministic. The results clearly shows that our approach of using Bayesian network is much better than the LEACH Deterministic approach, since the power levels of each node at the end of 25 rounds is much more than that of LEACH Deterministic. Figure 6 shown above highlights the power dispersion from round 1 to round 25 with LEACH Deterministic approach.

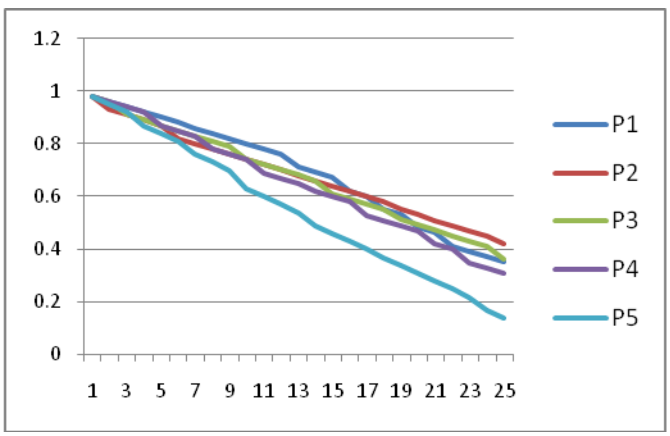


Figure 7, Power level of each node from round 1 to round 25

As in figure 7, figure 6 shows the relationship between power dispersion of all the five nodes (y-axis) against number of rounds (x-axis). The graphs shows that more than 30% power dispersion among five sensing nodes in this approach, where as using Bayesian Network approach power dispersion at this point is around 11%, therefore some improvement can be observed from the results shown. It can be analyzed that in this approach since power dispersion among the five node is high, therefore some nodes will more likely to die much earlier as compare to other nodes which will last longer due to their residual energy level resulting in nonuniform power consumption.

VI. CONCLUSIONS

Optimal selection of cluster head is highly imperative for the longevity of the whole wireless sensor network. In our research it is evident from the results obtained that proper application of Bayesian Network as tool to probabilistically select cluster heads is instrumental in achieving better results as compare with LEACH Deterministic approach. The results proved that the accumulated power of the entire cluster in our case is higher at the end of 25th round as compare to the LEACH approach. The power dispersion among all five nodes is also much less with the Bayesian network approach. The simulation carried out with LEACH Deterministic approach was with limited number of nodes, five in our case. Due to the time constrain it was not possible to run the simulation by taking a real life scenario with at least 100 sensor nodes to effective predict the behavior of wireless sensor network or to consider a bit larger cluster and variable cluster size. This simulation was carried out by using Microsoft Excel with the same algorithm employed as proposed by Handy, Haase and Timmerman in 2002.

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