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Research Article in Special Issue: Selected Papers from the 4th International Conference on Machine Learning, Image Processing, Network Security and Data Sciences (MIND-2022)

TOPSIS-based Optimal Cluster Head Selection for Wireless Sensor Network

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Received: 8 March 2023; **Accepted:** 28 March 2023

Abstract: Due to the advancement of electronics engineering technology, many types of sensors have been developed. But sensors are still battery-powered devices. Once the battery is dead, the sensors are of no use. So, energy optimization in wireless sensor networks is still a hot topic among researchers. This paper proposed a novel clustering method that uses the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) algorithm to select the Cluster Heads (CHs). TOPSIS is a Multi-Attribute Decision Making (MADM) based model which uses several conflicting attributes to select the best alternative. We have compared our proposed model with two other comparable models to evaluate the performance of our proposed model. The result shows that our proposed model performs better than other models.

***Keywords*:** Wireless Sensor Network, MADM, TOPSIS, energy optimization

1. Introduction

The Wireless Sensor Network (WSN) is an advanced technology to monitor any area for some physical events. It can be used for monitoring environmental activities like temperature, humidity, air quality, air pressure, etc., for surveillance purposes like monitoring the borders, home or field, for medical purposes like patient monitoring, etc. In WSN, hundreds of sensor nodes are deployed in the field for the monitoring purpose. The sensors are very small electronic devices with low computing power and limited energy. To analyze the sensed data, it is required to transmit it to the Base Station (BS). BS is a node that has high computing power and unlimited energy. BS is connected to the internet, so once the data is received at BS, it can be transmitted anywhere in the world. The main challenge in WSN is the transmission of data from the nodes to the BS in a very efficient way.

A lot of concepts are proposed for the data routing from sensors to the BS. Clustering is one of the most popular methods among researchers for efficient data routing. In clustering, some sensor nodes are selected as Cluster Heads (CHs). The remaining nodes, known as normal nodes, join these CHs to form the cluster. All the normal nodes transmit their data to their CH. The CHs preprocess the received data, aggregate it with their own data and transmit it to BS either directly if BS is closer or through multi-hop by transmitting it to any other CH close to the BS. The main challenge in

DOI: https://doi.org/10.37256/rrcs.2320232638

the clustering method is the selection of CH. Hundreds of techniques are proposed in the literature for the selection of CH. Some of the popular techniques are discussed in Section 2 of this paper.

We have proposed a novel CH selection technique based on Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) algorithm. The major contribution of our proposed work is given below:

- It uses five conflicting attributes in the TOPSIS algorithm for the selection of the best CH. The attributes are remaining energy, standard deviation of nearby nodes, average distance of nearby nodes, density and distance to BS. These attributes, when considered collectively have the ability to select the best CH and balance load among them.
- These attributes are also known as criteria. Each criterion has a fixed weight. If there are n criteria and if c_1, c_2, c_3, ….c_n are the weights of these criteria, then the sum of all criteria weights should be equal to 1, i.e.,

$$c_1 + c_2 + c_3 \ldots. c_n = 1 \tag{1}$$

  We have tuned these weights manually to get the best results.
- We have compared our proposed work with two other popular and comparable works on different parameters for the analysis of our proposed work.

The rest of the paper is organized as follows. The related work in Section 2 explains the TOPSIS method and the energy consumption model. The step-by-step output of the TOPSIS method, and the finally selected CHs are shown in Section 3. In Section 4, the comparison of our proposed work with other algorithms is made. In Section 5, the limitations, along with the future scopes of our proposed model are shown. In Section 6, we have talked about the conclusion of our proposed work. The references used in this paper are added at the end.

2. Related work

Lots of methods are proposed for the routing of data from sensors to BS. The Low Energy Adaptive Clustering Hierarchy (LEACH) was the first algorithm to introduce the concept of clustering in WSN [1]. In LEACH, initially, some nodes are selected as CH randomly. LEACH uses the CH rotation policy to balance the energy among the nodes. If a node is selected as CH in LEACH, it cannot be selected as CH again until all the remaining nodes become CH. LEACH has several drawbacks. It does not consider any parameter like Remaining Energy (RE), distance from BS, or distance of nearby nodes while selecting the CH. So, many models are proposed as an improvement over LEACH by considering these parameters. LEACH-C (centralized LEACH) uses the RE of nodes while selecting the CH [2]. Another proposed chain-based protocol, Power Efficient Gathering in Sensor Information Systems (PEGASIS), improves LEACH by more than 100% [3]. In PEGASIS, each node transmits its data to another nearby node closer to BS. So, a chain of data streams is created in PEGASIS. Hybrid Energy Efficient Distributed clustering (HEED) uses RE and density for the selection of CH [4]. HEED tries to improve the CH selection process, but it consumes huge amount of energy due to computation overhead. Energy Efficient Clustering Scheme (EECS) uses RE and the distance from the node to BS to select CHs [5].

Nature-inspired algorithms are also proposed for the selection of CH. In LEACH genetic algorithm (LEACH-GA), genetic algorithm was used for the election of better CHs [6]. In [7], Particle Swarm Optimization (PSO) is used with RE, distances to BS, node degree and headcount as parameters of the fitness function. Several other algorithms [8-14] also use PSO by selecting different parameters in the fitness function. Ant colony optimization is used in [15] to select CH.

Several Multi-Attribute Decision Making (MADM) based routing schemes are also proposed in WSN. In [16], a CH selection method is proposed using TOPSIS. In this method, number of neighbours, distance to sink, number of tasks and RE are used as parameters of TOPSIS. In [17], a MADM-based optimized CH selection method is proposed using eleven parameters. In [18], twenty parameters are used with MADM approaches for selecting the CH. In [19], a fuzzy-based Analytic Hierarchy Process (AHP) is used for the selection of CH with RE, cost and bandwidth as parameters.

In our proposed work, we have used the TOPSIS method with five parameters for the cluster head election. We have compared our proposed work with LEACH [1] and the TOPSIS-based algorithm discussed in [16]. The steps involved in the TOPSIS method are explained below.

2.1 *TOPSIS*

TOPSIS, proposed by Hwang and Yoon in 1981 [20], is used to select the best alternative. It uses several criteria with their respective criteria weights to select the best alternatives. The working of TOPSIS is quite simple. It tries to rank the alternatives based on their Euclidean distance from the Best Ideal Solution (BIS) and Worst Ideal Solution (WIS). An alternative will get the highest rank if it is closest to BIS and farthest to WIS. The TOPSIS method is explained below:

Step 1: Generate the data matrix of m alternatives and n criteria (D_{m*n}).

Step 2: Calculate the normalized data matrix (D'_{ij}) as shown in Equation 2.

$$D'_{ij} = \frac{D_{ij}}{\sqrt{\sum_{i=1}^{m} D_{ij}^2}} \tag{2}$$

where $i = 1, 2, \ldots m$ and $j = 1, 2, \ldots n$.

Step 3: Calculate the weighted normalized decision matrix D_{ij}^w.

$$D_{ij}^w = D'_{ij} * w_j \tag{3}$$

Step 4: Find BIS, S^+ and WIS, S^-.

$$S^+ = \{(\max(D_{ij}^w \mid i = 1, 2, \ldots m, j \in j_+), \min(D_{ij}^w \mid i = 1, 2, \ldots m, j \in j_-) \tag{4}$$

$$S^- = \{(\min(D_{ij}^w \mid i = 1, 2, \ldots m, j \in j_+), \max(D_{ij}^w \mid i = 1, 2, \ldots m, j \in j_-) \tag{5}$$

where j_+ represents beneficial criteria and j_- represents the non-beneficial criteria.

j_+ and $j_- = \{j = 1,2,...n\}$.

Step 5: Find the distance of alternatives from S^+ and S^-.

$$D_i^+ = \sqrt{\sum_{j=1}^{n} (D_{ij}^w - S^+)^2} \tag{6}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} (D_{ij}^w - S^-)^2} \tag{7}$$

where $i = 1, 2, \ldots m$ and D_i^+ and D_i^- represent the distance of alternative i from BIS and WIS respectively.

Step 6: Find the relative proximity P_i of the alternative from the negative ideal solution by using Equation 8.

$$P_i = \frac{D_i^-}{D_i^- + D_i^+} \tag{8}$$

Step 7: Rank the alternative on the basis of their relative proximity.

2.2 *Energy consumption model*

We have used the first-order radio model proposed in [1] for the calculation of consumed energy by sensor nodes. We have considered that energy is consumed by a sensor mainly in three activities.

(1) Energy consumption while transmitting the data (E_{TX}).

Energy consumption in transmitting l bits of data at distance d can be calculated as

$$E_{TX}(l,d)=\begin{cases} l*E_{elec}+l*\varepsilon_{fs},d^2 & d<d_o \\ l*E_{elec}+l*\varepsilon_{mp},d^4 & d<d_o \end{cases} \tag{9}$$

Here, E_{elec} is the energy consumed by electronic circuitry in processing the one bit of data, ε_{fs} and ε_{mp} are the energy consumed by a radio frequency (RF) amplifier in free space and multi-path data transmission. The d_o is a constant whose value can be calculated by Equation 10.

$$d_o=\sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}} \tag{10}$$

(2) Energy consumption while receiving the data (E_{RX}).
The energy consumed in receiving the data is the energy consumed by the electronic circuitry of the sensor. For receiving l bits of data, the consumed energy can be calculated by Equation 11.

$$E_{RX}(l)=l*E_{elec} \tag{11}$$

(3) Energy consumption while aggregating the data (E_{aggr}).
If there is m packet of data with k bits of packet size then the energy consumed by aggregating these m packets can be calculated by Equation 12.

$$E_{aggr}=(m*k)*R_{aggr}*E_{DA} \tag{12}$$

where E_{DA} is the energy consumed in the aggregation of 1 bit of data of a signal. The value of E_{DA} in our proposed model is 5 nJ/bit/signal. The aggregation ratio is represented by R_{aggr}.

3. Methodology

We have used five parameters in our proposed work to select the CH. The parameters are given in Table 1.

Table 1. Parameters used in our experiment

No.	Parameter	Type	Abbreviation	Weights
1	Remaining_Energy	Beneficial	C1	0.30
2	Distance_to_BS	Non_beneficial	C2	0.15
3	Density	Beneficial	C3	0.20
4	Avg_dist_NBN	Non_beneficial	C4	0.20
5	Std_devi_dist_NBN	Non_beneficial	C5	0.15

Here, Remaining_Energy is the remaining energy of the node in the current round and Distance_to_BS represents the distance of the node from the BS. Our third parameter is Density which is the number of nearby nodes within the distance d_o. The value of d_o can be calculated by Equation 10. The fourth parameter Avg_dist_NBN represents the average distance of nodes within the distance d_o. The last parameter Std_devi_dist_NBN represents the standard deviation of the distance of nodes within the distance d_o.

The data matrix of TOPSIS is shown in Table 2. We have implemented TOPSIS for 100 nodes, but we are showing the data of only 6 nodes to save space.

Table 2. Data matrix

	C1	C2	C3	C4	C5
s1	0.2	398.4506	24	49.93181	27.80269
s2	0.2	90.07259	17	57.57651	33.30304
s3	0.2	360.367	26	58.17877	26.39463
s4	0.2	332.8011	26	64.34502	31.06626
s5	0.2	379.6033	19	54.80101	32.85105
s6	0.2	133.6243	3	29.59998	98.38629

Here, s1, s2, ...s6 represent the nodes and C1, C2, …C5 represent the criteria as shown in Table 1. We have normalized our data matrix using Equation 2. The normalized matrix is shown in Table 3.

Table 3. Weighted normalized data matrix

	C1	C2	C3	C4	C5
s1	0.12	0.08	0.09	0.08	0.03
s2	0.12	0.02	0.07	0.09	0.04
s3	0.12	0.07	0.1	0.09	0.03
s4	0.12	0.07	0.1	0.1	0.04
s5	0.12	0.08	0.07	0.08	0.04
s6	0.12	0.03	0.1	0.05	0.12

BIS (S^+) and WIS (S^-) are calculated by using Equations 4 and 5. The result is shown in Table 4.

Table 4. BIS and WIS

	C1	C2	C3	C4	C5
S^+	0.12	0.02	0.1	0.05	0.03
S^-	0.12	0.08	0.01	0.1	0.12

The values of D^+ and D^- are calculated using Equations 6 and 7. The result is shown in Table 5. Here, s1, s2, …s6 represent the sensor nodes and D^+ and D^- represent the distance of alternatives from S^+ and S^-.

Table 5. Distance from BIS and WIS

	s1	s2	s3	s4	s5	s6
D^+	0.07	0.06	0.07	0.07	0.07	0.13
D^-	0.12	0.12	0.13	0.12	0.1	0.07

The relative distance with the worst solution is calculated by Equation 6. The result is shown in Table 6.

Table 6. Relative distance with worst solution

	s1	s2	s3	s4	s5	s6
P	0.64	0.67	0.65	0.63	0.58	0.37

Here, *P* represents the relative distance of alternatives. The ranking of alternatives is done on the basis of their closeness with the worst solution. The ranking of alternatives is shown in Table 7.

Table 7. Ranking of alternatives

	s2	s3	s1	s4	s5	s6
P	0.67	0.65	0.64	0.63	0.58	0.37
Rank	1	2	3	4	5	6

After the ranking of alternatives the nodes with best ranks will be selected as CHs. Here, the results are shown only for 6 nodes, but we have implemented this process for all alive nodes of WSN. We have selected the top 10% of nodes as CH. We have compared our proposed work with two other algorithms. The result of the comparison is shown in the next section.

4. Experiments and results

We have used MATLAB R2015a for the implementation of our proposed model. The parameters used in our experiment are given in Table 8.

Table 8. Parameters used in our experiment

No.	Parameter	Value
1	Area of WSN	200*200 m^2
2	Sensor nodes	100
3	Position of BS	(100,250)
4	E_{elec}	50 nJ
5	ε_{fs}	10 pJ/bit/m^2
6	ε_{mp}	0.0013 pJ/bit/m^4
7	Packet size	4000 bits
8	E_{DA}	5 nJ/bit/signal
9	d_o	87.7058 m
10	Initial energy (e)	0.2 J
11	CH percentage	10%
12	R_{aggr}	10%

The WSN used in our experiment is shown in Figure 1.

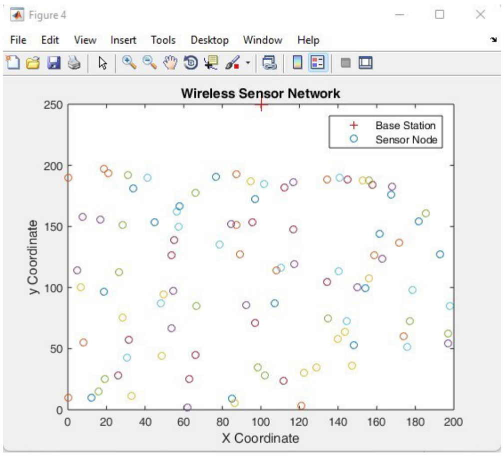

Figure 1. WSN used in our model

Here, circles represent the sensor nodes and the plus symbol represents the BS. The area considered is 200*200 m^2 which starts from coordinate (0,0) to coordinate (200,200). The area where sensors are deployed is known as the 'Area of Interest (AoI)'. We have considered that the BS is out of AoI. We have compared our proposed work with two other models. The first one is LEACH [1] and the other one is the algorithm proposed by Shelebaf and Tabatabaei [16]. In the results, we have used abbreviations for the algorithms which are shown in Table 9.

Table 9. Abbreviations used for different algorithms

No.	Algorithm	Abbreviations
1	LEACH proposed in [1]	Algo1
2	The algorithm proposed in [16]	Algo2
3	Our proposed algorithm	Algo3

Figure 2 shows the alive nodes in each round in each algorithm as well as the sum of the residual energy of all the alive nodes which is also known as the energy of the network. It can be seen that the number of alive nodes in the proposed algorithm is much higher than the other two compared algorithms. The reason is that our proposed algorithm optimizes the energy by selecting the optimal cluster head as well as by balancing the load among them.

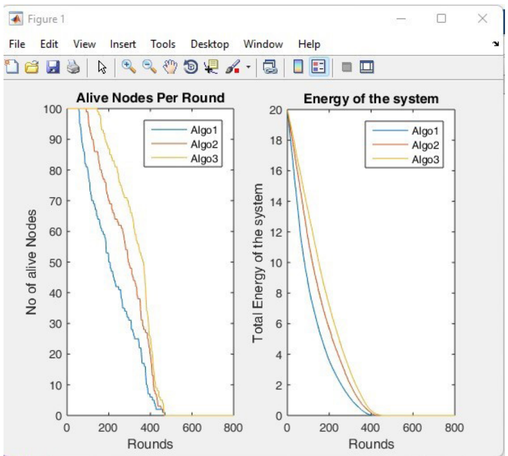

Figure 2. Comparison of alive nodes per round and RE of the network

In Figure 3, the energy consumption of WSN in each round, by each algorithm is shown. Our proposed model consumes the lowest energy in each round initially, but after a few rounds, it starts consuming more energy than the compared models. Since initially all the sensors are alive in all the models, so due to optimized energy consumption, our proposed model consumes the lowest energy, but after a few rounds, the number of alive nodes is reduced in Algo1 and Algo2, so the data transmitted to BS is also reduced. This causes low energy consumption by Algo1 and Algo2 after a few rounds.

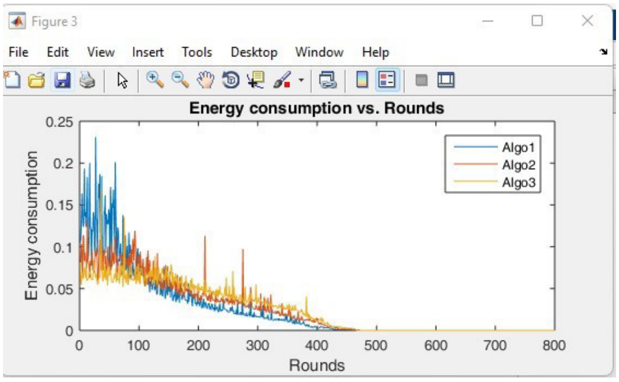

Figure 3. Comparison of energy consumed in each round by each algorithm

In Figure 4, the comparison of First Node Dead (FND), Half Node Dead (HND) and Last Node Dead (LND) of all three algorithms is shown. Our proposed algorithm (Algo3) performs best in the case of FND and HND. The reason for the better performance of our proposed model is that it selects better cluster heads by considering five parameters with an advanced MADM approach known as TOPSIS. The reason for the bad performance of our proposed algorithm in the case of LND is because in Algo1 and Algo2 more sensor nodes die earlier, so after a few rounds, the load on the nodes closer to BS is reduced. So, very few nodes which are closer to BS are alive in Algo1 and Algo2. The parameter LND is not so crucial because if more than 50% of the nodes of a network are dead, then the information received from the network may not be accurate. So, the wireless sensor network is discarded if more than 50% nodes of a network are dead.

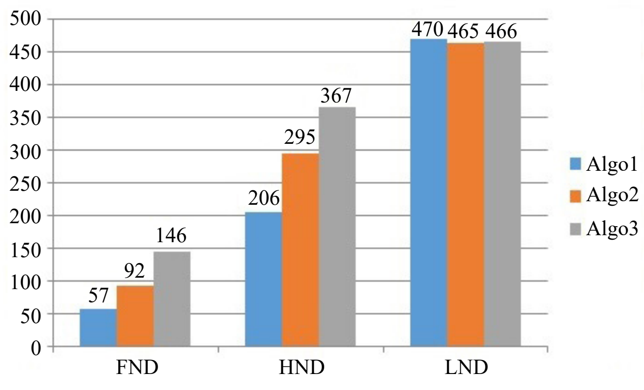

Figure 4. Comparison of FND, HND and LND

In Figure 5, the comparison of the RE of the network after 200 rounds is shown. The RE of the network is the sum of the RE of all alive nodes. It is clear from the figure that our proposed algorithm conserves energy by optimizing its utilization of it.

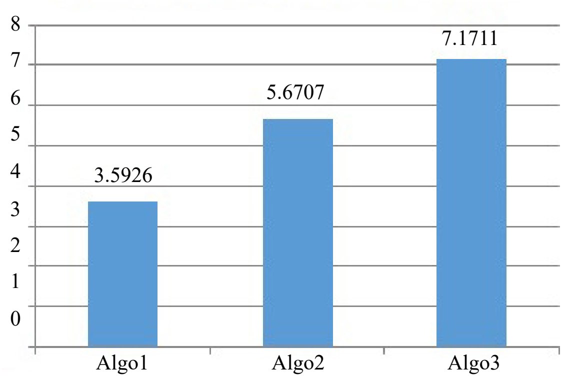

Figure 5. Comparison of RE of WSN after 200 rounds

5. Conclusion and future work

In this research work, our main focus was to develop an algorithm for the optimal utilization of the energy of WSN as well as balance the load among the CHs. For this work, we decided to use an advanced MADM approach known as TOPSIS. The results show that our proposed model balances the load and optimizes the energy in a better way than the compared algorithms. There are several limitations in our proposed work. We have considered that nodes are stationary. In future, the algorithm may be extended for mobile nodes. In our proposed model, all the computation is done at the BS. In future, some methods may be developed to select the CHs in a distributed manner. We have tried to use the best attribute for TOPSIS but there is always scope for the selection of the best combination of attributes.

Conflict of interest

The authors have no conflicts of interest to disclose.

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