Hindawi
Journal of Sensors
Volume 2023, Article ID 4343404, 29 pages
https://doi.org/10.1155/2023/4343404

Research Article

Load-Balanced Cluster Head Selection Enhancing Network Lifetime in WSN Using Hybrid Approach for IoT Applications

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Received 22 July 2022; Revised 17 October 2022; Accepted 31 March 2023; Published 9 May 2023

Academic Editor: Akhilesh Pathak

In recent times, the deployment of wireless sensor networks becomes important in revolutionary areas such as smart cities, environmental monitoring, smart transportation, and smart industries. The battery power of sensor nodes is limited due to which their efficient utilization is much necessary as the battery is irreplaceable. Efficient energy utilization is addressed as one of the important issues by many researchers recently in WSN. Clustering is one of the fundamental approaches used for efficient energy utilization in WSNs. The clustering method should be effective for the selection of optimal clusters with efficient energy consumption. Extensive modification in the clustering approaches leads to an increase in the lifetime of sensor nodes which is a unique way for network lifetime enhancement. As the technologies were taken to next the level where multiparameters need to be considered in almost every application in clustering, multiple factors affect the clustering and these factors were conflicting in nature too. Due to the conflicting nature of these factors, it becomes difficult to coordinate among them for optimized clustering. In this paper, we have considered multiattributes and made coordination among these attributes for optimal cluster head selection. We have considered Multi-Attribute Decision-Making (MADM) methods for CH's selection from the available alternatives by making suitable coordination among these attributes, and comparative analysis has been taken in LEACH, LEACH-C, EECS, HEED, HEEC, and DEECET algorithms. The experimental results validate that using MADM approaches, the proposed APRO algorithm proves to be one of the better exhibits for choosing the available CHs.

1. Introduction

Wireless sensor networks are the key step to any new technologies or applications as they can sense and monitor the environment. It collects the data, senses the data, and also makes a decision system for various applications [1, 2]. Sensor nodes have limited battery power and their replacement is not feasible. And it is a still challenge due to which network lifetime depleted and took more energy consumptions. Clustering is a useful approach in wireless sensor networks to increase network lifetime and improve energy efficiency. In clustering as shown in Figure 1, the sensor nodes were grouped into clusters, and from these clusters, CHs were chosen based on some parameters. After CH's selection, the data were transferred to the base station from respective cluster heads [3]. Earlier various algorithms have been presented by researchers which are known to be the basic algorithms for clustering such as LEACH [4, 5], LEACH-C [6], and HEED [7, 8]. In LEACH, the cluster heads were selected based on probabilistic approaches, where CHs have been randomly selected, but later on, more advancement has been made to this approach. But sometimes, the selection of cluster heads was based on the probabilistic method due to which energy consumption increases which leads to overheads. There are various types of methods for the selection of cluster heads as some authors have taken distance from CHs and their residual energy, and some have taken the number of neighbor nodes and residual energy [9–14]. But deciding only on these parameters will not provide optimal CH selection. Thus, the multiattribute needs to be considered [15, 16] for cluster heads. Sensor nodes were the basic in all the emerging fields whether it is IoT [17, 18], digital image processing, cloud computing, or artificial intelligence. Everywhere, sensors were needed for sensing the data and then sending the data

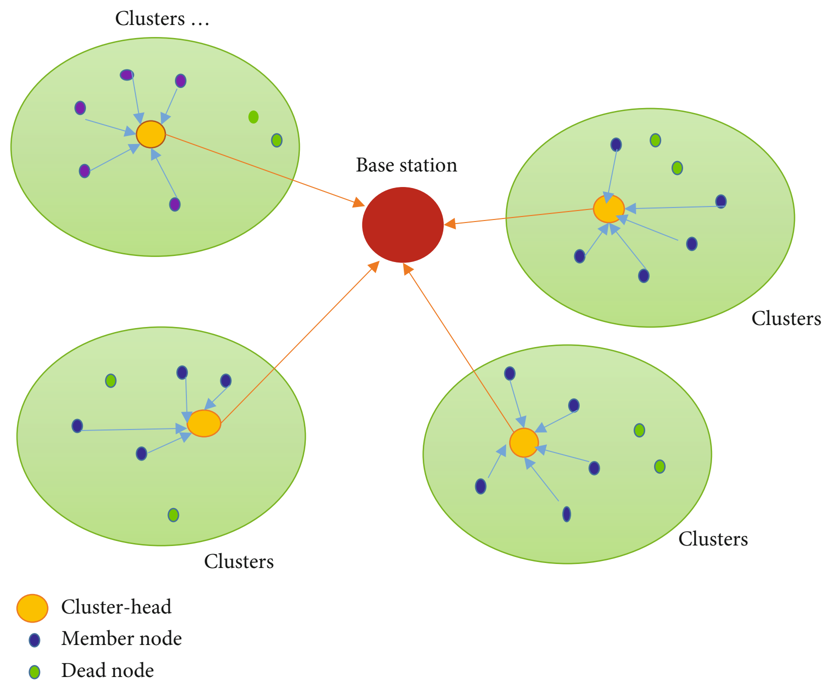

FIGURE 1: Clustering in WSN.

to the server. In today's era, people were accessing various facilities such as smart home appliances, smart watches, smart TV, smart traffic systems [19], and smart healthcare systems [20] all of these with the help of emerging technologies where sensors play an important role. Considering multiattributes and making coordination among them by Multi-AttributeDecision-Making (MADM) approaches [21, 22] will enhance the network lifetime of the network. Various technologies need optimal node deployment where the performance of applications increases with efficient energy consumption.

In recent technologies, everything is online and sensor nodes were the central part of revolutionary technologies. In a hostile environment, it is believed that energized nodes must be alive for long period but know the fact that their battery is irreplaceable or not feasible to change [23]. This necessity of sensor nodes to be alive for a long time in the network leads to the advent of new alternative approaches for energy-efficient techniques for WSNs for resolving traditional issues such as network lifetime, connectivity, accuracy, latency, distance from the base station, power, and efficient energy consumption; at the same time, these are conflicting in nature too. Thus, these conflicting factors need to be considered in the approach, and proper coordination is needed for making efficient cluster head selection which is the main part of any clustering approach. Various issues and open challenges have been faced by WSNs such as routing, data, topology, coverage, and security, and various clustering approaches have been given to the researchers for resolving these issues [24]. The clustering approach has been used for an efficient energy data process. Some cluster heads (CHs) were chosen from the normal nodes such as in LEACH [25] and HEED [26] and somewhere chosen from the advanced node sometimes known as gateways such as in [27–29], and selected CH is responsible for sending the data back to the base station itself after data aggregation, filtering, or compression. When individual sensor nodes send their data to the base station, energy is not efficiently used. Thus, with the clustering approach, efficient energy utilization is possible, and thus, network lifetime will be enhanced. The cluster head algorithm is used for selecting cluster heads to transmit data to the base station in an efficient way. Some of the CH algorithms are LEACH, LEACH-C, HEED, EECS, and many variants of the LEACH algorithm. In CH selection, the primary goal is to select cluster heads, but for optimal cluster head selection, many factors need to be considered such as energy consumption, connectivity, coverage, load balance, distance to the base station, and distance to neighbor's, but in earlier works, they only focus on one or two attributes, but with time, many updated algorithms were proposed. But in today's scenario, we have to consider multiattributes, and making coordination among them is necessary for finding optimal cluster heads. So, these can be applied to many IoT-based applications and fulfill the current requirement of the users. Optimal cluster head selection [30] leads to efficient energy utilization; therefore, now, researchers were focussing on this, as recently every technology needs sensors for data collection, sensing, and monitoring. Many conflicting attributes play a vital role in efficient energy consumption for data collection, but these attributes were not discovered till now. But there is a need to make coordination among these conflicting attributes which will improve the efficiency of the network. Thus, Multi-AttributeDecision-Making (MADM) is used for making the coordination among the conflicting attributes and selecting the best alternatives among them.

MADM (Multi-Attribute Decision-Making) [31] is an approach applied to solve a problem where the selection of the best alternative can be done from the given alternatives. MADM specifies how we can process the information of the multiple attributes to give the ranking among the given alternatives. In this paper, coordination among the multiple attributes has been done for finding the optimal solution. Sensor nodes were deployed almost in every field according to the applications, but seeing today's user requirement, we need to focus on the multiple attributes which lead to efficient energy which is lacking. We have considered multiconflicting attributes of sensor nodes for the cluster head selection. Results validate that making coordination among conflicting attributes is the better way to choose the cluster heads. In this paper, we have proposed MADM-based method for cluster head selection where network lifetime enhancement and load balance among the sensor nodes were obtained. The principle objective of our proposed work is as follows:

(i) To explore the multi-attribute-based cluster head selection by collaborating with the conflicting attributes. The enhancement of network lifetime and efficient energy consumption was evaluated in terms of FND, CHD, and LND

(ii) To conjoin among conflicting attributes and then to decide the selection of CHs which enhances the network lifetime and efficient energy consumption. The load among the sensor nodes was also balanced with optimal load balancing for sensor nodes

(iii) To evaluate the performance of the network using a multicriteria decision-making approach

The rest of this paper has been arranged as follows: the related work has been discussed in Related Work. The energy model considered for the simulation and parameters used for the experiment have been discussed in Assumption and System Model. The detail of the proposed algorithm and method has been discussed in Evolution Methods for the Selection of CHs Using MADM. Multiattributes taken in this research paper with their detailed description have been discussed in Attributes Considered for the Proposed Work. In Data Set Generation, the generation of data using MATLAB has been discussed. Simulation results and experimentation with case studies have been discussed in Simulation Results, and also, the analysis of the obtained results with their case studies has been discussed. Concluding remarks on the future scope have been discussed in Conclusion and Future Scope.

2. Related Work

Finding an energy-efficient data collection process in WSN is a big challenge. Data collection needs to be optimized as direct data collection will increase the communication heads which leads to less network lifetime. While facing this problem, some of the clustering solutions have been given by researchers [32, 33]. The clustering approach can be defined in several ways such as the CH selection methods (random, deterministic), objective of clustering (coverage, energy, and efficiency), clustering methods (distributed, centralized), or the architecture of the network for doing the communication (multihop, single hop). We can also classify the clustering methods into heuristic and metaheuristic methods. In this paper, we are doing single-hop communication for the wireless network.

LEACH [4] is a classical clustering algorithm that uses the probabilistic method for data collection based on the random number selection of nodes. Many LEACH algorithm variants have been developed for different purposes but have one important objective which is energy conservation. The main objective of the LEACH algorithm is efficient energy consumption by selecting the cluster heads on a rotation-based using a random number. There are several rounds in LEACH where each round is divided into two phases: the set-up phase and the steady phase. The concept used in the LEACH protocol is that it enforces less communication between the sensor node and the base station which increases the network lifetime. LEACH-C [13] is a variant of the LEACH protocol where all the decisions whether it is CH selection, distribution, or cluster formation are taken by the base station. LEACH-DCHS [34] is used for prolonging the network lifetime. Another protocol of LEACH is SLEACH [35] where the energy was harvested from the external source to the sensor node and the concept of solar power can be applied to distribute or centralize clustering. SLEACH [36, 37] is the first protocol that added the concept of security by using the SPIN protocol. This protocol uses the lightweight cryptographic technique in WSNs as this is a challenging task due to limited resources for the sensor nodes. ME-LEACH [38–40] means more energy-efficient LEACH extending the LEACH protocol by minimizing the distance between the sensor nodes and base station. EP-LEACH [41, 42] has improved the lifetime of the LEACH algorithm by using EH-WSN where the sensor nodes have a rechargeable battery that is charged from the environment itself.

HEED is another popular heuristic algorithm based on the single-hop transmission which does not depend upon the density of the sensor network. HEED algorithm considers residual energy and the number of neighboring nodes for selecting the cluster heads. This residual energy of sensor nodes is considered to be the primary attribute for selecting the cluster heads, and the average minimum reachable power works as a tie-breaker between the sensor nodes. The enhanced algorithm of HEED is named DWECH [43] which has the same primary parameter for the selection of cluster heads, but it also takes care of overlapping and unbalanced size when selecting the cluster heads. HEED has a good distribution of cluster heads over the network but has the disadvantage of not covering all nodes in the network. Both HEED and DWECH consume lots of energy due to overhead costs. FLOC [44, 45] is another heuristic algorithm that takes care of sensor nodes not getting overlapped and also creates an almost equal size of clusters such that each has one hop distance to the respective cluster heads. Energy-efficient clustering scheme (EECS) [46] is also another heuristic algorithm that reduces the unbalanced consumption of energy by considering the three attributes and also considering the respective weight cost factor for the sensor node. EEHC (energy-efficient heterogeneous cluster scheme) [47] provides the election probability weights that are directly related to the residual energy of the sensor node, whereas BEENISH [48] (balanced energy-efficient network-integrated super heterogeneous) protocol is also a clustering algorithm that assigns one of the four energy levels to the sensor node and uses this energy level for selecting the cluster heads. Enhanced developed distributed energy-efficient clustering for heterogeneous network (EDDEEC) [49] classifies nodes as normal nodes and advanced nodes and then changes the probability of becoming cluster heads.

Some of the metaheuristic algorithms were also proposed by the researchers in wireless sensor networks. Among them, the genetic algorithm is one of the most important algorithms used in the clustering approach for sensor networks where it reduces the communication distance of the target [50]. In [51], the authors propose a genetic algorithm-based fuzzy-optimized reclustering scheme to overcome the network lifetime failure, fixed routing path problem, and energy saving for the sensor network for the revolutionary area. The simulation results validate that the proposed algorithm for the network lifetime extension is 3.64-fold by preserving energy efficiency. In [52], the authors proposed a genetic algorithm for the dynamic clustering approach in IoT applications, and the simulation results validate that it has overcome the problem of a dynamic cluster relay node in terms of throughput and standard deviation for the data transmission. In [53], the authors propose the EEWC (energy-efficient weighted clustering) based on a genetic algorithm, and the proposed algorithm modifies the steady-state phase of LEACH and considered three attributes for the optimization which shows that the proposed algorithm is better than ERP, SEP, and IHCR. Some of them also use MADM-based approach for cluster head selection by considering 2 or 3 attributes. In [54], the authors propose an enhanced AHP-TOPSIS-based clustering algorithm for high-quality live video streaming flying in the ad hoc network. The proposed algorithms were simulated on OMNET++. It shows that video quality, UAV energy consumption, and the number of cluster heads needed have been improved when they used two models, namely, random waypoint and paparazzi. In [55], TOPSIS multicriteria decision-making algorithm has been used by OPNET software, and the proposed algorithm proved that it is suitable for clustering and selecting the cluster heads. The data transmission between the nodes has also been used for transmitting the files with improved efficiency of the network and sustainable routing path. In [56], the authors have proposed an ordered clustering based on PROMETHEE and the fuzzy c-mean clustering method. The author has finally proposed OFCM (ordered fuzzy c-mean clustering) for solving the problem of human development indexes, and comparison analysis also validates the efficiency of the OFCM approach.

But these approaches consider two or three factors in clustering which do not guarantee optimal clustering; thus, we need to consider more conflicting factors for achieving the optimal clustering for enhancing network lifetime. Less number of intermediate nodes for data transmission consumes more energy; thus, in [57], the authors suggested using an optimal number of intermediate nodes for the transmission of data enhancing the network lifetime. The authors in [58] have reviewed the renewable energy sources which will help WSN for recharging the battery of sensor nodes. They also discuss issues/challenges and provide future direction for the researcher to work on. In [59], the authors have proposed load-balanced adaptive position update (LAPU) for routing techniques which balances the load among sensor nodes in the selected path. Basically in this approach, the sensor nodes select the two best next hops for the data transmission based on the length queue and mobility of nodes and transmit the data to both selected nodes for balancing the load among sensor nodes. In [60], the authors have proposed a two-tier distributed fuzzy logic-based protocol for efficient data aggregation in multihop wireless sensor networks (TTDFP) for enhancing the network lifetime by combining the efficiency of routing and clustering phases along with two-tier fuzzy logic for tuning the parameters. In [61], a modified CLONal selection algorithm has been proposed for improving the energy efficiency of rule-based fuzzy systems. Here, CLONALG has been modified for constrained approximation problems. In [62], the author proposed hybrid gray wolf optimization (HGWO) for resolving the constrained resource problem in WSNs. These resources can be in any form such as bandwidth and energy consumption.

In [63], the authors have proposed energy-aware clustering and efficient cluster head selection by dividing the network into grids. This cluster head selection was based on only residual energy, distance to the base station, and distance to neighbors. In [64], the authors proposed a low energy clustering hierarchy for mobile sensor networks to not only enhance network lifetime but also reduce packet loss. In [65], the authors proposed a new routing technique for efficient consumption and increased network lifetime by optimal selection of cluster head. But here, cluster head selection is done only based on residual energy and distance to the base station. In [66], fuzzy-based clustering algorithms have been proposed where two types of sensors used, namely, free sensors for communicating to the base station and clustered sensor that sends sensed data to CH and the base station which were based on four parameters. In [67], an extension of the energy prediction with fuzzy logic has been proposed for increasing the network lifetime.

But these factors do not guarantee the optimal solutions in WSNs because many conflicting factors affect the energy consumption such as if it selects cluster heads (CHs) near the base station based on higher residual energy, but it may be possible that some sensor nodes have higher distance from the base station to send the data which consume more energy, which will degrade the efficiency of the sensor networks. We have already seen the problem of resource-constrained in the form of bandwidth and energy consumption which will drastically affect the network lifetime. So we need to focus on cooperating among the conflicting attributes to choose optimal cluster heads which enhance the network lifetime by properly and efficiently utilizing the resources. Thus, MADM is an emerging approach for applications based on WSNs by considering some important factors too. This paper focuses on the cooperation among the many conflicting attributes and then deciding on optimal cluster heads for efficient energy consumption.

3. Assumption and System Model

In this paper, we have assumed some predetermined values of the parameters and also made some assumptions for our simulation. In the simulation, we have taken an energy model during the data collection process. The considered parameter values and assumption made for simulation purposes have been discussed in this section as follows:

3.1. Assumptions. The following assumptions have been made in our simulation:

(i) Sensor nodes send the data from cluster heads to the base station

(ii) Here, sensor nodes are homogeneous

(iii) Here, the random uniform distribution of sensor nodes has been assumed

(iv) Some gateways were selected as cluster heads and sent the data to the base station

(v) Gateways are approximately six times higher energy than the normal sensor nodes

(vi) The base station knows the location of sensor nodes, gateways, and vice versa

(vii) The base station is considered to be the hefty node having the capability of communicating and computing without having any restriction on energy consumption

(viii) Sensor nodes were having the potential to transmit the data to the fluctuating energy level based on the distance from the sensor nodes

(ix) Sensor nodes are static

3.2. Energy Model. In WSN, most of the sensor nodes sense the data from the environment from their vicinity and send back data to the respective CHs, and CHs send this data to the base station by operating on the data. We need an energy model for transmitting the data, so we have taken the classical energy model for performing the operation mentioned above. The transmitter consumes energy for operating the radio electronics with amplifier power and only the receiver for operating the radio electronics.

In our experiment, we have considered both the free-space channel and multipath model. These models depended on the distance between the transmitter and receiver. Here, appropriate settings have been provided for preventing energy loss and providing power control at the power amplifier, i.e., if the distance for the transmission is less than d_0 which is the threshold distance that a free-space path will be used else a multipath model will be used. Here is an energy model; if l bit packets send at a distance d, then the required energy for the transmission is

$$E_{TRi} = E_{(TR_i-\mathrm{ele})} + E_{(TR_i-mp)},$$
$$E_{TRi} = \begin{cases} l * E_{\mathrm{ele}} + l * \varepsilon_{fs} d^2 & \text{if } d < d_0, \\ l * E_{\mathrm{ele}} + l * \varepsilon_{mp} d^4 & \text{if } d \geq d_0. \end{cases} \quad (1)$$

The energy consumption for receiving the message at the receiver end is given as

$$E_{REi} = E_{(REi-\mathrm{ele})}(l) = lE_{\mathrm{ele}}. \quad (2)$$

Here, E_{ele} is the electronic energy based on some factors such as filtering, signal spreading, modulation, and digital coding. And the amplifier energy is known as $\varepsilon_{fs}d^2$ or ε_{mp} d^4; this is based on the receiver distance and bit error rate. For our experimental analysis, these energy parameters for transmission purpose have been set as follows: $E_{\mathrm{ele}} = 50\,\mathrm{nJ/bit}$, $\varepsilon_{fs} = 10\,\mathrm{pJ/bit/m}$, and $\varepsilon_{mp} = 0.0013\,\mathrm{pJ/bit/m}$. For data aggregation, the energy consumption has been taken as 5 pJ/bit/signal. The optimal number of cluster heads (CHs) can be calculated as

$$k_{\mathrm{opt}} = \frac{\sqrt{n}}{\sqrt{2\pi}} \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}} \frac{M}{d^2 \text{ to BS}}. \quad (3)$$

Here, d^2 to BS is known as the distance from cluster heads (CHs) to the base station (BS), $M * M$ is the network deployment area, and n is the number of sensor nodes.

3.3. Parameters and Energy Model for the Simulation. Parameters used in the simulation for energy dissipation have been given in Tables 1 and 2 showing the parameters used for the repeated simulations in our experiment.

4. Attributes Considered for the Proposed Work

Here, we have considered multiattributes for our proposed work, and these are conflicting in nature shown in Figure 2. These attributes have an important impact on cluster head selection. Attributes considered in this paper were given below in the figure. These are conflicting attributes; thus, proper coordination among them is necessary for further use in other applications.

5. Data Set Generation

For the simulation purpose, we have used MATLAB for modeling the WSN. In our simulation, we have generated a random population of 20 for preserving the difference between the 20 alternative populations. The more difference helps us to understand the proposed APRO algorithm in a better way. The population generated in our experiment has been done by using the above equations for every given

Table 1: Parameters used in energy dissipation [4].

Parameters	Value and unit
Initial energy for every gateway	1 J
Initial energy for every node	0.2 J
ε_{fs}	$10 * 10^{-12}$ J
ε_{mp}	$0.0013 * 10^{-2}$ J
E_{TRi}	$50 * 10^{-9}$ J
E_{REi}	$50 * 10^{-9}$ J
EDA	$5 * 10^{-9}$ J
Data package length	4000 bits
Control package length	100 bits

Table 2: Parameters used in the simulation.

Parameters	Value/unit
Coordinates origin	(0,0)
Area	100*100, 200*200, 300*300 m^2
Total number of sensor nodes	100, 150, 200…
Base station coordinates	It is variable
Time for simulation	500, 750, and 1000 rounds
Simulation repeated time	3

alternative. Table 3 shows the brief descriptions about the attributes considered in our proposed work, whereas Table 4 shows the computed values of the attributes for modeled WSN by using the CHs selected for each alternative:

6. Evolution Methods for the Selection of CHs Using MADM

Many methods can be applied to select the best cluster heads (CHs). In this section, we have applied MADM-based methods such as AHP and PROMETHEE for ranking the alternative and selecting the best cluster heads (CHs) among them. Here, each method with its respective results has been discussed.

6.1. AHP (Analytical Hierarchy Process) Method for CH's Selection. Step 1: the first step is to normalize the data set (M_1) by using the following equation; we can denote the matrix by $(M_{1ij})_{mn}$, and the normalized data has been presented in Table 5

There are two types of factors: one is a beneficial factor and the other is a nonbeneficial factor. For the beneficial factor, we have to select the max value of each factor V_j^+ to compute the normalized value to the column i to M and $j = 1, 2, 3 \cdots n$.

$$M_{1ij} = \frac{M_{ij}}{V_j^+}. \tag{4}$$

And for nonbeneficial, the min value for each factor has been calculated V_j^-, where $j = 1, 2, 3 \cdots n$.

$$M_{1ij} = \frac{V_j^-}{M_{1ij}}. \tag{5}$$

The values of the normalized matrix lie between 0 and 1.

Step 2: after this, the relative importance matrix will be generated W_{n*n}

Step 3: geometric mean (GM) of each has been computed by using the following equation, and it is represented in Table 6

$$\mathrm{GM}_i = \prod_{i=1}^{n} W_{ij}, i = 1, 2, \cdots m \text{ and } j = 1, 2, \cdots n. \tag{6}$$

Step 4: in this step, a weighted matrix will be calculated $(M_2)_{n*1}$. Table 7 denotes the weighted matrix of the attributes

$$\mathrm{GM}_i = \frac{\mathrm{GM}_i}{\sum_{i=1}^{n} \mathrm{GM}_i}. \tag{7}$$

And also

$$\sum_{i=1}^{n} M_{2i} = 1. \tag{8}$$

Step 5: check the consistency:

(i) Compute the matrix M_3 and it is represented in Table 8.

$$M_{3n*1} = M_{1n*n} * M_{2n*1}. \tag{9}$$

(ii) Compute the matrix M_4 and it is represented in Table 9.

$$M_{4n*1} = \frac{M_{3n*1}}{M_{2n*1}}. \tag{10}$$

(iii) Compute $\lambda_{\max}$:

$$\lambda_{\max} = \frac{\sum_{i=1}^{n} M_{4i}}{n}. \tag{11}$$

Consistency index (CI) is as follows:

$$\mathrm{CI} = \frac{\lambda_{\max} - n}{n - 1}. \tag{12}$$

(iv) Compute consistency ratio:

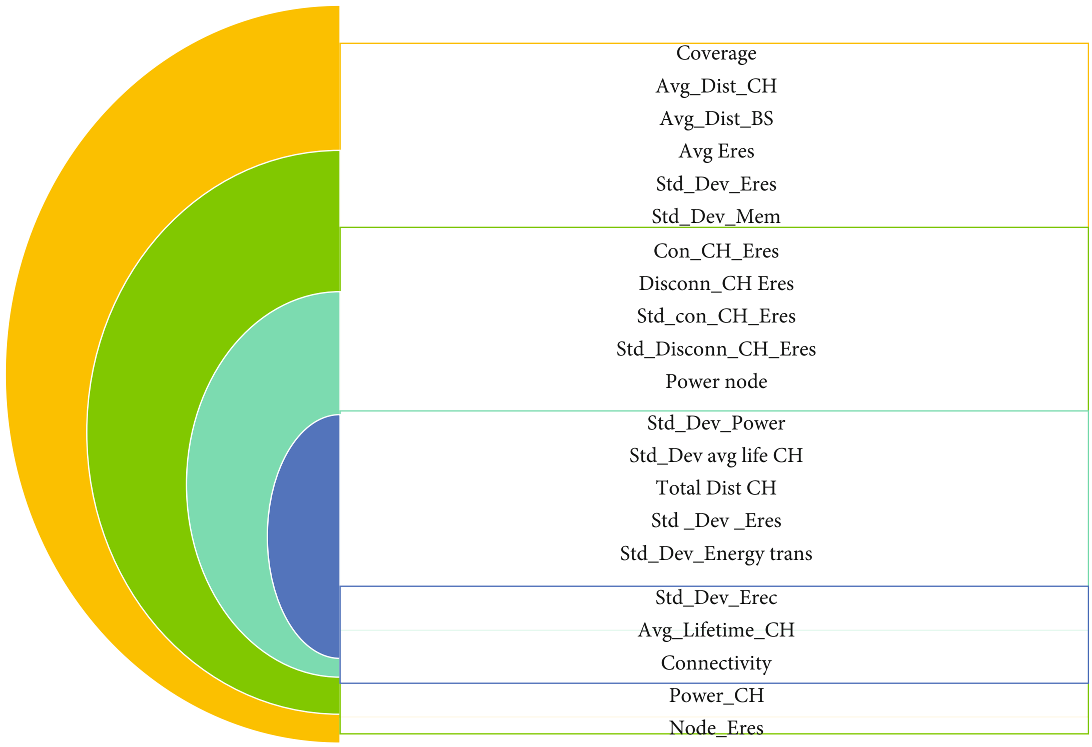

Figure 2: Attributes considered in the proposed work.

Table 3: Description of attributes.

Attributes	Brief description
CH-Cov	Percentage of sensor nodes distance from their respective cluster heads
BS-CH Connectivity	Connectivity of CH to the base station
Avg-CH Life	Average lifetime of cluster heads
Avg-Residual Energy	Average residual energy of sensor nodes
CH-Con-Avg Residual	Average residual energy of connected cluster heads
CH-Dcon-Avg Residual	Average residual energy of disconnected cluster heads
BS-CH Bearing	Load of cluster heads
Std Residual	Standard deviation of residual energy
Avg-BS Life	Lifetime of base station
Std_Avg_Ch_Life	Standard deviation of cluster head lifetime
Maximum_Dis_BS	Maximum distance to the base station
Avg_Dis_CHs	Average distance to cluster heads
Avg_BS_DIS	Average distance to base station
Std_CH_Con_Avg_Residual	Standard deviation residual energy of connected nodes
Std_CH_Dcon_Avg_Residual	Standard deviation residual energy of dis-connected nodes
Std_Residual	Standard deviation of residual energy
Node_Power	Power of sensor nodes
CH_Power	Power of cluster heads
Std_Power	Standard deviation of power
Std_Member Node	Standard deviation of member nodes
Std_Dev_Energy Trans	Standard deviation of energy transmission

Table 4: The computed value of attributes using modelled WSN.

Pop number	AT1	AT2	AT3	AT4	AT5	AT6	AT7	AT8	AT9	AT10	AT11	AT12	AT13	AT14	AT15	AT16	AT17	AT18	AT19	AT20	AT21
p1	100	42.36216	75.48834	0.500632	7.949843	0.00159	134.7252	0.6	0.004733	106.5489	754.8834	0.305308	2.479815	2.526502	0.309211	0.247014	0.002439	0.046685	0.399993	4.21136	4.52E-05
p2	97.35	27.64781	73.23843	0.590844	14.97331	0.002995	188.6028	0.6	0.005498	192.4052	732.3843	0.336078	3.838768	2.069676	0.260019	0.414693	0.002443	0.046493	0.399983	4.182947	8.13E-05
p3	100	25.85101	75.76089	0.442423	10.25671	0.002051	123.0495	0.6	0.004947	85.245	757.6089	0.21811	2.768477	1.65575	0.21717	0.216411	0.002659	0.047189	0.399931	4.154947	4.46E-05
p4	94.89	24.71355	86.05397	0.355837	15.80506	0.003161	148.6975	0.5	0.00563	130.8602	860.5397	0.202941	1.688419	1.869947	0.10286	0.2649	0.002604	0.04819	0.399968	4.125942	0.000156
p5	97.705	71.40099	72.46427	0.502839	13.08434	0.002617	225.0027	0.6	0.005264	292.223	724.6427	0.235293	2.985419	2.04297	0.270038	0.164349	0.002595	0.046899	0.399996	4.098374	7.11E-05
p6	99.3575	39.8865	69.20264	0.653394	12.66491	0.002533	504.6872	0.7	0.005214	1006.548	692.0264	0.292498	5.021191	1.512748	0.256218	0.262078	0.002685	0.047165	0.399919	4.070134	6.80E-05
p7	99.9825	38.55773	76.93263	0.460625	10.77961	0.002156	135.6407	0.6	0.005008	85.64074	769.3263	0.264736	2.864959	1.741286	0.308765	0.119939	0.002507	0.046546	0.399996	4.042229	4.44E-05
p8	100	60.3459	69.39238	0.723671	7.266361	0.001453	188.9398	0.7	0.004691	88.23473	693.9238	0.206317	5.382757	1.853948	0.209852	0.123075	0.00284	0.046266	0.399959	4.014036	4.18E-05
p9	94.615	50.66297	89.61767	0.461979	16.75112	0.00335	289.6506	0.5	0.005744	375.1004	896.1767	0.308652	1.713872	2.905919	0.29868	0.342258	0.002385	0.049112	0.399899	3.984999	0.000135
p10	93.7275	60.73158	82.4016	0.490068	10.51665	0.002103	513.9256	0.5	0.00499	1155.767	824.016	0.287279	1.5918	3.308875	0.304253	0.252419	0.00296	0.048933	0.399955	3.956912	0.000168
p11	92.475	31.71374	78.95862	0.621623	15.11952	0.003024	307.3728	0.5	0.005518	361.2157	789.5862	0.304075	3.644347	2.57188	0.232355	0.309969	0.002344	0.048011	0.399995	3.928457	0.000146
p12	100	48.98853	82.83877	0.450328	10.89954	0.00218	145.4711	0.6	0.005015	142.6179	828.3877	0.264371	1.725436	2.777847	0.290212	0.273077	0.002543	0.048357	0.399972	3.901172	3.95E-05
p13	99.47	52.21538	78.47428	0.530797	13.69671	0.002739	192.4369	0.5	0.005343	167.3531	784.7428	0.263519	2.338299	2.969674	0.320134	0.243651	0.002682	0.047351	0.399786	3.872966	4.60E-05
p14	100	51.50412	66.45519	0.516235	9.497368	0.001899	176.7652	0.5	0.004882	188.4023	664.5519	0.284803	3.011406	2.150942	0.317346	0.277782	0.002857	0.046623	0.399991	3.844796	4.39E-05
p15	100	39.63469	66.57997	0.527691	6.60303	0.001321	122.9159	0.9	0.004639	81.29884	665.7997	0.307114	4.910743	0.366162	0.318713	0.220047	0.002605	0.046035	0.399901	3.81673	3.55E-05
p16	96.575	60.15173	80.61157	0.314779	15.88081	0.003176	106.993	0.4	0.005639	75.11731	806.1157	0.251882	0.969824	2.177968	0.25899	0.281325	0.002718	0.048352	0.399849	3.787997	8.48E-05
p17	95.2825	40.05326	74.22112	0.372444	10.94532	0.002189	94.14851	0.7	0.005014	70.58152	742.2112	0.273516	3.463588	0.260854	0.233701	0.295826	0.00266	0.048688	0.399747	3.759846	0.000148
p18	98.055	49.4015	62.32353	0.566006	9.316652	0.001863	232.1911	0.7	0.004861	288.7712	623.2353	0.259286	4.821899	0.838164	0.144	0.281134	0.002653	0.047326	0.399997	3.731846	6.53E-05
p19	99.9975	24.09671	89.33146	0.601859	8.786353	0.001757	157.261	0.4	0.004818	64.62429	893.3146	0.16402	2.569741	3.448852	0.131124	0.199766	0.00269	0.049124	0.399994	3.703793	4.68E-05
p20	99.9925	38.17546	84.1947	0.520372	11.61034	0.002322	249.8117	0.4	0.005089	298.3125	841.947	0.275279	1.951679	3.252046	0.227809	0.285932	0.002438	0.048656	52.39001	3.675493	5.55E-05

Table 5: Normalization of AHP.

	AT1	AT2	AT3	AT4	AT5	AT6	AT7	AT8	AT9	AT10	AT11	AT12	AT13	AT14	AT15	AT16	AT17	AT18	AT19	AT20	AT21
p1	1	0.668826	0.525605	0.691795	0.830586	0.830586	0.262149	0.666667	0.980169	0.606522	0.825605	0.53723	0.460696	0.732563	0.332655	0.485554	0.961339	0.986084	0.007635	0.872757	0.785712
p2	0.9735	0.871559	0.750968	0.816455	0.440987	0.440987	0.366985	0.666667	0.843684	0.335876	0.850968	0.488042	0.71316	0.600106	0.395588	0.289222	0.959559	0.990143	0.007635	0.878685	0.436559
p3	1	0.932138	0.822635	0.611359	0.643777	0.643777	0.23943	0.666667	0.937641	0.758101	0.822635	0.752007	0.514323	0.480087	0.473641	0.554218	0.88169	0.975543	0.007634	0.884606	0.795808
p4	0.9489	0.97504	0.724238	0.491711	0.417779	0.417779	0.289337	0.555556	0.823902	0.493842	0.724238	0.808216	0.313672	0.542194	1	0.45277	0.900316	0.955289	0.007634	0.890825	0.22781
p5	0.97705	0.337484	0.860059	0.694845	0.504651	0.504651	0.437812	0.666667	0.881299	0.221147	0.860059	0.697091	0.554626	0.592362	0.380911	0.72978	0.90347	0.981571	0.007635	0.896817	0.499472
p6	0.993575	0.604132	0.900595	0.902889	0.521364	0.521364	0.982024	0.777778	0.889678	0.064204	0.900595	0.560758	0.932829	0.438624	0.401456	0.457645	0.873218	0.976037	0.007634	0.90304	0.522045
p7	0.999825	0.624951	0.810105	0.636511	0.612548	0.612548	0.263931	0.666667	0.926362	0.754597	0.810105	0.619563	0.532248	0.504889	0.333136	1	0.935243	0.989022	0.007635	0.909274	0.799448
p8	1	0.39931	0.898132	1	0.908712	0.908712	0.36764	0.777778	0.988977	0.732413	0.898132	0.794992	1	0.537555	0.490156	0.974515	0.82547	0.995004	0.007634	0.91566	0.848795
p9	0.94615	0.475628	0.695438	0.638383	0.394184	0.394184	0.563604	0.555556	0.807539	0.172285	0.695438	0.531409	0.3184	0.842576	0.344384	0.350433	0.983082	0.937347	0.007633	0.922332	0.26318
p10	0.937275	0.396774	0.756339	0.677197	0.627864	0.627864	1	0.555556	0.92963	0.055915	0.756339	0.570945	0.295722	0.959413	0.338075	0.475157	0.79206	0.940772	0.007634	0.928879	0.211809
p11	0.92475	0.759819	0.789319	0.858986	0.436722	0.436722	0.598088	0.555556	0.84068	0.178908	0.789319	0.539407	0.677041	0.745721	0.442687	0.386938	1	0.958845	0.007635	0.935607	0.24375
p12	1	0.491885	0.752347	0.622284	0.605808	0.605808	0.283059	0.666667	0.924957	0.453129	0.752347	0.620417	0.320549	0.805441	0.354432	0.439211	0.921999	0.951975	0.007635	0.942151	0.897991
p13	0.9947	0.461487	0.79419	0.733479	0.482089	0.482089	0.374445	0.555556	0.868149	0.386155	0.79419	0.622424	0.434405	0.861061	0.321304	0.492256	0.874112	0.972207	0.007631	0.949013	0.771043
p14	1	0.46786	0.937828	0.713356	0.695248	0.695248	0.343951	0.555556	0.950187	0.343012	0.937828	0.575909	0.559454	0.623669	0.324128	0.431773	0.820535	0.987389	0.007635	0.955966	0.807924
p15	1	0.60797	0.93607	0.729186	1	1	0.239171	1	1	0.794898	0.93607	0.53407	0.91231	0.106169	0.322737	0.545059	0.899869	1	0.007633	0.962995	1
p16	0.96575	0.400599	0.773134	0.434976	0.415787	0.415787	0.208188	0.444444	0.822586	0.860312	0.773134	0.651179	0.180172	0.631505	0.397161	0.426335	0.862615	0.952084	0.007632	0.9703	0.418816
p17	0.952825	0.601617	0.839701	0.51466	0.603274	0.603274	0.183195	0.777778	0.925139	0.915598	0.839701	0.599674	0.64346	0.075635	0.440137	0.405436	0.881286	0.945516	0.00763	0.977565	0.240169
p18	0.98055	0.487773	1	0.782133	0.708734	0.708734	0.451799	0.777778	0.954344	0.223791	1	0.632584	0.895805	0.243027	0.714308	0.426625	0.883562	0.972728	0.007635	0.9849	0.544049
p19	0.999975	1	0.697666	0.831676	0.75151	0.75151	0.305999	0.444444	0.962899	1	0.697666	1	0.477402	1	0.784453	0.600397	0.871472	0.937121	0.007635	0.992359	0.75918
p20	0.999925	0.631209	0.740231	0.719074	0.56872	0.56872	0.486085	0.444444	0.911574	0.216633	0.740231	0.595833	0.36258	0.942936	0.45152	0.419466	0.961546	0.946137	1	1	0.639372

Table 6: Geometric mean.

AT1	2.296165
AT2	1.785906
AT3	1.530776
AT4	2.296165
AT5	0.255129
AT6	0.255129
AT7	1.275647
AT8	2.296165
AT9	1.275647
AT10	0.255129
AT11	1.275647
AT12	0.255129
AT13	0.255129
AT14	0.765388
AT15	2.296165
AT16	0.255129
AT17	1.785906
AT18	1.785906
AT19	1.785906
AT20	2.296165
AT21	2.296165

Table 7: Weighted matrix.

AT1	0.080357
AT2	0.0625
AT3	0.053571
AT4	0.080357
AT5	0.008929
AT6	0.008929
AT7	0.044643
AT8	0.080357
AT9	0.044643
AT10	0.008929
AT11	0.044643
AT12	0.008929
AT13	0.008929
AT14	0.026786
AT15	0.080357
AT16	0.008929
AT17	0.0625
AT18	0.0625
AT19	0.0625
AT20	0.080357
AT21	0.080357

Table 8: Consistency check.

a3	
AT1	1.6875
AT2	1.3125
AT3	1.125
AT4	1.6875
AT5	0.1875
AT6	0.1875
AT7	0.9375
AT8	1.6875
AT9	0.9375
AT10	0.1875
AT11	0.9375
AT12	0.1875
AT13	0.1875
AT14	0.5625
AT15	1.6875
AT16	0.1875
AT17	1.3125
AT18	1.3125
AT19	1.3125
AT20	1.6875

Table 9: Matrix $M_{4.}$

a4	
AT1	21
AT2	21
AT3	21
AT4	21
AT5	21
AT6	21
AT7	21
AT8	21
AT9	21
AT10	21
AT11	21
AT12	21
AT13	21
AT14	21
AT15	21
AT16	21
AT17	21
AT18	21
AT19	21
AT20	21

$$CR = \frac{CI}{RI}. \quad (13)$$

Here, RI is the random index.

Step 6: calculate the value of P_i by using the SAW method. In our experiment, we used the SAW method for selecting the CH. The value is presented in Table 10

$$P_i = \sum_{j=1}^{n} M_{2i} * M_{1ij}, i = 1, 2, 3\, m. \quad (14)$$

Step 7: in this step, we finally rank the alternative according to the higher value of P_i. And the rank is presented in Table 11

6.2. PROMETHEE Method for CH Selection. Step 1: calculate the denomination matrix for each n attribute and m alternatives $m * m$ matrix. $Q_{j_{m*m}}$. For each attribute, the denomination matrix has been given in Tables 12–34. In Table 35, we have presented the abbreviation of attributes used in the simulation

Step 2: now, the corresponding weights of each attribute are multiplied by each denomination matrix, and the final matrix is calculated by doing the summation of each matrix. And the final denomination matrix is presented in Table 33

$$\left(M_{j_{m*m}}\right) = Q_{j_{m*m}} * w_j, \quad (15)$$

where $w_j = 1$.

$$Q_{m*m} = \sum_{j=1}^{n} \left(M_{j_{m*m}}\right), i = 1, 2, \cdots..m. \quad (16)$$

Step 3: now, compute $\$_i^+$ and $\$_i^-$ by adding rows and columns. This is presented in Table 36

Step 4: compute the net flow by using the following equation as presented in Table 37:

$$\$_i = \$_i^+ - \$_i^-. \quad (17)$$

Step 5: lastly, rank the alternative according to the higher value of $\$_i$, and the rank is given in Table 38

7. Simulation Results

This section evaluates the proposed APRO algorithm against other clustering algorithms under a different scenario. In this, MATLAB is used for the simulation, and we have compared the proposed algorithm by LEACH, LEACH-C, EECS, HEED, HEEC, and DEECET. We have performed the proposed APRO algorithm under different scenarios using three metrics FND, CHD, and Network_Dead. Here, network dead means when 75% of the nodes are dead. A total of five scenarios Table 39–43 have been considered where the simulation area, number of nodes, the initial energy of the sensor nodes, and base station position values are considered different. In all five scenarios, it is shown that the proposed algorithm preserves the energy of sensor nodes and outperforms the other algorithms. Here, we have taken five scenarios by changing the values of the simulation area, the number of nodes, and the base station position, and in all scenarios,

Table 10: SAW method.

P1	0.696925
P2	0.689571
P3	0.711684
P4	0.669327
P5	0.65802
P6	0.726547
P7	0.692058
P8	0.754268
P9	0.616516
P10	0.636602
P11	0.674155
P12	0.685208
P13	0.674693
P14	0.688882
P15	0.753036
P16	0.595946
P17	0.633541
P18	0.730995
P19	0.755554
P20	0.747793
P1	0.696925

Table 11: Rank of the alternatives.

Pop	Rank
1	8
2	10
3	7
4	15
5	16
6	6
7	9
8	2
9	19
10	17
11	14
12	12
13	13
14	11
15	3
16	20
17	18
18	5
19	1
20	4

Table 12: Denomination matrix for AT1.

Pop	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0	1	0	1	1	1	1	0	1	1	1	0	1	0	0	1	1	1	1	1
2	0	0	0	1	0	0	0	0	1	1	1	0	0	0	0	1	1	0	0	0
3	0	1	0	1	1	1	1	0	1	1	1	0	1	0	0	1	1	1	1	1
4	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0
5	0	1	0	1	0	0	0	0	1	1	1	0	0	0	0	1	1	0	0	0
6	0	1	0	1	1	0	0	0	1	1	1	0	0	0	0	1	1	1	0	0
7	0	1	0	1	1	1	0	0	1	1	1	0	1	0	0	1	1	1	0	0
8	0	1	0	1	1	1	1	0	1	1	1	0	1	0	0	1	1	1	1	1
9	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	1	0	1	1	1	1	0	1	1	1	0	1	0	0	1	1	1	1	1
13	0	1	0	1	1	1	0	0	1	1	1	0	0	0	0	1	1	1	0	0
14	0	1	0	1	1	1	1	0	1	1	1	0	1	0	0	1	1	1	1	1
15	0	1	0	1	1	1	1	0	1	1	1	0	1	0	0	1	1	1	1	1
16	0	0	0	1	0	0	0	0	1	1	1	0	0	0	0	0	1	0	0	0
17	0	0	0	1	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0
18	0	1	0	1	1	0	0	0	1	1	1	0	0	0	0	1	1	0	0	0
19	0	1	0	1	1	1	1	0	1	1	1	0	1	0	0	1	1	1	0	1
20	0	1	0	1	1	1	1	0	1	1	1	0	1	0	0	1	1	1	0	0

Table 13: Denomination matrix for AT2.

Pop	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Pop	1	2	3	4
1	0	0	0	0	1	0	0	1	1	1	0	1	1	1	0	1	0	0	0	0
2	1	0	0	0	1	1	1	1	1	1	1	1	1	1	1	2	1	0	0	0
3	1	1	0	0	1	1	1	1	1	1	1	1	1	1	1	3	1	1	0	0
4	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	4	1	1	1	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0
6	1	0	0	0	1	0	0	1	1	1	0	1	1	1	0	6	1	0	0	0
7	1	0	0	0	1	1	0	1	1	1	0	1	1	1	1	7	1	0	0	0
8	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	8	0	0	0	0
9	0	0	0	0	1	0	0	1	0	1	0	0	1	1	0	9	0	0	0	0
10	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0
11	1	0	0	0	1	1	1	1	1	1	0	1	1	1	1	11	1	0	0	0
12	0	0	0	0	1	0	0	1	1	1	0	0	1	1	0	12	0	0	0	0
13	0	0	0	0	1	0	0	1	0	1	0	0	0	0	0	13	0	0	0	0
14	0	0	0	0	1	0	0	1	0	1	0	0	1	0	0	14	0	0	0	0
15	1	0	0	0	1	1	0	1	1	1	0	1	1	1	0	15	1	0	0	0
16	0	0	0	0	1	0	0	1	0	1	0	0	0	0	0	16	0	0	0	0
17	1	0	0	0	1	0	0	1	1	1	0	1	1	1	0	17	1	0	0	0
18	0	0	0	0	1	0	0	1	1	1	0	0	1	1	0	18	0	0	0	0
19	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	19	1	1	1	1
20	1	0	0	0	1	1	1	1	1	1	0	1	1	1	1	20	1	0	0	0

Table 14: Denomination matrix for AT3.

Pop	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0	0	1	1	0	0	1	0	1	1	1	1	1	0	0	1	0	0	1	1
2	1	0	1	1	0	0	1	0	1	1	1	1	1	0	0	1	1	0	1	1
3	0	0	0	1	0	0	1	0	1	1	1	1	1	0	0	1	0	0	1	1
4	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0
5	1	1	1	1	0	0	1	0	1	1	1	1	1	0	0	1	1	0	1	1
6	1	1	1	1	1	0	1	1	1	1	1	1	1	0	0	1	1	0	1	1
7	0	0	0	1	0	0	0	0	1	1	1	1	1	0	0	1	0	0	1	1
8	1	1	1	1	1	0	1	0	1	1	1	1	1	0	0	1	1	0	1	1
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	1	0	0	0	0	1	0	0	1	0	0	0	0	0	0	1	1
11	0	0	0	1	0	0	0	0	1	1	0	1	0	0	0	1	0	0	1	1
12	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1
13	0	0	0	1	0	0	0	0	1	1	1	1	0	0	0	1	0	0	1	1
14	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	0	1	1
15	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	1	1	0	1	1
16	0	0	0	1	0	0	0	0	1	1	0	1	0	0	0	0	0	0	1	1
17	1	0	1	1	0	0	1	0	1	1	1	1	1	0	0	1	0	0	1	1
18	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1
19	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0

Table 15: Denomination matrix for AT4.

Pop	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0	0	1	1	0	0	1	0	1	1	0	1	0	0	0	1	1	0	0	0
2	1	0	1	1	1	0	1	0	1	1	0	1	1	1	1	1	1	1	0	1
3	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
5	1	0	1	1	0	0	1	0	1	1	0	1	0	0	0	1	1	0	0	0
6	1	1	1	1	1	0	1	0	1	1	1	1	1	1	1	1	1	1	1	1
7	0	0	1	1	0	0	0	0	0	0	0	1	0	0	0	1	1	0	0	0
8	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1
9	0	0	1	1	0	0	1	0	0	0	0	1	0	0	0	1	1	0	0	0
10	0	0	1	1	0	0	1	0	1	0	0	1	0	0	0	1	1	0	0	0
11	1	1	1	1	1	0	1	0	1	1	0	1	1	1	1	1	1	1	1	1
12	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0
13	1	0	1	1	1	0	1	0	1	1	0	1	0	1	1	1	1	0	0	1
14	1	0	1	1	1	0	1	0	1	1	0	1	0	0	0	1	1	0	0	0
15	1	0	1	1	1	0	1	0	1	1	0	1	0	1	0	1	1	0	0	1
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
18	1	0	1	1	1	0	1	0	1	1	0	1	1	1	1	1	1	0	0	1
19	1	1	1	1	1	0	1	0	1	1	0	1	1	1	1	1	1	1	0	1
20	1	0	1	1	1	0	1	0	1	1	0	1	0	1	0	1	1	0	0	0

Table 16: Denomination matrix for AT5.

Pop	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0	1	1	1	1	1	1	0	1	1	1	1	1	1	0	1	1	1	1	1
2	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	1	0	0	0	0
3	0	1	0	1	1	1	1	0	1	1	1	1	1	0	0	1	1	0	0	1
4	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0
5	0	1	0	1	0	0	0	0	1	0	1	0	1	0	0	1	0	0	0	0
6	0	1	0	1	1	0	0	0	1	0	1	0	1	0	0	1	0	0	0	0
7	0	1	0	1	1	1	0	0	1	0	1	1	1	0	0	1	1	0	0	1
8	1	1	1	1	1	1	1	0	1	1	1	1	1	1	0	1	1	1	1	1
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	1	0	1	1	1	1	0	1	0	1	1	1	0	0	1	1	0	0	1
11	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0
12	0	1	0	1	1	1	0	0	1	0	1	0	1	0	0	1	1	0	0	1
13	0	1	0	1	0	0	0	0	1	0	1	0	0	0	0	1	0	0	0	0
14	0	1	1	1	1	1	1	0	1	1	1	1	1	0	0	1	1	0	0	1
15	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1
16	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
17	0	1	0	1	1	1	0	0	1	0	1	0	1	0	0	1	0	0	0	1
18	0	1	1	1	1	1	1	0	1	1	1	1	1	1	0	1	1	0	0	1
19	0	1	1	1	1	1	1	0	1	1	1	1	1	1	0	1	1	1	0	1
20	0	1	0	1	1	1	0	0	1	0	1	0	1	0	0	1	0	0	0	0

Table 17: Denomination matrix for AT6.

Pop	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0	1	1	1	1	1	1	0	1	1	1	1	1	1	0	1	1	1	1	1
2	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	1	0	0	0	0
3	0	1	0	1	1	1	1	0	1	1	1	1	1	0	0	1	1	0	0	1
4	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0
5	0	1	0	1	0	0	0	0	1	0	1	0	1	0	0	1	0	0	0	0
6	0	1	0	1	1	0	0	0	1	0	1	0	1	0	0	1	0	0	0	0
7	0	1	0	1	1	1	0	0	1	0	1	1	1	0	0	1	1	0	0	1
8	1	1	1	1	1	1	1	0	1	1	1	1	1	1	0	1	1	1	1	1
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	1	0	1	1	1	1	0	1	0	1	1	1	0	0	1	1	0	0	1
11	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0
12	0	1	0	1	1	1	0	0	1	0	1	0	1	0	0	1	1	0	0	1
13	0	1	0	1	0	0	0	0	1	0	1	0	0	0	0	1	0	0	0	0
14	0	1	1	1	1	1	1	0	1	1	1	1	1	0	0	1	1	0	0	1
15	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1
16	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
17	0	1	0	1	1	1	0	0	1	0	1	0	1	0	0	1	0	0	0	1
18	0	1	1	1	1	1	1	0	1	1	1	1	1	1	0	1	1	0	0	1
19	0	1	1	1	1	1	1	0	1	1	1	1	1	1	0	1	1	1	0	1
20	0	1	0	1	1	1	0	0	1	0	1	0	1	0	0	1	0	0	0	0

Table 18: Denomination matrix for AT7.

Pop	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0
2	1	0	1	1	0	0	1	0	0	0	0	1	0	1	1	1	1	0	1	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0
4	1	0	1	0	0	0	1	0	0	0	0	1	0	0	1	1	1	0	0	0
5	1	1	1	1	0	0	1	1	0	0	0	1	1	1	1	1	1	0	1	0
6	1	1	1	1	1	0	1	1	1	0	1	1	1	1	1	1	1	1	1	1
7	1	0	1	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0
8	1	1	1	1	0	0	1	0	0	0	0	1	0	1	1	1	1	0	1	0
9	1	1	1	1	1	0	1	1	0	0	0	1	1	1	1	1	1	1	1	1
10	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1
11	1	1	1	1	1	0	1	1	1	0	0	1	1	1	1	1	1	1	1	1
12	1	0	1	0	0	0	1	0	0	0	0	0	0	0	1	1	1	0	0	0
13	1	1	1	1	0	0	1	1	0	0	0	1	0	1	1	1	1	0	1	0
14	1	0	1	1	0	0	1	0	0	0	0	1	0	0	1	1	1	0	1	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	1	1	1	1	1	0	1	1	0	0	0	1	1	1	1	1	1	0	1	0
19	1	0	1	1	0	0	1	0	0	0	0	1	0	0	1	1	1	0	0	0
20	1	1	1	1	1	0	1	1	0	0	0	1	1	1	1	1	1	1	1	0

Table 19: Denomination matrix for AT8.

Pop	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0	0	0	1	0	0	0	0	1	1	1	0	1	1	0	1	0	0	1	1
2	0	0	0	1	0	0	0	0	1	1	1	0	1	1	0	1	0	0	1	1
3	0	0	0	1	0	0	0	0	1	1	1	0	1	1	0	1	0	0	1	1
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1
5	0	0	0	1	0	0	0	0	1	1	1	0	1	1	0	1	0	0	1	1
6	1	1	1	1	1	0	1	0	1	1	1	1	1	1	0	1	0	0	1	1
7	0	0	0	1	0	0	0	0	1	1	1	0	1	1	0	1	0	0	1	1
8	1	1	1	1	1	0	1	0	1	1	1	1	1	1	0	1	0	0	1	1
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1
12	0	0	0	1	0	0	0	0	1	1	1	0	1	1	0	1	0	0	1	1
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1
15	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	1	1	1	1	1	0	1	0	1	1	1	1	1	1	0	1	0	0	1	1
18	1	1	1	1	1	0	1	0	1	1	1	1	1	1	0	1	0	0	1	1
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 20: Denomination matrix for AT9.

Pop	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0	1	1	1	1	1	1	0	1	1	1	1	1	1	0	1	1	1	1	1
2	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	1	0	0	0	0
3	0	1	0	1	1	1	1	0	1	1	1	1	1	0	0	1	1	0	0	1
4	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0
5	0	1	0	1	0	0	0	0	1	0	1	0	1	0	0	1	0	0	0	0
6	0	1	0	1	1	0	0	0	1	0	1	0	1	0	0	1	0	0	0	0
7	0	1	0	1	1	1	0	0	1	0	1	1	1	0	0	1	1	0	0	1
8	1	1	1	1	1	1	1	0	1	1	1	1	1	1	0	1	1	1	1	1
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	1	0	1	1	1	1	0	1	0	1	1	1	0	0	1	1	0	0	1
11	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0
12	0	1	0	1	1	1	0	0	1	0	1	0	1	0	0	1	0	0	0	1
13	0	1	0	1	0	0	0	0	1	0	1	0	0	0	0	1	0	0	0	0
14	0	1	1	1	1	1	1	0	1	1	1	1	1	0	0	1	1	0	0	1
15	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1
16	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
17	0	1	0	1	1	1	0	0	1	0	1	1	1	0	0	1	0	0	0	1
18	0	1	1	1	1	1	1	0	1	1	1	1	1	1	0	1	1	0	0	1
19	0	1	1	1	1	1	1	0	1	1	1	1	1	1	0	1	1	1	0	1
20	0	1	0	1	1	1	0	0	1	0	1	0	1	0	0	1	0	0	0	0

Table 21: Denomination matrix for AT10.

Pop	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0	1	0	1	1	1	0	0	1	1	1	1	1	1	0	0	0	1	0	1
2	0	0	0	0	1	1	0	0	1	1	1	0	0	0	0	0	0	1	0	1
3	1	1	0	1	1	1	1	1	1	1	1	1	1	1	0	0	0	1	0	1
4	0	1	0	0	1	1	0	0	1	1	1	1	1	1	0	0	0	1	0	1
5	0	0	0	0	0	1	0	0	1	1	1	0	0	0	0	0	0	0	0	1
6	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
7	1	1	0	1	1	1	0	1	1	1	1	1	1	1	0	0	0	1	0	1
8	1	1	0	1	1	1	0	0	1	1	1	1	1	1	0	0	0	1	0	1
9	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	1	0	0	1	1	0	0	0	0	0	0	0	0	0	0
12	0	1	0	0	1	1	0	0	1	1	1	0	1	1	0	0	0	1	0	1
13	0	1	0	0	1	1	0	0	1	1	1	0	0	1	0	0	0	1	0	1
14	0	1	0	0	1	1	0	0	1	1	1	0	0	0	0	0	0	1	0	1
15	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	1	0	1
16	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	1	0	1
17	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0	1
18	0	0	0	0	1	1	0	0	1	1	1	0	0	0	0	0	0	0	0	1
19	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1
20	0	0	0	0	0	1	0	0	1	1	1	0	0	0	0	0	0	0	0	0

Table 22: Denomination matrix for AT11.

Pop	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0	0	1	1	0	0	1	0	1	1	1	1	1	0	0	1	0	0	1	1
2	1	0	1	1	0	0	1	0	1	1	1	1	1	0	0	1	1	0	1	1
3	0	0	0	1	0	0	1	0	1	1	1	1	1	0	0	1	0	0	1	1
4	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0
5	1	1	1	1	0	0	1	0	1	1	1	1	1	0	0	1	1	0	1	1
6	1	1	1	1	1	0	1	1	1	1	1	1	1	0	0	1	1	0	1	1
7	0	0	0	1	0	0	0	0	1	1	1	1	1	0	0	1	0	0	1	1
8	1	1	1	1	1	0	1	0	1	1	1	1	1	0	0	1	1	0	1	1
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	1	0	0	0	0	1	0	0	1	0	0	0	0	0	0	1	1
11	0	0	0	1	0	0	0	0	1	1	0	1	0	0	0	1	0	0	1	1
12	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1
13	0	0	0	1	0	0	0	0	1	1	1	1	0	0	0	1	0	0	1	1
14	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	0	1	1
15	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	1	1	0	1	1
16	0	0	0	1	0	0	0	0	1	1	0	1	0	0	0	0	0	0	1	1
17	1	0	1	1	0	0	1	0	1	1	1	1	1	0	0	1	0	0	1	1
18	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1
19	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0

Table 23: Denomination matrix for AT12.

Pop	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0	1	1	1	1	1	1	0	1	1	1	1	1	1	0	1	1	1	1	1
2	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0	1	0	0	0	0
3	0	1	0	1	1	1	1	0	1	1	1	1	1	0	0	1	1	0	0	1
4	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0
5	0	1	0	1	0	0	0	0	1	0	1	0	1	0	0	1	0	0	0	0
6	0	1	0	1	1	0	0	0	1	0	1	0	1	0	0	1	0	0	0	0
7	0	1	0	1	1	1	0	0	1	0	1	1	1	0	0	1	1	0	0	1
8	1	1	1	1	1	1	1	0	1	1	1	1	1	1	0	1	1	1	1	1
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	1	0	1	1	1	1	0	1	0	1	1	1	0	0	1	1	0	0	1
11	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0
12	0	1	0	1	1	1	0	0	1	0	1	0	1	0	0	1	1	0	0	1
13	0	1	0	1	0	0	0	0	1	0	1	0	0	0	0	1	0	0	0	0
14	0	1	1	1	1	1	1	0	1	1	1	1	1	0	0	1	1	0	0	1
15	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1
16	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
17	0	1	0	1	1	1	0	0	1	0	1	0	1	0	0	1	0	0	0	1
18	0	1	1	1	1	1	1	0	1	1	1	1	1	1	0	1	1	0	0	1
19	0	1	1	1	1	1	1	0	1	1	1	1	1	1	0	1	1	1	0	1
20	0	1	0	1	1	1	0	0	1	0	1	0	1	0	0	1	0	0	0	0

Table 24: Denomination matrix for AT13.

Pop	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0	0	0	1	0	0	0	0	1	1	0	1	1	0	0	1	0	0	0	1
2	1	0	1	1	1	0	1	0	1	1	1	1	1	1	0	1	1	0	1	1
3	1	0	0	1	0	0	0	0	1	1	0	1	1	0	0	1	0	0	1	1
4	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0
5	1	0	1	1	0	0	1	0	1	1	0	1	1	0	0	1	0	0	1	1
6	1	1	1	1	1	0	1	0	1	1	1	1	1	1	1	1	1	1	1	1
7	1	0	1	1	0	0	0	0	1	1	0	1	1	0	0	1	0	0	1	1
8	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1
9	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
11	1	0	1	1	1	0	1	0	1	1	0	1	1	1	0	1	1	0	1	1
12	0	0	0	1	0	0	0	0	1	1	0	0	0	0	0	1	0	0	0	0
13	0	0	0	1	0	0	0	0	1	1	0	1	0	0	0	1	0	0	0	1
14	1	0	1	1	1	0	1	0	1	1	0	1	1	0	0	1	0	0	1	1
15	1	1	1	1	1	0	1	0	1	1	1	1	1	1	0	1	1	1	1	1
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	1	0	1	1	1	0	1	0	1	1	0	1	1	1	0	1	0	0	1	1
18	1	1	1	1	1	0	1	0	1	1	1	1	1	1	0	1	1	0	1	1
19	1	0	0	1	0	0	0	0	1	1	0	1	1	0	0	1	0	0	0	1
20	0	0	0	1	0	0	0	0	1	1	0	1	0	0	0	1	0	0	0	0

Table 25: Denomination matrix for AT14.

Pop	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0	1	1	1	1	1	1	1	0	0	0	0	0	1	1	1	1	1	0	0
2	0	0	1	1	1	1	1	1	0	0	0	0	0	0	1	0	1	1	0	0
3	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	1	1	0	0
4	0	0	1	0	0	1	1	1	0	0	0	0	0	0	1	0	1	1	0	0
5	0	0	1	1	0	1	1	1	0	0	0	0	0	0	1	0	1	1	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0	0
7	0	0	1	0	0	1	0	0	0	0	0	0	0	0	1	0	1	1	0	0
8	0	0	1	0	0	1	1	0	0	0	0	0	0	0	1	0	1	1	0	0
9	1	1	1	1	1	1	1	1	0	0	1	1	0	1	1	1	1	1	0	0
10	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	0	1
11	1	1	1	1	1	1	1	1	0	0	0	0	0	1	1	1	1	1	0	0
12	1	1	1	1	1	1	1	1	0	0	1	0	0	1	1	1	1	1	0	0
13	1	1	1	1	1	1	1	1	1	0	1	1	0	1	1	1	1	1	0	0
14	0	1	1	1	1	1	1	1	0	0	0	0	0	0	1	0	1	1	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
16	0	1	1	1	1	1	1	1	0	0	0	0	0	1	1	0	1	1	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0
19	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1
20	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	0	0

Table 26: Denomination matrix for AT15.

Pop	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0
2	1	0	0	0	1	0	1	0	1	1	0	1	1	1	1	0	0	0	0	0
3	1	1	0	0	1	1	1	0	1	1	1	1	1	1	1	1	1	0	0	1
4	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
5	1	0	0	0	0	0	1	0	1	1	0	1	1	1	1	0	0	0	0	0
6	1	1	0	0	1	0	1	0	1	1	0	1	1	1	1	1	0	0	0	0
7	1	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0
8	1	1	1	0	1	1	1	0	1	1	1	1	1	1	1	1	1	0	0	1
9	1	0	0	0	0	0	1	0	0	1	0	0	1	1	1	0	0	0	0	0
10	1	0	0	0	0	0	1	0	0	0	0	0	1	1	1	0	0	0	0	0
11	1	1	0	0	1	1	1	0	1	1	0	1	1	1	1	1	1	0	0	0
12	1	0	0	0	0	0	1	0	1	1	0	0	1	1	1	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
16	1	1	0	0	1	0	1	0	1	1	0	1	1	1	1	0	0	0	0	0
17	1	1	0	0	1	1	1	0	1	1	0	1	1	1	1	1	0	0	0	0
18	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	1
19	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1
20	1	1	0	0	1	1	1	0	1	1	1	1	1	1	1	1	1	0	0	0

Table 27: Denomination matrix for AT16.

Pop	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0	1	0	1	0	1	0	0	1	1	1	1	0	1	0	1	1	1	0	1
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	1	1	0	1	0	1	0	0	1	1	1	1	1	1	1	1	1	1	0	1
4	0	1	0	0	0	0	0	0	1	0	1	1	0	1	0	1	1	1	0	1
5	1	1	1	1	0	1	0	0	1	1	1	1	1	1	1	1	1	1	1	1
6	0	1	0	1	0	0	0	0	1	0	1	1	0	1	0	1	1	1	0	1
7	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1
8	1	1	1	1	1	1	0	0	1	1	1	1	1	1	1	1	1	1	1	1
9	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	1	0	1	0	1	0	0	1	0	1	1	0	1	0	1	1	1	0	1
11	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
12	0	1	0	0	0	0	0	0	1	0	1	0	0	1	0	1	1	1	0	1
13	1	1	0	1	0	1	0	0	1	1	1	1	0	1	0	1	1	1	0	1
14	0	1	0	0	0	0	0	0	1	0	1	0	0	0	0	1	1	1	0	1
15	1	1	0	1	0	1	0	0	1	1	1	1	1	1	0	1	1	1	0	1
16	0	1	0	0	0	0	0	0	1	0	1	0	0	0	0	0	1	0	0	1
17	0	1	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0
18	0	1	0	0	0	0	0	0	1	0	1	0	0	0	0	1	1	0	0	1
19	1	1	1	1	0	1	0	0	1	1	1	1	1	1	1	1	1	1	0	1
20	0	1	0	0	0	0	0	0	1	0	1	0	0	0	0	0	1	0	0	0

Table 28: Denomination matrix for AT17.

Pop	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0	1	1	1	1	1	1	1	0	1	0	1	1	1	1	1	1	1	1	0
2	0	0	1	1	1	1	1	1	0	1	0	1	1	1	1	1	1	1	1	0
3	0	0	0	0	0	1	0	1	0	1	0	0	1	1	0	1	1	0	1	0
4	0	0	1	0	0	1	0	1	0	1	0	0	1	1	1	1	1	1	1	0
5	0	0	1	1	0	1	0	1	0	1	0	0	1	1	1	1	1	1	1	0
6	0	0	0	0	0	0	0	1	0	1	0	0	0	1	0	1	0	0	1	0
7	0	0	1	1	1	1	0	1	0	1	0	1	1	1	1	1	1	1	1	0
8	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0
9	1	1	1	1	1	1	1	1	0	1	0	1	1	1	1	1	1	1	1	1
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1
12	0	0	1	1	1	1	0	1	0	1	0	0	1	1	1	1	1	1	1	0
13	0	0	0	0	0	1	0	1	0	1	0	0	0	1	0	1	0	0	1	0
14	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
15	0	0	1	0	0	1	0	1	0	1	0	0	1	1	0	1	1	1	1	0
16	0	0	0	0	0	0	0	1	0	1	0	0	0	1	0	0	0	0	0	0
17	0	0	0	0	0	1	0	1	0	1	0	0	1	1	0	1	0	0	1	0
18	0	0	1	0	0	1	0	1	0	1	0	0	1	1	0	1	1	0	1	0
19	0	0	0	0	0	0	0	1	0	1	0	0	0	1	0	1	0	0	0	0
20	1	1	1	1	1	1	1	1	0	1	0	1	1	1	1	1	1	1	1	0

Table 29: Denomination matrix for AT18.

Pop	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0	0	1	1	1	1	0	0	1	1	1	1	1	0	0	1	1	1	1	1
2	1	0	1	1	1	1	1	0	1	1	1	1	1	1	0	1	1	1	1	1
3	0	0	0	1	0	0	0	0	1	1	1	1	1	0	0	1	1	1	1	1
4	0	0	0	0	0	0	0	0	1	1	0	1	0	0	0	1	1	0	1	1
5	0	0	1	1	0	1	0	0	1	1	1	1	1	0	0	1	1	1	1	1
6	0	0	1	1	0	0	0	0	1	1	1	1	1	0	0	1	1	1	1	1
7	1	0	1	1	1	1	0	0	1	1	1	1	1	1	0	1	1	1	1	1
8	1	1	1	1	1	1	1	0	1	1	1	1	1	1	0	1	1	1	1	1
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
10	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0
11	0	0	0	1	0	0	0	0	1	1	0	1	0	0	0	1	1	0	1	1
12	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	1	0	1	1
13	0	0	0	1	0	0	0	0	1	1	1	1	0	0	0	1	1	0	1	1
14	1	0	1	1	1	1	0	0	1	1	1	1	1	0	0	1	1	1	1	1
15	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1
16	0	0	0	0	0	0	0	0	1	1	0	1	0	0	0	0	1	0	1	1
17	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	1	0
18	0	0	0	1	0	0	0	0	1	1	1	1	1	0	0	1	1	0	1	1
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	1	0	1	0

Table 30: Denomination matrix for AT19.

Pop	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0	1	1	1	0	1	0	1	1	1	0	1	1	1	1	1	1	0	0	0
2	0	0	1	1	0	1	0	1	1	1	0	1	1	0	1	1	1	0	0	0
3	0	0	0	0	0	1	0	0	1	0	0	0	1	0	1	1	1	0	0	0
4	0	0	1	0	0	1	0	1	1	1	0	0	1	0	1	1	1	0	0	0
5	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0
6	0	0	0	0	0	0	0	0	1	0	0	0	1	0	1	1	1	0	0	0
7	1	1	1	1	0	1	0	1	1	1	1	1	1	1	1	1	1	0	1	0
8	0	0	1	0	0	1	0	0	1	1	0	0	1	0	1	1	1	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1	0	0	0
10	0	0	1	0	0	1	0	0	1	0	0	0	1	0	1	1	1	0	0	0
11	1	1	1	1	0	1	0	1	1	1	0	1	1	1	1	1	1	0	1	0
12	0	0	1	1	0	1	0	1	1	1	0	0	1	0	1	1	1	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
14	0	1	1	1	0	1	0	1	1	1	0	1	1	0	1	1	1	0	0	0
15	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	1	1	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0
19	1	1	1	1	0	1	0	1	1	1	0	1	1	1	1	1	1	0	0	0
20	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0

Table 31: Denomination matrix for AT20.

Pop	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
9	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
10	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0
11	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0
12	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0
13	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0
14	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0
15	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0
16	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0
17	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0
18	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0
19	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
20	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0

Table 32: Denomination matrix for AT21.

Pop	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0	1	0	1	1	1	0	0	1	1	1	0	1	0	0	1	1	1	1	1
2	0	0	0	1	0	0	0	0	1	1	1	0	0	0	0	1	1	0	0	0
3	1	1	0	1	1	1	0	0	1	1	1	0	1	0	0	1	1	1	1	1
4	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
5	0	1	0	1	0	0	0	0	1	1	1	0	0	0	0	1	1	0	0	0
6	0	1	0	1	1	0	0	0	1	1	1	0	0	0	0	1	1	0	0	0
7	1	1	1	1	1	1	0	0	1	1	1	0	1	0	0	1	1	1	1	1
8	1	1	1	1	1	1	1	0	1	1	1	0	1	1	0	1	1	1	1	1
9	0	0	0	1	0	0	0	0	0	1	1	0	0	0	0	0	1	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0
12	1	1	1	1	1	1	1	1	1	1	1	0	1	1	0	1	1	1	1	1
13	0	1	0	1	1	1	0	0	1	1	1	0	0	0	0	1	1	1	1	1
14	1	1	1	1	1	1	1	0	1	1	1	0	1	0	0	1	1	1	1	1
15	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1
16	0	0	0	1	0	0	0	0	1	1	1	0	0	0	0	0	1	0	0	0
17	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
18	0	1	0	1	1	1	0	0	1	1	1	0	0	0	0	1	1	0	0	0
19	0	1	0	1	1	1	0	0	1	1	1	0	0	0	0	1	1	1	0	1
20	0	1	0	1	1	1	0	0	1	1	1	0	0	0	0	1	1	1	0	0

Table 33: Final denomination matrix.

Pop	1	2	3	4	5	6	7	8	9	10
1	0	0.196429	0.3125	0.455357	0.241071	0.1875	0.348214	0.089286	0.5	0.491071
2	0.375	0	0.258929	0.482143	0.267857	0.098214	0.401786	0.089286	0.5625	0.5
3	0.178571	0.3125	0	0.428571	0.303571	0.339286	0.401786	0.071429	0.5	0.5
4	0.196429	0.169643	0.223214	0	0.160714	0.1875	0.223214	0.178571	0.410714	0.25
5	0.330357	0.303571	0.267857	0.491071	0	0.053571	0.348214	0.071429	0.517857	0.455357
6	0.464286	0.553571	0.3125	0.464286	0.598214	0	0.392857	0.205357	0.616071	0.5
7	0.223214	0.169643	0.169643	0.428571	0.223214	0.258929	0	0.080357	0.419643	0.357143
8	0.482143	0.5625	0.5	0.473214	0.580357	0.366071	0.571429	0	0.517857	0.580357
9	0.151786	0.089286	0.151786	0.160714	0.133929	0.035714	0.232143	0.133929	0	0.241071
10	0.160714	0.151786	0.151786	0.321429	0.196429	0.151786	0.294643	0.071429	0.330357	0
11	0.3125	0.25	0.160714	0.321429	0.303571	0.178571	0.303571	0.133929	0.464286	0.339286
12	0.160714	0.196429	0.151786	0.4375	0.241071	0.1875	0.241071	0.089286	0.5	0.330357
13	0.169643	0.241071	0.151786	0.410714	0.258929	0.133929	0.160714	0.133929	0.383929	0.357143
14	0.241071	0.294643	0.321429	0.401786	0.428571	0.285714	0.401786	0.1875	0.357143	0.410714
15	0.410714	0.357143	0.339286	0.428571	0.482143	0.401786	0.419643	0.3125	0.5	0.491071
16	0.098214	0.133929	0.035714	0.214286	0.178571	0.044643	0.125	0.098214	0.348214	0.339286
17	0.348214	0.25	0.196429	0.419643	0.303571	0.160714	0.276786	0.071429	0.5	0.428571
18	0.401786	0.473214	0.455357	0.455357	0.607143	0.258929	0.464286	0.285714	0.580357	0.571429
19	0.330357	0.419643	0.383929	0.392857	0.410714	0.339286	0.455357	0.1875	0.526786	0.428571
20	0.303571	0.3125	0.151786	0.401786	0.4375	0.330357	0.375	0.133929	0.526786	0.330357

Table 34: Final denomination matrix.

	11	12	13	14	15	16	17	18	19	20
1	0.339286	0.330357	0.482143	0.330357	0.160714	0.553571	0.303571	0.25	0.321429	0.348214
2	0.401786	0.375	0.410714	0.357143	0.294643	0.517857	0.401786	0.178571	0.232143	0.339286
3	0.491071	0.339286	0.5	0.25	0.232143	0.616071	0.455357	0.196429	0.267857	0.5
4	0.25	0.214286	0.160714	0.169643	0.223214	0.4375	0.232143	0.196429	0.258929	0.25
5	0.348214	0.330357	0.392857	0.223214	0.169643	0.473214	0.348214	0.044643	0.241071	0.214286
6	0.473214	0.464286	0.517857	0.366071	0.25	0.607143	0.410714	0.3125	0.3125	0.321429
7	0.348214	0.330357	0.491071	0.25	0.232143	0.526786	0.375	0.1875	0.196429	0.276786
8	0.517857	0.482143	0.517857	0.383929	0.258929	0.553571	0.5	0.285714	0.464286	0.517857
9	0.107143	0.151786	0.1875	0.214286	0.151786	0.303571	0.151786	0.071429	0.125	0.125
10	0.232143	0.321429	0.214286	0.160714	0.160714	0.3125	0.223214	0.080357	0.223214	0.321429
11	0	0.375	0.276786	0.303571	0.303571	0.544643	0.303571	0.214286	0.3125	0.375
12	0.276786	0	0.375	0.276786	0.160714	0.455357	0.267857	0.1875	0.258929	0.348214
13	0.294643	0.276786	0	0.178571	0.160714	0.553571	0.25	0.125	0.223214	0.294643
14	0.267857	0.294643	0.392857	0	0.258929	0.526786	0.401786	0.125	0.3125	0.348214
15	0.348214	0.410714	0.491071	0.3125	0	0.526786	0.553571	0.3125	0.330357	0.428571
16	0.107143	0.196429	0.098214	0.125	0.125	0	0.169643	0.044643	0.098214	0.125
17	0.348214	0.383929	0.401786	0.25	0.098214	0.482143	0	0.071429	0.1875	0.267857
18	0.4375	0.464286	0.526786	0.526786	0.339286	0.607143	0.5	0	0.232143	0.4375
19	0.339286	0.392857	0.428571	0.339286	0.321429	0.473214	0.464286	0.419643	0	0.428571
20	0.276786	0.303571	0.357143	0.303571	0.223214	0.446429	0.383929	0.214286	0.142857	0

Table 35: Abbreviations of attribute.

Attributes used	Abbreviations
CH-Cov	AT1
BS-CH Connectivity	AT2
Avg-CH Life	AT3
Avg-Residual Energy	AT4
CH-Con-Avg Residual	AT5
CH-Dcon-Avg Residual	AT6
BS-CH Bearing	AT7
Std Residual	AT8
Avg-BS Life	AT9
Std_Avg_Ch_Life	AT10
Maximum_Dis_BS	AT11
Avg_Dis_CHs	AT12
Avg_BS_DIS	AT13
Std_CH_Con_Avg_Residual	AT14
Std_CH_Dcon_Avg_Residual	AT15
Std_Residual	AT16
Node_Power	AT17
CH_Power	AT18
Std_Power	AT19
Std_Member Node	AT20
Std_Dev_Energy Trans	AT21

Table 36: Vec Pos and Vec Neg.

	Vec Pos	Vec Neg
1	6.241071	5.339286
2	6.544643	5.4375
3	6.883929	4.696429
4	4.392857	7.589286
5	5.625	6.357143
6	8.142857	4
7	5.544643	6.4375
8	9.116071	2.625
9	2.919643	9.0625
10	4.080357	7.901786
11	5.776786	6.205357
12	5.142857	6.4375
13	4.758929	7.223214
14	6.258929	5.321429
15	7.857143	4.125
16	2.705357	9.517857
17	5.446429	6.696429
18	8.625	3.517857
19	7.482143	4.741071
20	5.955357	6.267857

our proposed algorithm (Table 44) performs better than LEACH, LEACH-C, EECS, HEED, HEEC, and DEECET. The performance has been measured in terms of the first node dead, the cluster head dead, and the last node dead. We measured network lifetime in terms of dead nodes, as network lifetime means how much time a network sustains.

Table 37: Net flow.

Alternatives	Net flow
1	0.901786
2	1.107143
3	2.1875
4	-3.19643
5	-0.73214
6	4.142857
7	-0.89286
8	6.491071
9	-6.14286
10	-3.82143
11	-0.42857
12	-1.29464
13	-2.46429
14	0.9375
15	3.732143
16	-6.8125
17	-1.25
18	5.107143
19	2.741071
20	-0.3125

Table 38: Rank of the PROMETHEE.

Pop	Rank
1	8
2	18
3	6
4	15
5	19
6	3
7	2
8	14
9	1
10	20
11	11
12	5
13	7
14	17
15	12
16	13
17	4
18	10
19	9
20	16

The proposed APRO method is a hybrid approach of AHP and PROMETHEE, and the time complexity of the algorithm is $o(mn^2)$ and $O(mnlogn)$, respectively, and the overall proposed APRO hybrid algorithmic complexity is $O(mnlogn)$.

Table 39: First scenario.

Parameter	Values
Area of deployment	200*200
Sensor nodes	150
Base station position	(100, 100)
Initial node power	.2 J

Table 40: Second scenario.

Parameter	Values
Area of deployment	250*250
Sensor nodes	150
Base station position	(100, 100)
Initial node power	.2 J

Table 41: Third scenario.

Parameter	Values
Area of deployment	300*300
Sensor nodes	200
Base station position	(100, 150)
Initial node power	.2 J

Table 42: Fourth scenario.

Parameter	Values
Area of deployment	400*400
Sensor nodes	250
Base station position	(150, 200)
Initial node power	.2 J

Table 43: Fifth scenario.

Parameter	Values
Area of deployment	500*500
Sensor nodes	1000
Base station position	(250, 250)
Initial node power	.2 J

Table 44: Abbreviations used for comparison of our proposed algorithms.

Abbreviations used for algorithms	Name of the algorithms
C1	APRO (proposed algorithm)
C2	LEACH
C3	LEACH-C
C4	EECS
C5	HEED
C6	HEEC
C7	DEECET

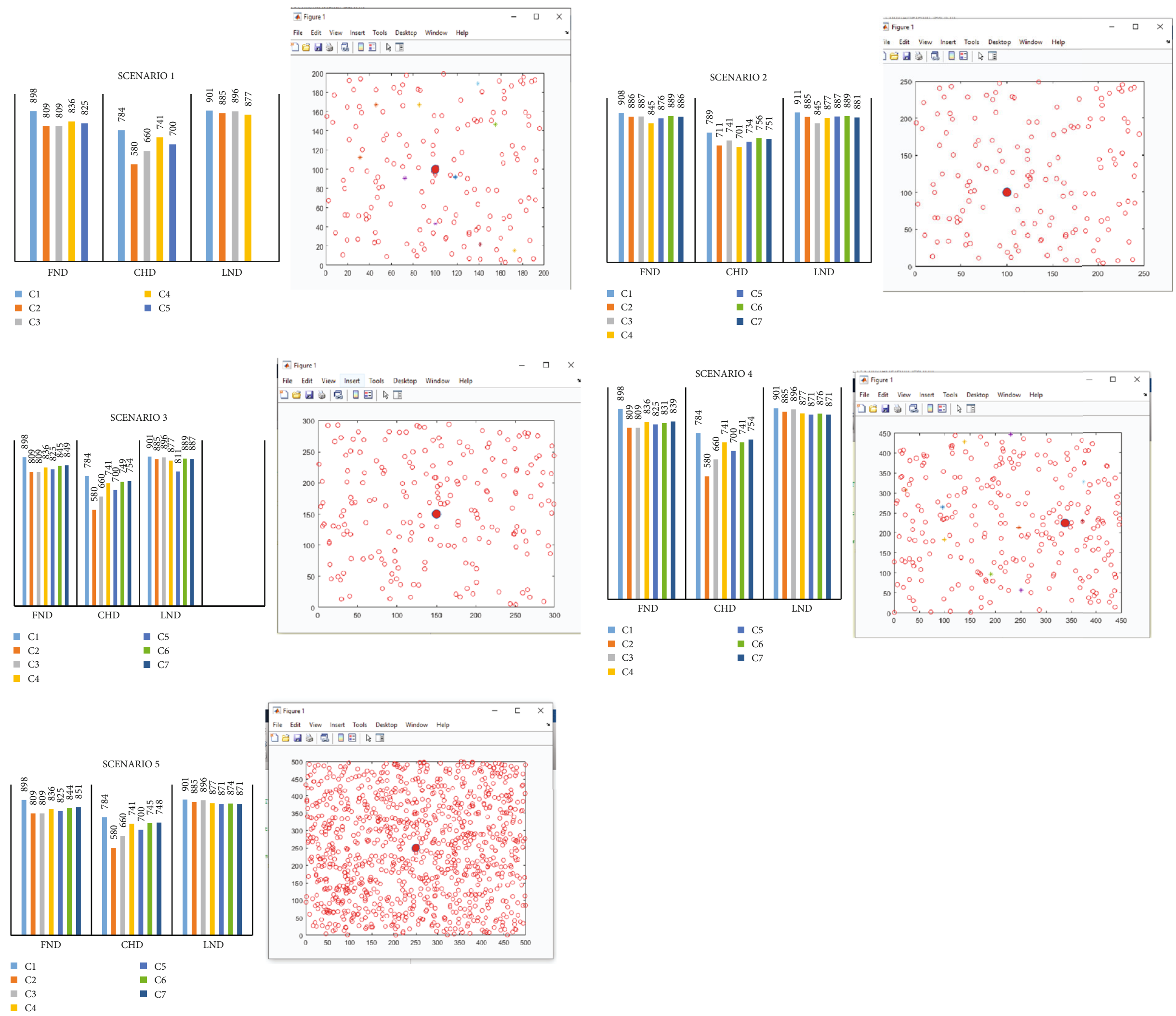

Figure 3: Performance of the experimental results.

The confidence interval of the proposed approach is 99% which can be calculated as

$$\text{Confidence Interval} = 20.6 \pm 0.219(\pm 1.1\%)[20.381 - 20.819],$$
$$\text{C.I} = \bar{x} \pm Z \times \frac{s}{\sqrt{n}} = 20.6 \pm 2.5758 \times \frac{1.2}{\sqrt{200}} 20.6 \pm 0.219. \tag{18}$$

Figure 3 shows that in all the scenario whether we change the simulation area, increase the number of sensor nodes, or change the base station position, the proposed APRO algorithm performs better than other algorithms. In the figure, we have also shown the simulated area with sensor nodes in each scenario so that we can better understand the scenarios. In our proposed APRO algorithm, applying multiattributes for cluster head selection shows that network lifetime has been increased with efficient energy consumption. Also considering every aspect of sensor nodes, load balance between nodes and thus efficient energy consumption helps in increasing the network lifetime.

7.1. Statistical Analysis. Here, Table 45 represents the statistical significance of analyzing the performance of the network. If we choose the alternative based on maximum residual, maximum coverage, and maximum connectivity, then the 1^{st} alternative is for maximum coverage, the 3^{rd} for maximum connectivity, and the 11^{th} for maximum residual energy. Although the rank of the best alternatives has been given the solution by our proposed algorithm, these alternatives are 8^{th}, 18^{th}, and 11^{th} (PROM ranking) and 8^{th}, 10^{th}, and 14^{th} (AHP ranking). If we choose alternative 1^{st} based on maximum coverage, then it will show that sensor nodes are near to the base station and they will consume less energy, but it will not guarantee that distance from CH to the base station is less and CHs are having higher residual energy for the data transmission. The chosen alternative shows that the solution is not optimal as it consumes more energy for data transmission which lowers network lifetime as other attributes were not optimal. The rank given to this alternative by PROMETHHE and AHP is 8^{th}.

If we choose 3^{rd} alternative based on maximum connectivity, then it will assure that CH is near the base station but

Table 45: Statistical significance of the attributes.

	AHP	PROMETHEE	Max residual	Max CN	Max COV
Ch-Cov	97.674	100	89.117	92.341	100
Bs-Ch Connectivity	.6138	.6138	.5816	.8954	.6389
Avg-Ch Life	2631.6713	2754.4364	2612.6781	2234.15167	2314.7827
Avg-Residual Energy	.6453	.6453	.69874	.5887	.6193
Ch-Con-Avg Residual	.3986	3.9876	3.2581	4.6897	3.7862
Ch-Dcon-Avg Residual	1.5637	1.5627	.56379	3.5788	2.6737
Bs-Ch Bearing	98.8967	98.9899	93.6578	91.2567	92.5364
Std Residual	2.6897	2.8967	2.3552	2.1547	2.4567
Avg-Bs Life	148.8753	169.6475	145.6742	154.7836	158.5362
Std_Avg_Ch_Life	167.3899	189.3748	156.7411	141.4748	190.3832
Maximum_Dis_Bs	575.2891	517.3849	784.3628	628.3718	616.3783
Avg_Dis_Chs	56.1123	56.4783	99.4738	78.4949	72.3949
Avg_BS_DIS	61.3849	56.3839	89.9401	78.4839	81.4788
Std_Ch_Con_Avg_Residual	.26178	.26894	.31473	.27671	.2134
Std_CH_Dcon_Avg_Residual	.2084	.2568	.3897	.2897	.2979
Std_Residual	.00156	.00167	.00238	.01383	.01898
Node_Power	.002146	.002146	.01278	.01238	.01287
Ch_Power	.00247	.00247	.00357	.003897	.00387
Std_Power	.004678	.004768	.005678	.005987	.006178
Std_Member Node	.28971	.28917	.36887	.34572	.37826
Std_Dev_Energy Trans	.00237	.00267	.01837	.01987	.02397

not guarantee higher residual energy. The sensor nodes other than the CH will be far away from the base station. As normal sensor nodes were at a higher distance, they require higher residual energy for data transmission. In this case, the network lifetime and residual energy will be lower. The rank given by the proposed algorithm is 6^{th} and 7^{th}, respectively. If we choose the 8^{th} alternative based on higher maximum residual energy, then it will give higher residual energy to sensor nodes. But sensor nodes were not equally distributed and sensor nodes' loads were also not balanced which causes a lower network lifetime. The rank given by our proposed APRO algorithm to this alternative is 11^{th} and 14^{th}. The other attribute values prove that the above results were not optimal; thus, we can say that with many limitations, the solutions were not optimal. Thus, we have to consider other attributes for CH's selection for data transmission. Such selected CHs should have a maximum lifetime with evenly distributed sensor nodes and have efficient energy consumption. The proposed algorithm provides optimal CH selection where all attributes have their optimal values and the simulation results were evaluated in terms of FND, CHD, and LND.

8. Conclusion and Future Scope

The proposed APRO algorithm provides a load-balanced and increased network lifetime for the selection of cluster heads by considering the twenty-one attributes. All the attributes were considered and synchronized among them for the data collection process. The selected cluster heads (CHs) have a balanced load among the sensor nodes with optimal energy consumption for the data transmission to the base station. The results validate the outcome of our proposed algorithm which verify consume optimal energy consumption for data transmissions. Results show that the considered 21 attributes play an important role in efficient energy consumption and increased network lifetime. As far as energy consumption is considered to be the most important factor in sensor networks, thus sensor nodes consume less energy and also balance the load among the sensor nodes. So, our proposed algorithm favored the data transmission and collection for a longer time in the network. Also, we have taken some scenarios in which we have changed the number of sensor nodes, deployment area, and base station position, where we can see that our proposed algorithm performs well compared to other algorithms. This shows that our proposed algorithm is scalable to small or large deployment areas and applications. We conclude that our proposed algorithm performs better than the other algorithms and our results validate as well.

In the future automatic weight, an assignment can be done using the fuzzy logic approach in place of relative weight. Automatic weight assignment can be done for enhancing the performance of the network. Further, we can move to the multihop transmission of data.

Data Availability

Data will be made available after making reasonable request from the author.

Conflicts of Interest

There is no conflict of interest among the authors.

Authors' Contributions

The authors have given consent for the publication.

Acknowledgments

The first author is thankful for the UGC-BHU-NET fellowship. The corresponding author is grateful for IoE grant of the Banaras Hindu University.

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