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Research Article

Cluster Head Selection in Wireless Sensor Networks under Fuzzy Environment

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Clustering is one of the important methods for prolonging the network lifetime in wireless sensor networks (WSNs). It involves grouping of sensor nodes into clusters and electing cluster heads (CHs) for all the clusters. CHs collect the data from respective cluster's nodes and forward the aggregated data to base station. A major challenge in WSNs is to select appropriate cluster heads. In this paper, we present a fuzzy decision-making approach for the selection of cluster heads. Fuzzy multiple attribute decision-making (MADM) approach is used to select CHs using three criteria including residual energy, number of neighbors, and the distance from the base station of the nodes. The simulation results demonstrate that this approach is more effective in prolonging the network lifetime than the distributed hierarchical agglomerative clustering (DHAC) protocol in homogeneous environments.

1. Introduction

Advancements in low-power electronic devices integrated with wireless communication capabilities are one of the recent areas of research in the field of the wireless sensor networks (WSNs). WSNs consist of spatially distributed autonomous sensors distributed over a region of interest to observe some phenomenon through either some random or strategic methods. Considerable amount of work has enabled the design, the implementation, and the deployment of these sensor networks tailored to the unique requirement of sensing and monitoring in real-time applications. These nodes have onboard wireless modules which consist of microcontroller, transreceiver, and power and memory units. A sensor mode is mounted on the node with multiple types of sensors depending on the type of application such as environmental monitoring [1], surveillance [2], military applications, automation in transportation, health [3], and industrial applications [4].

One of the stringent requirements of these nodes is the efficient use of the stored energy. Several algorithms have been designed for efficient management of nodes energy in WSNs using various clustering schemes [5, 6]. WSN divides clusters each having a coordinator (cluster head) responsible for gathering the data from the nodes and sending it to the sink (base station). Sensors are often deployed densely to satisfy the coverage requirement, which enables certain nodes to enter the sleep mode thereby allowing significant energy savings. The cluster heads can be selected randomly or based on one or more criteria. Selection of cluster head largely affects WSNs lifetime. Ideal cluster head is the one which has the highest residual energy, the maximum number of neighbor nodes, and the smallest distance from base station. Simultaneous consideration of all these criteria in CHs selection is tedious task and can be solved using multiple attribute decision-making (MADM) approaches [7–10]. A number of MADM approaches are reported and have been successfully applied in various scientific-, engineering-, and social-science based decision-making problems. These methods quantitatively select alternatives based on their multiple attributes/criteria. In real-time problem, it is often found that the estimation of the exact values of all the criteria is difficult.

In such cases fuzzy-based MADM methodologies [11–13] are found to be efficient and effective. In the present paper, we have made an attempt to employ these approaches in order to prolonging the life time of WSNs.

2. Background

A number of clustering protocols have been explored in order to obtain the effective energy usage in WSNs. Heinzelman et al. [14] proposed low-energy adaptive cluster hierarchy (LEACH). It is based on randomized rotation of the CHs to distribute the energy load among the sensor nodes evenly in the entire network. Each node elects itself as a CH based on a probabilistic scheme and broadcasts its availability to all the sensor nodes present in the area. The received signal strength is the prime parameter for determining the communication distance between the nodes. The CH performs aggregation of the packets received from all the nodes present in their cluster. Also, all the nodes get a chance to become the CH to balance the overall 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. Kumar et al. [15] proposed energy-efficient heterogeneous clustered (EEHC) scheme 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 the 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. Distributed hierarchical agglomerative clustering (DHAC) [16] classifies sensor nodes into appropriate groups instead of simply gathering nodes to some randomly selected CHs. The application and the evaluation of methods of various dendrogram techniques such as SLINK, CLINK, UPGMA, and WPGAM, with quantitative and qualitative data, are demonstrated in this method. The hybrid energy-efficient distributed protocol (HEED) [17] is 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 operating under low communication cost can become CHs. Multiple CHs are used for transferring the data to the base station using the concept of multihop communication. But HEED does not guarantee the optimum number of elected CHs. Multicriteria decision-making-based approach, trapezoidal fuzzy AHP (FAHP), and hierarchical fuzzy integral [18], have been investigated in clustering on WSNs. The selection of cluster heads is optimized to develop a distributed energy-efficient clustering algorithm using three criteria including energy status; QoS impact and location. According to these criteria, each node computes a composite value by using fuzzy integral, which is mapped onto the time axis, and a time-trigger mechanism makes the node broadcast cluster-head information. Karaca et al. [19] proposed analytic hierarchy Process (AHP), which is used to centralize CH selection scheme. 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 reported that the AHP approach improves the network lifetime remarkably.

3. System Model and Assumptions

The following assumptions are considered in the present study.

(1) Nodes are dispersed randomly in a 100×100 square unit region following a uniform distribution.

(2) All the nodes send hello messages to the base station containing their local information.

(3) The initial number of clusters is fixed by taking the optimum value and keeps on varying with the node density once the nodes start dying. The smaller clusters merge with the bigger ones.

(4) The base station (BS) is a node with no energy constraint and enhanced computation capabilities and placed at the center of the field.

(5) A simple radio energy dissipation model [14] in transmitting a k bit message over a distance d to achieve an acceptable signal-to-noise ratio (SNR) is used. Energy consumption in data transmission can be estimated as

$$E_{TX} = \begin{cases} k * E_{\text{elec}} + k * \varepsilon_{\text{fs}} * d^2 & \text{if } d \le d_o, \\ k * E_{\text{elec}} + k * \varepsilon_{\text{mp}} * d^4 & \text{if } d \ge d_o, \end{cases} \tag{1}$$

where E_{elec} is the energy dissipated per bit to run the transmitter or the receiver circuit, ε_{fs} is the energy consumed in the amplifier when $d \le d_o$ and ε_{mp} is the energy consumed in the amplifier when $d \ge d_o$. The energy consumed while reception is

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

4. Multicriteria Decision-Making (MCDM) Approaches

MCDM techniques have been applied for quantitative decision-making problems in wide range of scientific and engineering fields. MCDM can be divided into two main categories: multiobjective decision-making (MODM) [10] and multiattribute decision making (MADM) approaches [7]. MODM selects alternatives which are nondominating in view of all criteria under study. On the other hand, MADM techniques quantitatively compare and rank alternatives based on the degree of desirability of their attributes being considered for the study. In the present study, MODM (Pareto optimal technique) and MADM (fuzzy TOPSIS) approaches are used to select cluster heads.

4.1. Pareto Optimal Solution. The Pareto optimal solutions are nondominated in a given solution space (Figure 1) as described by the economist Vilfredo Pareto [20]. In multiobjective decision-making problems, the solution space is

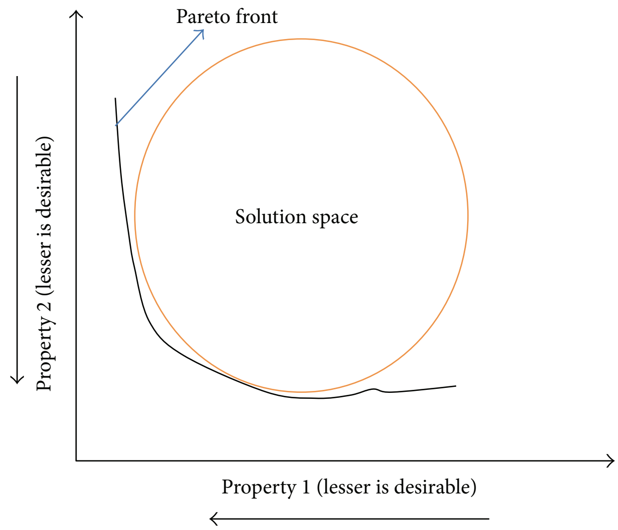

FIGURE 1: Schematic for Pareto optimal solution in two-dimensional space.

defined as a region consisting of all possible solutions. Solution space can be classified into three sets, namely, (a) completely dominated, (b) neither dominated, nor dominating and (c) nondominated. 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. Nondominated solutions are the alternatives that have the best trade-off between properties and are not dominated by any other alternative in the solution space.

4.2. Fuzzy Membership Function. It is often difficult to assign precise values of attributes of the sensor nodes in each cycle. The merit of using fuzzy approach is to assign the relative importance of criteria using fuzzy numbers instead of precise numbers. Linguistic variables are used in fuzzy logic to evaluate the importance of the criteria and the ratings of different alternatives with respect to various criteria. In the present algorithm, the existing precise values are transformed into five levels, fuzzy linguistic variables: very low (VL), low (L), medium (M), high (H), and very high (VH).

As a rule of thumb, each rank is assigned an evenly spread membership function that has an interval of 0.30 or 0.25, and a transformation table is shown in Table 1. For example, the fuzzy variable, VL, has its associated triangular fuzzy number with the minimum of 0.00, mode of 0.10, and maximum of 0.25. Similarly, other variables L, M, H, and VH have similar trend as shown. Figure 2 illustrates the fuzzy membership function [12].

4.3. Fuzzy TOPSIS Approach. Technique for order preference by similarity to ideal solution (TOPSIS) is one of the MADM approaches 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 [12]. The optimum alternative has the shortest distance from the positive ideal solution (the best possible case) and the furthest distance from the negative ideal solution (worst possible case), respectively. This technique has been widely applied in various scientific and engineering applications [12, 21–23]. Sometimes it is difficult to assign a precise performance rating to an alternative for the attributes under consideration. Thus, to solve this issue, fuzzy approach can be used to assign the relative importance of attributes using fuzzy numbers instead of precise numbers. This section is an extension of TOPSIS to the fuzzy environment [11–13], which is helpful in solving the decision-making problem under fuzzy environment. The fuzzy TOPSIS can be applied on decision matrix as

TABLE 1: Transformation of fuzzy membership function.

Rank	Membership functions
Very low (VL)	(0.00, 0.10, 0.25)
Low (L)	(0.15, 0.30, 0.45)
Medium (M)	(0.35, 0.50, 0.65)
High (H)	(0.55, 0.70, 0.85)
Very high (VH)	(0.75, 0.90, 1.00)

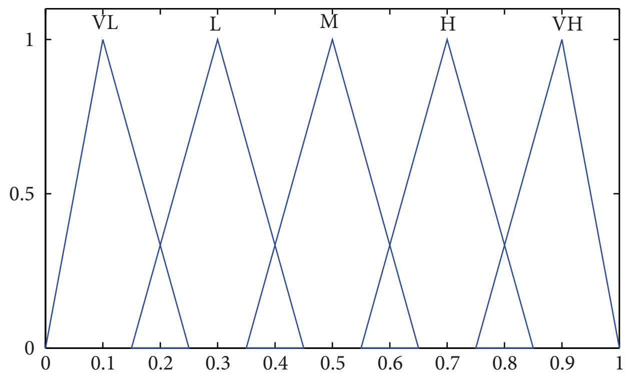

FIGURE 2: Fuzzy triangular membership functions.

$$D = \begin{array}{c c} & \begin{array}{ccccc} C_1 & C_2 & C_3 & C_4 & C_5 \end{array} \\ \begin{array}{c} A1 \\ A2 \\ A3 \\ A4 \\ A5 \end{array} & \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \tilde{x}_{13} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \tilde{x}_{23} & \cdots & \tilde{x}_{2n} \\ \tilde{x}_{31} & \tilde{x}_{32} & \tilde{x}_{33} & \cdots & \tilde{x}_{3n} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \tilde{x}_{m3} & \cdots & \tilde{x}_{mn} \end{bmatrix} \end{array} \quad (3)$$

$$\widetilde{W} = [w_1, w_2, \ldots w_n],$$

where $\tilde{x}_{ij}$, $i = 1, 2, 3, \ldots m$, $j = 1, 2, 3, \ldots, n$ and $\tilde{w}_j$, $j = 1, 2, \ldots, n$, are linguistic triangular fuzzy numbers, $x_{ij} = (a_{ij}, b_{ij}, c_{ij})$, and $\tilde{w}_j = (w_{j1}, w_{j2}, w_{j3})$. Note that x_{ij} is the performance rating of the ith alternative. $\tilde{w}_j$ represents the weight of the jth criterion, C_j. The normalized fuzzy decision matrix denoted by $\widetilde{R}$ is given as

$$\widetilde{R} = [\tilde{r}_{ij}]_{m\times n}. \quad (4)$$

The weighted normalized fuzzy decision matrix is

$$\widetilde{V} = \begin{bmatrix} w_1\widetilde{r}_{11} & w_2\widetilde{r}_{12} & \cdots & w_n\widetilde{r}_{1n} \\ w_1\widetilde{r}_{21} & w_2\widetilde{r}_{22} & \cdots & w_n\widetilde{r}_{2n} \\ \vdots & \vdots & \dots & \vdots \\ w_1\widetilde{r}_{m1} & w_2\widetilde{r}_{n2} & \dots & w_n\widetilde{r}_{mn} \end{bmatrix}, \quad (5)$$

$$\widetilde{V} = \begin{bmatrix} \widetilde{v}_{11} & \widetilde{v}_{12} & \cdots & \widetilde{v}_{1n} \\ \widetilde{v}_{21} & \widetilde{v}_{22} & \cdots & \widetilde{v}_{2n} \\ \vdots & \vdots & \dots & \vdots \\ \widetilde{v}_{m1} & \widetilde{v}_{n2} & \cdots & \widetilde{v}_{mn} \end{bmatrix}. \quad (6)$$

Steps for fuzzy TOPSIS procedure are as follows.

Step 1. Choose the linguistic ratings ($\widetilde{x}_{ij}$), $i = 1, 2, 3, \dots, m$ and $j = 1, 2, 3, \dots, n$ for alternatives with respect to criteria and the appropriate linguistic variables ($\widetilde{w}_j$, $j = 1, 2, \dots, n$) for the weight of the criteria. If the range of triangular fuzzy numbers belongs to $[0, 1]$, then there is no need for a normalization.

Step 2. Obtain the weighted normalized fuzzy decision matrix given by (6).

Step 3. The selection of an alternative is based on the shortest distance from the positive ideal solution (A^+) and the furthest from the negative ideal solution (A^-), which are defined as

$$\begin{aligned} A^+ &= \{\widetilde{v}_1^+, \widetilde{v}_2^+, \dots, \widetilde{v}_n^+\} \\ &= \left\{\left(\max_i \widetilde{v}_{ij} \mid i = 1, \dots, m\right),\ j = 1, 2, \dots, n\right\}, \\ A^- &= \{\widetilde{v}_1^-, \widetilde{v}_2^-, \dots, \widetilde{v}_n^-\} \\ &= \left\{\left(\min_i \widetilde{v}_{ij} \mid i = 1, \dots, m\right),\ j = 1, 2, \dots, n\right\}. \end{aligned} \quad (7)$$

Step 4. The separation measures are the distances of each alternative from A^+ and A^- given as

$$\begin{aligned} d_i^+ &= \sum_{j=1}^{n} d\left(\widetilde{v}_{ij}, v_j^+\right), \quad i = 1, 2, \dots, m, \\ d_i^- &= \sum_{j=1}^{n} d\left(\widetilde{v}_{ij}, v_j^-\right), \quad i = 1, 2, \dots, m. \end{aligned} \quad (8)$$

Step 5. TOPSIS rank indices can be estimated as

$$CC_i = \frac{d_i^-}{d_i^+ + d_i^-}. \quad (9)$$

Nodes of higher TOPSIS index are selected for cluster heads.

5. Cluster Formation and Data Transfer Methodologies

All the selected CHs now send advertisement messages in the network declaring their presence as cluster heads. Each node now measures the distance from all the cluster heads. 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 reclustered based on the distance with the selected cluster head using a distance matrix, DM ($m \times n$), given as follows:

$$\mathrm{DM} = \begin{bmatrix} d_{\mathrm{CH1},x1} & d_{\mathrm{CH1},x2} & \cdots & d_{\mathrm{CH1},xn} \\ d_{\mathrm{CH2},x1} & d_{\mathrm{CH2},x2} & \cdots & d_{\mathrm{CH2},xn} \\ \vdots & \vdots & \vdots & \vdots \\ d_{\mathrm{CH}m,x1} & d_{\mathrm{CH}m,x2} & d_{\mathrm{CH}m,x3} & d_{\mathrm{CH}m,xn} \end{bmatrix}, \quad (10)$$

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

$$d_{p,q} = \left[\left(p_x - q_x\right)^2 + \left(p_y - q_y\right)^2\right]^{1/2}. \quad (11)$$

Each element $d_{i,j}$ in the distance matrix represents the distance between the ith cluster head and jth node. The column containing the minimum value represents the cluster number to be joined by the corresponding node. For example, if $d_{\mathrm{CH2},x1}$ is the minimum value in the first column, in this situation the node x_1 gets associated 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 sends 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 reclustering methodology is also adopted in LEACH protocol, where CHs are elected by using the probabilistic approach rather than the deterministic technique. The operation of reclustering 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 the number of clusters. The amount of information also decreases with the fewer nodes left in the physical area.

6. Results and Discussions

In each cycle, it is important to decide the numbers of clusters/CHs that exist in the WSN for maximizing the

Table 2: Decision matrix for fuzzy TOPSIS analysis in the second cycle.

Cluster head no.	Residual energy, Eo (joules), C1	Number of neighbors, n, C2	Distance from sink, d, C3
CH1	0.9998	7	21.583
CH2	0.9998	9	24.2745
CH3	0.9887	8	20.9972
CH4	0.9894	10	39.3231
CH5	0.9998	6	23.2092
CH6	0.9998	10	39.8408
CH7	0.9998	3	7.6944
CH8	0.9988	4	4.5873
CH9	0.9998	9	25.5698
CH10	0.9947	6	10.6745
CH11	0.9964	5	9.8442
CH12	0.9998	4	16.642
CH13	0.9919	9	24.2008
CH14	0.9998	6	17.6095

Table 3: Normalized decision matrix for fuzzy TOPSIS.

Cluster head no.	C1	C2	C3
CH1	0.9996	0.5714	0.5179
CH2	0.9988	0.8571	0.4416
CH3	0.0000	0.7143	0.5345
CH4	0.0590	1.0000	0.0147
CH5	0.9998	0.4286	0.4718
CH6	0.9998	1.0000	0.0000
CH7	0.9995	0.0000	0.9119
CH8	0.9096	0.1429	1.0000
CH9	1.0000	0.8571	0.4048
CH10	0.5433	0.4286	0.8273
CH11	0.6900	0.2857	0.8509
CH12	0.9996	0.1429	0.6581
CH13	0.2917	0.8571	0.4436
CH14	0.9998	0.4286	0.6306
Weight	0.5	0.25	0.25

energy efficiency. We have estimated the optimum number of clusters, k_{opt} [24], as

$$k_{\text{opt}} = \sqrt{\frac{\varepsilon_{\text{fs}}}{\pi\left(\varepsilon_{\text{mp}} d_{\text{toBS}}^4 - E_{\text{elec}}\right)}} M\sqrt{N}. \quad (12)$$

The value of k_{opt} is estimated in the range of $9 < k_{\text{opt}} < 11$ when the base station is placed away from the field. In the present study, we divide the network into ten clusters each having a cluster head. For this purpose, we have screened sensor nodes using Pareto optimal solution. Pareto optimal CHs are selected using three criteria including residual energy of the node, minimum distance from the base station, and the number of neighbor nodes. It is to be noted that maximum residual energy, least distance of the nodes from base station and maximum number of neighbor nodes are desirable for cluster head selection. The Pareto optimal nodes shown in Figure 3 (red-colored dots) are the optimum selection in view of previously mentioned three criteria whose values are shown in Table 2 for the 2nd cycle of simulation. Similar calculation is performed in each cycle for short listing Pareto optimal sensor nodes. These attributes of the criteria are further normalized in the range $[0, 1]$ given in Table 3. We have assigned 0.5, 0.25, and 0.25 subjective weights to residual energy, number of neighbors, and, distance from base station, respectively. Membership function (discussed in Section 4.2) is used to convert the values (in Table 3) into linguistic variables as shown in Table 4. Further fuzzy linguistic variables are transformed into fuzzy triangular membership function as shown in Table 5 and fuzzy-weighted decision matrix using (6) as shown in Table 6. We define the fuzzy positive and

Table 4: Decision matrix using fuzzy linguistic variables.

Cluster head no.	C1	C2	C3
CH1	VH	M	M
CH2	VH	VH	M
CH3	VL	H	M
CH4	VL	VL	VL
CH5	VH	M	M
CH6	VH	VL	VL
CH7	VH	VL	VH
CH8	VH	VL	VL
CH9	VL	VH	M
CH10	M	M	VH
CH11	H	L	H
CH12	VH	VL	H
CH13	L	VH	M
CH14	VH	M	H
Weight	VH	M	M

Table 5: Fuzzy decision matrix and fuzzy attribute weights.

Cluster head no.	C1	C2	C3
CH1	(0.75, 0.9, 1)	(0.35, 0.5, 0.65)	(0.35, 0.5, 0.65)
CH2	(0.75, 0.9, 1)	(0.75, 0.9, 1)	(0.35, 0.5, 0.65)
CH3	(0, 0.1, 0.25)	(0.55, 0.7, 0.85)	(0.35, 0.5, 0.65)
CH4	(0, 0.1, 0.25)	(0.75, 0.9, 1)	(0, 0.1, 0.25)
CH5	(0.75, 0.9, 1)	(0.35, 0.5, 0.65)	(0.35, 0.5, 0.65)
CH6	(0.75, 0.9, 1)	(0.75, 0.9, 1)	(0, 0.1, 0.25)
CH7	(0.75, 0.9, 1)	(0, 0.1, 0.25)	(0.75, 0.9, 1)
CH8	(0.75, 0.9, 1)	(0, 0.1, 0.25)	(0.75, 0.9, 1)
CH9	(0.75, 0.9, 1)	(0.75, 0.9, 1)	(0.35, 0.5, 0.65)
CH10	(0.35, 0.5, 0.65)	(0.35, 0.5, 0.65)	(0.75, 0.9, 1)
CH11	(0.55, 0.7, 0.85)	(0.15, 0.3, 0.45)	(0.75, 0.9, 1)
CH12	(0.75, 0.9, 1)	(0, 0.1, 0.25)	(0.55, 0.7, 0.85)
CH13	(0.15, 0.3, 0.45)	(0.75, 0.9, 1)	(0.35, 0.5, 0.65)
CH14	(0.75, 0.9, 1)	(0.35, 0.5, 0.65)	(0.55, 0.7, 0.85)
Weight	(0.75, 0.9, 1)	(0.35, 0.5, 0.65)	(0.35, 0.5, 0.65)

Table 6: Fuzzy-weighted decision matrix.

Cluster head no.	C1	C2	C3
CH1	(0.5625, 0.8100, 1.0000)	(0.1225, 0.2500, 0.4225)	(0.1225, 0.2500, 0.4225)
CH2	(0.5625, 0.8100, 1.0000)	(0.2625, 0.4500, 0.6500)	(0.1225, 0.2500, 0.4225)
CH3	(0, 0.0900, 0.2500)	(0.1925, 0.3500, 0.5525)	(0.1225, 0.2500, 0.4225)
CH4	(0, 0.0900, 0.2500)	(0.2625, 0.4500, 0.6500)	(0, 0.0500, 0.1625)
CH5	(0.5625, 0.8100, 1.0000)	(0.1225, 0.2500, 0.4225)	(0.1225, 0.2500, 0.4225)
CH6	(0.5625, 0.8100, 1.0000)	(0.2625, 0.4500, 0.6500)	(0, 0.0500, 0.1625)
CH7	(0.5625, 0.8100, 1.0000)	(0, 0.0500, 0.1625)	(0.2625, 0.4500, 0.6500)
CH8	(0.5625, 0.8100, 1.0000)	(0, 0.0500, 0.1625)	(0.2625, 0.4500, 0.6500)
CH9	(0.5625, 0.8100, 1.0000)	(0.2625, 0.4500, 0.6500)	(0.1225, 0.2500, 0.4225)
CH10	(0.2625, 0.4500, 0.6500)	(0.1225, 0.2500, 0.4225)	(0.2625, 0.4500, 0.6500)
CH11	(0.4125, 0.6300, 0.8500)	(0.0525, 0.1500, 0.2925)	(0.2625, 0.4500, 0.6500)
CH12	(0.5625, 0.8100, 1.0000)	(0, 0.0500, 0.1625)	(0.1925, 0.3500, 0.5525)
CH13	(0.1125, 0.2700, 0.4500)	(0.2625, 0.4500, 0.6500)	(0.1225, 0.2500, 0.4225)
CH14	(0.5625, 0.8100, 1.0000)	(0.1225, 0.2500, 0.4225)	(0.1925, 0.3500, 0.5525)

Table 7: Fuzzy TOPSIS analysis.

CH	C1	C2	C3	d_i^+	d_i^-	CC_i
CH1	(0.5625, 0.8100, 1.0000)	(0.1225, 0.2500, 0.4225)	(0.1225, 0.2500, 0.4225)	1.0893	0.9100	0.5448
CH2	(0.5625, 0.8100, 1.0000)	(0.2625, 0.4500, 0.6500)	(0.1225, 0.2500, 0.4225)	0.9768	0.9870	0.4974
CH3	(0, 0.0900, 0.2500)	(0.1925, 0.3500, 0.5525)	(0.1225, 0.2500, 0.4225)	1.3331	0.5136	0.7219
CH4	(0, 0.0900, 0.2500)	(0.2625, 0.4500, 0.6500)	(0, 0.0500, 0.1625)	1.4099	0.5143	0.7327
CH5	(0.5625, 0.8100, 1.0000)	(0.1225, 0.2500, 0.4225)	(0.1225, 0.2500, 0.4225)	1.0893	0.9100	0.5448
CH6	(0.5625, 0.8100, 1.0000)	(0.2625, 0.4500, 0.6500)	(0, 0.0500, 0.1625)	1.1255	0.9479	0.5428
CH7	(0.5625, 0.8100, 1.0000)	(0, 0.0500, 0.1625)	(0.2625, 0.4500, 0.6500)	1.1255	0.9479	0.5428
CH8	(0.5625, 0.8100, 1.0000)	(0, 0.0500, 0.1625)	(0.2625, 0.4500, 0.6500)	1.1255	0.9479	0.5428
CH9	(0.5625, 0.8100, 1.0000)	(0.2625, 0.4500, 0.6500)	(0.1225, 0.2500, 0.4225)	0.9768	0.9870	0.4974
CH10	(0.2625, 0.4500, 0.6500)	(0.1225, 0.2500, 0.4225)	(0.2625, 0.4500, 0.6500)	1.0960	0.7402	0.5969
CH11	(0.4125, 0.6300, 0.8500)	(0.0525, 0.1500, 0.2925)	(0.2625, 0.4500, 0.6500)	1.0946	0.8355	0.5671
CH12	(0.5625, 0.8100, 1.0000)	(0, 0.0500, 0.1625)	(0.1925, 0.3500, 0.5525)	1.1699	0.9067	0.5634
CH13	(0.1125, 0.2700, 0.4500)	(0.2625, 0.4500, 0.6500)	(0.1225, 0.2500, 0.4225)	1.1914	0.6424	0.6497
CH14	(0.5625, 0.8100, 1.0000)	(0.1225, 0.2500, 0.4225)	(0.1925, 0.3500, 0.5525)	1.0277	0.9475	0.5203
A^+	$\tilde{v}_1^+ = (1, 1, 1)$	$\tilde{v}_2^+ = (1, 1, 1)$	$\tilde{v}_3^+ = (1, 1, 1)$			
A^-	$\tilde{v}_1^- = (0, 0, 0)$	$\tilde{v}_2^- = (0, 0, 0)$	$\tilde{v}_3^- = (0, 0, 0)$			
Weights	(0.75, 0.9, 1)	(0.35, 0.5, 0.65)	(0.35, 0.5, 0.65)			

negative ideal solutions (Step 3) and computed separation measures (Step 4) and rank indices (Step 5) for Pareto optimal sensor nodes. Table 7 shows the Pareto optimal nodes, their properties, and fuzzy TOPSIS indices in the 2nd cycle. Table 8 lists top ten cluster heads (from Table 7) selected in the second cycle. Similar ranking is performed in each cycle until all the sensor dies.

Table 9 provides the simulation parameters used in our experiments. Each cycle consists of clustering and data transmission phase. In clustering phase, the top ten CHs are selected and form a cluster based on the Euclidean distance. The CHs are selected for each cycle till all the nodes consume their entire energy. The base station is placed far away from the field. The lifetime of the network is measured in terms of the number of cycles until the first node in the network runs out of its entire energy. Figure 4 shows the results of the experiment, where sensor nodes are deployed randomly on a square area of $100 \times 100\,\mathrm{m}^2$ and network lifetime is plotted, which shows the number of alive nodes over the time in cycles. The results are finally compared with a well-known DHAC protocol. It is reported that DHAC is more energy efficient than other methods including LEACH and LEACH-C. All results are expressed in averages taken over 20 random independent experiments. It is observed that the network lifetime (when first node dies) is higher for fuzzy TOPSIS approach than that of DHAC (Figure 4). It shows that the present approach is more effective in WSNs.

7. Conclusions

Fuzzy decision-making-based energy-efficient scheme is proposed for WSNs. Fuzzy TOPSIS technique is used for the

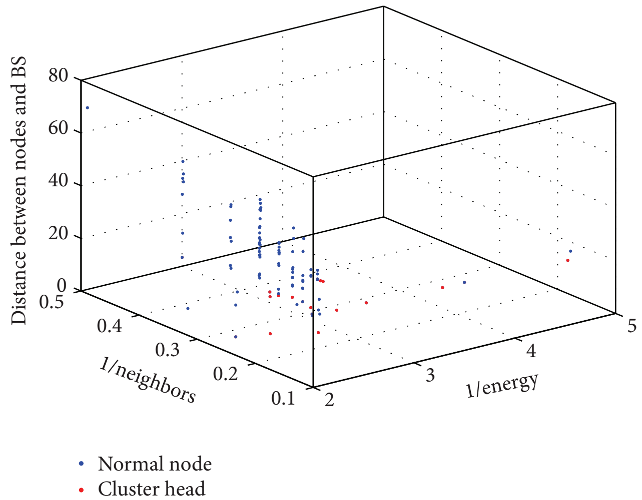

Figure 3: Pareto optimal plot for sensor nodes.

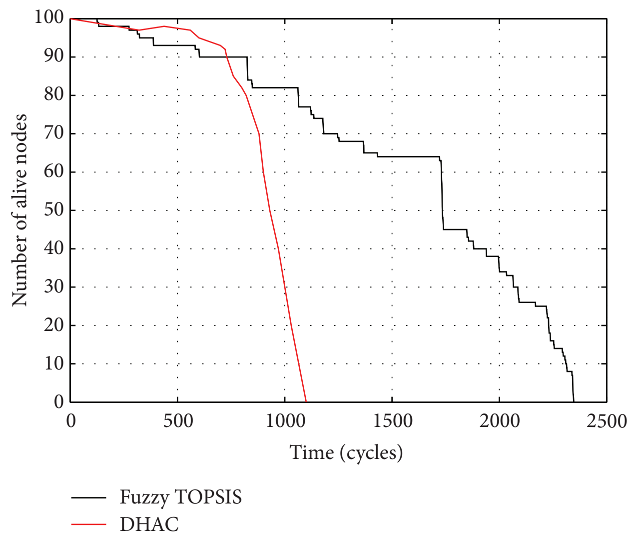

Figure 4: Network lifetime comparison.

Table 8: Top ten CHs in the 2nd cycle selected based on fuzzy TOPSIS ranks.

Rank	Cluster head
1	CH4
2	CH3
3	CH13
4	CH10
5	CH11
6	CH12
7	CH1
8	CH5
9	CH6
10	CH7

Table 9: Simulation parameters used for WSNs.

Description	Symbol	Value
Number of nodes in the system	N	100
Initial energy of node	E_{initial}	1 J
BS location	—	(50, 50)
Size of the data packet	—	500 bytes
Hello/broadcast/CH_join message	—	25 bytes
Energy consumed by the amplifier to be transmitted at a short distance	ε_{fs}	10 pJ/bit/m^2
Energy consumed by the amplifier to be transmitted at a longer distance	ε_{mp}	0.0013 pJ/bit/m^4
Energy consumed in the electronics circuit to be transmitted or receive the signal	E_{elec}	50 nJ/bit

selection of cluster heads in WSNs. Three criteria including residual energy distance of the nodes from base station and the number of neighbor nodes are considered in order to optimize the number of clusters/cluster heads. Simulated network lifetime is compared with the lifetime achieved from DHAC protocol. Simulations results demonstrate that fuzzy TOPSIS achieves significant energy saving and prolonging network lifetime compared to DHAC protocol.

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