Clusterhead Selection Using Multiple Attribute Decision Making (MADM) Approach in Wireless Sensor Networks

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Abstract. Cluster head (CH) plays an important role in aggregating and forwarding data in a wireless sensor networks (WSNs). The major challenge in WSNs is an appropriate selection of cluster heads for gathering data from nodes. In this paper, we present a multi-criterion approach for the selection of cluster heads (CHs) using Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). Three attributes are considered for the selection of CHs, namely residual energy, number of neighbors and distance from the base station. The simulation results demonstrate that the present approach is more effective than another Low-energy Adaptive Cluster Hierarchy (LEACH) protocol in prolonging the network lifetime.

Keywords: Wireless Sensor Networks, Clustering, TOPSIS, Optimum.

1 Introduction

The WSNs have recently attracted widespread attention as they can be deployed without the need of existing communication infrastructure. They have a wide range of applications in forest fire detection [1], surveillance [2], audio and video retrieval [3], healthcare [4] etc. These networks consist of nodes having sensing, data processing, and communicating components [5] for data collection from the remote or inaccessible areas. One of the stringent requirements of these nodes is the efficient use of available energy as it is difficult to recharge or replace their batteries once they are deployed. A variety of algorithms have been designed to cater the need of conservation of energy in WSNs. Clustering is a statistical technique used for grouping the sensor nodes into clusters based on several attributes like location, residual energy, distance from the base station, signal strength or connectivity etc. The nodes present in each cluster are responsible for sensing the physical phenomenon under consideration. Each cluster has a coordinator called cluster head, which is responsible for gathering the data from the nodes present in the cluster. Once the CH drains its entire energy, there is a need to replace the cluster head. Thus, in each cycle of data transmission, re-clustering can be done to rotate the position of

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cluster head to enhance the overall network lifetime of the system. The selection of cluster heads may either be chosen random or it can be based on one or more criteria. A systematic approach to cluster head selection process is necessary in order to select the optimum clusters for the WSN application.

In the present study, the sensor nodes are first screened using Pareto-optimal solution [6] and further TOPSIS is used to select the best cluster heads based on three different criteria. After the cluster heads are selected, clusters are formed using minimum Euclidean distance of nodes from the base station. Multiple criteria approaches have been used in a variety of applications using including MOECS [7] and TOPSIS [8].

The rest of the paper is organized as follows. Section 2 highlights the background and related work, section 3 briefly illustrates the system model used in our protocol, section 4 presents the optimum number of cluster head, section 5 presents the MADM techniques, section 6 presents the empirical illustrations, sections 7 presents the discussions and simulations results and finally section 8 presents the conclusion.

2 Background and Related Work

Several algorithms have been proposed for the selection of cluster heads but very few of them are based on multi attribute decision making approach in wireless sensor networks.

The Low-energy Adaptive Cluster Hierarchy (LEACH) [9] is the most popular routing protocol in WSN based on randomized rotation of the CHs. Each node elects itself as a CH based on a probabilistic scheme and broadcast its availability to all the sensor nodes present in the area. The communication between different nodes is based on the received signal strength and clusters are formed based on the minimum communication cost. The CH present in each cluster performs aggregation of the packets received from all the nodes present in its cluster. Also all the nodes are given a chance to become the CH to balance the over all energy consumption across the network. Although the complexity of LEACH is low, the algorithm is not energy efficient due to irregular distribution of the CHs.

EEHC [10] is another protocol which works in heterogeneous environment in which a percentage of nodes are equipped with more energy than others. The nodes play the role of a cluster head based on weighted election probabilities according to the residual energy. Though the concept of heterogeneity is introduced, this protocol does not consider different parameters for the selection of CHs. The Hybrid Energy Efficient Distributed Protocol (HEED) [11] is another single-hop clustering protocol in which CHs are selected based on a hybrid metric consisting of residual energy and neighbors proximity. Nodes having high residual energy and operates under low communication cost can become CHs. Multiple CHs are used for transferring the data to the base station if a particular CH is far apart using the concept of multi-hop communication. But HEED cannot guarantee the optimum number of elected CHs.

Another algorithm based on AHP (Analytical Hierarchy Process) [12] is a centralized CH selection scheme using Multi Criteria Decision Making Approach approach to select appropriate CHs. The factors contributing to the network lifetime are Residual energy, mobility and the distance to the involved cluster centroid. CHs are selected in each cycle based on the mobility and the remaining energy of the nodes. It is shown that the AHP approach can improve the network lifetime remarkably, especially for differentiated initial energy of nodes.

EECS [13] is a multi criteria approach for the selection of CHs and the formation of clusters based on three factors including residue to dual energy, distance between node the CH and distance between CH and BS. Thus a cost factor is calculated for associating nodes with CHs. An overhead of this scheme is the wastage of energy due to sending of messages by all the nodes in the network. This technique is further modified in MOECS [7], which considers a multi-criterion optimization for the formation of clusters only. An optimum number of cluster heads are chosen and nodes join a cluster based on the multiple attributes such as residual energy and distances thereby utilizing the local information only.

In the proposed study, the concept of multi criterion optimization is used in the selection of cluster heads unlike in the case of MOECS, where it is done for the formation of clusters. A Pareto optimal approach is used to find out a set of cluster heads which are further ranked in each cycle using TOPSIS. An optimum number of the best clusters heads are selected after the ranking and clusters are formed by attracting nodes with maximum received signal strength.

3 System Model

The following assumptions are made for our network;

1. Nodes are distributed randomly in a 100x100 square region following a uniform distribution.
2. The initial number of clusters is fixed by taking the optimum value (discussed in section 4) and keeps on varying with the node density once the nodes starts dying. The smaller clusters merge with the bigger ones.
3. The BS is a node who is responsible for gathering the entire data from all the CHs and has no energy constraint.
4. A simple radio energy dissipation model [9] in transmitting a *k bit* message over a distance *d* to achieve an acceptable Signal-to-noise ratio (SNR) is used. Energy consumed for transmission is given by

$$E_{TX} = \begin{matrix} k * E_{elec} + k * \varepsilon_{fs} * d^2 \;\; if \;\; d \le do \\ k * E_{elec} + k * \varepsilon_{mp} * d^4 \;\; if \;\; d \ge do \end{matrix}, \quad (1)$$

where E_{elec} is the energy dissipated per bit to run the transmitter or the receiver circuit, ε_{fs} and ε_{mp} are the energy consumed in the amplifier and depend on the amplifier model. By equating the two expressions at $d=d_o$, we have,

$$d_o = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}}$$

The energy consumed while reception is

$$E_{RX} = k * E_{elec} \tag{2}$$

4 The Selection Procedure for Optimum Number of Cluster Heads

In each cycle, it is very important to decide the numbers of clusters present in the area for maximizing the energy efficiency. Each cluster has a cluster head that is responsible for the data aggregation of the data received from its cluster members and does not take part in the sensing operation. For our experiment, two ranges of distances between nodes and base station are observed when the base station is placed firstly in the centre of the field and secondly far away from the field: 2 m < $dist_{toBS}$ < 70 m and 75 m < $dist_{toBS}$ < 182 m. An estimate for the optimum number of clusters, k_{opt} [14] is given by

$$k_{opt} = \sqrt{\frac{\varepsilon_{fs}}{\pi(\varepsilon_{mp} d_{toBS}^4 - E_{elec})}}.M\sqrt{N} \tag{3}$$

Using the above equation, we calculate the optimum number of clusters to be 9< k_{opt} <11 when the base station is placed away from the field. Also in Fig. 1, we

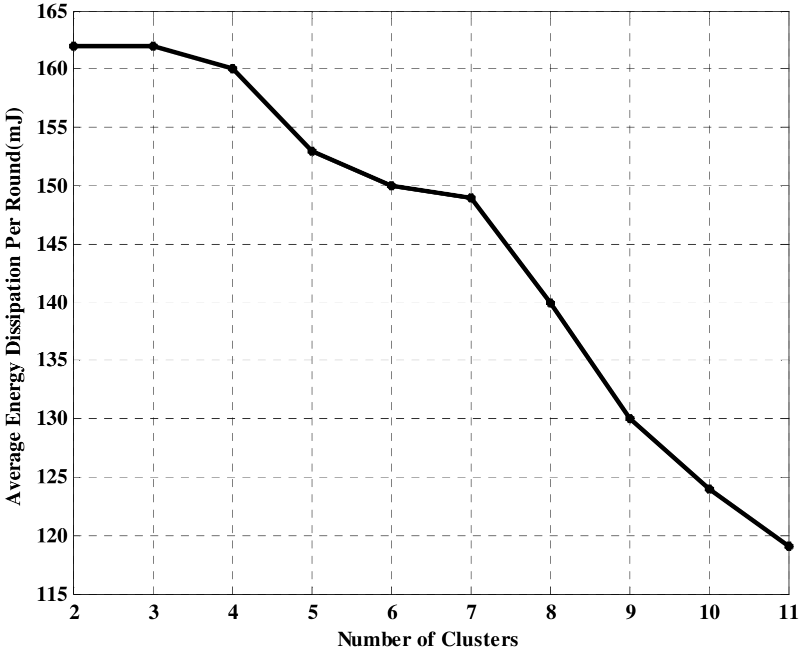

Fig. 1. Average Energy per cycle versus number of clusters in TOPSIS

have shown the average energy dissipated per cycle as a function of the number of clusters by two MADM approaches. It is observed that as the number of clusters increases the average energy dissipation decreases. The simulation results of energy dissipation cover the range as obtained through analytical results of equation (3). Thus for this algorithms, we set the number of clusters to be 10.

5 The MADM Techniques

The Multiple Attribute Decision Making (MADM) methods have been widely used to solve a variety of uncertainty problems. MADM models are capable of selecting the best alternative out of a given list of alternatives based on their prioritized attributes. There is always some extent of uncertainty in these clustered algorithms as which nodes should be chosen as CHs and what criteria should be adopted? In the present study, a well known MADM technique (TOPSIS) is used rank the cluster heads. The three attributes which are residual energy, number of neighbors and distance of nodes from the base station are chosen in some percentage for the selection of CHs. Nodes with higher residual energy, maximum number of neighbors and lesser distance from the base stations are given priority to become a CH. In each cycle, the entire network is re-clustered with the fresh selection of CHs on the basis of ranking done by TOPSIS. Once CHs are selected, each node will join a particular CH based on minimum distance and clusters are formed. Further the algorithm is divided into cycles composed of setup and data transmission phases. In setup phase, cluster heads are selected using a MADM technique and clusters are formed. In the data transmission phase, all the nodes send the data to their respective cluster heads, which is further transferred to the base station by the CH after data aggregation.

5.1 Initialization

Initially each node sends their location information of co-ordinates (location), residual energy and distance from the base station to the base station. The information received from all the nodes is processed and stored as separate records by the base station along with their status of being dead or alive. If a node has expired all of its energy after few rounds of data transmission, then it is declared as dead. Further the number of neighbors within the close vicinity of each node is also estimated and stored by the base station.

5.2 Cluster Head Selection Techniques

A set of cluster heads are selected using Pareto optimal theory using three criteria (mentioned earlier). Since the number of cluster heads given by Pareto front is not fixed in each cycle, they are further ranked using TOPSIS and an optimum number of top ranked CHs are chosen for clustering.

5.2.1 Pareto-Optimal Solution

The Pareto-optimal solutions [15,16] are non-dominated in a given solution space as described by economist Vilfredo Pareto. In multi objective decision making problems, the solution space is defined as a region consisting of all possible solutions (real and otherwise). Solution space can be classified into three sets namely a) Completely dominated, b) Neither dominated nor dominating and c) Non-dominated. In a completely dominated solution there exists at least one (real) alternative which completely overshadows all the properties of all the alternatives in a desirable manner. In the second type of set the alternatives have properties some of which are dominated by the others while the rest are dominating, thus, they are also not ideal for application. Non-dominated solutions are the alternatives that have the best trade-off between properties and are not dominated by any other alternative in the solution space.

In one-dimensional problem, there exists only one such alternative that satisfies the Pareto-optimality test. However, most of the engineering problems are multi-dimensional in nature. Various multi-objective evolutionary algorithms (MOEAs) are extensively investigated for Pareto-optimal solution in multi-objective decision making problems. In the present study, the cluster heads are obtained through Pareto-optimal solutions.

The Pareto solution for the selection of cluster based on three criteria residual energy of the node, minimum distance from the base station and number of neighbors is shown in Fig 2. It is observed that cluster heads (shown in red dots in Fig 2) are selected based on three criteria with maximum energy and neighbors and minimum distance from the base station. In this paper, we have used three criteria for the better selection of cluster heads.

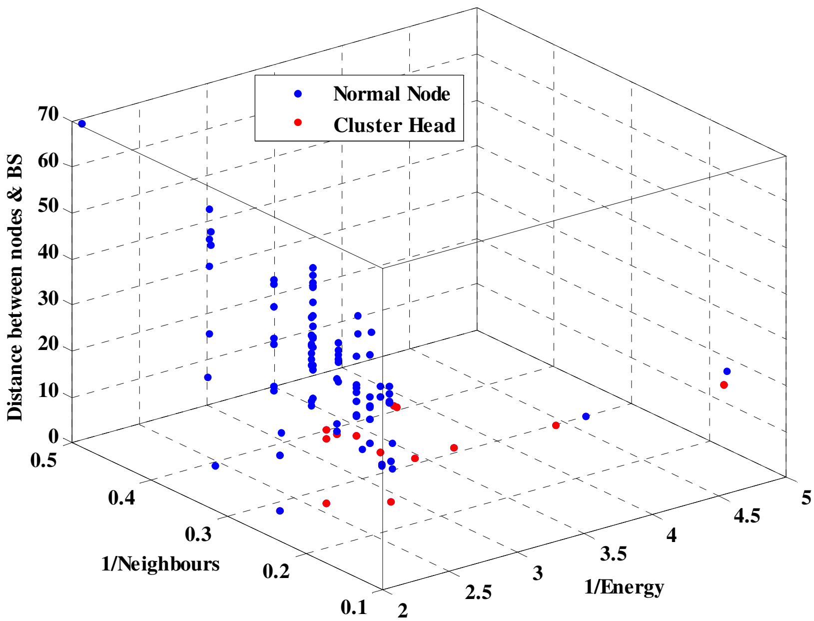

Fig. 2. Pareto-optimal solutions using three criteria

5.2.2 Ranking Using MADM Approaches

The number of CHs selected using Pareto optimal solution is different for each cycle. These CHs are further ranked using the TOPSIS and the top CHs with highest indexes are selected in an optimum number described in section 4. The three MADM techniques are described in details as follows.

TOPSIS Model

Hwang and Yoon first suggested TOPSIS in 1981 in which a decision matrix having '*m*' alternatives and '*n*' attributes can be assumed to be problem of '*n*' dimensional hyperplane having '*m*' points whose location is given by the value of their attributes. The chosen alternative should have the farthest distance from the positive ideal solution (best possible case) and the shortest distance from the negative ideal solution (worst possible case) respectively. This technique has been widely applied in various research applications [17,18,19]. The TOPSIS method involves the following steps:

Step 1: Obtain the normalized decision matrix;

$$r_{ij} = \frac{X_{ij}}{\sqrt{\left(\sum_{i=1}^{m} X_{ij}^{2}\right)}}\ ;\ \forall j \tag{4}$$

Where r_{ij} indicates the normalised value of alternative A_i w.r.t. criterion C_j.
Step 2: Obtain the weighted normalised decision matrix;

$$V_{ij} = [r_{ij}]_{mxn} * [W_j] \tag{5}$$

where W_j is the weight of the j_{th} criterion and $\sum_{j=1}^{n} W_j = 1$.

Step 3: The selection of an alternative using TOPSIS method is based on the shortest distance from the positive ideal solution (A^+) and the farthest from the negative-ideal solution (A^-), which are defined as;

$$A^+ = \left[(\max(V_{ij}), j \in J_1), (\min(V_{ij}), j \in J_2), i = 1,2,3,....m\right]; \forall j \tag{6}$$

$$A^- = \left[(\min(V_{ij}), j \in J_1), (\max(V_{ij}), j \in J_2), i = 1,2,3,....m\right]; \forall j \tag{7}$$

where, J_1 corresponds to benefit criteria and J_2 corresponds to cost criteria.
Step 4: Separation measures which are measured using Euclidean distance from the positive and negative ideal solutions are;

$$S_i^+ = \left[\sum_{j=1}^{m} \left(V_{ij} - V_j^+\right)^2\right]^{0.5},\ \text{i=1,2,3...} \tag{8}$$

$$S_i^- = \left[\sum_{j=1}^{m} \left(V_{ij} - V_j^-\right)^2\right]^{0.5},\ \text{i=1,2,3,...} \tag{9}$$

Step 5: Obtain relative closeness of alternatives to the ideal solution;

$$C_i^+ = \frac{S_i^-}{S_i^- + S_i^+} \tag{10}$$

In each cycle of data transmission, C_i^+ is calculated for all the cluster heads obtained through Pareto theory, where larger value indicates better performance of the alternative. Thus all the CHs are ranked in decreasing order of C_i^+ and the best CHs are chosen from the top.

5.3 Cluster Formation and Data Transmission

All the selected CHs now send advertisement messages in the network declaring their presence as cluster heads. Each node now measures distance from all the cluster heads, form a vector having ten entries (optimum value for number of CHs is taken as 10 here). The node joins the CH with minimum distance and sends a message to the nearest cluster head. If the distance between the node and the CH is more than its distance to the BS, the node will communicate with the BS directly. Otherwise it joins cluster based on the nearest distance (Euclidean distance), thereby forming clusters. The nodes are re-clustered based on the distance with the selected cluster head using a distance matrix, DM (m x n) given as follows;

$$DM = \begin{bmatrix} d_{CH1,x1} & d_{CH1,x2} & .. & d_{CH1,xn} \\ d_{CH2,x1} & d_{CH2,x2} & .. & d_{CH2,xn} \\ \vdots & \vdots & \vdots & \\ d_{CHm,x1} & d_{CHm,x2} & d_{CHm,x3} & d_{CHm,xn} \end{bmatrix} \tag{11}$$

where d is the Euclidean distance between CH and a node based on its location information. If y and z represent the location of two nodes p and q, then the Euclidean distance is

$$d_{p,q} = [(p_x - q_x)^2 + (p_y - q_y)^2]^{1/2} \tag{12}$$

Each element $d_{i,j}$ in the distance matrix represents the distance between the i^{th} clusterhead and j^{th} node. The column containing the minimum value represents the cluster number to be joined by the corresponding node. For example, if $d_{CH2,x1}$ is the minimum value in the first column, in this situation the node x_1 gets associate with the second cluster where CH2 is cluster head.

Once the clusters are formed, the CH assigns a time slot for each member after receiving all CH_join messages from all the nodes. Each cluster head is responsible for gathering the data from all the nodes in the cluster. When a frame of data from all the members is received, the CH send the frame to the base station after applying data aggregation. The CH must remain in active state while the member nodes can go to sleep mode from time to time. It is to be noted that the re-clustering methodology is also adopted in LEACH protocol where CHs are elected by using the probabilistic approach rather than deterministic technique. The operation of re-clustering and data transmission continues for many cycles until the death of all the nodes. If the size of the cluster is smaller than the predefined threshold, the cluster merges with the neighboring clusters. With the start of the death of nodes, it is found that there are a lesser number of nodes present in each cluster now. Thus as the number of alive nodes starts decreasing with cycles, the number of clusters also decreases and the decrease in the number of alive nodes eventually results in the reduction in number of clusters. The amount of information also decreases with the fewer nodes left in the physical area.

6 Empirical Illustrations

TOPSIS Model

In each cycle of algorithm, new CHs are selected and clusters are formed. We consider a specific cycle (cycle no-02) for the empirical analysis of Topsis method in which 14 cluster heads are short listed by Pareto optimal solutions and the data is given in Table 1. Firstly the first two factors Eo and n are taken in reciprocal so that all the three criteria can be used in decreasing order in Pareto solutions given in Table 2. Based on the first step of the TOPSIS procedure, each element is normalized by Eq. (4). The resulting normalized decision matrix for the TOPSIS analysis is shown as Table 3. Table 4 finally shows the final results of step 3, 4 & 5, which calculates positive ($\mathbf{A}^{+}$) and negative ($\mathbf{A}^{-}$) ideal solutions, distances of each CH from them and

Table 1. Decision Matrix for TOPSIS Analysis in second Cycle

Cluster Head No.	Residual Energy, Eo (Joules)(C1)	Number of Neighbors, n (C2)	Distance from Sink, d (C3)
CH1	0.4998	7	21.5830
CH2	0.4998	9	24.2745
CH3	0.4887	8	20.9972
CH4	0.4894	10	39.3231
CH5	0.4998	6	23.2092
CH6	0.4998	10	39.8408
CH7	0.4998	3	7.6944
CH8	0.4988	4	4.5873
CH9	0.4998	9	25.5698
CH10	0.4947	6	10.6745
CH11	0.4964	5	9.8442
CH12	0.4998	4	16.6420
CH13	0.4919	9	24.2008
CH14	0.4998	6	17.6095

Table 2. First level normalized decision matrix for TOPSIS Analysis

Cluster Head No.	Reciprocal of Eo, 1/Eo (Joules)	Reciprocal of n	Distance from Sink, d
CH1	2.0009	0.1429	21.5830
CH2	2.0009	0.1111	24.2745
CH3	2.0462	0.1250	20.9972
CH4	2.0434	0.1000	39.3231
CH5	2.0008	0.1667	23.2092
CH6	2.0008	0.1000	39.8408
CH7	2.0009	0.3333	7.6944
CH8	2.0049	0.2500	4.5873
CH9	2.0008	0.1111	25.5698
CH10	2.0213	0.1667	10.6745
CH11	2.0147	0.2000	9.8442
CH12	2.0009	0.2500	16.6420
CH13	2.0327	0.1111	24.2008
CH14	2.0008	0.1667	17.6095

Table 3. Second level normalized decision matrix for TOPSIS Analysis using Eq 4

Cluster Head No.	C1	C2	C3
CH1	0.2658	0.2124	0.2529
CH2	0.2658	0.1652	0.2844
CH3	0.2718	0.1858	0.2460
CH4	0.2714	0.1487	0.4607
CH5	0.2658	0.2478	0.2719
CH6	0.2658	0.1487	0.4668
CH7	0.2658	0.4955	0.0901
CH8	0.2663	0.3716	0.0537
CH9	0.2658	0.1652	0.2996
CH10	0.2685	0.2478	0.1251
CH11	0.2676	0.2973	0.1153
CH12	0.2658	0.3716	0.1950
CH13	0.2700	0.1652	0.2835
CH14	0.2658	0.2478	0.2063
Weight	0.5	0.25	0.25

relative closeness (C_i^+) given in Table 5. The CH with higher C_i^+ in TOPSIS are chosen and given the ranks as given below-

CH10 > CH11 > CH14 > CH3 > CH8 > CH1 > CH13 > CH2 > CH9 > CH5 > CH12 > CH7 > CH4 > CH6

Our attention should focus on the top few optimum choices as derived in section 4, according to which the top ten CHs should be picked and ten clusters are formed. This scenario will be repeated in every cycle during the setup phase where CHs are selected and clusters are formed.

Table 4. TOPSIS Analysis Results

Cluster Head No.	C1	C2	C3	S_i^+	S_i^-	$C_i^+ = \frac{S_i^-}{S_i^- + S_i^+}$
CH1	0.1329	0.0531	0.0632	0.0523	0.0	0.6294
CH2	0.1329	0.0413	0.0711	0.0578	0.0	0.6202
CH3	0.1359	0.0465	0.0615	0.049	0.0	0.6597
CH4	0.1357	0.0372	0.1152	0.1018	0.0	0.4601
CH5	0.1329	0.0619	0.0680	0.0599	0.0	0.5683
CH6	0.1329	0.0372	0.1167	0.1033	0.0	0.4566
CH7	0.1329	0.1239	0.0225	0.0872	0.0	0.5193
CH8	0.1331	0.0929	0.0134	0.0557	0.1	0.6592
CH9	0.1329	0.0413	0.0749	0.0616	0.0	0.6006
CH10	0.1342	0.0619	0.0313	0.0306	0.1	0.7755
CH11	0.1338	0.0743	0.0288	0.0402	0.1	0.7149
CH12	0.1329	0.0929	0.0487	0.066	0.0	0.5311
CH13	0.1350	0.0413	0.0709	0.0576	0.0	0.6210
CH14	0.1329	0.0619	0.0516	0.0455	0.0	0.6641
A^+	0.1329	0.0372	0.0134			
A^-	0.1359	0.1239	0.1167			

7 Discussions and Simulations Results

The simulator is developed in MATLAB in which TOPSIS is used for the selection of cluster heads and clusters are formed. A network model similar to [9] is used in which operation progresses in cycles. Table 5 provides the simulation parameters used in our experiments. Each cycle consists of clustering and data transmission phase. In clustering phase, the top ten CHs according to the three criteria are summarized in Table 6.

Table 5. Simulation parameters for transmission

Description	Symbol	Value
Number of nodes in the system	N	100
BS Location	-	(50, 175)
Size of the data packet	-	500 bytes
Hello / Broadcast / CH_Join message	-	25 bytes
Energy consumed by the amplifier to transmit at a short distance	ε_{fs}	10 pJ/bit/m^2
Energy consumed by the amplifier to transmit at a longer distance	ε_{mp}	0.0013 pJ/bit/m^4
Energy consumed in the electronics circuit to transmit or receive the signal	E_{elec}	50 nJ/bit

Table 6. Top ten CHs in 2nd cycle from TOPSIS

Rank	Cluster Head
1	CH10
2	CH11
3	CH14
4	CH3
5	CH8
6	CH11
7	CH13
8	CH2
9	CH9
10	CH5

In each cycle of algorithm, re-clustering is done to select the best optimum number of cluster heads as shown in Table 7 for the second cycle and the same process is repeated for every cycle till all the nodes expire their entire energy. The three chosen attributes for the selection of CHs are taken in appropriate proportions and the average results of network lifetime are considered.

In the present study, a MADM approach called TOPSIS is simulated taking the three attributes into account and compared with LEACH protocol. The base station is placed far away from the field. The lifetime of the network is measured in terms of number of cycles until the first node in the network runs out of its entire energy. Fig 3

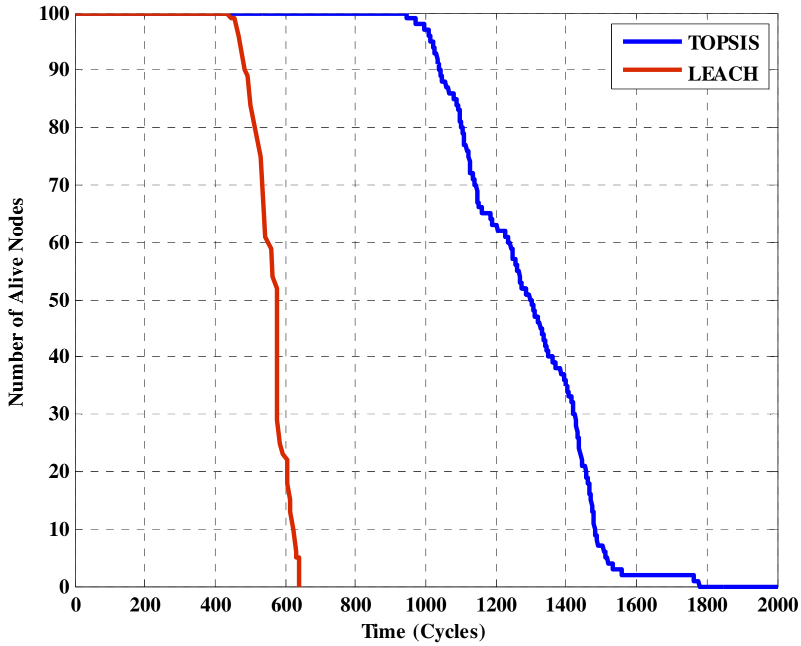

Fig. 3. Network Lifetime in cycles

shows the results of the experiment, where sensor nodes are deployed randomly on a square area of 100x100 m and network lifetime is plotted, which shows the number of alive nodes over the time in cycles. All results are expressed in averages taken over 20 random independent experiments. It is shown that the network lifetime (when first node dies) of TOPSIS (946 cycles) is 117 % higher than LEACH. It can be observed that TOPSIS outperforms Leach by a good margin in terms of network lifetime. Also the stability region remains highest in TOPSIS as compared to Leach.

8 Conclusions

In this paper, we have presented a method to select and rank cluster heads using TOPSIS in WSNs. Further it is compared with LEACH in terms of network lifetime. The optimum numbers of cluster heads are selected by using the ranking done by TOPSIS and clusters are formed. Simulations results demonstrate that TOPSIS achieves significant energy savings and enhances network lifetime compared to LEACH. In the proposed methodology, we have considered three attributes in different proportions of weights and average results are plotted. In future, we will consider more attributes for the cluster head selection.

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