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Recommended System for Cluster Head Selection in a Remote Sensor Cloud Environment Using the Fuzzy-Based Multi-Criteria Decision-Making Technique

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Abstract: Clustering is an energy-efficient routing algorithm in a sensor cloud environment (SCE). The clustering sensor nodes communicate with the base station via a cluster head (CH), which can be selected based on the remaining energy, the base station distance, or the distance from the neighboring nodes. If the CH is selected based on the remaining energy and the base station is far away from the cluster head, then it is not an energy-efficient selection technique. The same applies to other criteria. For CH selection, a single criterion is not sufficient. Moreover, the traditional clustering algorithm head nodes keep changing in every round. Therefore, the traditional algorithm energy consumption is less, and nodes die faster. In this paper, the fuzzy multi-criteria decision-making (F-MCDM) technique is used for CH selection and a threshold value is fixed for the CH selection. The fuzzy analytical hierarchy process (AHP) and the fuzzy analytical network process (ANP) are used for CH selection. The performance evaluation results exhibit a 5% improvement compared to the fuzzy AHP clustering method and 10% improvement compared to the traditional method in terms of stability, energy consumption, throughput, and control overhead.

Keywords: sensor cloud environment; clustering; fuzzy multi-criteria decision-making; fuzzy analytical hierarchy process; fuzzy analytical network process; energy consumption



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1. Introduction

A sensor cloud (SC) is a group of wireless sensor networks (WSNs) that perform their work under the cloud [1]. As illustrated in Figure 1, an SC has three major components, which include clients who take the services from the cloud; clouds that provide services and storage of resources on demand; and WSN, which senses a variety of applications and sends data to the cloud through a sink. Here, the base station (BS) is replaced by the cloud.

SCs have various applications such as Nimbits [2], Pachube platform [3], Ubiquitous Healthcare Monitoring [4], disaster detection [5], Google Health [6], Microsoft Health Vault [7], agriculture [8], traffic monitoring, and wildlife monitoring [9,10]. Privacy and cost-effectiveness are primary concerns in data collection and sensing. Due to the compactness of SCs, limited power is supplied, and therefore effective and efficient utilization of power in SC is required [11].

WSN clustering is a way to consume power using CH selection as it acts as a gateway between the BS and member nodes. CHs gather data from the member nodes by using the time division multiple access (TDMA) method and send the data collected to the BS [12]. In a sensor cloud environment (SCE), different types of cluster-based routing protocols exist.

Low energy adaptive clustering hierarchy (LEACH) is one of the basic cluster-based routing algorithms [13]. LEACH has four phases, namely network deployment phase, neighbor discovery phase, cluster formation and CH selection phase, and communication phase. For CH selection, a different criterion needs to be considered. The main aim of the LEACH algorithm is energy consumption. In LEACH, CH is selected based on residual energy, node density, distance to the sink, or the average distance between a node and its neighbor. A single criterion is used for CH selection in real time. Having a single criterion is not enough for the head node chosen because if the residual energy of a head node is high and the distance to the sink of that node is also high, then we cannot say that it is energy-efficient communication. The same goes for the other criteria. Therefore, to solve such problems, in this work, the multi-criteria decision-making (MCDM) technique was considered for CH selection in a remote SC environment. The MCDM technique has been designed to identify the desired alternatives and arrange alternatives in a small number of categories; the rank of the alternatives gives the preference order. In the MCDM technique, decision matrixes have four major parts, namely alternatives, attributes, weight, and performance concerning attributes. In an SCE, we identified different criteria for CH selection and used the MCDM technique to calculate the rank from different criteria, sub-criteria, and their alternatives. In this technique, a pairwise comparison matrix was created from the criteria with respect to different alternatives, and the weight of the matrix was calculated from the matrix. The fuzzy analytical hierarchy process (AHP), the fuzzy analytical network process (ANP), and the technique for order preference by similarity to the ideal solution (TOPSIS) are popular MCDM techniques [14]. Another problem that occurs in the traditional LEACH algorithm is that the CHs are changed in every round and the process is continued till the last nodes have died. In this process, the energy utilization is greater and network lifetime is less. Therefore, to solve this problem, we used the threshold value for CH selection and the MCDM technique to calculate the threshold value. The LEACH is a hierarchical architecture; therefore, to solve this problem, in this paper, we considered two MCDM [15] algorithms: the fuzzy analytical hierarchy process (FAHP) [16] and the fuzzy analytical network process (FANP) [17]. The FAHP MCDM is used to solve tree- or hierarchy-like structures, but if the criteria and sub-criteria are increased, then it looks like network- or mesh-type architecture. This problem was solved by using the FANP MCDM technique. In the LEACH algorithm, we went further and modified the last two phases, these being the CH selection and the communication phase. The novelty of our method is that we used the FMCDM technique for CH selection in an SCE. Using this method, we reduced the consumption of energy and increased network stability and lifetime in inter-cluster and intra-cluster multi-hop communication models in WSNs.

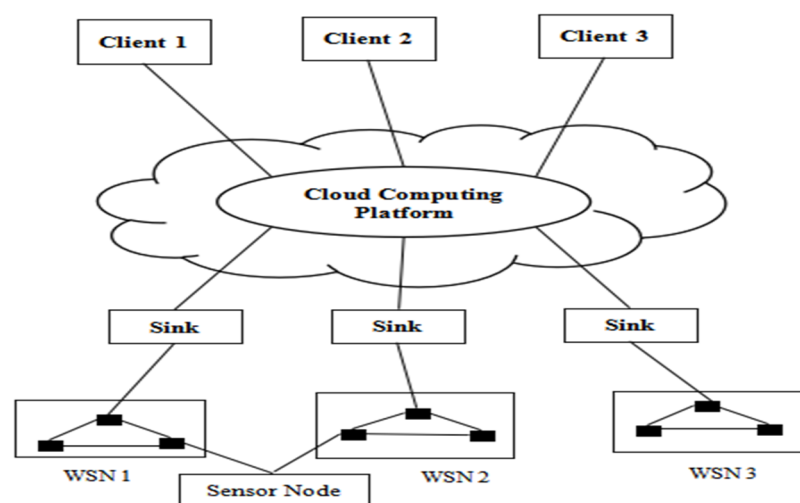


Figure 1. Sensor cloud environment architecture [1].

This paper is organized as follows. Section 2 is a review of CH selection techniques for WSN. CH selection using the fuzzy MCDM techniques FAHP and FANP is discussed in Section 3, and so too is the CH selection algorithm. In Section 4, the result analysis of the proposed technique is discussed. The concluding remarks are discussed in Section 5.

2. Related Work

In 1981, Hwang and Yoon proposed a network algorithm where they considered that the nodes are created different clusters and each cluster has head node (one of the cluster nodes) and remaining are member nodes. Head node has possibility to exhaust battery power quickly. Therefore, dynamically changing the head nodes may be implemented using rounds [18]. In 2002, Heinzelman et al. has proposed to improve LEACH algorithm based on principle election of cluster head [19]. In 2004, Younis and Fahny [20] developed 'Hybrid Energy-Efficient Distributed' algorithm based on basis of the residual energy of cluster head nodes. In 2006, Kim and Chung [21] focuses on mobile nodes. In 2013 Azada and Sharma proposed a TOPSIS technique [22] focused on 'Multiple Attribute Decision Making' approach of cluster leaders' election. In 2016, Alami et al. [20], proposed and energy efficient fuzzy technique for CH selection in WSN. The main aim of the work was to reduce the energy consumption and increased the network life span using fuzzy parameter. In 2017, Khan et al. proposed fuzzy-TOPSIS based election of cluster head in mobile network using four criteria and compared with the traditional LEACH and Fuzzy [23]. In 2018, Liuhaio Chen et al. [24,25], proposed the clustering algorithm on the basis of K-means and PROMETHEE methods. In 2019 Y. Zhao et al. focused on a CH selection and dynamic distributed clustering method. The authors considered the protocol and the clustering algorithm [LTE-M] [26]. In 2019, P. Mukherjee et al. focused on CH selection using AHP method [27,28]. In 2020, Dezert et al., proposed a modified Belief function base on inter-criteria analysis using MCDM method [29]. In 2021, Alidrisi proposed supply chain model using MCDM method [30]. In this paper, big data was used as a platform for finding the role of green supply chain model (GSCM) over the supply chain finance and the fuzzy ANP technique is used as MCDM method. In 2021, Rekha and Gupta surveyed different CH selection method in WSN. They surveyed different algorithm like probabilistic, fuzzy logic, adaptive, and multi-attribute decision making techniques and discussed different challenges in network [31].

From the related work, we concluded that CH selection depends upon several criteria and the fuzzy MCDM method was used to calculate the rank from the several criteria. In this paper, we attempt to provide a framework for CH selection in remote SC environment by which is important for head node selection due to existence of several clusters and nodes position. Therefore, the main aim of this research is to build criteria from the node position for CH selection in SC environment and to calculate weight for CH selection considering their importance level. The entire process will be discussed in the next section.

3. Proposed Work

3.1. Cluster Head Selection Using Fuzzy MCDM Techniques

Clustering mechanisms have four phases, namely network deployment phase, neighbor discovery phase, cluster formation and CH selection phase, and communication phase. In this paper, we mainly focus on CH selection. Here, CHs are not changed in every round, so it minimized the control overhead in the set-up phase. CH changes are dependent on the threshold value. If the threshold value is less than the other member, neighbor nodes, then re-clustering is occurring. In the proposed work, clustering scheme nodes take the decision themselves based on ranking index value which is obtained from four criteria for head selection. In real time, remote SC environment problem arises for CH selections using a decision model because their exact complexity is unknown. Therefore, the problem can be resolved by absolute representation of crisp values [32]. So, the fuzzy set theory is put in place to solve this problem.

In this work, MCDM techniques: AHP and ANP with fuzzy sets have been considered for CH selection. We used Chang's method [33,34] to solve the pair wise comparison matrix in the triangular method, and by using Buckley's method [35], we can calculate the weight for both criteria and alternatives. The steps are as follows:

Step 1: To calculate the pair wise comparison matrix by using Chang method [35]. Where \tilde{T}^k represents the decision maker's preference of via triangular numbers of criterion over criterion.

$$\tilde{T}^k = \begin{bmatrix} \tilde{m}_{11}^k & \tilde{m}_{12}^k & \dots & \tilde{m}_{1n}^k \\ \tilde{m}_{21}^k & \dots & \dots & \tilde{m}_{2n}^k \\ \dots & \dots & \dots & \dots \\ \tilde{m}_{n1}^k & \tilde{m}_{n2}^k & \dots & \tilde{m}_{nn}^k \end{bmatrix} \quad (1)$$

Step 2: When more than one decision maker (\tilde{m}_{ij}^k) required, then calculate the average of preference of each decision maker (\tilde{m}_{ij}) and Equation (2) is calculated in.

$$\tilde{m}_{ij} = \frac{\sum_{k=1}^K \tilde{m}_{ij}^k}{K} \quad (2)$$

Step 3: Update the pair wise comparison matrix on the basis of average preferences and shows the matrix \tilde{T} in Equation (3).

$$\tilde{T} = \begin{bmatrix} \tilde{m}_{11} & \dots & \tilde{m}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{m}_{n1} & \dots & \tilde{m}_{nn} \end{bmatrix} \quad (3)$$

Step 4: Calculate the geometric mean of the triangular fuzzy number by the Buckley [27] method of each individual criterion as shown in Equation (4); (\tilde{g}_i) represents the triangular values.

$$\tilde{g}_i = \left(\prod_{j=1}^n \tilde{m}_{ij} \right), i = 1, 2, \dots, n \quad (4)$$

Step 5: Calculate the fuzzy weight \tilde{w}_i from the Equation (5). 1st we have to find the summation of (\tilde{g}_i) and also find the inverse power of summation vector. Then change the fuzzy triangular number and reorder in increasing manner.

$$\begin{aligned} \tilde{w}_i &= \tilde{g}_i \otimes (\tilde{g}_i \oplus \tilde{g}_i \oplus \dots \oplus \tilde{g}_i)^{-1} \\ &= (lw_i, mw_i, uw_i) \end{aligned} \quad (5)$$

Step 6: The \tilde{w}_i are still triangular fuzzy numbers, so de-fuzzification needed. Here we used Chou [22] and Chang [26] method for de-fuzzification. The Equation (6) is applied for de-fuzzification.

$$q_i = \frac{(lw_i, mw_i, uw_i)}{3} \quad (6)$$

Step 7: Then q_i is now a non-fuzzy number. So, the normalization is needed. The Equation (7) shows the normalization l_i equation.

$$l_i = \frac{q_i}{\sum_{n=1}^n q_i} \quad (7)$$

3.2. CH Selection Fuzzy AHP Modes

In this section, FAHP method has been developed for CH selection to improve the network lifetime and to minimize the energy consumption in the remote SC environment. In FAHP, the pair wise comparison matrix is performed by the linguistic variables for both criteria and the alternatives, which are represented by triangular numbers. Figure 2 shows the interdependency relationship between the criteria. Here, four main criteria have been selected: residual energy (RE), node density (ND), distance to the sink (DS) and the average distance between nodes and neighbors (ADN).

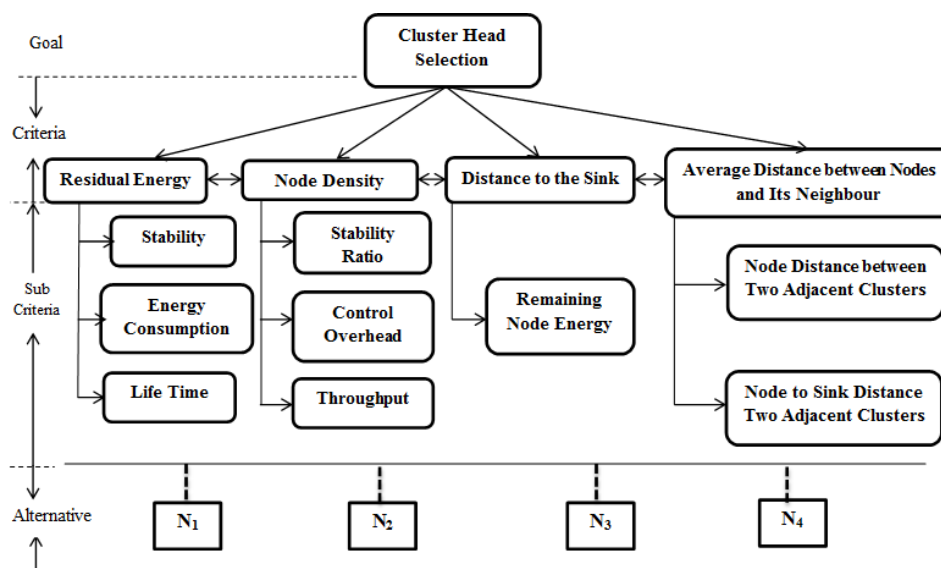


Figure 2. Cluster head selection criteria.

We first calculate the pair wise comparison matrix by using Chang method. Table 1 shows the pair wise comparison fuzzy matrix.

Table 1. Pair wise comparison matrix of criteria.

Criteria	RE	ND	DS	ADN
RE	(1,1,1)	(1,1,3/2)	(1/3,2/5,1/2)	(3/2,2,5/2)
ND	(2/3,1,1)	(1,1,1)	(2/3,1,1)	(1,3/2,2)
DS	(2,5/2,3)	(1,1,3/2)	(1,1,1)	(2,5/2,3)
ADN	(2/3,1/2,2/3)	(1/2,2/3,1)	(1/3,2/5,1/2)	(1,1,1)

Following the 1st step, we have to calculate the geometric mean from the fuzzy comparison matrix from the Equation (4).

$$\tilde{g}_i = \left(\prod_{j=1}^n \tilde{m}_{ij} \right) = \left[\left(1 * 1 * \frac{1}{3} * \frac{3}{2} \right)^{\frac{1}{4}} ; \left(1 * 1 * \frac{2}{5} * 2 \right)^{\frac{1}{4}} ; \left(1 * \frac{3}{2} * \frac{1}{2} * \frac{5}{2} \right)^{\frac{1}{4}} \right] = [0.84; 0.96; 1.17] \tag{8}$$

Hence, in Table 2, shows the geometric mean (\tilde{g}_i) of all criteria. Total value, inverse values are also calculated and increasing order of the triangular fuzzy number is shown in the last row of Table 2.

In the next step we have to calculate the weight \tilde{w}_i of the criteria form the Equation (5), as shown in Table 3.

Now the next step is calculating the non-fuzzy weight q_i of each criterion and also calculate the normalized weight l_i of each criterion. Table 4 shows the normalized weight l_i and non-fuzzy weight.

Table 2. Geometric mean matrix of criteria.

Criteria		\tilde{g}_i	
RE	0.84	0.96	1.17
ND	0.82	1.1	1.2
DS	1.41	1.61	1.91
AND	0.51	0.60	0.76
Total	3.58	4.28	5.04
Inverse	0.28	0.23	0.2
Increasing Order	0.2	0.23	0.28

Table 3. Weighted matrix of criteria.

Criteria		\tilde{w}_i	
RE	0.2	0.22	0.33
ND	0.16	0.26	0.34
DS	0.28	0.37	0.53
AND	0.10	0.14	0.21

Table 4. Non-fuzzy weighted and normalized weight matrix of criteria.

Criteria	q_i	l_i
RE	0.25	0.24
ND	0.25	0.24
DS	0.39	0.39
ADN	0.15	0.13

3.3. Determining the Weights of Sub-Criteria and Alternatives with Respect to the Criteria

After calculating the normalized weight and non-fuzzy weight, we calculate weight of sub-criteria and alternatives. Same procedure is applied for both the cases. The sub criteria are Stability (SB), Energy Consumption (EC), and lifetime (LT), CH stability ratio (CHR), control overhead (CO), throughput (TP), remaining energy of the node (RNE), node distance between two adjacent clusters (NDAC), node to sink distance between two adjacent clusters (NSAC). Tables 5–13 show the steps for weight calculation.

Step 1: Table 5 shows the comparison matrix of sub-criteria with respect to RE.

Step 2: Similar way we have to calculate geometric mean (\tilde{g}_i), weight, non-fuzzy weight q_i and normalized weight l_i . Tables 6–9 show the calculated value of the sub-criteria with respect to the RE.

Table 5. Shows the comparison matrix of sub-criteria with respect to the residual energy (RE).

Sub-Criteria	SB	EC	LT
SB	(1,1,1)	(2,5/2,3)	(1,3/2,2)
EC	(1/3,2/5,1/2)	(1,1,1)	(3/2,2,5/2)
LT	(1/2,2/3,1)	(2/5,1/2,2/3)	(1,1,1)

Table 6. Shows the geometric mean of the matrix.

Criteria		\tilde{g}_i	
SB	1.26	1.55	1.8
EC	0.8	0.92	1.08
LT	0.6	0.7	0.9
Total	2.66	3.17	3.78
Inverse	0.38	0.31	0.26
Increasing Order	0.26	0.31	0.38

Table 7. Weighted matrix of criteria.

Criteria		\tilde{w}_i	
SB	0.33	0.48	0.68
EC	0.21	0.22	0.41
LT	0.19	0.22	0.34

Table 8. Non-fuzzy weighted and normalized matrix of criteria.

Criteria	q_i	l_i
SB	0.5	0.45
EC	0.3	0.27
LT	0.3	0.28

Table 9. Pair wise comparison matrix of alternatives.

Criteria	N1	N2	N3	N4
N1	(1,1,1)	(2/3,1,1)	(1,3/2,2)	(2/5,1/2,2/3)
N2	(1,1,2/3)	(1,1,1)	(1,1,3/2)	(3/2,1,1)
N3	(1/2,2/3,1)	(2/3,1,1)	(1, 1, 1)	(1/2,2/3,1)
N4	(3/2,2,5/2)	(1,1,3/2)	(1,3/2,2)	(1, 1, 1)

Table 10. Geometric mean matrix of alternatives.

Criteria		\tilde{g}_i	
N1	0.72	0.93	1.07
N2	0.90	1	1.22
N3	0.63	1.07	1
N4	1.1	1.31	1.65
Total	3.35	4.31	4.94
Inverse	0.3	0.23	0.20
Increasing Order	0.2	0.23	0.3

Table 11. Weighted matrix of alternatives.

Criteria		\tilde{w}_i	
N1	0.14	0.21	0.32
N2	0.18	0.23	0.4
N3	0.13	0.25	0.3
N4	0.22	0.30	0.5

Table 12. Non-fuzzy weighted and normalized matrix of criteria.

Criteria	q_i	l_i
N1	0.22	0.20
N2	0.27	0.25
N3	0.23	0.22
N4	0.34	0.32

Table 13. Normalized non-fuzzy weighted calculation of alternatives for criteria.

Criteria	RE	ND	DS	ADN
N1	0.35	0.33	0.29	0.28
N2	0.26	0.27	0.26	0.21
N3	0.19	0.18	0.23	0.22
N4	0.20	0.22	0.22	0.29

The weighted matrix is calculated in Table 7 with respect to the RE.

The Table 8 shows the non-fuzzy weighted matrix calculation.

The Table 9 shows the pair-wise comparison matrix with respect to the alternatives.

Next, we have to calculate comparison matrix the geometric mean (\tilde{g}_i), weight, non-fuzzy weight q_i and normalized weight l_i . The Tables 10–14 show the calculated value of the alternatives with respect to the RE. Here, four nodes are considered as a alternatives N_1, N_2, N_3, N_4 .

Table 14. Aggregated results of each alternative according to each criterion.

Criteria	Alternatives with Respect to Criteria				
	Weight	N1	N2	N3	N4
RE	0.36	0.35	0.26	0.19	0.2
ND	0.27	0.33	0.27	0.18	0.22
DS	0.2	0.29	0.26	0.23	0.22
ADN	0.2	0.28	0.21	0.22	0.29
Total		0.31	0.25	0.21	0.23

Table 10 shows the geometric mean of the matrix.

Table 11 shows the weighted matrix calculation.

Hence, node 1 has the highest probability to act as a CH with respect to the 4 criteria in fuzzy AHP method. The N1 is the highest priority of the matrix. However, when the number of criteria or sub-criteria are increased fuzzy AHP method does not work properly then looks like a network-based structure in which computation time also increased. As both MCDM techniques are multi-hop communication, fuzzy ANP method is introduced for network like architecture. Details of the fuzzy ANP method is discussed in the next section below.

3.4. CH Selection Fuzzy ANP Mode

In this section, FANP method has been developed for CH selection to improve the network lifetime and to minimize the energy consumption in the remote SC environment. In FANP, the pair wise comparison matrix is performed by the linguistic variables for both criteria and the alternatives, which are represented by triangular numbers.

Figure 2 shows in the interdependency relationship between the criteria. Here, four main criteria have been selected: residual energy (RE), node density (ND), distance to the sink (DS) and the average distance between nodes and neighbor (ADN).

Step 1: Calculate the inner dependency matrix for CH selection criteria with respect to the RE, ND, DS and ADN. Table 15 shows the inner dependency matrix of all criteria with respect to RE. The normalized non-fuzzy relative weights of each alternative for each criterion are shown in Table 15.

Table 15. Inner dependence matrix of the CH selection with respect to 'RE'.

Criteria	ND	DS	AND
ND	(1,1,1)	(1,1,3/2)	(1,3/2,2)
DS	(2/3,1,1)	(1,1,1)	(1,1,3/2)
ADN	(1/2,2/3,1)	(2/3,1,1)	(1,1,1)

Step 2: Similar way we have to calculate geometric mean (\tilde{g}_i), weight, non-fuzzy weight q_i and normalized weight l_i . Tables 16–18 show the calculated value of the sub-criteria with respect to the RE.

Table 16. Geometric mean matrix of the CH selection with respect to 'RE'.

Criteria	\tilde{g}_i		
ND	1	1.15	1.44
DS	0.87	1	1.15
AND	0.69	0.87	1
Total	2.56	3.02	3.59
Inverse	0.39	0.33	0.28
Increasing Order	0.28	0.33	0.39

Table 17. Weighted matrix of the CH selection with respect to 'RE'.

Criteria	\tilde{w}_i		
SB	0.28	0.38	0.56
EC	0.24	0.33	0.45
LT	0.19	0.29	0.39

Table 18. Non-fuzzy matrix and normalized matrix of the CH selection with respect to 'RE'.

Criteria	q_i	l_i
SB	0.41	0.38
EC	0.34	0.33
LT	0.29	0.29

3.5. Determining the Weights of Sub-Criteria and Alternatives with Respect to the Criteria

After the calculation of normalized weight and non-fuzzy weight, we have to calculate the weight of sub-criteria and alternatives. Same procedure is applied for both the cases. The sub criteria are stability (SB), energy consumption (EC), lifetime (LT), CH stability ratio (CHR), control overhead (CO), throughput (TP), remaining energy of the node (RNE), node distance between two adjacent clusters (NDAC), node to sink distance between two adjacent clusters (NSAC). Tables 19–22 show the steps of weight calculation.

Table 19. Pair wise comparison matrix with respect to the stability among the sub-criteria 'residual energy'.

Criteria	EC	LT
EC	(1,1,1)	(1,1,3/2)
LT	(2/3,1,1)	(1,1,1)

Table 20. Geometric mean matrix with respect to the stability among the sub-criteria 'residual energy'.

Criteria	\tilde{g}_i		
EC	1	1	1.22
LT	0.82	1	1
Total	1.82	2	2.22
Inverse	0.55	0.5	0.45
Increasing Order	0.45	0.5	0.55

Table 21. Weighted matrix with respect to the stability among the sub-criteria 'residual energy'.

Criteria	\tilde{w}_i		
EC	0.45	0.5	0.67
LT	0.37	0.5	0.5

Table 22. Non fuzzy weighted matrix and normalized weighted with respect to the stability among the sub-criteria ‘residual energy’.

Criteria	q_i	l_i
EC	0.54	0.54
LT	0.46	0.46

Step 1: Table 19 shows the comparison matrix of sub-criteria with respect to the residual energy (RE) sub-criteria stability.

Step 2: In a similar way, we have to calculate geometric mean (\tilde{g}_i), weight, non-fuzzy weight q_i and normalized weight l_i . Tables 21–24 show the calculated value of the sub-criteria with respect to the RE.

Table 23. Weighted super matrix formed every sub-criteria for CH selection.

Criteria	Sub-Criteria	RE				ND		DS	ADN	
		SB	EC	LT	CHSR	CO	TP	RNE	NDAC	NSAC
EC	SB	0	0.41	0.71	0.35	0.36	0.3	0.35	0.37	0.36
	EC	0.45	0	0.29	0.32	0.33	0.38	0.33	0.37	0.31
	LT	0.37	0.29	0	0.33	0.33	0.34	0.37	0.31	0.34
ND	CHSR	0.35	0.33	0.37	0	0.61	0.54	0.35	0.33	0.32
	CO	0.34	0.38	0.31	0.54	0	0.47	0.32	0.35	0.35
	TP	0.32	0.3	0.32	0.47	0.43	0	0.32	0.32	0.32
DS	RNE	1	1	1	1	1	1	0	1	1
ADN	NDAC	0.54	0.61	0.43	0.52	0.5	0.54	0.63	0	1
	NSAC	0.47	0.43	0.61	0.47	0.5	0.47	0.44	1	0

Table 24. Normalized weighted super matrix based on CH selection.

Normalized Weighted Super Matrix										
Criteria	Sub-Criteria	RE				ND		DS	ADN	
		SB	EC	LT	CHSR	CO	TP	RNE	NDAC	NSAC
EC	SB	0	0.59	0.71	0.38	0.36	0.3	0.21	0.37	0.36
	EC	0.54	0	0.29	0.33	0.32	0.37	0.2	0.33	0.31
	LT	0.46	0.41	0	0.29	0.32	0.33	0.59	0.30	0.33
ND	CHSR	0.35	0.33	0.37	0	0.59	0.54	0.35	0.33	0.35
	CO	0.34	0.38	0.31	0.54	0	0.46	0.32	0.35	0.4
	TP	0.31	0.29	0.32	0.46	0.41	0	0.33	0.32	0.35
DS	RNE	1	1	1	1	1	1	0	1	1
ADN	NDAC	0.54	0.59	0.41	0.5	0.53	0.53	0.59	0	1
	NSAC	0.46	0.41	0.59	0.5	0.47	0.47	0.41	1	0

Then calculate the weight of the super matrix, limited super matrix and alternative weighted based on sub factor CH selection form Tables 23–27 respectively. Tables 23–27 show the best strategy of the alternatives.

Table 25. Alternative weighted based on sub-criteria CH selection.

Alternatives	Over Criteria								
	SB	EC	LT	CHSR	CO	TP	RNE	NDAC	NSAC
N1	0.25	0.34	0.45	0.33	0.32	0.29	0.30	0.30	0.29
N2	0.30	0.26	0.34	0.28	0.24	0.28	0.27	0.23	0.29
N3	0.27	0.29	0.22	0.19	0.24	0.26	0.24	0.24	0.23
N4	0.22	0.19	0.22	0.23	0.61	0.23	0.33	0.32	0.23

Table 26. Pair wise comparison matrix of four alternative nodes based on CH.

Alternatives	N1	N2	N3	N4
N1	(1,1,1)	(1,1,3/2)	(1,3/2,2)	(1,1,3/2)
N2	(2/3,1,1)	(1,1,1)	(1,1,3/2)	(1,3/2,2)
N3	(1/2,2/3,1)	(2/3,1,1)	(1,1,1)	(1,1,1)
N4	(2/3,1,1)	(1/2,2/3,1)	(1,1,1)	(1,1,1)

Table 27. Find normalized weight of alternatives to find the best strategy.

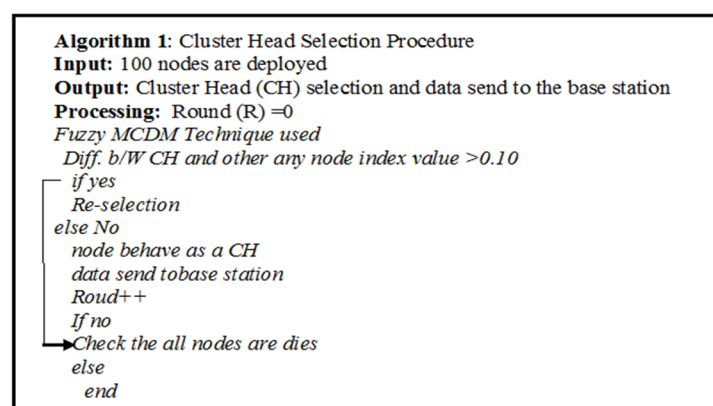
Alternatives	I_i
N1	0.29
N2	0.27
N3	0.22
N4	0.22

Hence, node 1 has the highest probability to act as a CH with respect to the 4 criteria in fuzzy ANP method.

In the traditional LEACH algorithm, CH selection depends upon the single criterion and every round CHs are changed. In the proposed algorithm, the CHs do not change in every round and the fuzzy MCDM method is used for CH selection. In the next subsection the proposed algorithm will be discussed.

3.6. Proposed Algorithm

Once round clusters are formed, member nodes are communicating with the CHs. If the index value-consistency ratio (CR) of CH is lesser than the index value of any nodes addition to the threshold value (here 0.1) then CHs cannot act as CH node. Therefore, further selection processes will be started. We also calculate consistency index (CI) value from the pairwise comparison matrix. $CI = (\lambda_{max} - n)/(n - 1)$ where, λ_{max} is the Eigen value of the pairwise matrix and n is the number of criteria. $CR = CI/RI$, where RI is random inconsistency (RI) indices, and the value is given by the Saaty value of $CR \leq 0.1$ that we used. In this way, we can control frequent changes of head in every round. This process continues till all nodes are died in the particular network. Figure 3 displays the CH selection algorithm.

**Figure 3.** Cluster head Selection algorithm.

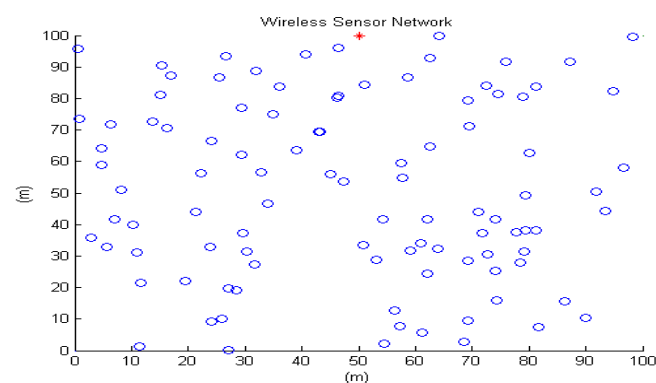
4. Experiments and Evaluation

For experiments and evaluation, we used simulations and compared between LEACH and our proposed work. For the simulation, we considered MATLAB software. Here, we discuss the simulation parameter and results in Table 28.

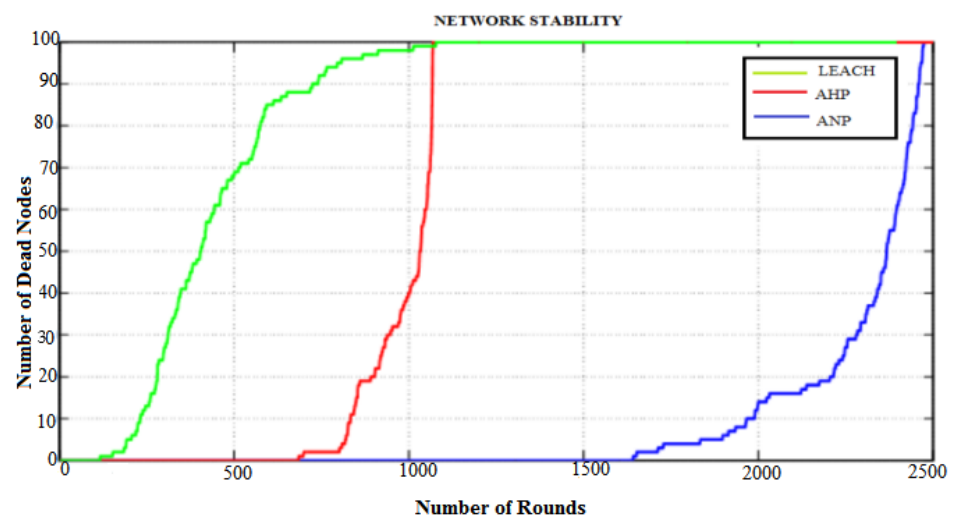
Table 28. Simulation environment.

Parameter	Value
Area of Network	100 m × 100 m
n (Number of Nodes)	100
sn (Sink Position)	50 × 100
Packet Size (data)	4000 bits
Hello Packet Size	200 bits
Sink Position	1.5 m × 0.5 m × 0.5 m
Initial Energy	0.5 Joules
Data Aggregation Energy	50 pJ/bit/report
ET_r (Transmitter Electronics)	50 nJ/bit
ET_e (Receiver Electronics)	50 nJ/bit
E_{amp} (Transmit Amplifier)	100 pJ/bit/m ²

For the purpose of simulation, the parameters shown in Table 17 have been considered. Figure 4 shows the node deployment in wireless sensor network. One-hundred nodes are deployed in the particular area where the red mark shows the base station of the network. The total area of the network is 100 × 100 (sqm). The initial nodes are consuming 0.5 Joules. Target of the sink position is (50 × 100).

**Figure 4.** Node deployment in wireless sensor network.

We compared the result with respect to following parameter like energy consumption, stability, network lifespan, control overhead, and throughput. The results will be discussed from Figures 5–9.

**Figure 5.** Stability.

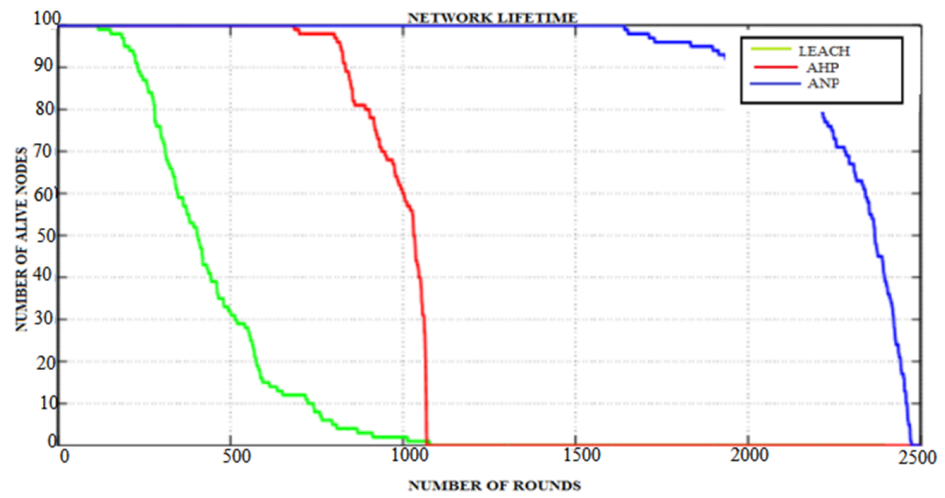


Figure 6. Lifetime.

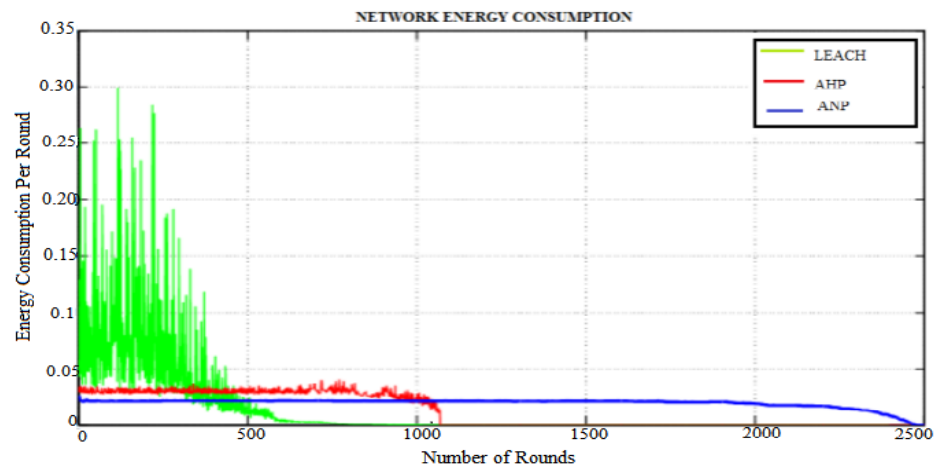


Figure 7. Energy Consumption.

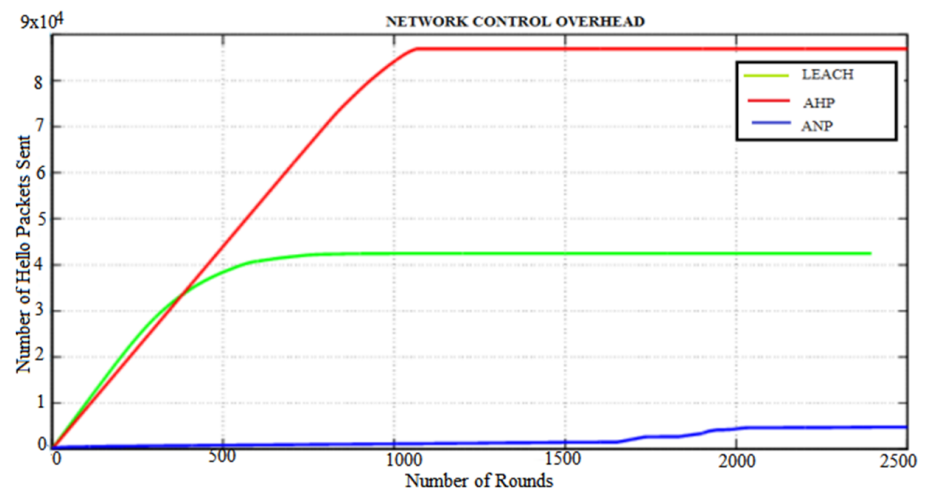


Figure 8. Overhead.

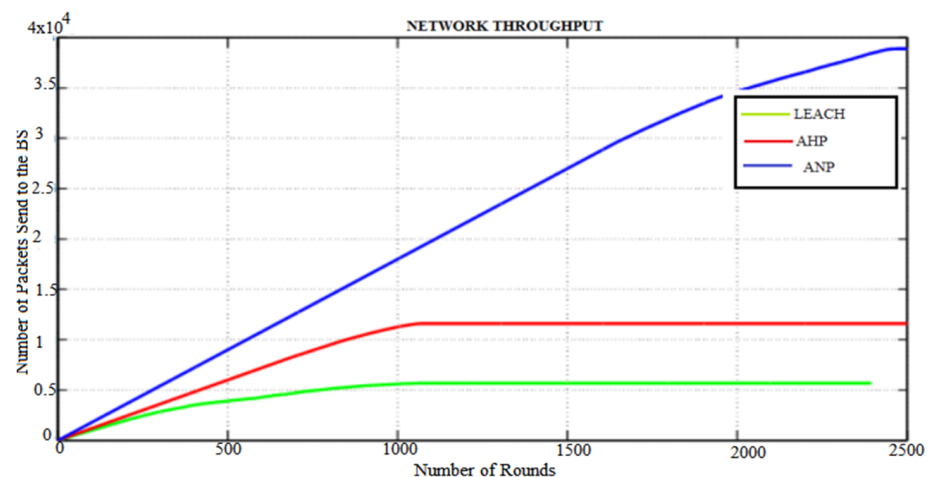


Figure 9. Throughput.

Stability: The stability of the network is depicted in Figure 5. The first node dies in 170 rounds of LEACH (approximately), and the first node dies in 530 rounds of the fuzzy AHP. However, in the proposed fuzzy ANP it dies around 1600 round (approximately) as shown in the figure below. Thus, the proposed F-ANP technique performs well.

Life Span: Life span of the whole network is depicted in Figure 6. In fuzzy AHP, the last node dies in approximately 1100 rounds; in comparison it takes approximately one thousand rounds of LEACH and it occurs at 2400 rounds in the proposed fuzzy ANP mechanism. This is due to the multi-criteria.

Energy Consumption: The per round energy of the network is recorded in Figure 7. The proposed method uses less energy than fuzzy AHP because of the changing cluster leader.

Overhead: The overhead of the signal is shown in Figure 8, in which it is minimized in our proposed method compared to the traditional LEACH and fuzzy AHP.

Throughput: The throughput of the network is depicted in Figure 9, which indicates that the throughput is high for our proposed mechanism in comparison to others because the fuzzy ANP is adopted in multi-hop.

5. Conclusions

In this paper, we proposed a novel algorithm based on fuzzy ANP and LEACH under single cast-based LEACH network nodes, which are homogeneous in nature. Energy efficiency, network lifetime, stability, and number of packet delivery were selected as main criteria and compared with the traditional LEACH network and fuzzy AHP method. The proposed algorithm was evaluated in terms of energy efficiency, stability, and network lifetime. We have considered the fuzzy algorithm in which the nodes have the option to act as a CH or not. In the proposed method, we control the heads that change frequently. If the index value of CH is lesser than the index value of any node in addition to the threshold value (here 0.1) then the CHs will not act as a CH node. Accordingly, further selection processes will continue. This process continues till all of the nodes are asleep in the network. Multi-criteria decision making has been used for the cluster head selection in which multi-hopping increases the stability and lifetime.

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