Research Article

Efficient Routing Approach Using a Collaborative Strategy

Layla Aziz [ID] **and Hanane Aznaoui** [ID]

Computer Science Department, Cadi Ayyad University-FSTG, Morocco

Correspondence should be addressed to Layla Aziz; layla.az1@gmail.com

Wireless sensor networks (WSNs) are a huge number of sensors, which are distributed in area monitoring to collect important signals. WSNs are widely used in several applications such as home automation, environment, and healthcare monitoring. However, most of these applications face various difficulties due to sensor design. Therefore, the major challenge of designing WSNs is saving the energy consumed during communication and extending the network lifetime. Multicriteria Decision Analysis (MCDA) methods have been exploited for saving network energy. However, the majority of researches focus on the Cluster Head (CH) selection. In this paper, we aim to enhance the process of forwarder selection using an efficient combined multicriteria model. The proposed scheme improved the intercluster communication by controlling the distance separating CHs from the sink node. To minimize the cluster density, this work consists of activating only sensor nodes that detect enough strong signals. The activation phase presents a fault-tolerant technique to succeed in the communication process. Moreover, the proposed work is aimed at selecting the most efficient hops, which are responsible for routing data to the sink using the Analytic Hierarchy Process (AHP) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) methods. Simulation results proved that our new protocol maximized the residual energy by 15% and 25% and the network lifetime by 35% and 47% compared to the Distributed Clustering Protocol using Voting and Priority (DCPVP) and Low-Energy Adaptive Clustering Hierarchy (LEACH), respectively.

1. Introduction

WSNs [1, 2, 3] can be defined as a huge number of nodes that occupy a target area. Their main role is sensing critical events and forwarding them to the sink node for making the right and required decisions. The simple architecture of this kind of network eases their use in various applications as home automation healthcare monitoring and pollution control. Although they are widely used for easing our lifestyle, they have limited power resources. Therefore, resolving this problem is required more. Wireless communication tasks are proven to have a high energy consumption rate compared to remaining sensor node tasks. Hence, saving energy during data routing permits enhancing the network performances and achieving the real goal of the applications. Recently, the majority of researchers have directed their research works in this context to design efficient routing protocols. However, wireless applications suffer from communication complications due to the sensors' energy constraint. The clustering

mechanism has proven its efficiency among more effective solutions designed previously. It is, therefore, widely used for achieving sensor distribution inside a target area. It consists of organizing sensor nodes in a predefined number of groups (clusters) for easing communication between sensors. In each group, one sensor is picked as a node leader named CH for leading communication inside and outside its group. Even though several improvements have been done for selecting the network leaders efficiently, wireless communication is still inefficient. Effective leaders' selection is insufficient for making successful communication because it is based on data forwarders too. This work is aimed at minimizing the energy consumed while data transmitting by selecting efficient forwarders. We use a combined AHP-TOPSIS model for ensuring successful transmission using important criteria where both intracluster and intercluster factors are considered. This paper is organized as follows: In Section 2, we review well-known clustered protocols like LEACH and recent routing protocols based on multicriteria decision

making. Section 3 proves the choice of method. Section 4 presents the multicriteria decision analysis methods. Section 5 describes our novel approach in detail. Section 6 represents the performance evaluation where our method is compared to the DCPVP and LEACH schemes. Section 7 summarizes the proposed work.

2. Related Works

The clustering technique represents an alternative solution for maximizing the network lifetime. Clustered approaches reduced transmitted messages inside clusters by aggregating sensed events by CHs. Cluster leaders play a vital role while they have to succeed in transmission tasks for both direct and multihop communication. In this section, we review various clustered approaches citing those based on multi-criteria decision analysis. The LEACH protocol [4] is one of the routing techniques based on the clustering mechanism. It is mainly composed of two phases: setup end steady phases. The first one consists of selecting CHs using the following probability:

$$\mathrm{Tp}(n) = \begin{cases} \dfrac{P_r}{1 - P_r(r_n \bmod (1/P_r))} & \text{if } n \text{ in } G, \\ 0 & \text{else,} \end{cases} \quad (1)$$

where P_r and r_n represent the percentage proposed for CHs in the network and round, respectively. The second phase focuses on routing data directly to the sink node. CH selection and the data routing way represent the critical limitations of LEACH. Thus, various clustered approaches have been designed for improving network lifetime. In [5], the authors proposed an improved version of LEACH, where the clustering method is based on two types of clusters: superclusters and miniclusters. Initially, sensors are organized in superclusters where SCH is elected for making data aggregation. Then, miniclusters are formed from the supercluster's members and MCH represents a leader inside the minicluster that aggregated sensed data and transmitted them to SCH. Its selection considered residual energy and cluster density factors using

$$Q_i(t) = \frac{E_i(t) \cdot k \cdot \text{density}}{E_{\text{initial}}}. \quad (2)$$

A networks' lifetime is increased thanks to the use of two clusters. In [6], the authors designed a location-based protocol named Energy-Efficient Grid-based Clustering and Routing Protocol (GCMRA). The GCMRA process consists of dividing the network into several grids. Nodes are distributed in grids forming several clusters. After the cluster construction step, the remaining nodes elect the most efficient node as CH. The number of clusters are fixed by the number of grids and the network size. The next step is based on determining the node that will be the CH using the sum of distances to each cluster node. The node that has the minimum sum and sufficient energy level according to a predefined threshold is picked as CH. Moreover, it uses multihop

communication between the CHs and the BS. In [7], the authors proposed the DCPVP protocol. This routing scheme is aimed at selecting CHs using priority and voting techniques. Each node generates a priority list of its neighbors using a weighted function. Then, sensors broadcast a vote-packet to select the best CH. Collected data is routed using a multihop way. The DCPVP protocol has enhanced the network performances compared to classical clustered approaches. Some approaches are based on renewable energy to save energy in wireless sensor networks [8, 9]. However, renewable resources are unstable and unsuitable for critical applications where making a decision requires low delay. In [10], the authors designed an energy-efficient data gathering protocol in an unequal clustered WSN using fuzzy multiple criteria decision making (DGUCF). This protocol allows selecting CH using an intuitionistic fuzzy analytic process and hierarchical fuzzy integral. In [11], the authors proposed another routing method called a multiobjective fuzzy clustering algorithm that was explored for saving energy. Moreover, this approach improved network distribution in WSNs. The authors in [12] designed a reliable energy-efficient multilevel routing algorithm for WSNs. This algorithm enhances the clusters' formation by introducing different critical factors: remaining energy level, neighbor size, and sensor centrality. Due to the combination of these factors, energy dissipation is more reduced and the network lifetime is also increased. In [13], the authors explored an effective routing method for minimizing CH selection using the Analytical Network Process (ANP) model. This work optimizes CH selection and its reselection considering essential parameters, which improved network performances. Another work based on CH selection is proposed in [14]. The authors contribute to the CH selection problem using the TOPSIS method. To make an effective CH selection, four parameters are used as inputs of TOPSIS. In most existing studies using the clustering mechanism, the authors contribute to CH selection or enhance the communication between CHs and the sink node. Novel techniques are proposed for maximizing the coverage of clusters. However, handling data redundancy is not taken into account as the most essential routing concern. Additionally, forwarder selection is rarely taken into account where only global criteria are considered. The applications of the MCDM to the problem of maximizing network lifetime are mostly applied to the CH selection or reselection problems. In the present study, we design a novel approach based on data redundancy where an intelligent activation phase is proposed. Moreover, we propose the use of the AHP-TOPSIS model for resolving the forwarder selection problem. In this stage, we consider the most important criteria and their subcriteria for making an efficient forwarder selection. The next section explains our motivation to use the integrated AHP-TOPSIS model.

3. Positioning of the Contribution

The majority of the previously reviewed research works consist of enhancing CH selection or reselection, improving the number of hop counts, and enhancing cluster formation and data aggregation. Even though various efficient routing

TABLE 1: Comparison of proposed with individual AHP and TOPSIS methods.

Criteria	AHP	TOPSIS	AHP-TOPSIS
Use hierarchical structure	X		X
To provide objective criteria weight	X		X
Comparison of ideal solution		X	X
Ranking method	X	X	X
Be easy to understand	X	X	X

TABLE 2: Criteria importance meaning.

Relative importance	Meaning
1	Equal
3	Weak
5	Strong
7	Demonstrated over the others
9	Absolute

TABLE 3: RCI values.

Criteria number	RCI values
1	0
2	0
3	0.58
4	0.90
5	1.12
6	1.24
7	1.32
8	1.41
9	1.45
10	1.49

schemes have been designed, data redundancy and forwarder selection are not considered as important routing goals. However, for ensuring data reachability and ease of making a decision according to sensed events, efficient data control and forwarder selection are required more. In this paper, we propose an effective routing scheme based on a smart activation phase to handle data redundancy and an efficient forwarder selection using a combined multicriteria decision-making model. Among the available MCDM techniques, we use the integrated AHP-TOPSIS. This hybrid model exploits the advantages of both the AHP and TOPSIS method. Table 1 illustrates the advantage of using the integrated AHP-TOPSIS model over the individual MCDM methods [15]. Hence, the AHP-TOPSIS model is selected as a suitable model for making an effective forwarder selection considering essential criteria. The next section describes the combined model used.

4. Multicriteria Decision Analysis (MCDA)

In our daily and professional life, we are in front of making the right decisions. MCDA [16, 17] represents an important science that allows making decisions. It is exploited in different fields such as economics, mathematics, and social science. This leads to the appearance of several methods for finding the most adapted solution to the situation studied. Lai et al. in 1994 [18] have categorized the decision problems in four categories: the choice problem that has the main goal of selecting the best element among a subset of elements. The second type is the sorting problem which focuses on sorting options into ordered groups named categories. This regrouping is done to reduce the options' number. The third type is the ranking problem consisting of ordering options from best to worst. The fourth type is the description problem, which has the main goal of describing options for understanding the problem characteristics. Our problem is selecting the efficient elements for routing data. Consequently, our case is the selection or choice problem and the TOPSIS method is adapted to our case and we use the AHP model for defining the different criteria weights.

4.1. Description of the AHP Model. This model is designed by Saaty [19] for resolving and structuring complex problems. The first step is aimed at decomposing the decision problem into various criteria. However, it is mandatory to determine the criteria weights. Consequently, the AHP method is more suitable for such a situation. It is exploited for defining the

weight of each criterion using the pair-wise comparison [20]. The process of this model is mainly based on different steps: The first step consists of structuring the decision hierarchy considering the essential objective of the study and determining the criteria and subcriteria. The second is establishing a set of all judgments in the comparison matrix where we use the pair-wise comparison to compare the elements set to itself. The scale of pair-wise comparison is depicted in Table 2.

The third step is aimed at calculating the adequate eigenvectors to the maximal eigenvalues for defining the relative importance of factors.

The fourth step consists of the verification of the judgments' consistency compared to the Consistency Index (CI) and Consistency Ratio (CR) [21]:

$$CI = \frac{\mu_{\max} - n}{n - 1}, \tag{3}$$

where $\mu_{\max}$ represents the eigenvalue that corresponds to the pair-wise comparison matrix and n represents the number of different elements considered for the comparison. CR is determined as follows [22]:

$$CR = \frac{CI}{RCI}, \tag{4}$$

where RCI represents random CI as shown in Table 3.

The values of CR are evaluated according to the value 0.1: a CR value is acceptable only if it is less than 0.1, otherwise, it is required to revise this pair-wise comparison.

4.2. Description of the TOPSIS Method. The TOPSIS [23, 24] method was exploited in different applications. The main idea of this method consists of selecting the most relevant solution, which is characterized by its nearness to the ideal solution and its farness from the nonideal solution. The TOPSIS process is based on these steps: The first one is aimed at gathering the actions' performances to the criteria. The second consists of normalizing the previous performances and forming a normalized matrix.

The next step is based on weighting the resulting matrix in the previous step. After that, the TOPSIS process continues with finding the distances to the ideal and the nonideal solutions. The last step consists of calculating the closeness from the previously calculated distances. Collecting the performances of m alternatives according to n criteria is done by the decision matrix M_{ij} where $i = 1, \cdots, m$ and $j = 1, \cdots, n$. For accomplishing the second step of normalization, we can use the following equations: the distributive normalization consists of dividing the performances by the square root of the squared elements:

$$M'_{ij} = \frac{M_{ij}}{\sqrt{\sum_{j=1}^{n} M_{ij}^2}} \quad \text{for } i = 1, \cdots, m \text{ and } j = 1, \cdots, n. \quad (5)$$

The ideal normalization consists of dividing all performances by the maximal score in case of criterion maximization and by the minimal value in case of criterion minimization.

The next step consists of constructing the weighted normalized matrix from the previous normalized matrix and the weights. This matrix can be expressed as follows:

$$M^*_{ij} = Wt_j \cdot M'_{ij}. \quad (6)$$

In the following step, we will use the previously calculated scores for comparing all actions to a positive (ideal) action and a negative (anti-ideal) action. We can apply several methods to define these actions: the first way is based on grouping the most relevant and the worst performance on all criteria in the second decision matrix. Hence, the ideal action (A^*) can be expressed as follows:

$$A^* = \left(M^*_j, \quad j = 1, 2, \cdots n \right) = (M^*_1, M^*_2, \cdots, M^*_n),$$
$$M^*_j = \max_i \left(M'_{ij} \right), \quad (7)$$
$$A^*_- = \left(\min_i M^*_{ij}, \quad i = 1, \cdots, m \text{ and } j = 1, \cdots, n \right).$$

The negative virtual action A^- is expressed as follows:

$$A_- = \left(\min_i M^*_{ij}, \quad i = 1, \cdots, m \text{ and } j = 1, \cdots, n \right),$$
$$M^*_j = \min_i \left(M'_{ij} \right), \quad (8)$$
$$A^- = \left(M^*_j, \quad j = 1, 2, \cdots n \right) = (M^*_1, M^*_2, \cdots M^*_n).$$

```
Initialize the constants α, β and threshold.
Initialize the list of avtive nodes ListSS ⟵ ∅.
for k ∈ [|1, #ListNodes|] do
    if ROUND! = 0 then
        Compute w_k ⟵ ad(k, s) + βE_r^t(k)
    end if
    if sj = = nj + aj then
        if wk > threshold then
            ListSS ⟵ {ListSS, k}
        end if
    end if
end for
ListNodes ⟵ ListSS
```

ALGORITHM 1: Network size control.

```
initialize l_max
C' ⟵ ListSS
for lk ∈ ListSS do
    Compute w_ij(l) ⟵ P_cv + E_r + d_t osink
end for
for ij ∈ A do
    W_ij ⟵ w_ij
end for
while C'! = ∅ do
    c ⟵ c + 1
    for l ∈ C' do
        d_l ⟵ ∑_{j∈C}' w_lj
        Class(c) ⟵ {l ∈ C|d_min = ∑_{j∈C}' w_lj
        C' ⟵ C' class(c)
    end for
    for k ∈ L(c) do
        Class_node(k) ⟵ c
    end for
end while
l_max ⟵ l
```

ALGORITHM 2: CH election.

TABLE 4: Matrix of global importance criteria.

Criteria	C1	C2	C3	Weights
C1	1	7	5	0.72
C2	0.14	1	0.33	0.08
C3	0.20	3	1	0.19

We can assume that the absolute points $A^* = (1, \cdots, 1)$ and $A^- = (0, \cdots, 0)$ can be defined independently to the problem actions. The negative and positive points are determined by the decision-maker with respect to the previous ideal and anti-ideal points calculated by the precedent detailed methods. The fourth step consists of calculating the distances

TABLE 5: Pair-wise comparison matrix for subcriteria.

Subcriteria	C11	C12	C13	C21	C22	C23	C31	C32	C33	Local weights
C11	1	5	9							0.74
C12	0.20	1	3							0.18
C13	0.11	0.33	1							0.07
C21				1	0.2	5				0.21
C22				5	1	9				0.72
C23				0.20	0.11	1				0.06
C31							1	0.14	0.33	0.08
C32							7	1	5	0.72
C33							3	0.20	1	0.2

TABLE 6: Global weights for criteria and subcriteria.

Criteria	Level 1	Subcriteria	Level 2
CH	0.72	Residual energy	0.53
		Distance to sink	0.13
		Coverage	0.06
Intracluster communication	0.08	Cluster energy	0.017
		Active member number	0.057
		Distance between active members and CH	0.005
Intercluster communication	0.19	Cluster energy	0.015
		Distance to remaining CHs	0.136
		Distance to sink	0.04

(D_i^* and D_i^-) of all actions to the ideal and the anti-ideal points using the following:

$$D_i^* = \sqrt{\sum_{j=1}^{n} \left(M_{ij}^* - M_j^* \right)^2}, \quad i = (1, \cdots, m), \tag{9}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} \left(M_{ij}^* - M_j^* \right)^2}, \quad i = (1, \cdots, m). \tag{10}$$

The fifth step consists of calculating the closeness coefficient using this formula which includes the previous distances:

$$C_i^* = \frac{D_i^-}{D_i^- + D_i^*}, \quad i = (1, \cdots, m). \tag{11}$$

The closeness value has to be in the interval $[0, 1]$. The closeness coefficient that approaches 1 means that the action is closer to the positive point and farthest from the negative point.

5. Proposed Work

Energy efficiency is influenced by different factors. It is, therefore, more preferred to integrate various factors to enhance network communication. To achieve this goal and

TABLE 7: Input values of the TOPSIS method.

Criteria	Weights	CH1	CH2	CH3	CH4	CH5
C11	0.53	5	5	9	3	7
C12	0.13	3	3	5	7	5
C13	0.06	3	5	3	5	9
C21	0.17	5	3	9	3	3
C22	0.057	3	7	3	7	9
C23	0.005	7	5	7	3	9
C31	0.015	9	3	5	5	3
C32	0.136	3	3	5	3	3
C33	0.04	5	5	7	3	7

succeed in network communication, we propose an efficient routing protocol. The new approach is aimed at taking into account intercluster and intracluster factors during data routing. Various routing methods have been explored for performing such purposes. Among these approaches, we use those based on MCDM. However, the majority of previous works focus on the efficient selection using multicriteria analysis methods based on random weights. The main objective of this work is enhancing the network energy consumed. The new approach is mainly divided into three phases. The first phase consists of achieving the cluster size control to

TABLE 8: Weighted normalized matrix.

Criteria	CH1	CH2	CH3	CH4	CH5	P	A*	A⁻
C11	0.192	0.192	0.346	0.115	0.269	+	0.34	0.011
C12	0.036	0.036	0.060	0.084	0.06	−	0.036	0.084
C13	0.014	0.024	0.014	0.024	0.044	+	0.044	0.014
C21	0.0073	0.0044	0.0132	0.0044	0.0044	+	0.0132	0.0044
C22	0.012	0.028	0.012	0.028	0.036	−	0.012	0.036
C23	0.002	0.001	0.002	0.001	0.003	−	0.001	0.003
C31	0.011	0.003	0.006	0.006	0.003	+	0.011	0.003
C32	0.052	0.052	0.087	0.052	0.05	−	0.052	0.087
C33	0.015	0.015	0.02	0.009	0.02	−	0.009	0.02

improve intercluster communication. This is done by activating only sensors that detected the strong-enough signals. Also, active nodes are grouped in clusters taking into account CH coverage. The second phase is aimed at selecting efficient CHs using a weighted function where we consider the residual energy and the distance from the sink as essential parameters. The last phase is data routing, which is aimed at making the efficient election of next hops using two efficient multicriteria analysis methods. The first method is exploited for calculating the different criteria weights. Then, the second is aimed at ranking the set of alternatives for selecting the best forwarder. In fact, we use the AHP model for calculating criteria weights and the TOPSIS method for ranking alternatives. Consequently, we can elect efficient CHs that will be responsible for routing the detected signals. Moreover, we select the most efficient hops for routing data, which improves the efficiency of our proposed protocol.

5.1. Network Model. In this paper, we assume the following assumptions:

(1) Sensor nodes are fixed and resourced by the same initial energy and have similar capabilities in terms of storage and processing

(2) Each node is identified by its ID

(3) BS is sufficiently resourced and has a huge storage and computation capacity

(4) A sensor node is considered dead when its energy is completely consumed

(5) Its battery cannot be rechargeable

(6) Sensors use a similar power level for communication or interconnection tasks

(7) Each node can communicate its collected data to its CH

(8) Sensor nodes are capable of switching from run to sleep mode for responding to TDMA (Time Division Multiple Access) orders

5.2. Energy Consumption Model. Several works have modeled energy consumption [25]. The energy consumed by a sensor

TABLE 9: Alternative ranking.

	D^*	D^-	C_i^*	Rank
CH1	0.157	0.1008	0.39	3
CH2	0.156	0.098	0.385	4
CH3	0.053	0.23	0.814	1
CH4	0.23	0.039	0.141	5
CH5	0.086	0.162	0.653	2

for performing processing and transition states can be expressed as follows:

$$E_{pr} = E_{st} + E_{tr}, \tag{12}$$

where E_{st} is the energy consumed by the state processing and E_{tr} is the energy drained while in state transition. However, more sensor energy is consumed during data routing. Therefore, we adopt the same model used in [26]. The energy consumed by the wireless communication module combines two propagation models: free space and two-ray ground using a distance threshold.

$$E_{wc} = E_{tx}$$
$$\text{or } E_w = E_{rx}. \tag{13}$$

The energy consumption of a message of L bits that travels through a distance d is expressed by

$$E_{TX}(l, d) = \begin{cases} lE_{elec} + E_{fs} * d^2, & d \le d_0, \\ lE_{elec} + E_{fmp} * d^4, & d > d_0, \end{cases} \tag{14}$$

where E_{elec} is the energy consumed to electronically operate the transmitter or receiver, E_{fs} is free space fading, and E_{mp} is multipath fading.

TABLE 10: Sensitivity analysis cases.

Cases	C11	C12	C13	C21	C22	C23	C31	C32	C33
1 (main case)	0.53	0.13	0.06	0.017	0.057	0.005	0.015	0.136	0.04
2	0.53	0.06	0.13	0.017	0.057	0.005	0.015	0.136	0.04
3	0.53	0.13	0.06	0.057	0.017	0.005	0.015	0.136	0.04
4	0.53	0.13	0.06	0.017	0.005	0.057	0.015	0.136	0.04
5	0.53	0.13	0.06	0.057	0.005	0.017	0.015	0.136	0.04
6	0.53	0.13	0.06	0.017	0.057	0.005	0.136	0.015	0.04
7	0.53	0.13	0.06	0.017	0.057	0.005	0.136	0.04	0.015
8	0.53	0.13	0.06	0.017	0.057	0.005	0.04	0.136	0.015
9 (equal)	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07

TABLE 11: Results of sensitivity analysis.

Cases	CH1	CH2	CH3	CH4	CH5	Rank
Case 1 (main)	0.39	0.385	0.814	0.141	0.653	CH3→CH5→CH1→CH2→CH4
Case 2	0.353	0.359	0.756	0.155	0.671	CH3→CH5→CH2→CH1→CH4
Case 3	0.383	0.381	0.814	0.138	0.649	CH3→CH5→CH1→CH2→CH4
Case 4	0.383	0.388	0.807	0.159	0.654	CH3→CH5→CH2→CH1→CH4
Case 5	0.3829	0.3822	0.814	0.14	0.649	CH3→CH5→CH1→CH2→CH4
Case 6	0.423	0.35	0.796	0.107	0.593	CH3→CH5→CH1→CH2→CH4
Case 7	0.424	0.351	0.797	0.104	0.595	CH3→CH5→CH1→CH2→CH4
Case 8	0.39	0.383	0.814	0.137	0.65	CH3→CH5→CH1→CH2→CH4
Case 9 (equal)	0.534	0.400	0.518	0.403	0.392	CH3→CH5→CH1→CH2→CH4

In the reception stage, energy is expressed by

$$E_{\text{RX}} = lE_{\text{elec}}. \tag{15}$$

5.3. Algorithms

5.3.1. Network Size Control Phase. In WSNs, sensor nodes are distributed on the sensing area to accomplish data sensing tasks. However, a sensor may detect identical events. To control the network size and handle data redundancy, this work consists of activating only sensors that have enough detected signals. This allows reducing the energy consumed by sensors that have weakly detected signals. However, they are in sleep mode until a strong-enough signal will be detected. Moreover, this reduced the number of messages handled by each CH and reduced significantly the energy consumed while in intracluster communication. Hence, activating only some sensors controls the network size and eases the routing phase. We assume that noisy signals at sensor node j are identically and independently distributed $(j \cdot j \cdot d)$ and follows a Gaussian distribution $n_j N(0, 1)$. Hence, each node can take a binary decision using the following equations:

$$\text{H1}: S_j = a_j + n_j, \tag{16}$$

$$\text{H0}: S_j = n_j, \tag{17}$$

where S_j represents the measure of the signal at node n_j and a_j is the signal amplitude associated with the event detected
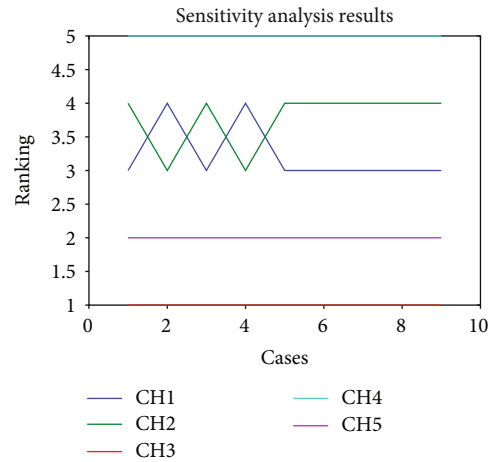

FIGURE 1: Sensitivity analysis results.

TABLE 12: Parameters values.

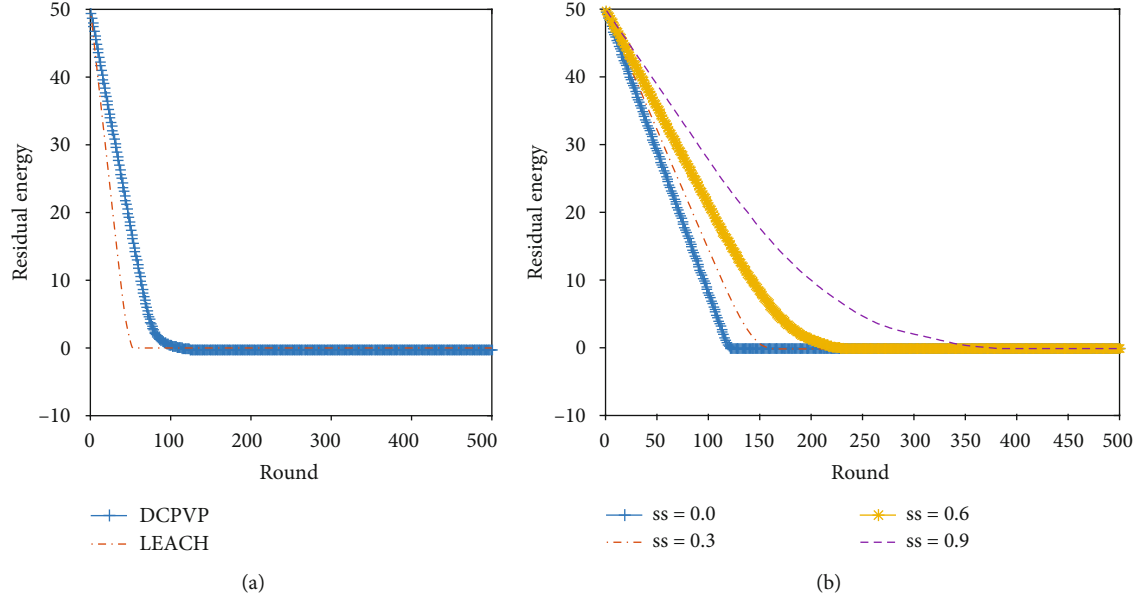| Parameter	Value
Initial target area	50 * 50
Initial number of nodes	100
BS location	(50, 50)
Packet size	500 bytes
Number of rounds	500

(a)

(b)

FIGURE 2: The residual energy for our approach (b), DCPVP, and LEACH protocols (a) for a network size of 50 ∗ 50.
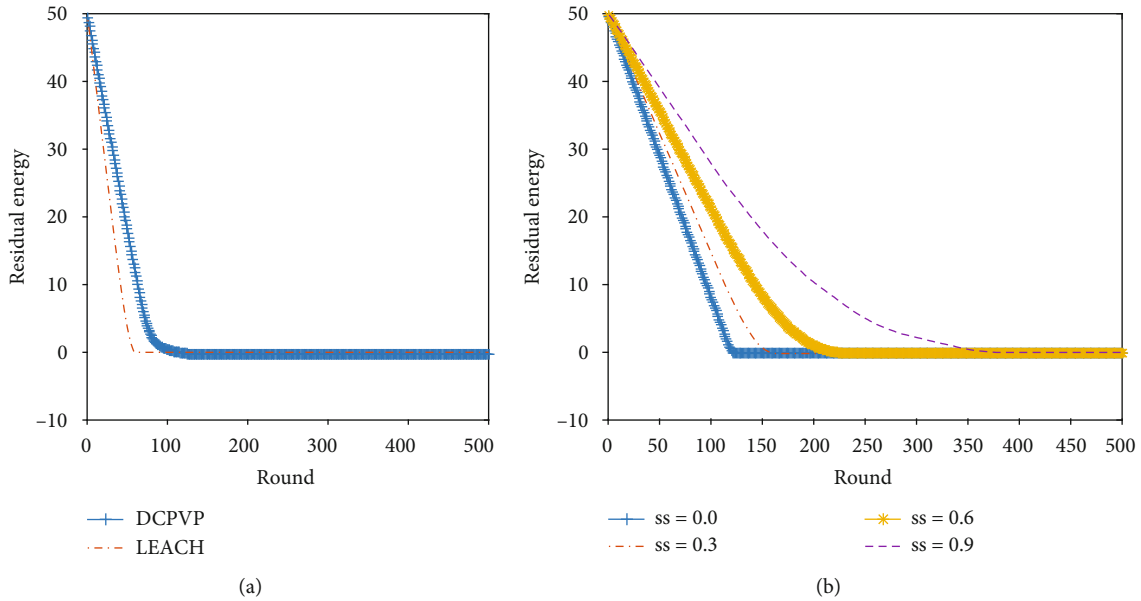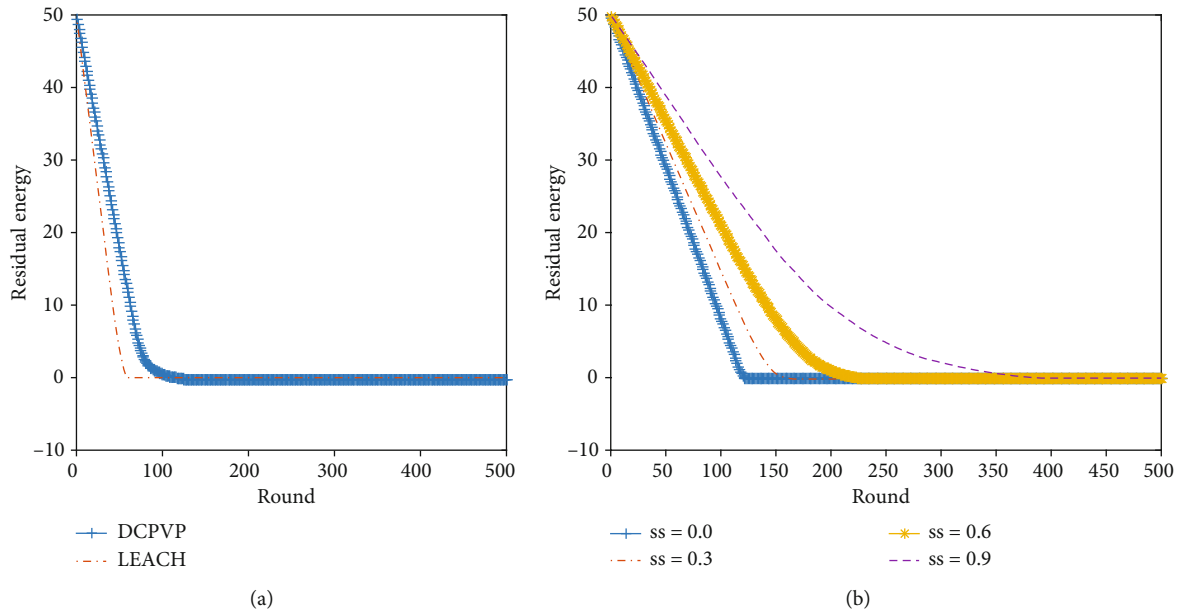

(a)

(b)

FIGURE 3: The residual energy for our approach (b), DCPVP, and LEACH protocols (a) for a network size of 100 ∗ 100.

($a_j \in R +$). We assume that each sensor node uses the same threshold to detect the event. Hence, it is authorized to report its decision only if its measured signal is larger than ss.

The steps of this phase are described in Algorithm 1.

5.3.2. CH Election Phase. Most research works focus on minimizing network energy. However, data reachability is required more for different monitoring applications. In some cases, signals are sensed to impose their reachability due to their importance level. Although the majority of clustered approaches are characterized by their implementation simplicity, forwarder routing did not consider the problem of coverage. In this work, we present an effective routing method that takes into account the forwarders' coverage. In general, the coverage concept is known as the coverage area. Let A_m represent active nodes' set and C_l is the global set. $C(A_m)$ expresses the coverage area of node set C_l. Regional coverage can be expressed as $P_{cv} = C(A_m)/C(C_l)$. However, calculating $C(C_l)$ is too complex. We, therefore, model target area as a circle centered at the candidate CH with radius R. The coverage function between CH and an active node is defined as follows:

$$P_{cv}(CH, a) = \begin{cases} 1 & \text{if } d(CH, a) \leq R, \\ 0 & else, \end{cases} \tag{18}$$

FIGURE 4: The residual energy for our approach (b), DCPVP, and LEACH protocols (a) for a network size of 150 * 150.
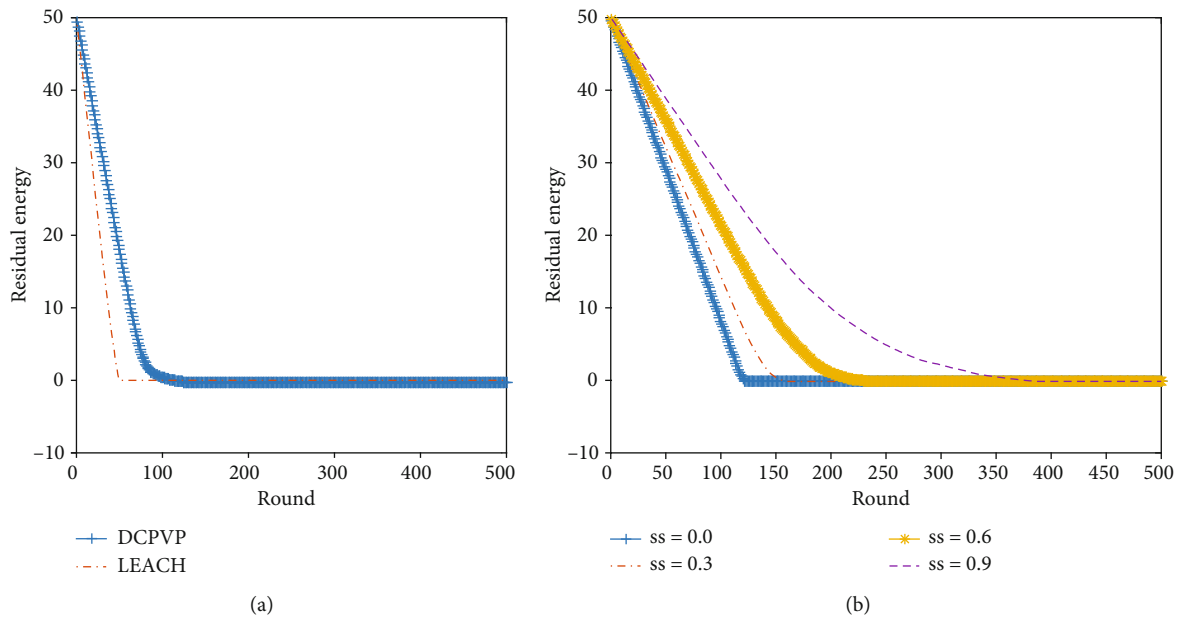

FIGURE 5: The residual energy for our approach (b), DCPVP, and LEACH protocols (a) for a network size of 200 * 200.

where $d(CH, a)$ is the Euclidean distance between candidate CH and the active node a.

As CHs have a vital role in wireless communication, we use an effective scoring function that takes into account CH residual energy and CH distance from sink and CH coverage. The different steps of Algorithm 2 are described below:

5.3.3. Data Routing Phase. Several studies have proven that network energy is consumed more while routing data. Hence, saving energy while performing such tasks is required more to improve network performances. Recent works have exploited MCDA techniques; however, the majority of them

resolved routing selection using random weights. In this work, we use the hybrid AHP-TOPSIS model for routing data effectively. In fact, we use the AHP method to generate criteria weights and the TOPSIS technique for ranking available forwarders. Ranking takes into account the CH election, intracluster communication criteria, and intercluster communication criteria. Consequently, the CHs that will be responsible for routing data are well elected using the main important criteria and subcriteria. The following numerical example presents more details about our approach. Besides, we study the impact of criteria weights to prove the efficiency of the proposed work.
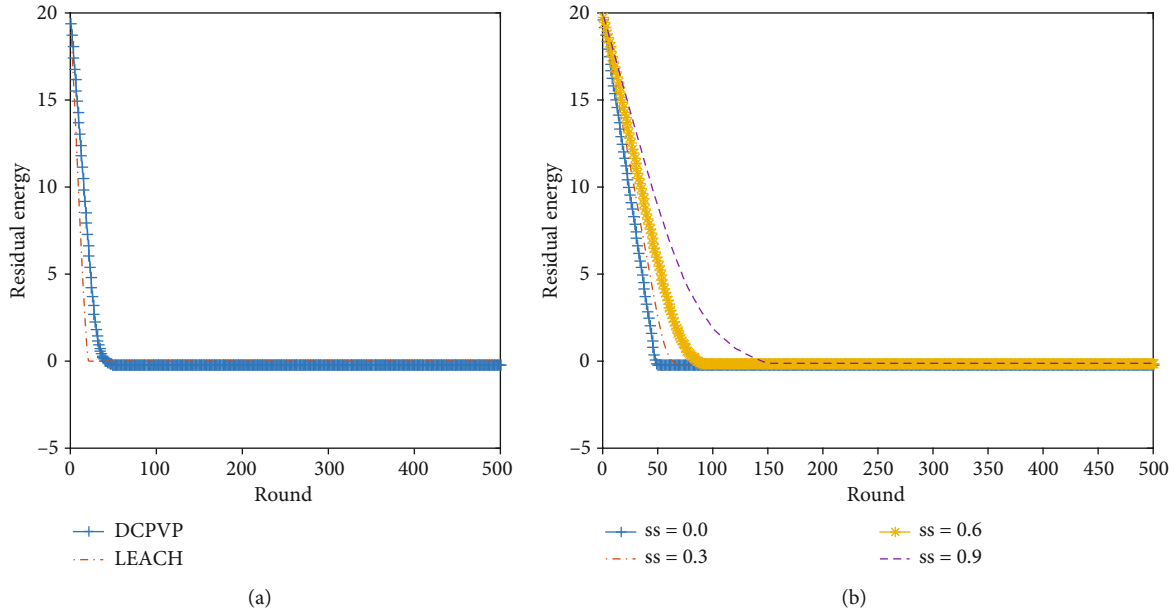
(a)

(b)

FIGURE 6: The residual energy for our approach (b), DCPVP, and LEACH protocols (a) for E0 = 0.2.
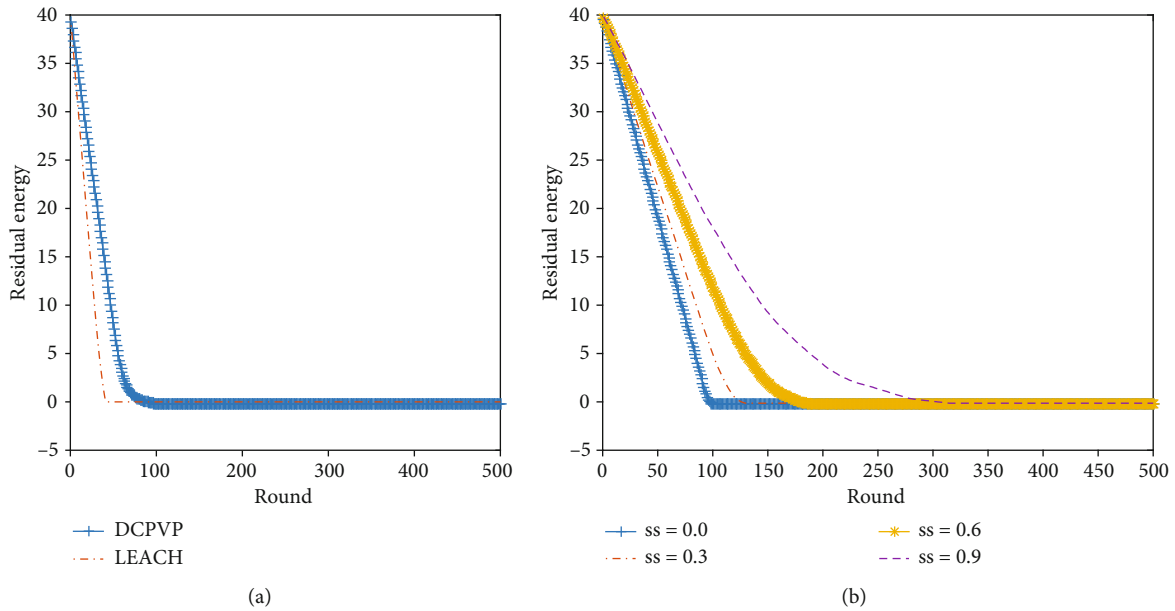

(a)

(b)

FIGURE 7: The residual energy for our approach (b), DCPVP, and LEACH protocols (a) for E0 = 0.4.

5.3.4. Numerical Illustration. The main purpose of this work is ranking routing forwarders using the combined decision-making AHP-TOPSIS model. In fact, the AHP method is exploited for weight generation while TOPSIS is aimed at ranking forwarders. In other words, the process of AHP allows calculating the weight of each criterion instead of attributing it randomly. The first step consists of the presentation of the hierarchy model for forwarder ranking. In this model, we consider three global criteria and three subcriteria for each criterion. In this section, we present a numerical example for the AHP-TOPSIS model in our case. In this example, we aim to choose the most efficient CH forwarder

among available CHs. Table 4 represents the importance of global criteria. The pair-wise comparison matrix for subcriteria is shown in Table 5. All matrices are consistent because the consistency rates of the comparison criteria of the main criteria and subcriteria are less than 0.1 with values of 0.047, 0.019, 0.09, and 0.047, respectively. Table 6 regroups all global weights that are used as inputs for the next stage of ranking. Global weights (level 2) are obtained by multiplying the local weights by the weight of the relevant criteria (level 1). For example, for subcriterion C11, the local weight is 0.74, and for the CH criterion, the local weight is 0.72. Therefore, the overall weight of C11 is $0.74 * 0.72 = 0.53$.
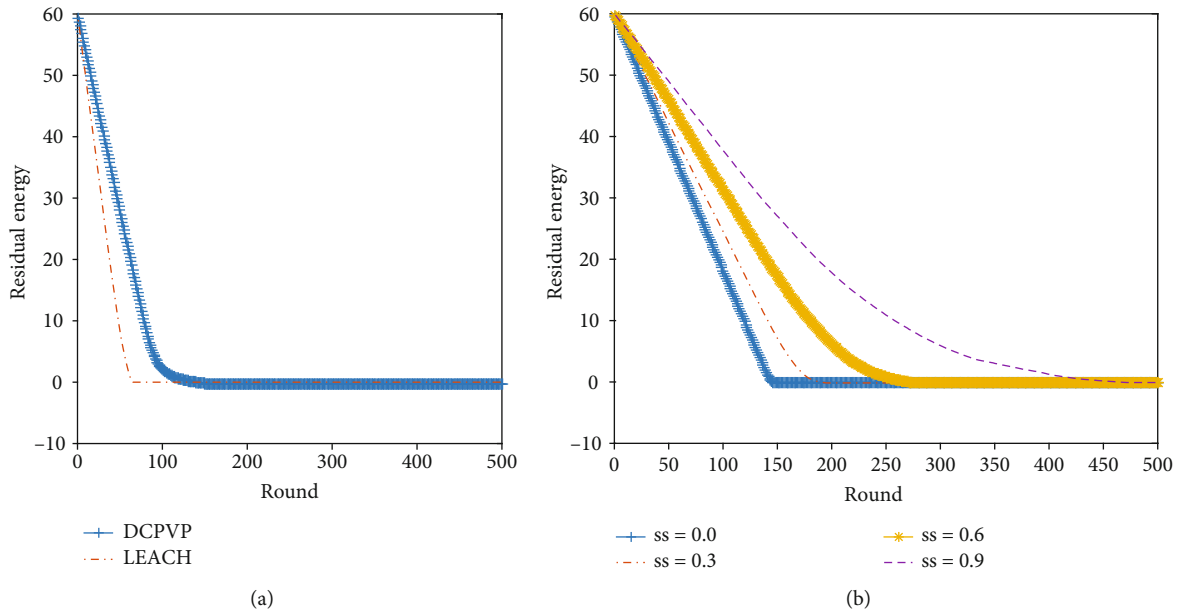
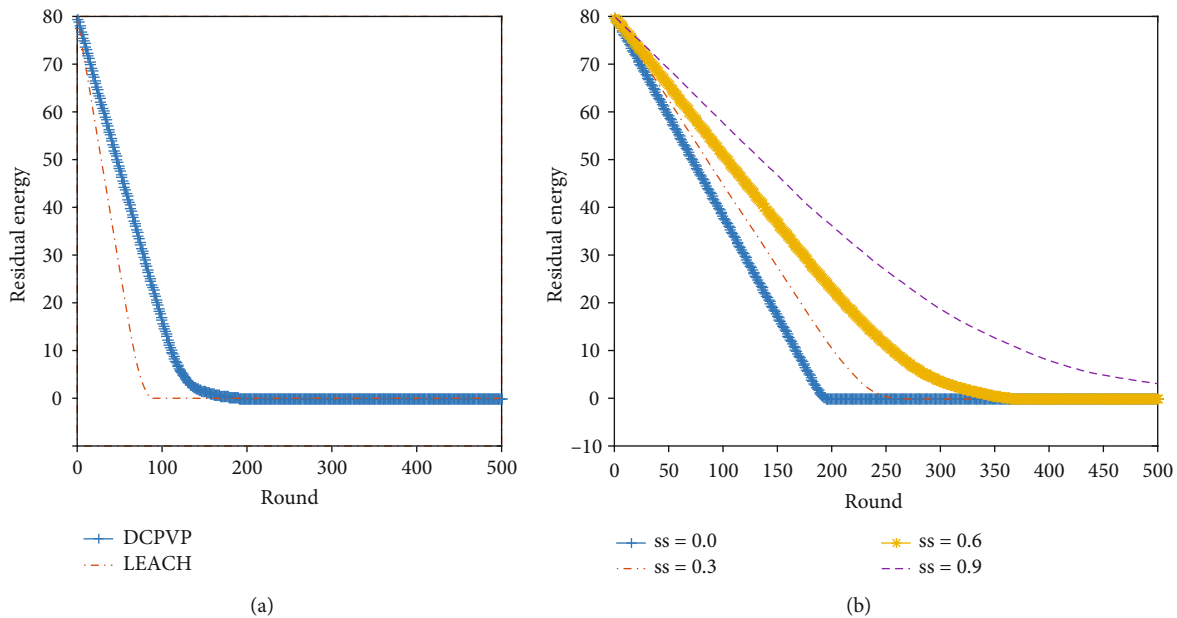Figure 8: The residual energy for our approach (b), DCPVP, and LEACH protocols (a) for E0 = 0.6.

Figure 9: The residual energy for our approach (b), DCPVP, and LEACH protocols (a) for E0 = 0.8.

After calculating all criteria weights using the AHP model, we use these generated weights for ranking the available alternatives. We present the input values of the TOPSIS method in Table 7.

This section is aimed at ranking CHs using the TOPSIS technique, and we present in Table 8 the weighted normalized matrix obtained by multiplying each column with its associated weight using equations (5) and (6). For each criterion, we calculate the positive and negative ideal solutions (A^*, A^-) using equations (7) and (8).

The ranking step is performed using equations (9), (10), and (11). Table 9 depicts the final evaluation of alternatives,

and it can be visually seen that CH3 represents the best forwarder.

5.3.5. Sensitivity Analysis. In this section, our objective is analyzing the combined model: AHP-TOPSIS. We make, therefore, an alternative evaluation under different weights where two weights are permuted while the remaining weights are constant. Table 10 represents the evaluation cases considered.

In each case, we applied all model steps for ranking alternatives. From sensitivity analysis results (Table 11 and Figure 1), we conclude that the main case represents
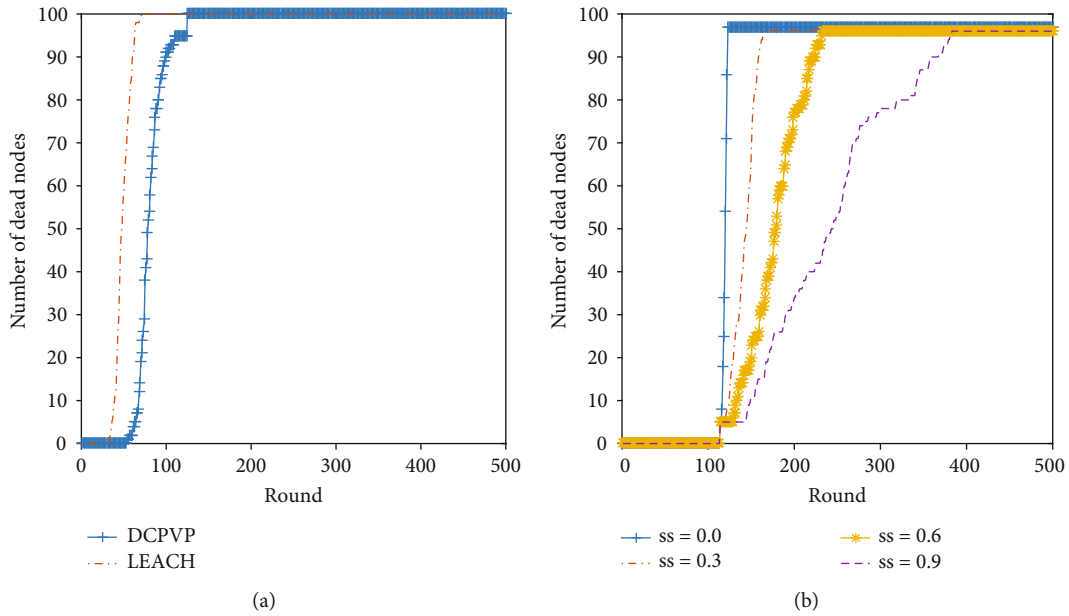
(a)

(b)

FIGURE 10: The number of dead nodes for our approach (b), DCPVP, and LEACH protocols (a) for a network size 50 * 50.
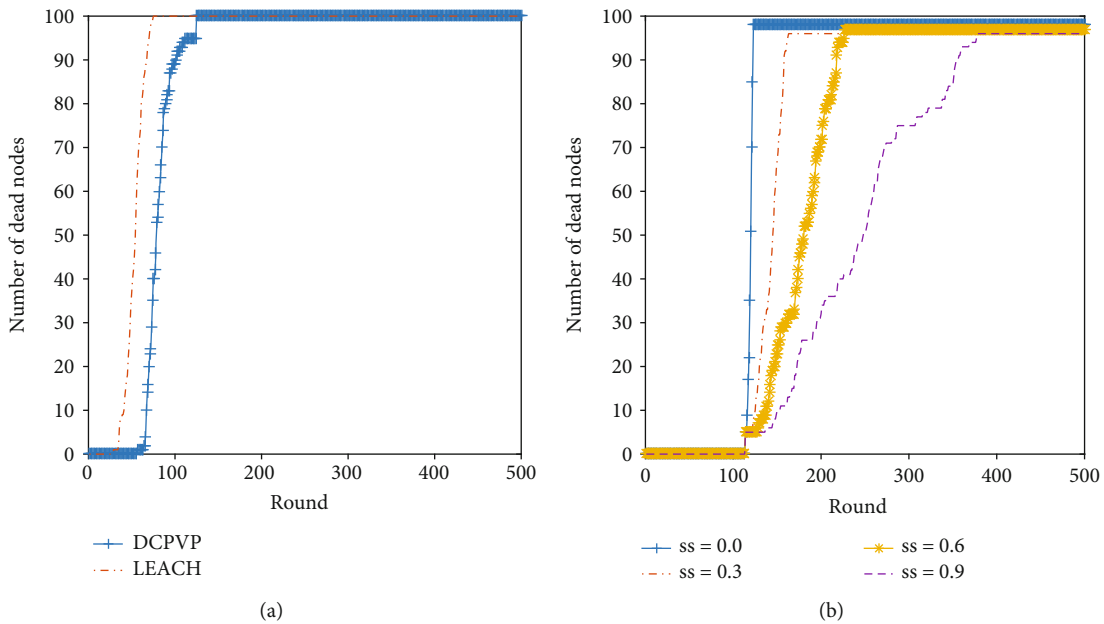

(a)

(b)

FIGURE 11: The number of dead nodes for our approach (b), DCPVP, and LEACH protocols (a) for a network size 100 * 100.

alternative ranking originally. Moreover, CH3 keeps its highest rank in all cases compared to the other CHs. CH3 has the highest score, even if we attribute equal weights to criteria.

Consequently, we can conclude that our decision-making process is insensitive to criteria weights.

6. Simulation Results

To evaluate our approach performances, we compare it with DCPVP and LEACH protocols. To do so, we consider two different scenarios. The first one consists of varying the network

size, and the second focuses on varying the initial residual energy. Table 12 describes the parameters' values. In the studied scenarios, sensors are distributed in the target area with the same initial energy. A sensor belongs to the list of dead nodes if its energy level is null. It is, therefore, removed from the active list and cluster construction and routing packet processes. To prove experiment exactitude, all results represent the average value of 20 runs.

6.1. Energy Efficiency. In this section, we present the examination of the energy efficiency of the proposed work using
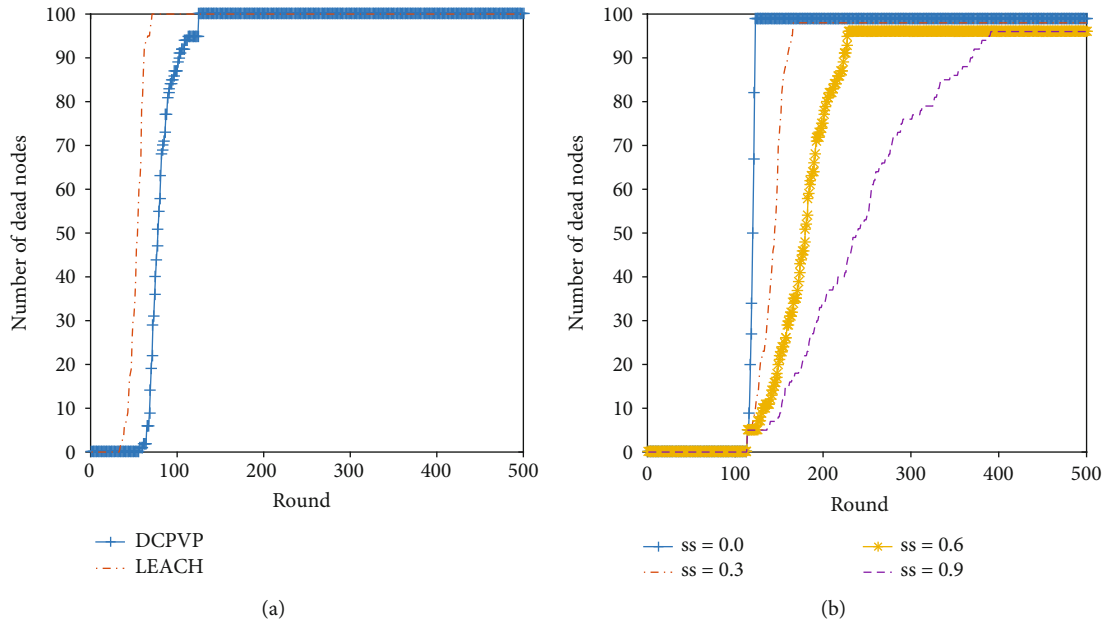
FIGURE 12: The number of dead nodes for our approach (b), DCPVP, and LEACH protocols (a) for a network size 150 ∗ 150.
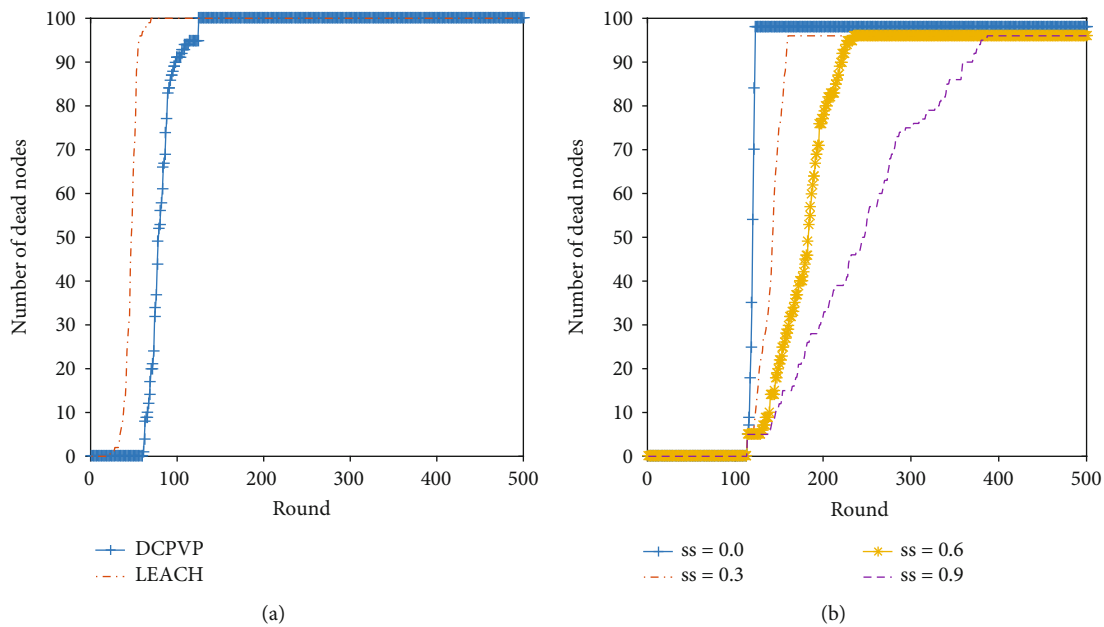

FIGURE 13: The number of dead nodes for our approach (b), DCPVP, and LEACH protocols (a) for a network size 200 ∗ 200.

different levels of ss (strong signal threshold) for two different scenarios. The first one is based on the network size evaluation and the second focuses on making the approach examination using different initial energy levels. Figures 2–9 depict the energy consumed by our novel approach, DCPVP, and LEACH protocols for the first and second scenarios, respectively. The x-axis represents the number of rounds, while the y-axis shows the values of energy consumed by the compared approaches. DCPVP and LEACH protocols show much higher values than our

new protocol for various ss values. This is justified by their CH selection process that neglects the leaders' coverage. This drained, therefore, more energy due to the transmission of redundant data. Moreover, the LEACH protocol shows the highest values compared to DCPVP and our approach. This is justified by the use of a probabilistic method for selecting the CH and the direct communication between CHs and the sink node. However, the proposed protocol shows a significant reduction of the energy consumed due to the effective CH election process where an efficient weighted function is
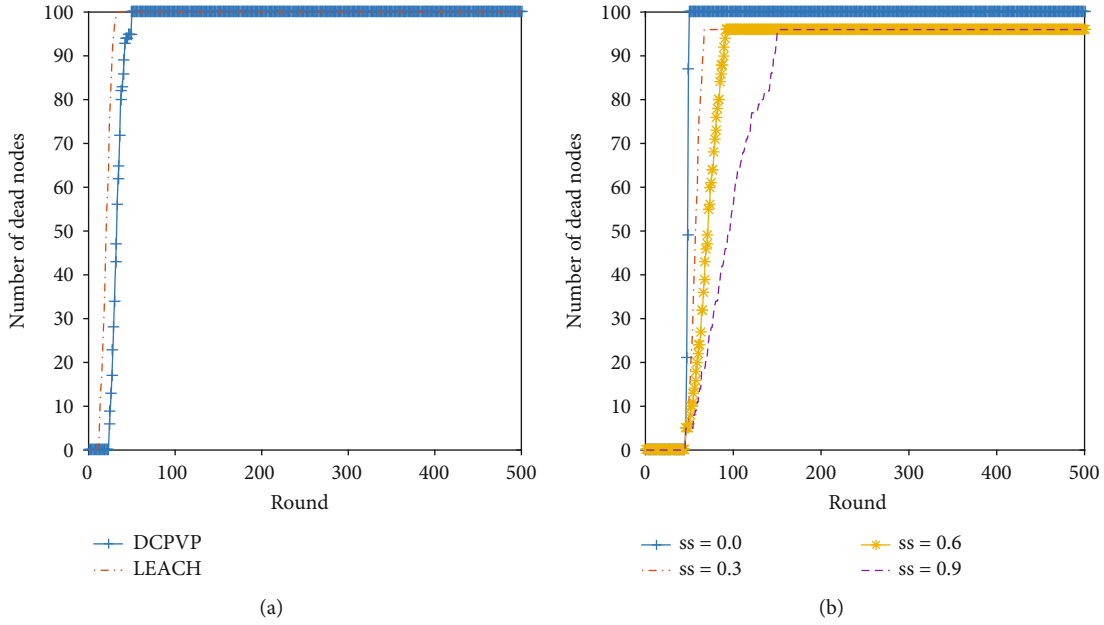
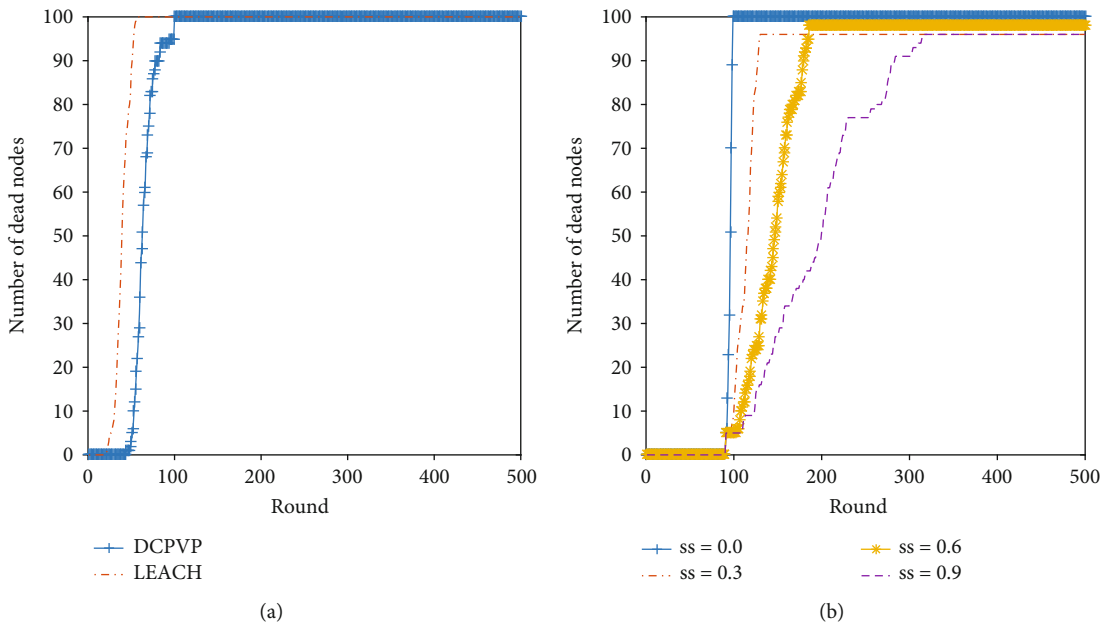FIGURE 14: The number of dead nodes for our approach (b), DCPVP, and LEACH protocols (a) for E0 = 0.2.

FIGURE 15: The number of dead nodes our approach (b), DCPVP, and LEACH protocols (a) for E0 = 0.4.

explored. CH selection considers three important parameters: residual energy, distance from sink, and CH coverage. Also, our approach follows a strategy of node activation in the network for handling communication between CHs and their members. Only nodes with strong-enough signals could communicate their detected signals while the remaining sensors are in sleep mode until an important event is detected. This way of communication allows reducing the number of nodes that interact and hence enhances the network performances. The proposed scheme improved the routing phase using the multihop communication between clusters and the sink node. The communication process is controlled using the MCDM technique where two methods are combined for selecting efficient CHs responsible for routing data. In this phase, various criteria are considered which are grouped in three contexts where each one includes the important subcriteria for achieving this phase effectively. The use of the hybrid multicriteria model improved well data routing compared to the DCPVP protocol.
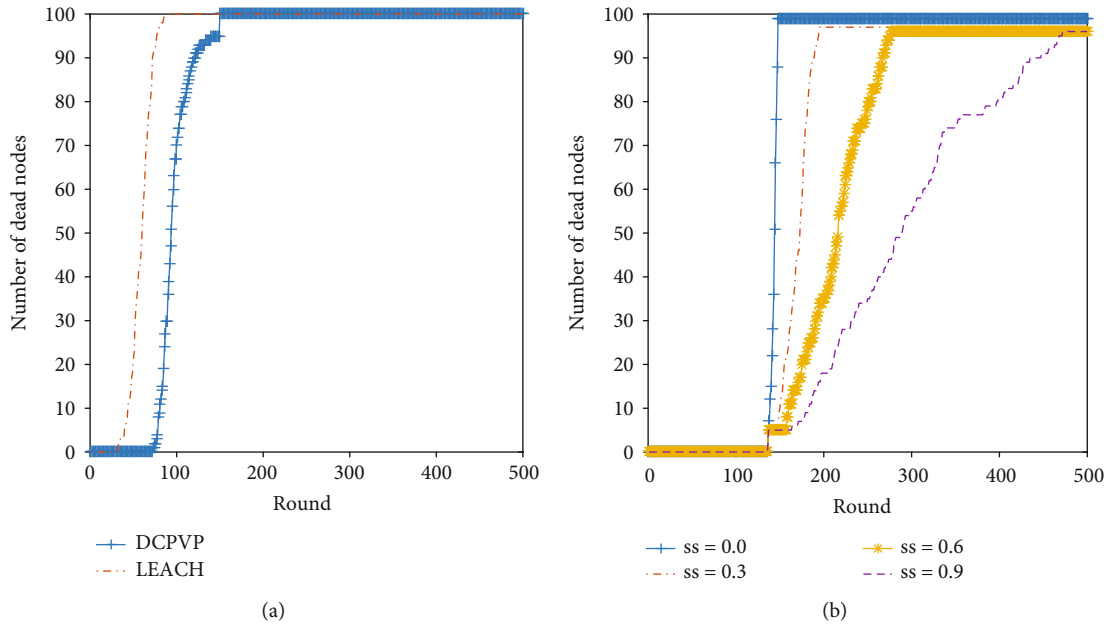
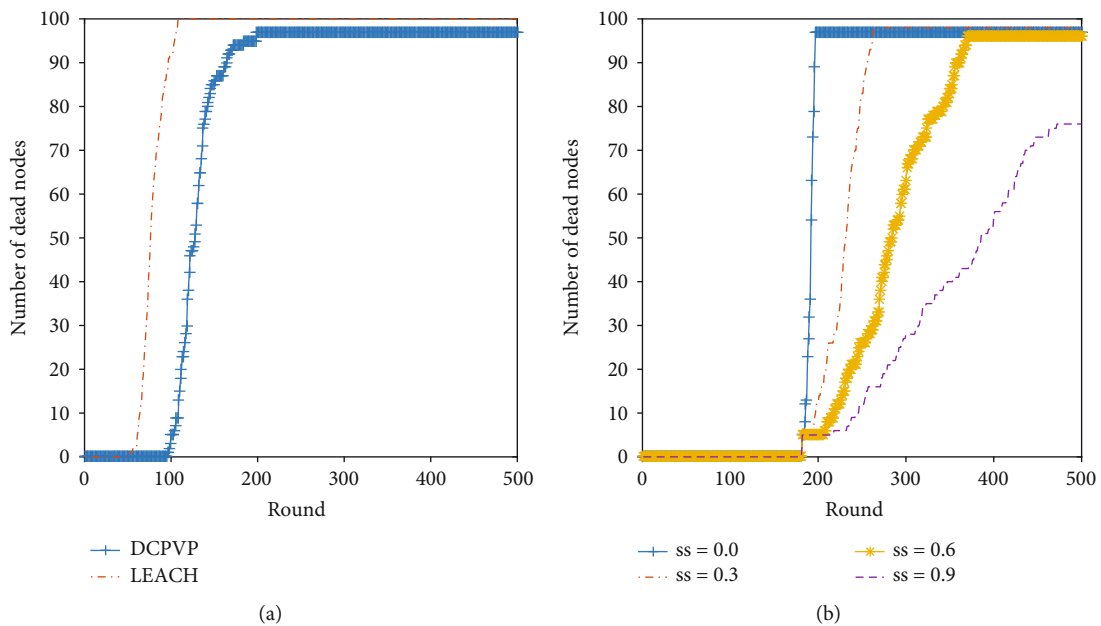FIGURE 16: The number of dead nodes for our approach (b), DCPVP, and LEACH protocols (a) for E0 = 0.6.

FIGURE 17: The number of dead nodes for our approach (b), DCPVP, and LEAsCH protocols (a) for E0 = 0.8.

6.2. *Number of Alive Nodes.* Our approach is evaluated using the network lifetime parameter. Figures 10–17 depict the number of alive nodes of the novel approach, LEACH, and DCPVP protocols for the first and second scenario, respectively. It is shown from curves that our scheme prolongs the network lifetime for different ss values. This is justified by the use of a strong weighted function for electing the most effective CHs among available nodes. Moreover, an activation technique is used for controlling the number of nodes that interact inside clusters. On the other hand,

our approach exploits an efficient MCDA-combined method for controlling the distance between clusters and the sink. Taking into account all these requirements improved significantly the network life of CHs compared to the LEACH and DCPVP schemes. Consequently, the network lifetime is well increased compared to the DCPVP approach. However, LEACH and DCPVP have low values due to the energy consumed during the intercluster communication because there is no control of the number of sensors that communicate inside each cluster and redundant signals

are routed. The LEACH protocol has shown the lowest values because it uses direct communication between CHs and the sink. This consumed more energy and hence increased the number of dead nodes. However, the data routing phase of our scheme is performed according to the hybrid AHP-TOPSIS model where three global contexts are considered. Forwarder selection is based on different vital factors that influence the network's lifetime. The combination of these factors improved significantly the network lifetime.

7. Conclusion

WSNs are widely used for various applications such as environmental applications, home automation, and patient monitoring. However, sensors are energy-constrained devices due to their tiny architecture. Indeed, they are responsible for performing several tasks such as self-distribution, data collection, and routing cooperation. Data routing consumed more energy compared to event sensing or other communication tasks. Hence, enhancing the rate of energy drained while routing represents a critical challenge for the research community. The clustering mechanism has shown its efficiency for performing the network organization and represents an effective solution compared to classical routing methods. However, existing routing schemes have rarely focused on forwarder selection. In this work, an efficient routing scheme is proposed as the solution of both CH and forwarder selection problems. A strong weighted function is exploited to pick CHs effectively and an activation algorithm is proposed for handling sensed signals' redundancy. Various researchers have improved clustered approaches using MCDM methods. However, the majority of research works consisted of the CH selection problem and the use of random criteria weights. In this work, we use a combined AHP-TOPSIS model for making forwarder selection. We use the AHP method for weight generation and TOPSIS for forwarder ranking. Moreover, sensitivity analysis results are discussed for analyzing the AHP-TOPSIS model in our case and proving the originality of forwarder ranking. In all cases, results illustrate the prioritizing stability where CH3 is ranked as the most relevant forwarder. Simulation results indicate that this model improved network performances significantly compared to the related scheme. We conclude that the AHP-TOPSIS tool may become a promising model for prioritizing data forwarders in WSN. As future work, we intend to use the integrated AHP-TOPSIS tool with other routing approaches considering real applications.

Data Availability

All data are included in the paper.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

[1] S. Jabbar, M. Asif Habib, A. A. Minhas et al., "Analysis of factors affecting energy aware routing in wireless sensor network," *Wireless Communications and Mobile Computing*, vol. 2018, Article ID 9087269, 21 pages, 2018.

[2] Z. Fei, B. Li, S. Yang, C. Xing, H. Chen, and L. Hanzo, "A survey of multi-objective optimization in wireless sensor networks: metrics, algorithms, and open problems," *IEEE Communications Surveys & Tutorials*, vol. 19, no. 1, pp. 550–586, 2017.

[3] L. Aziz, S. Raghay, and A. Jamali, "A new improved algorithm of LEACH protocol for wireless sensor networks," in *Proceedings of 2014 Mediterranean Microwave Symposium (MMS2014)*, pp. 1–5, Marrakech, Morocco, 2014.

[4] L. Aziz, S. Raghay, H. Aznaoui, and A. Jamali, "A new approach based on a genetic algorithm and an agent cluster head to optimize energy in wireless sensor networks," in *2016 International Conference on Information Technology for Organizations Development (IT4OD)*, pp. 1–5, Fez, Morocco, 2016.

[5] W. Akkari, B. Bouhdid, and A. Belghith, "LEATCH: low energy adaptive tier clustering hierarchy," *Procedia Computer Science*, vol. 52, pp. 365–372, 2015.

[6] S. Jannu and P. K. Jana, "Energy efficient grid based clustering and routing algorithms for wireless sensor networks," in *2014 Fourth International Conference on Communication Systems and Network Technologies*, pp. 63–68, Bhopal, India, 2014.

[7] H. Hematkhah and Y. Kavian, "DCPVP: Distributed clustering protocol using voting and priority for wireless sensor networks," *Sensors*, vol. 15, no. 3, pp. 5763–5782, 2015.

[8] W.-K. Lee, M. J. W. Schubert, B.-Y. Ooi, and S. J.-Q. Ho, "Multi-source energy harvesting and storage for floating wireless sensor network nodes with long range communication capability," *IEEE Transactions on Industry Applications*, vol. 54, no. 3, pp. 2606–2615, 2018.

[9] H. U. Yildiz, V. C. Gungor, and B. Tavli, "A hybrid energy harvesting framework for energy efficiency in wireless sensor networks based smart grid applications," in *2018 17th Annual Mediterranean Ad Hoc Networking Workshop (Med-Hoc-Net)*, pp. 1–6, Capri, Italy, 2017.

[10] X. Song, Q. Zhang, W. Sun, and W. Wei, "Energy-efficient data gathering protocol in unequal clustered WSN utilizing fuzzy multiple criteria decision making," *Journal of Intelligent & Fuzzy Systems*, vol. 32, no. 5, pp. 3461–3473, 2017.

[11] P. Nayak and A. Devulapalli, "A fuzzy logic-based clustering algorithm for WSN to extend the network lifetime," *IEEE Sensors Journal*, vol. 16, no. 1, pp. 137–144, 2016.

[12] Z. Yu, X. Fu, Y. Cai, and M. C. Vuran, "A reliable energy-efficient multi-level routing algorithm for wireless sensor networks using Fuzzy petri nets," *Sensors*, vol. 11, no. 3, pp. 3381–3400, 2011.

[13] H. Farman, H. Javed, B. Jan et al., "Analytical network process based optimum cluster head selection in wireless sensor network," *PLoS One*, vol. 12, no. 7, article e0180848, 2017.

[14] F. Hamzeloei and M. K. Dermany, "A TOPSIS based cluster head selection for wireless sensor network," *Procedia Computer Science*, vol. 98, pp. 8–15, 2016.

[15] M. Ahmed, M. N. Qureshi, J. Mallick, M. A. Hasan, and M. Hussain, "Decision support model for design of high-performance concrete mixtures using two-phase AHP-

TOPSIS approach," *Advances in Civil Engineering*, vol. 2019, Article ID 1696131, 8 pages, 2019.

[16] S. Latif, S. Mahfooz, B. Jan et al., "Multicriteria based next forwarder selection for data dissemination in vehicular ad hoc networks using analytical network process," *Mathematical Problems in Engineering*, vol. 2017, Article ID 4671892, 18 pages, 2017.

[17] H. Aznaoui, S. Raghay, L. Aziz, and A. Ait-Mlouk, "A comparative study of routing protocols in WSN," in *2015 5th International Conference on Information & Communication Technology and Accessibility (ICTA)*, pp. 1–6, Marrakech, Morocco, 2015.

[18] Y.-J. Lai, T.-Y. Liu, and C.-L. Hwang, "TOPSIS for MODM," *European Journal of Operational Research*, vol. 76, no. 3, pp. 486–500, 1994.

[19] T. L. Saaty, "How to make a decision: the analytic hierarchy process," *Interfaces*, vol. 24, no. 6, pp. 19–43, 1994.

[20] L. Li, S. Bai, M. Leng, L. Wang, and X. Chen, "Finding missing links in complex networks: a multiple-attribute decision-making method," *Complexity*, vol. 2018, Article ID 3579758, 16 pages, 2018.

[21] J.-T. Hsueh and C.-Y. Lin, "Integrating the AHP and TOPSIS decision processes for evaluating the optimal collection strategy in reverse logistic for the TPI," *International Journal of Green Energy*, vol. 14, no. 14, pp. 1209–1220, 2017.

[22] A. Çalık, S. Çizmecioğlu, and A. Akpınar, "An integrated AHP-TOPSIS framework for foreign direct investment in Turkey," *Journal of Multi-Criteria Decision Analysis*, vol. 26, no. 5-6, pp. 296–307, 2019.

[23] M. Behzadian, S. K. Otaghsara, M. Yazdani, and J. Ignatius, "A state-of the-art survey of TOPSIS applications," *Expert Systems with Applications*, vol. 39, no. 17, pp. 13051–13069, 2012.

[24] S. Akcan and M. Güldeş, "Integrated multicriteria decision-making methods to solve supplier selection problem: a case study in a hospital," *Journal of Healthcare Engineering*, vol. 2019, Article ID 5614892, 10 pages, 2019.

[25] P. S. Mann and S. Singh, "Energy efficient clustering protocol based on improved metaheuristic in wireless sensor networks," *Journal of Network and Computer Applications*, vol. 83, pp. 40–52, 2017.

[26] G. S. Arumugam and T. Ponnuchamy, "EE-LEACH: development of energy-efficient LEACH Protocol for data gathering in WSN," *EURASIP Journal on Wireless Communications and Networking*, vol. 2015, no. 1, 2015.