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# Reliability-Based Cluster Head Selection Methodology Using Fuzzy Logic for Performance Improvement in WSNs

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**ABSTRACT** Prolonging the network lifetime is one of the vital challenges in wireless sensor networks (WSNs). Typically, the lifespan of WSNs can be increased by a technique called clustering, which plays a significant role in simplifying intra-domain routing. The clustering method accounts only a small number of nodes, which are randomly selected as cluster heads (CHs). The main responsibility of CHs is to receive collected data or information from its member nodes and to aggregate the received data and convey the received data to the sink (Sk) or base station (BSn). In this paper, we have proposed a method namely “reliability-based enhanced technique for the ordering of preference by similarity ideal solution (RE-TOPSIS)” combining with fuzzy logic which uses multi-criteria decision making (MCDM) approach aiding in the effective and reliable selection of CHs. It also uses the conventional LEACH protocol to enable one-time CH selection or scheduling in each cluster based on RE-TOPSIS rank index value. This process completely eliminates the need of CH selection process in each round of LEACH’s setup state cycle. We have accounted for various criteria such as 1) residual energy; 2) distances between adjacent nodes; 3) energy utilization rates; 4) availability of neighboring nodes; 5) distances between the sink and CHs as well as distances between CHs to member nodes; and 6) the reliability index for completely devising the new scheme. The simulations are accomplished to assess or suggest the performances of the proposed RE-TOPSIS and to compare its performances with the performances of the existing protocols. The results show that the proposed scheme enhances the network lifespan, conserves energy, and introduces a considerable reduction in the frequency of CH selection per cycle by about 20%–25% as compared with the contemporary fuzzy-TOPSIS and LEACH protocols and finally the metrics of the proposed RE-TOPSIS are highlighted.

**INDEX TERMS** Aggregation, Bayesian networks, clustering, energy, efficiency, lifespan, multi decision, MCDM, reliability, TOPSIS.

## I. INTRODUCTION

Reliability (Ri) is an important parameter and also features in Quality of Service (QoS) in a communication network. Especially in WSNs, reliability is most necessary in WSN applications like intelligent monitoring in industries, military investigation operations, and so on. Especially in WSNs, Ri is most necessary in distributed data-intensive applications like smart grid industrial surveillance, military investigation

operations, smart agriculture applications etc. Ri ensures the quality of information transmission and provides assurance of guaranteed delivery of information in WSNs (e.g., received information is perfect or not). For getting more accurate results at the receiver side, effective reliability assessment is very much useful to make an improved selection of network topology and efficient data transferring protocols for WSNs [1].

Generally, WSN deployment consists of massive bulk of sensing equipment with transmission capability distributed arbitrarily in an extensively large field in which sensors

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are placed. The other communication factors like interference, congestion, topology change, jitter etc., may lead to failure or delay in routing. So, in the dynamic nature of WSN, routing reevaluation is more important and not necessary for static or fixed evaluation models. Sensor node may fail to operate due to energy depletion and accidental damages to hardware parts. Normally, link failures may happen at only one end of the network.

There are many factors that affect the data transfer mechanism. Generally the link failure or channel communication problems due to multi-path fading, channel interference, collision due to data blocking, and other sources in the communication path between sensors. Channel problems are mostly recorded to occur in two states namely, normal and failure states. But, recent results have shown another additional state namely multi-mode failure. Because of the above issues, reliability achievement in WSNs environment becomes a challenging problem.

A Fuzzy Logic is a concept in which boundaries can change with conditions or context instead of being fixed for all. TOPSIS is the acronym of Technique for Order of Preference by Similarity to Ideal resolution [2]. TOPSIS could be a multi-criteria higher cognitive process technique. The Multi-Criteria Decision-Making (MCDM) analysis contains variety of higher cognitive process steps as well as advisement of criteria and ranking of alternatives [3]. The advisement of criteria will mirror the individual preferences of the choice maker. The decision maker preferences are reflected in the weighting criteria. The aggregate function that is to be optimized is obtained using the weighted sum of the objectives. The main parts of Sensor Nodes (SNs) are data collection and data conversion, /memory storage with processing, transmitting, receiving, mobilizing and position finding (localization) units and finally a power supply unit as shown in Fig. 1.

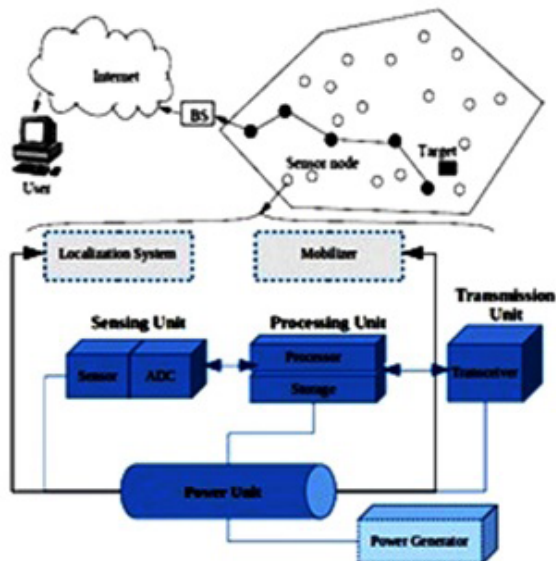


FIGURE 1. WSN architecture.

Bio-Fertigation, hierarchical health monitoring, military applications, natural disaster detection, and management are some of the applications of Fuzzy based multi-objective WSNs.

Clustering sensors are one of the significant methods for extending the life period of WSNs. In the context of networking, clustering is the process of grouping sensor nodes into suitable clusters followed by electing CHs. Time-Division Multiple Access (TDMA) technique is used by the CHs for receiving and aggregating the data from their respective clusters. The data are collected, decompressed and aggregated in order to remove redundancy before sending them to the BS. LEACH algorithm consists of *set-up* and *steady-state phases*. Among the sensor nodes, the fixed probable CHs are chosen in the set-up phase. Within the spectrum of the transmission range, the elected CHs broadcast their locations and meta-information as advertisements.

Radio Signal Strength Indicator (RSSI) gives the location of the remaining nodes within the population which can be associated to a particular CH by sending the desired request and collecting multiple advertisements in the form of broadcast messages from different CHs, using high RSSI values [2]. In this paper a reinforced method entitled “Reliability-based Enhanced Technique for Ordering of Preference by Similarity Ideal Solution (RE-TOPSIS)” by combining Reliability criterion with Fuzzy Logic which employs Multi-Criteria Decision-Making (MCDM) approach aiding in the effective and reliable selection of CHs. This is done by adding an additional parameter namely Reliability Index. It also uses the LEACH protocol to enable one-time scheduling in each cluster based on the proposed RE-TOPSIS rank index value.

## II. LITERATURE REVIEW

Many clustering protocols have been investigated in the recent past to limit valuable power utilization in WSNs. The major role played by F-TOPSIS drove CH selection methodology to enhance the efficiency of energy utilization in WSN. F-TOPSIS can help in the objective and systematic evaluation of alternatives for multi-criteria attributes [4]. In this paper, we have described the F-TOPSIS method with a set of criteria which are used for the effective selection of CH from a group of sensor nodes. A large mass of sensor nodes, that constitutes the atomic blocks of the network, are arbitrarily positioned to collect information like ecological conditions, atmospheric environment, geographical parameters etc., from the sensing field. Micro-Electro-Mechanical-Systems (MEMS) have reinforced the production of WSN-Enabled systems at exponentially reduced scales.

In paper [5], the authors have intended to increase the network lifespan and scalability through balancing a load of sensor nodes and through network structure control in WSN. CH selection is based on the hybridization of centralized gridding to elect CH and distributed clustering method. There is no reliability and integrity considered for data delivery and CH election. In a stable election using only three fuzzy

parameters approach (SEFP) [6], the method focused only on the three fuzzy parameters such as residual energy of individual sensor node, distance to the base station (BS), and the sum of closeness between a sensor node and other sensor nodes (area distance). Only three attributes are considered and compared with LEACH and SEP. There is no sink distance from each cluster and not considered reliability as an important factor. In paper [7], cluster formation using fuzzy logic (CFFL) has been proposed and the method focused on the cluster formation phase and CH election phase. CH election phase used only two attributes residual energy and distance between CH and BS. Other important parameters such as reliability, number of neighbor nodes and distances between nodes to the CH were not considered. Simulation results of the proposed method were compared only with LEACH.

The proposed algorithm, using static sensor nodes in the network with homogeneous characteristics which is not always suitable for agriculture, Forest fire detection and Health care monitoring system. These area need to collect sensitive and non-sensitive types of different kinds of data. Sensor with heterogeneous characteristics are only suitable [8].

TOPSIS method is used in many engineering applications and businesses. F-TOPSIS elects the excellent alternative attributes based on the concept of compromised solutions [2]. The longest Euclidean distance is chosen as the negative ideal solution and shortest Euclidean distance is chosen as the positive ideal solution. The approach contains formation of an  $M \times N$  matrix, where  $M$  is the wide variety of alternatives and  $N$  is the wide variety of attributes to each alternative. AI-based techniques have also been used to make several decisions related to irrigational systems but the drawbacks of these techniques are that since they require complex computations they are prevented from being used in optimally configured nodes in WSN. Five deterministic attributes have been outlined for selecting a suitable CH [9]. These criteria include residual energy (remaining available power of the node), power consumption rate of each nodes, node density (number of neighbor nodes per unit area), the average Euclidian distance between neighboring nodes and distances from the nodes to the sink. To reduce the energy consumption or to optimize the energy utilization, the distances between CHs or the distances between CHs and sink are determined by a threshold-based intra-cluster and inter-cluster multi-hop communication mechanisms. Efficient sleep wakeup mechanisms used and also one time scheduling proposed to reduce the election process in its every rounding process Conventional mobility with octagonal path /route /trajectory model has been proposed to make the most of the proper load-distribution of the network and condenses the average latency based on time-critical applications in WSNs [8].

Koucheryavy and Osamy [10] introduced the LEACH protocol. CH election is based on a randomized rotation basis to balance the energy distribution across the sensor

nodes available in the entire network. A probabilistic scheme used to choose each sensor node itself to become CH and to advertise its availability to remaining nodes within the area. The data communication distances between the nodes are identified by calculating an important parameter RSSI. An aggregation process is mandatory and is performed only by the CH when the data is received from its neighboring nodes present in their respective clusters. The overall energy consumption is balanced by giving chance to become CH for all available nodes in its cluster. The proposed algorithm uses low complexity LEACH protocol and has not improved the energy consumption effectively due to the irregular election process/distribution of CHs.

In LEACH protocol, every node is acknowledged with the residual energy and localization parameters of nearby nodes in the cluster. Enhanced-LEACH (E-LEACH) in [11], [12] is an alternative method, in which the requirement of the number of CHs in the WSN, may be incremented by the square of the available number of SNs, which will optimize the amount of energy utilized. Two Level hierarchy LEACH (TL-LEACH) protocol [13] helps in achieving effective use of energy by rotation of CHs. TL-LEACH uses Primary and Secondary level CHs. Secondary CHs are responsible for processing and accumulating the received data from its member nodes from the sensing field. The received data is further processed by two primary CHs and delivering processed data to the BSn. The significance of using TL-LEACH protocol is that it is operated on an optimal number of sensor nodes to communicate with the BSn, hence increasing the network lifetime of the WSN and decreasing the energy utilization metrics.

Performance of LEACH protocol is enhanced using Centralized LEACH Protocol C-LEACH [14]. C-LEACH is observed to provide better throughput than LEACH algorithm. In this protocol, nodes send information regarding residual energy based on their positions. This information is received by the BSn, which selects clusters and governs the CHs and member nodes. CHs are selected based on the nodes' highest residual energy and their location details (distance) in the Hybrid Energy-Efficient Distributed (HEED) Protocol [15]. This protocol helps in providing mobility to sensor nodes. As discussed in C-LEACH protocol, CHs are mobile; therefore, they increase the load on the network. This requires that the energy and conservation of energy are done using modified LEACH known as Agricultural LEACH (A-LEACH) protocol [16]. Sensor nodes periodically send *Hello* packets to the neighbors within its vicinity, followed by inter-domain neighbor discovery protocol that increases the control overhead in the network due to the centralized scheme. CH changes after every cycle and consequently, the control overheads in the packets also increase.

An energy efficient CH selection scheme is introduced in A-LEACH, which improves the network life period of WSN. A-LEACH protocol uses a new scheme for CH selection, which significantly reduces the amount of energy consumed. The performance of the A-LEACH protocol increases the

network lifetime considerably. The A-LEACH protocol not only increases the information bandwidth utilization of the network but also provides a desirable output particularly on reliable data transfer and link connectivity faster thus enabling mobile WSN to be more consistent and interconnected in critical conditions without requiring any temporal maintenance costs.

A new energy-aware robust multi-objective method has been proposed namely Reliability-based Enhanced Technique for Ordering of Preference by Similarity-Ideal-Solution (RE-TOPSIS) using Fuzzy Logic which employs Multi-Criteria-Decision-Making (MCDM) approach aiding in the effective and reliable selection of CHs. It also uses the already existing LEACH protocol to enable one-time scheduling in each cluster, based on RE-TOPSIS rank index value. We have introduced an important additional parameter and proposed a new scheme called RE-TOPSIS as already indicated above. This process completely eliminates the need of CH selection process in each round of LEACH's setup state cycle. Various criteria like residual energy, distances between adjacent nodes, energy utilization rates, availability of neighboring nodes and distances between the sink and CHs as well as distances between CHs to member nodes and also the newly introduced Reliability Index have been considered for completely devising the new scheme.

### III. THE PROPOSED SCHEME

In this section, a description of the proposed RE-TOPSIS scheme is given for an efficient selection of CH, which is a distributed mechanism by introducing a Reliability Index in the F-TOPSIS method [17]. Sensor nodes take autonomous decisions based on ranking indices obtained by using the proposed E-TOPSIS method by using six different criteria for CH selection. This proposed method removes deficiencies in the existing fuzzy based CH selection process. The elected CH broadcasts its status to its nearby nodes within the spectrum of its transmission range. Because it uses a distributed algorithm, nodes can take a self-directed decision to be selected themselves as CHs. The remaining member nodes receive multiple status updates from other CHs within their transmission range, and to link with the CH based on the Euclidian distances and maximum relative RSSI values. All nodes operate on their own indices values as of their neighboring nodes.

#### A. ENHANCED RE-CLUSTERING

The proposed scheme ensures that the CH selection process is not changed for every round, hence eliminating the computational expenses during the setup phase. The reelection of CHs is triggered when the elected CH residual energy reduces to a predetermined threshold value. Re-clustering is performed only when the elected CH threshold value is comparatively lower than the threshold values of other neighboring nodes. Re-clustering succeeds with the selection of the next eligible sensor node to become the CH. This selection process is based on the rank index value calculated using the F-TOPSIS

CH selection process. This procedure is called One-Time Scheduling CH Selection process [16].

In this proposed RE-TOPSIS method, the CH selection process is divided into six sub-processing phases as listed below:

1. Sensor Nodes Deployment,
2. Adjacency establishment,
3. CH selection using the proposed method,
4. Cluster formation,
5. Re-cluster or CH selection and
6. Message Transfer.

The above CH selection procedure is further elaborated in the following sections.

#### 1) SENSOR NODES DEPLOYMENT

Generally, in the WSN environment, homogeneous types of sensor nodes with low battery back-up are deployed in a random manner as shown in Fig. 2. In the Figure, we consider the BSn to be at the center of the sensing field which is identified with an 'x' mark. All other sensor nodes are identified with the symbol 'o'. The initial network knowledge is gathered by the sink node through the broadcast of *Hello* packets. The reply messages from the field contain the location information about the nodes, node IDs and their available energy levels. Through this information, the sink node is able to learn the complete network topology.

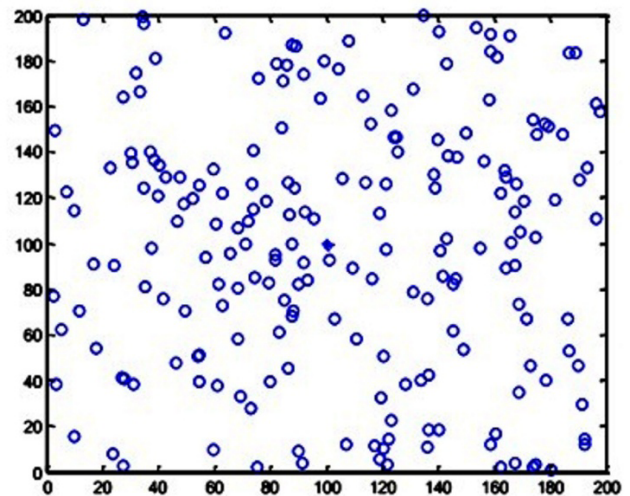


FIGURE 2. Network deployment.

Fig. 2 represents the network that we have considered and shows the placing of Sensor Nodes (SNs) located in the sensing field. 200 sensor nodes are arbitrarily distributed within a fixed square boundary of 200m  $\times$  200m. The BSn is located at the center of the region and its coordinates are (100,100). In the network deployment, a node distribution which is randomized and unevenly distributed was chosen.

#### 2) ADJACENCY ESTABLISHMENT

Adjacent node identification is very important in a network to learn the number of adjacencies possible and identify the

transmission range ( $T_R$ ) of each node. This is achieved by sending *Hello* packets through nodes' interfaces and getting a reply from the adjacent nodes which contain six conditional information called attributes of the adjacent nodes. *Carrier Sense Multiple Access* (CSMA) techniques are used to avoid collisions in the network [3], [17], [18].

### 3) CH SELECTION USING THE PROPOSED METHOD.

When the WSN is being set up for the first time, the SNs will be new and unused, hence have initial values for the respective criteria used to select CHs. Therefore, initially, we allocate CH statuses based on the distances from the Sink Node only [19], [20]. Only 5-10% of the nodes will become CHs when we use the LEACH protocol. In the proposed RE-TOPSIS method, after a period of time  $T$  from the initialization, the SNs including the CHs will start to possess different values of CH selection criteria which will be described in the subsequent sections. The proposed RE-TOPSIS method enhances the time period for the reselection of CHs instead of One Time Scheduling by taking into account the variability of SNs qualities. Understanding factors such as energy retention and reliability of the SNs (including the CHs) can be assessed using the following six attributes.

- Residual Energy (Joule)  $C_1$ ,
- Availability of Neighbor nodes ( $n$ )  $C_2$ ,
- Distance from Sink ( $d$ )  $C_3$ ,
- Energy Dissipation Rate  $C_4$ ,
- Average Distance between neighbor nodes  $C_5$  and
- Reliability index  $C_6$  (Default Value: 0).

### B. CALCULATION OF RELIABILITY INDEX $C_6$

The failure rate of a system is defined as the rate of failure points of the subsystems in a system in real-time. In order to decrease the rate of system failure, we intend to reduce the aggregated sum of failure points in all the nodes of the network. In layman terms, we need to formulate a scheduling process such that the timing constraint is compensated and the sum of failure rates of all nodes is minimized.

Because of the random deployment from the sky, nodes may fail to communicate with the sink node from their locations. We need to measure the probability of the failure rate associated with each sensor node to improve the quality of the WSN. The dominant cause of unreliability in the communication channel of WSNs [21] is the simultaneous failure of multiple sensor nodes. The inclusion of a reliability index ( $R$ ) as a control parameter in the CH selection process, avoids the selection of sensor nodes that have a higher probability of failures. The method of calculation of the probability of failure is explained below.

A simple reliability index selection criterion model via a directed graph is introduced where the set of nodes in the directed graph characterize arbitrary variables starting from  $X_1, X_2, \dots, X_N$ . Fig. 3 describes a joint probability allocation based on the factorization of the modeled arbitrary

variables [22] and is given as below.

$$P(X_1, X_2, \dots, X_N) = \prod_{i=1}^N P(X_i | pa(X_i)) \quad (1)$$

The above equation is the name for Bayesian networks chain rule. The individual elements  $P(X_i | pa(X_i))$  are known as Conditional Probability Distributions (CPDs). A Bayesian chain rule is a pair  $\beta = (g, p)$  in which  $p$  factorizes over  $g$ , and in which  $p$  is precise as a fixed of CPDs related to  $g$ 's nodes [23].

$p$  is the allocation and is often annotated as  $p_\beta$ . The probability of failure of each CH acts as a Relay Node Function (**RNF**) in the sensor network and necessarily be calculated prior to every node associating itself to the Nearby-Relay-Node (**NRN**). There are different significant causes of malfunctioning that have been identified in this proposed analysis in order to categorize the critical malfunction possibility rate [24]. The system may fail due to environmental effects, malfunctioning of communication links, malfunctioning of physical internal components inside the node and due to total exhausting of the battery. Fig. 3 shows a simple reliability selection criteria model, consisting of the following four attributes.

- $P(e)$  = Marginal probability of Environmental risks- (malfunction due to ecological conditions)
- $P(l)$  = Marginal probability of Connectivity risks- (probability of breakdown due to improper channel connection or link)
- $P(h)$  = Marginal probability of Hardware and configurational risks- malfunctioning of the physical component within the node (other than battery and link) and
- $P(b)$  = Marginal probability of power source risks- (probability of breakdown due to total drain of the battery).

$P(r)$  = Conditional Reliability- the probability of CH acting as Relay-Node Function crashes due to the above four or any one of the causes. Using (1), the probability of relay- node crash can be computed as

$$P(r) = \prod_{f=1}^N P(g | pa(r_i)) \quad (2)$$

where,  $G$  is number of a sensor node in a matrix and  $Pa(r_i)$  are conditional attributes among sensor nodes in the matrix.

Now substituting the attributes in (2), we get

$$P(r) = \prod_{f=1}^N P(g | e, l, h, b) \quad (3)$$

where 'e' is energy, 'l' is link, 'h' is hardware, 'b' is node energy and 'r' is the Reliability Index of a node.

The probability of RNF failure of a CH depends on the deviation of the probability of any one of the causes (e, l, h or b), more than one or all of the four causes mentioned in Fig. 3 which are explained below.

- e - Ecological effects normally not permanent, always unpredictable and the damages could possibly be because of heavy rain, sudden earth-quake, unexpected landslide, falling of trees due to storm and cyclone or any

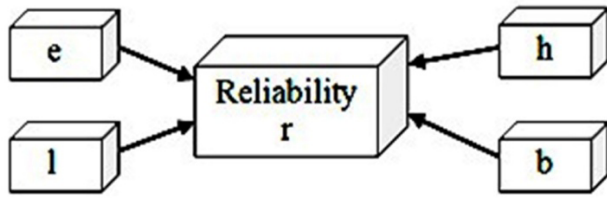


FIGURE 3. Reliability selection criteria model-RSCM.

other disaster caused due to planned or unplanned activities by human being, animals or by nature.

- l - Communication path failure or malfunctioning which is due to internal and external interferences, malfunctioning of the antenna etc.
- h - Sensor Node malfunctioning is mainly due to the improper function of software or unavailability of software, improper function of inbuilt units like a micro-controller or supporting memory devices and physical damage of hardware component or improper device deployment conditions.
- b- Battery failure is due to improper physical connections with the nodes, the complete exhaustion of power or operational failures in the unit due to critical deployment situations. This breakdown is permanent.

Reliability Selection Criteria Model (RSCM) accounts the above four criteria to calculate the marginal probability of failure rate for every intermediary forwarder node in the WSN [25]. The optimal route from each node and to reach BS<sub>n</sub> is calculated by (3). The deterministic factors such as environmental factors, connection failure, component failure, and input constraints are used for calculating the marginal probability. However, it is highly sophisticated task to formulate the correlation between power usages in terms of Joules per unit time to the marginal probability of failure. This association is non-linear in nature.

Initially, C<sub>2</sub>, C<sub>5</sub>, and C<sub>6</sub> fields in the Hello packets are empty as they do not contain any relevant data. After distribution of Node-ID and Position meta-data with their neighbors, each node can pervasively calculate different values such as node distances and availability of neighbor nodes and exchange them with the successive Hello packets [26]. The member nodes within the vicinity or range of a cluster will receive the subsequent Hello packets with the updated information. After acknowledging Hello packets from neighbor nodes, a sensor node revises its adjacency table (T<sub>k</sub>) with adjacent node's ID and selection criteria along with its own information as shown in Fig.3.

A Decision Matrix (DM) is constructed based on these criteria. It is shown below in Fig. 4 and is further evaluated using various processing techniques [27].

The Membership Functions derived from Fuzzy based selection criteria are often sophisticated to assign deterministic values from the criteria of the sensor nodes in a periodic manner. The significance of using fuzzy based clustering approach is to compare the correlation of criteria using

$$T_k = \begin{matrix} & \begin{matrix} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 \end{matrix} \\ \begin{matrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \vdots \\ \alpha_{n+1} \end{matrix} & \begin{pmatrix} \chi_{1,1} & \chi_{1,2} & \chi_{1,3} & \chi_{1,4} & \chi_{1,5} & \chi_{1,6} \\ \chi_{2,1} & \chi_{2,2} & \chi_{2,3} & \chi_{2,4} & \chi_{2,5} & \chi_{2,6} \\ \chi_{3,1} & \chi_{3,2} & \chi_{3,3} & \chi_{3,4} & \chi_{3,5} & \chi_{3,6} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \chi_{n+1,1} & \chi_{n+1,2} & \chi_{n+1,3} & \chi_{n+1,4} & \chi_{n+1,5} & \chi_{n+1,6} \end{pmatrix} \end{matrix}$$

FIGURE 4. Six attribute decision matrix DM.

linguistic variables instead of real integers. Usually, it is hard to allocate exact estimations of qualities of the member nodes in each round. The value of utilizing fuzzy methodology is to allot the general significance of criteria utilizing fuzzy numbers rather than exact numbers. Semantic factors are utilized in fuzzy rationale to assess the significance of the attributes and the appraisals of various choices concerning different criteria.

In the present calculation, the current exact qualities are changed into seven dimension triangular fuzzy phonetic factors. As a standard guideline of thumb, each graded position is allocated an equally extended participation work that has a period of 0.15 or 0.30, and a conversion table is given in Table 1. For instance, the fuzzy variable, VVL, has its related triangular fuzzy number with a starting value of 0.00, has a highest value 1 at 0.10, and an extreme value of 0 at 0.15. Figure 2 represents the fluffy participation work utilized in our strategy.

TABLE 1. Membership functions using fuzzy values.

Rank	Membership function
Very Very Low (VVL)	(0.00, 0.10, 0.15)
Very Low (VL)	(0.15, 0.20, 0.30)
Low (L)	(0.20, 0.30, 0.45)
Medium (M)	(0.30, 0.45, 0.60)
High (H)	(0.45, 0.60, 0.75)
Very High (VH)	(0.75, 0.80, 0.90)
Very Very high (VVH)	(0.80, 0.90, 1.00)

C. FUZZY TOPSIS APPROACH

Fuzzy-TOPSIS is a hybrid approach in which a DM comprising of “m” alternatives and “n” attributes can be understood as a problem of “n” dimensional hyper plane with “m” focus points whose positions are determined by the virtue of their attributes.

The ideal option has the most limited separation from the positive perfect arrangement PIS (the most ideal case) and the most distant separation from the negative perfect arrangement NIS (most exceedingly terrible conceivable case), separately. This strategy has been generally connected in different logical and designing applications. Occasionally it is hard to allocate an exact execution rating to a substitute option for

the attributes under consideration. Along these lines to settle this issue, a fuzzy methodology can be utilized to assign the overall significance of attributes using fuzzy values rather than exact numbers. This area is an augmentation of TOPSIS to the fuzzy condition, which is useful in taking care of the basic decision-making issues under fuzzy conditions. The Fuzzy TOPSIS can be implemented on a matrix as

$$\tilde{V} = \begin{pmatrix} W.\tilde{X}_{1,1} & W.\tilde{X}_{1,2} & W.\tilde{X}_{1,3} & W.\tilde{X}_{1,4} & W.\tilde{X}_{1,5} & W.\tilde{X}_{1,6} \\ W.\tilde{X}_{2,1} & W.\tilde{X}_{2,2} & W.\tilde{X}_{2,3} & W.\tilde{X}_{2,4} & W.\tilde{X}_{2,5} & W.\tilde{X}_{2,6} \\ W.\tilde{X}_{3,1} & W.\tilde{X}_{3,2} & W.\tilde{X}_{3,3} & W.\tilde{X}_{3,4} & W.\tilde{X}_{3,5} & W.\tilde{X}_{3,6} \\ W.\tilde{X}_{4,1} & W.\tilde{X}_{4,2} & W.\tilde{X}_{4,3} & W.\tilde{X}_{4,4} & W.\tilde{X}_{4,5} & W.\tilde{X}_{4,6} \\ W.\tilde{X}_{5,1} & W.\tilde{X}_{5,2} & W.\tilde{X}_{5,3} & W.\tilde{X}_{5,4} & W.\tilde{X}_{5,5} & W.\tilde{X}_{5,6} \\ W.\tilde{X}_{6,1} & W.\tilde{X}_{6,2} & W.\tilde{X}_{6,3} & W.\tilde{X}_{6,4} & W.\tilde{X}_{6,5} & W.\tilde{X}_{6,6} \\ W.\tilde{X}_{7,1} & W.\tilde{X}_{7,2} & W.\tilde{X}_{7,3} & W.\tilde{X}_{7,4} & W.\tilde{X}_{7,5} & W.\tilde{X}_{7,6} \\ W.\tilde{X}_{m1} & W.\tilde{X}_{m2} & W.\tilde{X}_{m3} & W.\tilde{X}_{m4} & W.\tilde{X}_{m5} & W.\tilde{X}_{m6} \end{pmatrix} \quad (4)$$

where  $\tilde{W} = [w_1, w_2, w_3, \dots, w_n]$  and  $\tilde{x}_{ij}, i = 1, 2, 3, 4, \dots, m, j = 1, 2, 3, 4, \dots, n$  and  $\tilde{w}_j, j = 1, 2, \dots, n$ , are triangular linguistic variables,  $x_{ij} = (a_{ij}, b_{ij}, c_{ij})$ , and  $\tilde{w}_j = (w_{j1}, w_{j2}, w_{j3})$  the performance rating of the  $i^{th}$  alternative is denoted by  $\tilde{w}_{ji}$  and the weight of the  $j^{th}$  criteria is denoted by  $\tilde{w}_j$  The normalized fuzzy based DM denoted by  $\tilde{R}$  as given below:

$$\tilde{R} = [\tilde{r}_{ij}]_{m \times n} \quad (5)$$

The weighted normalized fuzzy DM is

$$D = \begin{matrix} & C_1 & C_2 & C_3 & C_4 & C_5 & C_6 \\ A_1 & \tilde{X}_{1,1} & \tilde{X}_{1,2} & \tilde{X}_{1,3} & \tilde{X}_{1,4} & \tilde{X}_{1,5} & \tilde{X}_{1,6} \\ A_2 & \tilde{X}_{2,1} & \tilde{X}_{2,2} & \tilde{X}_{2,3} & \tilde{X}_{2,4} & \tilde{X}_{2,5} & \tilde{X}_{2,6} \\ A_3 & \tilde{X}_{3,1} & \tilde{X}_{3,2} & \tilde{X}_{3,3} & \tilde{X}_{3,4} & \tilde{X}_{3,5} & \tilde{X}_{3,6} \\ A_4 & \tilde{X}_{4,1} & \tilde{X}_{4,2} & \tilde{X}_{4,3} & \tilde{X}_{4,4} & \tilde{X}_{4,5} & \tilde{X}_{4,6} \\ A_5 & \tilde{X}_{5,1} & \tilde{X}_{5,2} & \tilde{X}_{5,3} & \tilde{X}_{5,4} & \tilde{X}_{5,5} & \tilde{X}_{5,6} \\ A_6 & \tilde{X}_{6,1} & \tilde{X}_{6,2} & \tilde{X}_{6,3} & \tilde{X}_{6,4} & \tilde{X}_{6,5} & \tilde{X}_{6,6} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ A_m & \tilde{X}_{m1} & \tilde{X}_{m2} & \tilde{X}_{m3} & \tilde{X}_{m4} & \tilde{X}_{m5} & \tilde{X}_{m6} \end{matrix} \quad (6)$$

which can be rewritten as

$$\tilde{V} = \begin{pmatrix} \tilde{V}_{1,1} & \tilde{V}_{1,2} & \tilde{V}_{1,3} & \tilde{V}_{1,4} & \tilde{V}_{1,5} & \tilde{V}_{1,6} \\ \tilde{V}_{2,1} & \tilde{V}_{2,2} & \tilde{V}_{2,3} & \tilde{V}_{2,4} & \tilde{V}_{2,5} & \tilde{V}_{2,6} \\ \tilde{V}_{3,1} & \tilde{V}_{3,2} & \tilde{V}_{3,3} & \tilde{V}_{3,4} & \tilde{V}_{3,5} & \tilde{V}_{3,6} \\ \tilde{V}_{4,1} & \tilde{V}_{4,2} & \tilde{V}_{4,3} & \tilde{V}_{4,4} & \tilde{V}_{4,5} & \tilde{V}_{4,6} \\ \tilde{V}_{5,1} & \tilde{V}_{5,2} & \tilde{V}_{5,3} & \tilde{V}_{5,4} & \tilde{V}_{5,5} & \tilde{V}_{5,6} \\ \tilde{V}_{6,1} & \tilde{V}_{6,2} & \tilde{V}_{6,3} & \tilde{V}_{6,4} & \tilde{V}_{6,5} & \tilde{V}_{6,6} \\ \tilde{V}_{7,1} & \tilde{V}_{7,2} & \tilde{V}_{7,3} & \tilde{V}_{7,4} & \tilde{V}_{7,5} & \tilde{V}_{7,6} \\ \tilde{V}_{m1} & \tilde{V}_{m2} & \tilde{V}_{m3} & \tilde{V}_{m4} & \tilde{V}_{m5} & \tilde{V}_{m6} \end{pmatrix} \quad (7)$$

where  $V_{ij} = w\tilde{X}_{ij}$ .

The RE-TOPSIS procedure is illustrated as follows.

1) STEPS TO DETERMINE RANK BASED ON RE-TOPSIS

Step 1: Based on the DM, the first step is to construct the normalized matrix. Normalized matrix gives us the relative information, which is given in (8). This normalized matrix is further used for constructing a weighted DM discussed in the next step.

Normalized Decision Matrix (NDM) =

$$R_{ij} = \frac{X_{ij}}{\sqrt{\sum_{i=1}^m X_{ij}^2}} \quad (8)$$

Step 2: Though all selected criteria are not of importance, it is necessary to order them based on the rank index values. Filtering is done for which a weighted DM ( $V_k$ ) is designed by multiplying each element of the normalized matrix by a random weight. Weighted DM calculation is given below in (9). The weighted DM is built by multiplying each element of the NDM by a random weight matrix  $V_k$ . i.e.,

$$V_k = V_{ij} = W_j \times R_{ij} \quad (9)$$

Expanding further, we get DM with Weighted values as shown in (10).

$$V_k = \begin{bmatrix} X_{1,1} & X_{1,2} & X_{1,3} & X_{1,4} & X_{1,5} & X_{1,6} \\ X_{2,1} & X_{2,2} & X_{2,3} & X_{2,4} & X_{2,5} & X_{2,6} \\ N_{3,1} & N_{3,1} & N_{3,1} & N_{3,1} & N_{3,1} & N_{3,1} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ X_{n+1,1} & X_{n+1,2} & X_{n+1,3} & X_{n+1,4} & X_{n+1,5} & X_{n+1,6} \end{bmatrix} \quad (10)$$

Step 3: Identifying the alternative is based on the optimal distance between **Positive Ideal Solution (PIS)** and **Negative Ideal Solution (NIS)** by using the following equations:

$$PIS = (X_1^+, X_2^+, \dots, X_n^+) \\ = [(max_i X_{ij} | i = 1, \dots, m), j = 1, \dots, (n + 1)] \quad (11)$$

$$NIS = (X_1^-, X_2^-, \dots, X_n^-) \\ = [(min_i X_{ij} | i = 1, \dots, m), j = 1, \dots, (n + 1)] \quad (12)$$

where  $J$  is related to the valuable attributes in a column matrix and  $J'$  is related to the non-valuable attributes in column matrix. Alternatively, the optimal distance from the PIS and the maximal distance from the NIS will produce the most suitable solution.

Step 4: Distances are calculated for each alternative (row =  $D_j$ ) between PIS and NIS and are given as

$$D_j^+ = \sum_{i=1}^6 \sqrt{\sum_{j=1}^{n+1} (X_{ij} - X_j^+)^2} \quad (13)$$

$$D_j^- = \sum_{i=1}^6 \sqrt{\sum_{j=1}^{n+1} (X_{ij} - X_j^-)^2} \quad (14)$$

Step 5: The final step of Rank Index (RI) calculation is done according to the formula given in (15) [2].

$$RI = \frac{D_j^-}{D_j^+ + D_j^-} \tag{15}$$

The node with the highest RI value broadcasts its status as the CH in that region. Other nodes within the field with minimum distances send joint requests to the nearest CH and act as MNs of that cluster. The CH receives joint request messages from neighboring nodes and acknowledges all of its MNs. In this sequence, the entire network is heterogeneously divided into many clusters and internally, the member node with the highest residual energy is elected as the CH. This process goes on successively and CHs are hence selected by clusters. Once clusters are created with CHs, all MNs in each cluster start unilateral data transfer with their corresponding CHs.

Along with the regular data transfer, they also verify the index values with their neighborhood table. Re-clustering is initiated when the specific threshold value and the index value of a precise node are relatively more than the sum of indices of a CH. Appropriately these criteria are checked with their initial values and any changes in threshold and rank indices are reflected in the positions of the sensor nodes to become CHs. Initially, a table is formulated based on index and threshold values, subsequently, the changes are recorded. This table is fundamental to the process of selection of CH. We have implemented RE-TOPSIS technique which deals with the judicious selection of CH. The complete process of our proposed system is discussed below and represented using the flow diagram as given in Fig. 5.

The below Tables 2 and 3 shows the DM and Normalized DM values respectively used for RE-TOPSIS Analysis. The Normalized Decision Matrix values given in Table 3 are calculated using (8).

Each criterion is associated with a preference or weight 'W<sub>i</sub>'. These weights are cumulative to data-intensive applications; however, for our proposed RE-TOPSIS scheme the membership functions using Fuzzy values are given in Table 4.

TABLE 2. Parameters for decision matrix in RE-TOPSIS analysis.

CH No.	Residual Energy (joule) C1	Number of Neighbours, n C2	Distance from sink, d C3	Dissipation Energy C4	Avg. Distance between neighbour nodes C5	Reliability Index C6
CH1	0.9997	6	21.358	0.5635	1.314	0.24
CH2	0.9998	8	23.998	0.5393	0.987	0.42
CH3	0.9885	7	27.001	0.5192	1.581	0.13
CH4	0.9992	9	39.058	0.5454	1.198	0.17
CH5	0.9997	5	33.989	0.5091	1.109	0.10
CH6	0.9943	6	10.584	0.5225	1.107	0.21
CH7	0.9985	3	14.401	0.5507	1.290	0.31
CH8	0.9920	8	30.015	0.5294	1.114	0.20

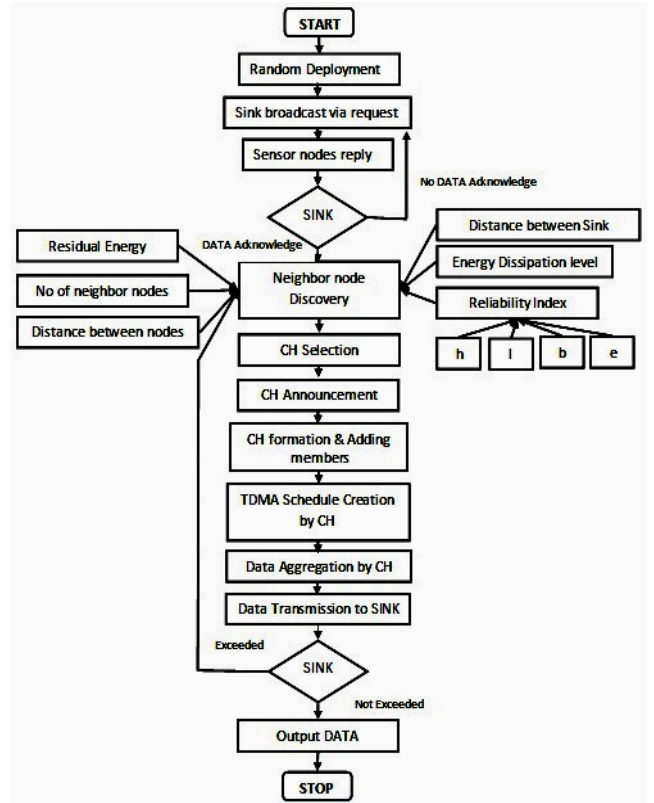


FIGURE 5. Flow chart representation of CH selection based on index and threshold values.

TABLE 3. Normalized decision matrix for E-TOPSIS analysis.

CH No.	C1	C2	C3	C4	C5	C6
CH1	0.3547	0.3145	0.3009	0.3766	0.3793	0.3500
CH2	0.3547	0.4193	0.3381	0.3605	0.2849	0.6126
CH3	0.3542	0.3669	0.3805	0.3470	0.4564	0.1896
CH4	0.3509	0.4717	0.5504	0.3645	0.5720	0.2479
CH5	0.3547	0.2621	0.3240	0.3403	0.3210	0.1459
CH6	0.3527	0.3145	0.1491	0.3426	0.3196	0.3063
CH7	0.3542	0.1572	0.2029	0.3413	0.3725	0.4522
CH8	0.3519	0.4193	0.42305	0.3539	0.3216	0.2917
Weight	0.15	0.15	0.15	0.20	0.15	0.20

TABLE 4. Membership functions using fuzzy values.

Rank	Membership function
Very Very Low (VVL)	(0.00, 0.10, 0.15)
Very Low (VL)	(0.15, 0.20, 0.30)
Low (L)	(0.20, 0.30, 0.45)
Medium (M)	(0.30, 0.45, 0.60)
High (H)	(0.45, 0.60, 0.75)
Very High (VH)	(0.75, 0.80, 0.90)
Very Very high (VVH)	(0.80, 0.90, 1.00)

After normalization of the DM, a weighted DM is formed using all the six attributes in (9);

The PIS and NIS are calculated using (11) and (12). The measures of separation are determined using n-dimensional Euclidean distances of each criterion using the NIS and PIS, which are shown in (13) and (14) respectively.



TABLE 5. Weighted normalized decision matrix of RE-TOPSIS.

CH No.	C1	C2	C3	C4	C5	C6
CH1	0.0532	0.0471	0.0451	0.0755	0.0569	0.0700
CH2	0.0532	0.0628	0.0507	0.0721	0.0427	0.1225
CH3	0.0531	0.0550	0.0570	0.0694	0.0685	0.0379
CH4	0.0526	0.0707	0.0825	0.0729	0.0858	0.0496
CH5	0.0532	0.0393	0.0486	0.0680	0.0482	0.0292
CH6	0.0529	0.0471	0.0224	0.0685	0.0479	0.0613
CH7	0.0531	0.0235	0.0304	0.0682	0.0559	0.0904
CH8	0.0527	0.0628	0.0634	0.0705	0.0482	0.0583
Weight	0.15	0.15	0.15	0.20	0.15	0.20

#### IV. CLUSTER FORMATION

Multiple clusters are formed based on the rank indices values. The CH broadcasts its status within its vicinity of the transmission ranges. The remaining nodes within that region are directly connected with the CH by sending a joint request message. Depending on the density of members available in the cluster, the CH adopts a TDMA scheduling schema to avoid congestion in the channel. CHs remain static in one cycle to decrease load due to the initial phase. If a CH residual energy exceeds its preset threshold value, then the re-election process is executed.

#### V. MESSAGE TRANSFER MECHANISM

Once the successful CH selection and formation is done, a Message Transfer Mechanism is initiated. An efficient and useful model is built by using rank index values based on multi-hop communication mechanism between clusters and within the clusters. When the distance between a CH and an MN is within the transmission range of the CH, then direct communication takes place between them. If the distance between the CH and a MN exceeds the transmission range of the CH, then the data transfer takes place in a multi-hop manner to the nearest CH. When the relative distance between the sink node and a CH with respect to a MN is not within the transmission range of either, another CH node is selected as a relay node to deliver data in a multi-hop manner to avoid unnecessary utilization of residual energy.

#### VI. TIME COMPLEXITY ANALYSIS

As per the RE-TOPSIS method, the algorithmic complexity to compute the Decision Matrix (DM)  $T_k$ , for all the six criteria will be done in  $O(k \times n)$ , 'k' representing the number of criteria which is a constant. Hence it is safe to conclude that it will be achieved within a time complexity of  $O(n)$ .

Algorithm for Big O Notation process:

A Normalized Fuzzy-Decision Matrix,  $\hat{R}_{n \times k} = [a_{ij}, b_{ij}, c_{ij}]$  is computed for each node.

For  $i = 1: n$

Compute  $a_{ij} = \min (T_k(a_{ij}))$ . This can be achieved in  $O(n)$ .

Compute  $b_{ij} = n^{-1} \sum (T_k(b_{ij}))$ . This can be achieved in  $O(n)$ .

TABLE 6. Rank index based on (15).

Rank	Cluster Head	Rank Index
1	CH4	0.5514
2	CH7	0.4308
3	CH1	0.4242
4	CH3	0.3710
5	CH6	0.2916
6	CH5	0.2167
7	CH2	0.1399
8	CH8	0.1315

Compute  $c_{ij} = \max (T_k(c_{ij}))$ . This can also be achieved in  $O(n)$ .

This above cumulative code is executed in  $O(n^2)$ .

In our paper, Equation 6 denotes the Normalized Fuzzy Decision Matrix, which is algorithmically executed as shown above. Hence,  $\hat{R}$  can be computed in  $O(n^2)$  time.

Next, The weighted Normalized Fuzzy-Decision Matrix,  $V = [w_1 a_{ij}, w_2 b_{ij}, w_3 c_{ij}]$  is computed for each node, where  $w_1, w_2$  and  $w_3$  are weights.

Initialize Weight Matrix,  $W_{k \times 1} = [w_1, w_2, w_3, \dots, w_k]$

Compute Normalized DM,  $V = W^{-1} \cdot \hat{R}$

Hence, V can be computed in  $O(kn^2)$  time.

#### VII. SIMULATION RESULTS AND ANALYSIS

Using Network Simulation package NS2 and the simulation parameters given in Table 7, various experiments were carried out to assess the performances of the proposed RE-TOPSIS method. The simulation results are measured with the popular protocol LEACH and Fuzzy environment based CH selection schemes.

TABLE 7. Simulation parameters.

Parameters	Value
Sensing Field	100 m x 100 m
No. of nodes deployed	100
Sink Location	(50, 50)
Initial Energy	0.5J
Sensing Range	20 m
Packet Size	500 bytes
Hello packet size	25 bytes
Aggregation Energy Consumption	50 pJ/bit
Transmission energy ( $E_{TX}$ )	100 nJ / bit
Reception energy ( $E_{RX}$ )	50 nJ / bit
Transmitter amplifier energy ( $E_{amp}$ )	100 pJ / bit / m <sup>2</sup>

Energy consumption during the data transfer over a distance  $d$ , between the sensor nodes can be estimated from Eqs. (13) and (14)

$$E_{TX} = (L, d) = \begin{cases} L * E_{elec} + L * \epsilon_{fs} * d^2 & \text{if } d \leq d_0' \\ L * E_{elec} + L * \epsilon_{mp} * d^4 & \text{if } d > d_0' \end{cases} \quad (16)$$

Similarly while receiving data, energy consumption rate is given by Eq. (17):

$$E_{RX} = k * E_{elec} \quad (17)$$

where:

$E_{TX} \Rightarrow$  Transmitter Energy consumption / bit (L),

$E_{RX} \Rightarrow$  Receiver Energy consumption / bit,

$S_{select} \Rightarrow$  one bit of data transfer cost for circuit energy consumption

$\epsilon_{fs} \Rightarrow$  line-of-sight path through free space coefficient (path loss),

$\epsilon_{mp} \Rightarrow$  line-of-sight path through multipath coefficient (path loss),

$k \Rightarrow$  number of data packets transmitted in bits,

$d \Rightarrow l$ -bit data packet energy consumption over a distance and

$d_0 \Rightarrow$  The threshold distance for transmission.

In this model, the reference energy for each node is to be considered as an average energy  $E(r)$ . It is the energy to start with that every sensor node should possess in a current round to maintain the network to become active to a specific degree. Under such ideal condition the network and nodes have uniformly consumed the power and in the meantime all the nodes die simultaneously.

Hence, we can assess the average energy  $E(r)$  of  $r^{th}$  round as follows:

$$\bar{E}(r) = \frac{1}{N} E_{total} (1 - \frac{r}{R}) \quad (18)$$

where,  $R$  denotes the total life period of the network.  $\bar{E}(r)$  describes the energy consumption of every node in each round, which is also the objective that tries to attain an energy efficient algorithm.  $N$  denotes the nodes availability in the network and  $r$  indicates a single cycle or round.

In the proposed RE-TOPSIS, power utilization in the network can be considerably optimized by selecting a judicious parameter namely Reliability Index. In this work, like any other traditional routing protocol, the sensor nodes are not selected randomly without knowing the residual energy of the nodes. Moreover, Transmission and Reception process of a sensor node consumes more energy when compared to other operations. Hence, the probability of choosing the same node as the next hop node is considerably reduced. Thereby, the total energy has been balanced and effectively used. All these tasks lead to energy conservation and hence extending the overall network life span as evaluated against the other protocols. These claims are quite evident as illustrated in Figs. 6, 7 and 8.

The performances of the proposed RE-TOPSIS are compared with the performances of the LEACH and the existing F-TOPSIS protocols. The transmission rate is varied from 10 kB to 38 kB in steps of 2kB for RE-TOPSIS traffic and energy is measured during each interval. The Average Energy Consumption ( $Avg\_Energy \times 10^3$ ) per interval during the data transmission is calculated using the formula given in (14). Through simulation, the other performance metrics such as throughput and delay are evaluated and compared as stated above.

Fig. 6 illustrates the performance metrics of the proposed RE-TOPSIS protocol compared with the F-TOPSIS

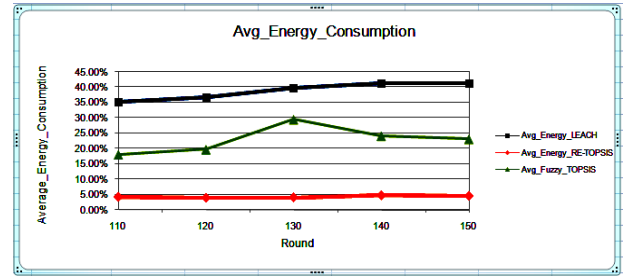


FIGURE 6. Average energy consumption.

and LEACH protocols. The results show that the average power utilization of the proposed RE-TOPSIS methodology is much lower when compared to the energy consumption of LEACH and marginally less than the energy consumption of F-TOPSIS.

The data pertaining to messages may be conveyed over a communication channel in the form of physical or logical connection, or via means of a certain intermediate network. This delivery of data packets is measured via throughput, which is usually calculated in the unit of bits per second (bit/s or bps), and frequently the unit is in received number of packets per unit time (p/s or pps) or packets collected by the receiver per time slot.

Fig. 7 shows the simulation result, which gives enhanced result when we use RE-TOPSIS as compared with existing F-TOPSIS and LEACH Protocols and hence, the result shows an improved network lifetime using the proposed RE-TOPSIS.

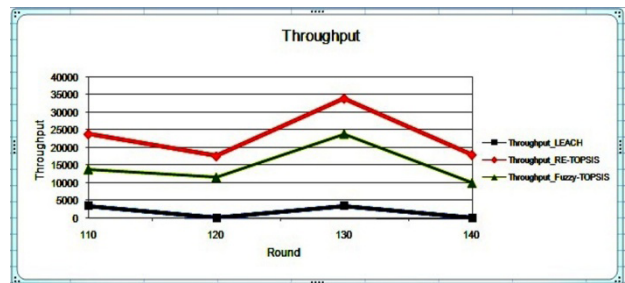


FIGURE 7. Result on round Vs throughput.

Delay time may be increased in delivering a packet across dominating networks due to several communication channel factors. Reliability is calculated in a network by measuring total Round Trip Time (RTT). It is nothing but the total time taken to transmit and receive data packets between nodes. Due to congestion of traffic, delay in delivering the packets will occur in the live network. Delay directly affects the network performance. Fig 8 shows the time taken to deliver the number of packets per round from the sink to the source (CH). The proposed RE-TOPSIS scheme shows the much improved result when compared to LEACH and F-TOPSIS.

We have also simulated the proposed protocol with varying population of sensor nodes. First we recorded the

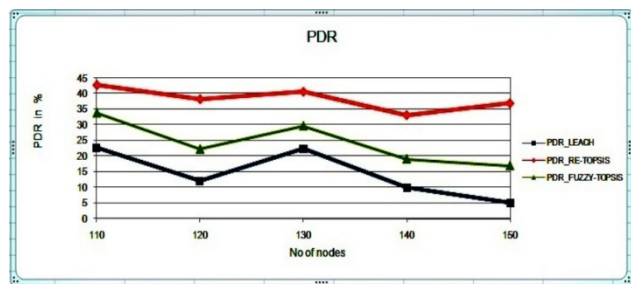


FIGURE 8. Number of packets delivered vs no of nodes.

performance and network lifetime for initial population = 100 nodes and contrasted the results with population = 5000 and population = 10000 using Matlab™. The results are presented below:

TABLE 8. Time complexity on RE-TOPSIS with varying population of sensor nodes.

Initial Population Size	Time-elapased for different operations (in sec)				Average CPU time elapased $T_{avg} = (T_{dist} + T_{DM} + T_{WDM} + T_{RDM}) / (T_{final} - T_{initial})$
	Computing Node-to-Sink Distances in time - $T_{dist}$	Computing 6-Attributes DM in time - $T_{DM}$	Computing Weighted Normalized Fuzzy-DM in time - $T_{WDM}$	Computing Rank ordered Decision Matrix in time - $T_{RDM}$	
100	0.001	0.0387	0.0261	0.0674	0.090067
5000	0.001	0.0520	0.103	0.0719	0.12230
10000	1.233	1.212	0.988	0.510	1.68741

The tabulated results clearly indicate that there is no significant variation in the elapsed time. Regarding scalability is concerned, the protocol is robust against topological and initialization parameters. As a conclusive statement, it is safe to account that the computational complexity is distributed only in the Base Station (BS) and not within the clusters, hence relieving sensor nodes from largely coupled and complex operations. The applicability of the proposed model can be extrapolated to different wireless sensor network use-cases.

VIII. CONCLUSION

In WSN, sensor nodes are connected with constrained battery power. Due to frequent change in topology, the power utilization of sensor nodes is considerably reduced. This vital property causes additional challenges to communication protocols. In this paper, a new protocol, namely RE-TOPSIS, for reliable and reduced energy consumption of nodes and judicious selection of CH is proposed. In RE\_TOPSIS we have measured the QoS performance factors like Throughput, Delay and Packet Delivery Ratio.

By using the new proposed RE-TOPSIS protocol, we have chosen the best CH using the rank index value by means of which the network lifetime is extended.

Firstly, we have proposed a novel methodology for Cluster Head Selection based on introducing six attributes to measure the best rank index value. The performance of the newly proposed RE-TOPSIS method is contrasted with the performances of the existing traditional LEACH protocol and Fuzzy-TOPSIS.

The addition of a sixth parameter Reliability in the RE-TOPSIS is crucial in reducing the overall network failures and confirms the stability of nodes and therefore improving reliability multifold. This new methodology considerably enhances the better selection of Cluster Heads and also reducing the frequency of selecting CH. This reduces the energy consumption and extends the lifetime of the network.

Furthermore, the reduction in reliability overheads contributes to the prolongation of the lifespan of the WSN. Because of which it is possible to achieve a more packet delivery ratio (PDR) and decreased delay in delivering the packets. Simulation case studies illustrate that the proposed scheme enhances the network lifespan, conserves energy and reduces the frequency of CH selection per round by about 20-25% as compared to the CH selection in the conventional Fuzzy-TOPSIS and LEACH protocols. Hence RE-TOPSIS can be employed to create a robust network that is more reliable with less data loss and long lasting than the existing protocols applied to WSN networks.

REFERENCES

- [1] X. Zhu, Y. Lu, J. H. Han, and L. Shi, "Transmission reliability evaluation for wireless sensor networks," *Int. J. Distrib. Sensor Netw.*, vol. 12, no. 2, Feb. 2016, Art. no. 1346079.
- [2] B. M. Khana, R. Bilal, and R. Young, "Fuzzy-TOPSIS based Cluster Head selection in mobile wireless sensor networks," *J. Electr. Syst. Inf. Technol.*, vol. 5, no. 3, pp. 928-943, Dec. 2016.
- [3] P. Azad and V. Sharma, "Cluster head selection in wireless sensor networks under fuzzy environment," *ISRN Sensor Netw.*, vol. 1, 2013, pp. 1-8.
- [4] B. M. Muhammad and R. Bilal, "Fuzzy-topsis-based Cluster head selection in mobile wireless sensor networks: Cluster head selection in mobile WSN," in *Proc. Handbook Res. Recent Develop. Intell. Commun. Appl.*, 2017, pp. 312-343.
- [5] J.-S. Lee, and T.-Y. Kao, "An improved three-layer low-energy adaptive Clustering hierarchy for wireless sensor networks," *IEEE Internet Things J.*, vol. 3, no. 6, pp. 951-958, Dec. 2016.
- [6] H. E. Alami and A. Najid, "SEFP: A new routing approach using fuzzy logic for Clustered heterogeneous wireless sensor networks," *Int. J. Smart Sens. Intell. Syst.*, vol. 8, no. 4, pp. 1-21, Dec. 2015.
- [7] H. E. Alami and A. Najid, "CFFL: Cluster formation using fuzzy logic for wireless sensor networks," in *Proc. IEEE/ACS 12th Int. Conf. Comput. Syst. Appl. (AICCSA)*, Nov. 2015, pp. 1-6.
- [8] H. E. Alami and A. Najid, "Fuzzy logic based Clustering algorithm for wireless sensor networks," *Int. J. Fuzzy Syst. Appl.*, vol. 6, no. 4, pp. 63-82, 2017.
- [9] C. Hwang and K. Yoon, *Multiple Attribute Decision-Making Methods and Application*. New York, NY, USA: Springer, 1981.
- [10] S. Opricovic and G.-H. Tzeng, "Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPS," *Eur. J. Oper. Res.*, vol. 156, no. 2, pp. 445-455, Jul. 2004.
- [11] N. Kumar and J. Kaur, "Improved leach protocol for wireless sensor networks," in *Proc. 7th Int. Conf. Wireless Commun., Netw. Mobile Comput.*, Sep. 2011, pp. 1-5.
- [12] A. Koucheryavy and A. S. W. Osamy, "Enhanced LEACH protocol for wireless sensor networks," St. Petersburg Univ. Telecommun., Petersburg, Russia, Tech. Rep., 2009.
- [13] M. Saidu, E. N. Onwuka, M. Okwori, and A. Umar, "An enhanced leach routing algorithm for energy conservation in a wireless sensor network," *Int. J. Wireless Microw. technol.*, vol. 6, pp. 59-71, Jul. 2016.

- [14] V. Loscri, G. Morabito, and S. Marano, "A two-levels hierarchy for low-energy adaptive Clustering hierarchy (TL-LEACH)," in *Proc. IEEE Veh. Technol. Conf.*, vol. 62, no. 3, Sep. 2005, pp. 1809–1813.
- [15] R. Mehta, A. Pandey, and P. Kapadia, "Reforming Clusters using C-LEACH in wireless sensor networks," in *Proc. Int. Conf. Comput. Commun. Inform.*, Jan. 2012, pp. 1–4.
- [16] H. Kour and A. K. Sharma, "Hybrid energy efficient distributed protocol for heterogeneous wireless sensor network," *Int. J. Comput. Appl.*, vol. 4, no. 6, pp. 1–5, Jul. 2010.
- [17] S. Murugaanandam and V. Ganapathy, "Energy efficient Clustering method in WSN for automated intelligent bio-fertigation monitor and control," *Int. J. Control Theory Appl.*, vol. 9, no. 12, pp. 5753–5760, 2016.
- [18] T.-C. Chu and T.-C. Lin, "Improved extensions of the TOPSIS for group decisionmaking under fuzzy environment," *J. Inf. Optim. Sci.*, vol. 23, no. 2, pp. 273–286, Jun. 2002.
- [19] S. Murugaanandam and V. Ganapathy, "Balanced energy efficient clustering (BEEC) method for heterogeneous wireless sensor networks using NS2," *Int. J. Control Theory Appl.*, vol. 9, no. 14, pp. 6711–6720, 2016.
- [20] J. Ma W. Lou, Y. Wu, X.-Y. Li, and G. Chen, "Energy efficient TDMA sleep scheduling in wireless sensor networks," in *Proc. IEEE INFOCOM*, Apr. 2009, pp. 630–638.
- [21] M. Ankush, *Bayesian Network Technologies: Applications and Graphical Models*. Philadelphia, PA, USA: IGI Global, 2007.
- [22] J. Long, M. Dong, K. Ota, A. Liu, and S. Hai, "Reliability guaranteed efficient data gathering in wireless sensor networks," *IEEE Access*, vol. 3, pp. 430–444, 2015.
- [23] L. A. Laranjeira and G. N. Rodrigues, "Border effect analysis for reliability assurance and continuous connectivity of wireless sensor networks in the presence of sensor failures," *IEEE Trans. Wireless Commun.*, vol. 13, no. 8, pp. 4232–4246, Aug. 2014.
- [24] A. Munir and A. Gordon-Ross, "Markov modeling of fault-tolerant wireless sensor networks," in *Proc. 20th Int. Conf. Comput. Commun. Netw. (ICCCN)*, Maui, HI, USA, Jul./Aug. 2011, pp. 1–6.
- [25] M. Anjum, M. A. Haque, and N. Ahmad, "Analysis and ranking of software reliability models based on weighted criteria value," *IJ Inf. Technol. Comput. Sci.*, vol. 2, pp. 1–14, Jan. 2013.
- [26] D. Lin, C. Lu, H. Huang, and J. Jia, "RSCM: Region selection and concurrency model for multi-class weather recognition," *IEEE Trans. Image Process.*, vol. 26, no. 9, pp. 4145–4167, Sep. 2017.
- [27] R. Logambigai, S. Ganapathy, and A. Kannan, "Energy-efficient grid-based routing algorithm using intelligent fuzzy rules for wireless sensor networks," *Comput. Electr. Eng.*, vol. 68, pp. 62–75, May 2018.



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