Knowledge and Decision Systems with Applications

www.kadsa.org
eISSN: 3079-6318

Optimizing Cluster Head Selection for Reliable and Efficient WSNs under Uncertainty

Supriyan Sen[1*], Umesh Sarkar[2], Santosh Mukherjee[3]
supriyan_sen@rediffmail.com[1], umeshsarkar.cis@gmail.com[2],santoshvu1@gmail.com[3]

[1,2] Department of Computer and Information Science, Raiganj University, West Bengal India
[3] Department of Business Administration, Raiganj University, West Bengal India

ARTICLE INFO

Article history:
Received 4 March 2025
Received in revised form 10 April 2025
Accepted 9 May 2025
Available online 24 May 2025

Keywords: WSNs; Cluster Head; LEACH

ABSTRACT

WSNs are often deployed in harsh and challenging environments where nodes may have limited energy and be prone to failure, reliability is an essential component of these networks. Cluster reliability is one of the approaches that can lead WSNs to reliable communication and energy efficiency at the highest degree of order. Cluster reliability is defined as the ability of a cluster to retain its structure and functionality over time, especially in the event of node failures or other unfavourable circumstances. The majority of current clustering protocol-based research focuses on (i) cluster Head Role (ii) cluster formation, (iii) data accuracy, and (iv TDMA schedule creation, all of which entirely ignore the importance of appropriate cluster head selections, which have a significant impact on WSN energy efficiency. The network has been divided into optimum clusters in this study employing a hierarchical clustering agglomerative approach after the optimal number of clusters has been established and confirmed by beta CV cluster validity Indexing. Each node's value is determined by the fitness function proposed in this study using parameters such as (i) residual energy, (ii) distance from sink, (iii) SNR (signal to noise ratio), and (iv) average distance. The weight parameter is determined using the entropy-weighted technique. It has been noted that our suggested method, which is shown in Figure 5, has 20% and 10% longer network lifetimes in comparison to the LEACH and LEACH-FC protocols. Finally, the obtained results have been validated by the testing of statistical hypotheses.

1. Introduction

Wireless Sensor Networks (WSNs) have emerged as a vital research area in wireless communication and sensing, comprising small, low-cost sensor nodes equipped with sensing, processing, and communication capabilities, enabling real-time monitoring, data collection, and control across diverse applications such as environmental monitoring [1], healthcare [2], smart cities [3], and industrial automation [4]. These networks bridge the physical and digital worlds by transmitting data

* *Corresponding author.*
E-mail address: supriyan_sen@rediffmail.com

https://doi.org/10.59543/kadsa.v1i.13875

wirelessly to central nodes for analysis [5], with each sensor node limited by residual energy, necessitating optimal energy use. Clustering techniques like LEACH [6], HEED [7], EECS [8], PEGASIS [9], and TEEN [10] enhance energy efficiency and network longevity by optimizing resource utilization, though cluster reliability—critical for robust communication, fault tolerance, load balancing, and resilience—often remains unaddressed. To address this, a fitness function weighted by entropy [11] evaluates node importance within clusters, while Katz centrality integrates with this function to assess cluster reliability, with the proposed approach's energy efficiency compared against existing protocols.

2. Related Work

In the study of Kabashkin [12] proposes a method to extend WSN lifetime by using redundant batteries in cluster-based systems. A Markov model analyzes sensor node reliability, evaluating failure modes and optimizing energy preservation for prolonged autonomy. The main focus of Park et al. [13] is reliable sink-to-sensors data delivery in wireless sensor networks, identifying unique challenges and proposing a scalable framework. The solution leverages WSN characteristics for efficient reliability, validated via ns2 simulations. The research of Chen et al. [14] explores Reliability Improved Cooperative Communication (RICC), a novel data collection technique, in order to improve the reliability of cooperative communications based on random network coding in multi-hop relay WSNs. The recommended technique has improved reliability without compromising the network's total lifespan. Bogatyrev et al.[15] focus Cluster systems to enhance reliability and fault tolerance by consolidating resources, using duplicated nodes for load balancing or redundant calculations. Studies focus on improving cluster readiness for real-time requests, ensuring stable service traffic. Mismatched results trigger recalculations, optimizing performance and fault recovery. The research of Jin et al. [16] proposes a novel way to measure the dependability of WSN nodes through the utilization of both temporal and spatial correlation of the collected data. A disturbance analysis method that simulates disturbances experienced during node operation is used to create a data reliability evaluation model for WSN nodes. The model includes the evidence reasoning (ER) rule in an unpredictably changing environment. The model's effectiveness has been tested using wireless sensors at the Intel Berkeley research facility. The inclusion of disturbance analysis in the ER rule provides a practical technique to evaluate the reliability of WSN data. The goal of Zou et al. [17] study is to addresses distributed fault-tolerant consensus tracking for heterogeneous, switched nonlinear multi agent systems with unknown dynamics and topology. A novel protocol using fuzzy logic systems and Lyapunov methods ensures consensus despite actuator faults and arbitrary switching, validated by numerical simulations. The research of Rathee [18] offers an IoT-based artificial neural network for secure big data processing in multihoming networks using Bayesian Rule (BR) and Levenberg-Marquardt (LM) algorithms. It evaluates AI-assisted mechanisms through metrics like classification accuracy, time, sensitivity, specificity, ROC, and F-measure. The study addresses gaps in automated security and efficiency for multihoming big data processing, integrating IoT and AI for enhanced performance. In the area of complex social networks, Xu et al. [19] explores the challenges tied to ensuring dependability in mobile wireless sensor networks (MWSNs). The study focuses on key hurdles such as large-scale implementation, streamlined data processing, and delay tolerance in MWSNs. To tackle these challenges, researchers have introduced swarm intelligence-based bio-inspired optimization algorithms and advanced machine learning techniques. The paper also delves into various aspects of network reliability, including methods for evaluating topological robustness in industrial settings and predictive approaches for identifying potential failures in MWSNs.

.

3. Methodology

3.1 Basic concepts of fuzzy sets

In classical (crisp) set theory, an element either fully belongs or does not belong to a set. However, in fuzzy set theory, introduced by Lotfi Zadeh [20], elements can have partial membership in a set. This allows for representing uncertainty and vagueness in real-world scenarios where boundaries are not sharply defined.

A fuzzy set A in a universe of discourse is X defined as: $A = \{(x, \mu_A(x) | \in X\}$.

Where $\mu_A(x)$ is a of A,and $\mu_A(x) \in [0,1]$ degree of membership x of in A.

A fuzzy number $\tilde{A} = (a,b,c)$, where $a \le b \le c$ is called triangular fuzzy number (TFN) whose membership function $\mu_{\tilde{A}}(x): X \to [0,1]$ is as follows:

$$\mu_{\tilde{A}}(x) = \begin{cases} \dfrac{x-a}{b-a} & \text{if } a < x \le b \\ 0 & \text{if } x \le a \, or \, x \ge c \\ \dfrac{c-x}{c-b} & \text{if } b < x < c \end{cases}$$

3.2 Entropy Weighted Method

The concept of entropy was initially presented by the German scientist R. Clausius in 1865 [21, 22]. It indicates the disorder or insanity of a thermodynamic process and is a phase characteristic of matter. Shannon entropy measures the uncertainty or information content in a probability distribution. We have use Shannon entropy in this research to express uncertainty

Assume that $X = \left(x_{ij}\right)_{m \times n}$ be the decision matrix and $s = (s_1, s_2, ..., s_n)$, where $0 \le s_j \le 1$ and $\sum s_j = 1$ be the weight vector with regard to the m alternatives $A_i (i = 1, 2, ..., m)$ and n criterion $C_j (j = 1, 2, ..., n)$. Now, we can calculate the weight s_j, $j = 1, 2, ..., n$ using the following steps:

Step 1: Compute $T_{ij} = \dfrac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}$

Step 2: Compute $K_j = -\dfrac{1}{\log(m)} \sum_{i=1}^{m} x_{ij} \log(T_{ij})$.

It is to be that $T_{ij} \log T_{ij} \to 0$, when $T_{ij} \to 0$

Step 3: Compute $U_j = 1 - K_j$

Step 4: Compute $s_j = \dfrac{U_j}{\sum_{j=1}^{n} U_j} = \dfrac{1 - K_j}{\sum_{j=1}^{n} (1 - K_j)}$

3.3 Signal-to-Noise Ratio (SNR)

SNR is a fundamental concept in communication systems and signal processing [23–26]. It calculates the strength of a desired signal relative to the background noise of the system. SNR is commonly used to assess the accuracy and dependability of a signal transmission. SNR calculates the ratio between the strength of the unwanted noise and the beneficial signal. A greater signal-to-noise ratio (SNR) indicates a stronger, more reliable signal, whereas a lower SNR suggests a weaker, more susceptible to interference and distortion signal. SNR, which is often stated in decibels (dB), is calculated by dividing the signal power by the noise power. The following is the formula for SNR in dB:

$$SNR\_dB = 10 \times \log_{10}\left(\frac{P_{signal}}{P_{noise}}\right) \tag{1}$$

Where P_{signal} represents the power of the signal and P_{noise} represents the power of the noise. A higher SNR indicates better signal clarity, while a low SNR means more noise interference.

4. Symbols and notations

We have taken into account a WSN here under the following assertions:

- Every node in a square is dispersed equally and at random.
- Communication with the nodes that might be impacted by multi-path attenuation is made possible by the base station's positioning beyond the square's borders.
- Multi-path attenuation has no effect on node-to-node communication.
- The nodes are cohesive since they have the same capabilities and starting battery energy, but they also carry out distinct tasks at particular times.
- Each node in the network has the ability to communicate not only with the base station (BS) but also with any other node.
- The nodes remain static throughout the operation, which implies they are stationary and do not move.
- Each node perceives its environment and emits a signal of equal duration.
- The primary source of the unpredictability and fuzziness of the initial energy supply of nodes, the distance between sensor nodes and base stations, the size of the message, voltage metrics, transmission energy, and other aspects connected to sensor nodes is the hazardous and unpredictable natural environment. Table 1 lists the symbols used in this paper.

Table 1: list of symbols

Symbol	Description
$d\beta$	The base station's range

$d\beta_0$	The predetermined distance to the base station for measurement
(CL_{hx}, CL_{hy})	Co-ordinate of cluster head in a WSNs
$(\beta X_x, \beta X_y)$	Cluster head location in a WSNs base station
IN_{eng}	Basic energy
EE_{eng}	Electronics energy
EE_{DT}	Utilization of energy during transmission of information
λ_{fs}	Enhancement of energy to eradicate open space
λ_{mp}	Acceleration of energy to traverse the multi-path
EE_{DR}	Energy usage during data receiving
OP_{cl}	The ideal number of cluster heads
L_{Data}	Data length
$Node_N$	number of nodes overall in the network
KN	Node count in a cluster
M	Extend cover

5. System Model definition and formulation

The system infrastructure consists of a large number of sensor nodes and a single BS. All sensor nodes fall into one of two categories: CHs or common nodes. Common nodes are responsible for monitoring environmental data and transmitting the sensed data to the CHs. In order to function as the CH node, the common nodes are carefully selected. The data that the CHs get from the common nodes is compiled and sent to the BS.

A first-degree radio model serves as the foundation for the network's energy model. The only factor considered is the energy consumption during communication. The energy spent for data gathering, aggregation, and transmission is included in the total energy used. When a common node and a cluster head node exchange data of a certain size L_{Data}, the energy consumption can be determined using Equation 2.

$$EE_{DT}(L_{Data}, d\beta) = EE_{eng} * L_{Data} + \mu_{mp} * L_{Data} \tag{2}$$

$$EE_{DR}(L_{Data}) = EE_{eng} * L_{Data} \tag{3}$$

The energy used to transmit an L_{Data} -bit of data is designated as $EE_{DT}(L_{Data}, d\beta)$, and the energy used to receive that data is designated as $EE_{DR}(L_{Data})$. The energy consumption of the amplifier during the transmission phase can be calculated using Equation 2, where λ_{mp} is the amplifier's energy utilization during the transmitting phase.

$$\lambda_{mp} = \begin{cases} \lambda_{fs} d\beta^2 \text{ if } d\beta \le d\beta_0 \\ \lambda_{mp} d\beta^4 \text{ if } d\beta > d\beta_0 \end{cases} \tag{4}$$

The sensor node will employ the open-space propagation model if the distance value $d\beta$ is below a predetermined threshold value $d\beta_0$ or equal to it. Conversely, in scenarios where the system employs a multipath fading channel, Equation 5 can be employed to ascertain the $d\beta_0$ value by taking into account the communication energy parameters λ_{fs} and λ_{mp} .

$$d\beta_0 = \sqrt{\frac{\lambda_{fs}}{\lambda_{mp}}} \tag{5}$$

It's crucial to precisely count the network's cluster heads in order to increase WSN lifetime and energy efficiency. As a result of our research, we have determined the ideal cluster size, OP_{cl} [27], which is important for fulfilling the mentioned goals. Equation 6 uses to determine the optimal number of CHs which is given below:

$$OP_{cl} = \sqrt{\frac{\lambda_{fs}\, Node_N}{\pi(\lambda_{mp} d\beta_{toBS}^4 - EE_{eng})}} M \tag{6}$$

Here, M and $Node_N$ are denoted as the extent covered and quantity of nodes within the system.

6. Experimental Setup and Result

Clustering is one of the major issues when it concern with enhancing the lifetime of WSNs. In order to perform optimal clustering Hierarchical clustering has been applied in this research. The entire network has been divided into number of cluster based on the values of OP_{cl}. CHs selection in another issue which effects the WSNs life time. To find the CHs of each cluster we have implemented Algorithm 1 which takes residual energy, distance from the sink, SNR value and data accuracy into account. In our studies we have deployed 96 nodes over $100\text{X}100\,\text{m}^2$ area depicted in Figure 1 where BS is located in $(50,170)$ coordinate. The nodes are deployed randomly over the specific area.

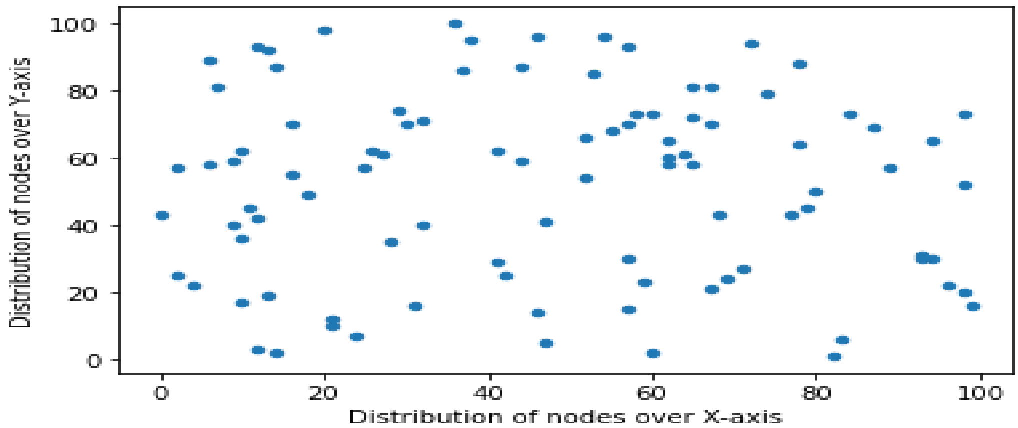

Figure 1: Distribution of 96 nodes over $100\text{X}100\,\text{m}^2$ network.

The total packet size is 77.5 bytes, with 22.5 bytes for the headers and 50 bytes for the core message. The channel's bandwidth is set to 1 Mb/s. BS refers to a node with increased computing power and no energy constraints. It has been discovered that unreliable or erratic connectivity may increase transmission noise and affect the batteries in sensor node nodes. Batteries directly affect residual energy, which reduces the network's longevity. Additionally, noisy data are a concern and require for greater careens. For replacement, the distance between the sensors, logic, and actuators is essential. As a result, we considered the following fuzzy parameters shown in Table 2.

Table 2: Simulation parameter with Defuzzified values

Parameters	**Assumed Parametric Value**	**Defuzzified Value**
$Node_N$	96[#]	96
IN_{eng}	(0.7, 0.9, 1.1) J/bit/m^2	0.9 J/bit/m^2
Coordinate of BS	(50,170)[#]	(50,170)
Size of the data packet	(495,500,510) byte	501.25 byte
Hello/broadcast/CH join message	(20,22.5,25) byte	22.5 bytes
λ_{fs}	(8,10,12) J/bit/m^2	10 J/bit/m^2
λ_{mp}	(0.002,0.0023,0.0025) J/bit/m^2	0.00227 J/bit/m^2
EE_{eng}	(47,50,51) J/bit/m^2	49.33 J/bit/m^2
OP_{cl}	9[#]	9

[#]Not considered as fuzzy valued.

To create cluster with optimize number of clusters we have use hierarchical clustering agglomerative approach [28-29]. Agglomerative clustering is a hierarchical clustering method that starts by treating each data point as an individual cluster. It then iteratively merges the closest pairs of clusters based on a chosen distance metric and linkage criterion like single, complete, or average linkage. The process continues until all data points are merged into a single cluster or until a stopping condition is met. The result is a dendrogram, a tree-like structure that visually represents the sequence of merges and the distances at which they occurred. This approach allows for flexibility in choosing the number of clusters by cutting the dendrogram at a desired level. Agglomerative clustering is useful for exploring nested groupings in data but can be computationally expensive for large datasets due to its O(n^3) time complexity. Figure 2 shows the distribution of 96 data points into OP_{cl} number of cluster using hierarchical clustering.

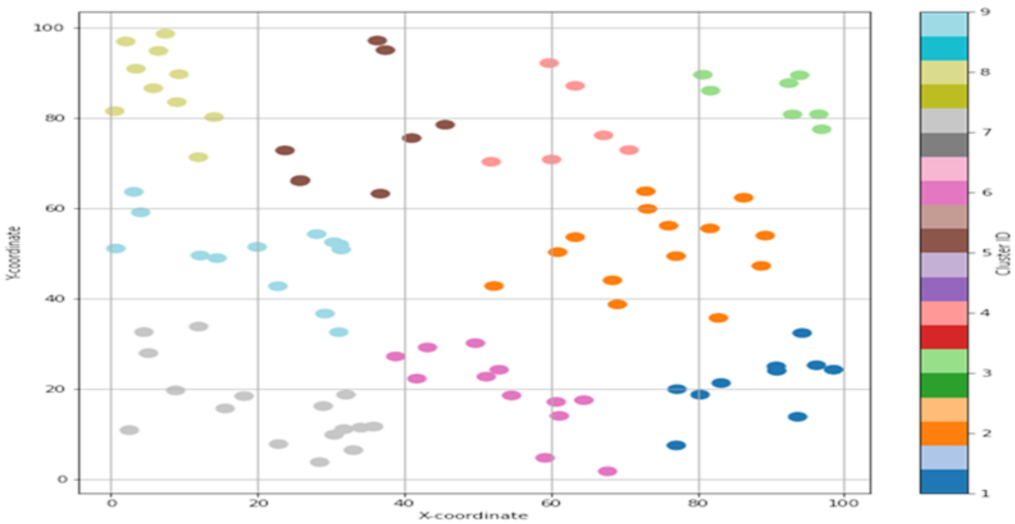

Figure 2: Using a hierarchical clustering technique 96 nodes has been clustered into 9 clusters

A dendrogram [30] is built to graphically represent the hierarchical structure of the clusters during the merging or splitting of clusters in hierarchical clustering. To understand the order of merges or splits about the clustering structure dendrogram is very helpful. Figure 3 shows the dendogram of the clusters depicted in Figure 2.

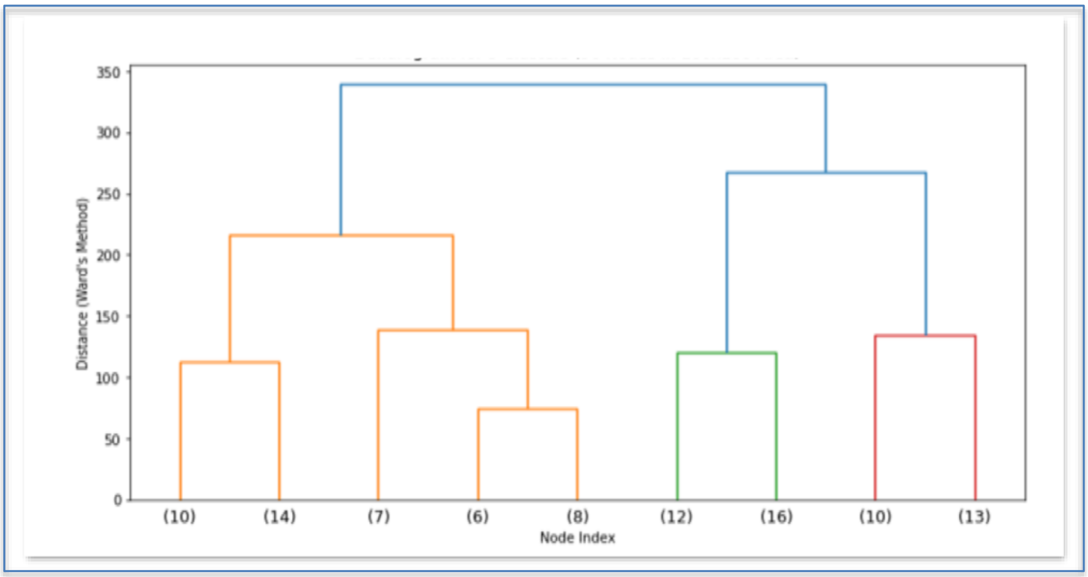

Figure 3: Dendogram of 96 nodes which has been used to create clusters using hierarchical clustering

The Beta Conditional Variance index [Beta CV] [31] is a cluster validity measure used to evaluate the quality of clustering results by assessing the compactness and separation of clusters. It compares the intra-cluster variance is how closely points are packed within a cluster to the inter-cluster variance is how well-separated different clusters are. The beta CV can be formulated as:

$$Beta\,CV = \frac{Intra\,Cluster\,Variance}{Inter\,Cluster\,Variance} = \frac{\frac{1}{N}\sum^{K}\sum d(x,y)}{\frac{1}{N(N-1)}\sum_{i=1}^{k}\sum_{j\neq i}\sum_{x\in C_i,\,y\in C_j} d(x,y)} \tag{7}$$

Where is a $d(x,y)$ distance metric.

In order to perform our experiment we have calculated the range of optimal cluster OP_{cl} using (6) and verified by equation 7. Here $\mathrm{Node}_N = 96$ nodes, $\mathrm{M} = 100\,\mathrm{m}$, $\lambda_{fs} = 10\,\mathrm{pJ}$ and $\lambda_{\mathrm{mp}} = 0.00227\,\mathrm{pJ}$. Here the calculated range of optimal cluster is in between 6 to 10. i.e., $6 < OP_{cl} < 10$. In our experiment we have choose the values of OP_{cl} as 9. To prove the value of OP_{cl} we have taken all the 96 nodes and validate the value using Beta CV value by using equation 7. Figure 4 demonstrate the scenario.

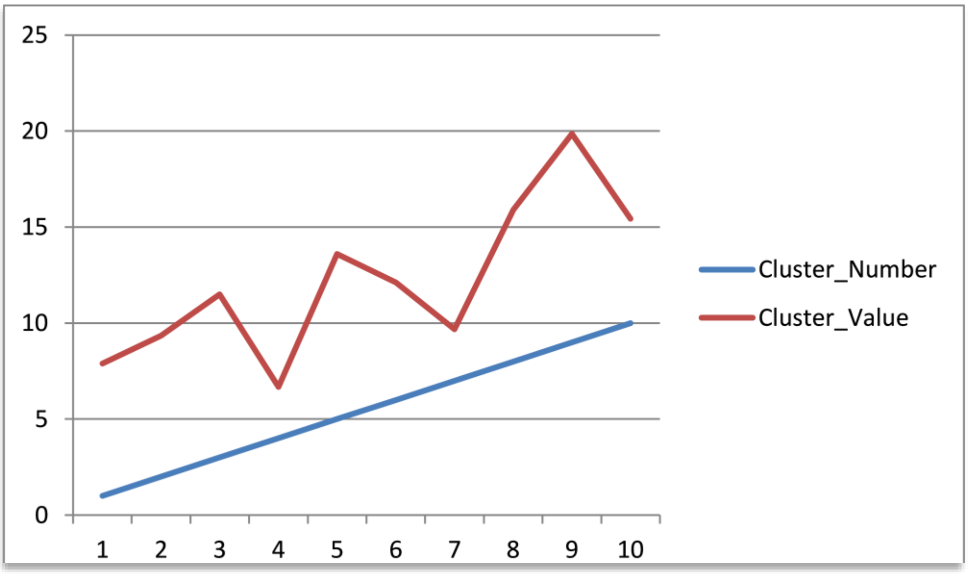

Figure 4: Maximum value of Beta CV index shows in cluster 9

In this study we have assumed the nodes in the network are not only connected to the BS also are also connected to each other via intermediate nodes. After clustering is being performed by the hierarchical clustering, nodes of same clusters will only be communicates to each other. Nodes of other clusters will terminate their connection. Once the CHs have been chosen the nodes may send the data to CHs directly or by the intermediate nodes which has been determined by shortest path algorithm. In this study we have calculate the path from source to CHs by using Floyd-Warshall algorithm [32-33]. The energy consumption in both scenarios has been compared before transmitting data either directly or through intermediate nodes [34-35]. The solution has been selected from the one with lower energy consumption. In order to choose the right CHs we have introduce a fitness function which takes parameters residual energy (β_1), distance from the Original Station (β_2), SNR Value (β_3) and average distance (β_4) into its account. The weight of each parameter has been calculated by entropy method which is shown in Table 3.

Table 3: Entropy weighted value of each parameter

Properties	β_1	β_2	β_3	β_4
Weight	0.1180	0.1182	0.3660	0.3378

Once the weight has been calculated by using entropy method equation 7 can be used to find the fitness values of each node. Nodes with highest fitness values with respect to each cluster have been selected as CHs by using equation 8.

$$F^{i}_{fitness}(\beta_1,\beta_2,\beta_3,\beta_4) = \beta_1\,(\text{residual energy}) + \frac{\beta_2}{(\text{dist from station})} + \beta_3\,(\text{SNR}) + \beta_4\,(Avg\ Distance) \quad (7)$$

Table 4 shows the CHs with all their parameter values and Table 5 contains the CHs with respect to their fitness values.

Table 4: 9 cluster head with respect to their all parameter values

Cluster Head	**Distance from Base Station**	**SNR Value(dB)**	**Average Distance**	**Residual Energy**
CH1	75.120	17	2.87	0.8733
CH2	89.381	16	1.91	0.8685
CH3	68.712	12	3.96	0.8712
CH4	65.008	15	1.89	0.8622
CH5	90.249	13	2.73	0.8739
CH6	66.658	11	4.90	0.8545
CH7	92.802	12	3.91	0.8648
CH8	45.688	11	4.24	0.8719
CH9	43.880	16	2.96	0.8650

Table 5: Cluster Head with their Fitness values

Cluster Head	CH1	CH2	CH3	CH4	CH5	CH6	CH7	CH8	CH9
Fitness Values	0.4978	0.4966	0.4967	0.4950	0.4952	0.4956	0.4948	0.4942	0.4933

Node selection criteria

Using a hierarchical clustering agglomerative approach, all nodes must be part of the cluster in order to choose the right CHs. Equation 7 was used to choose CHs, and algorithm 1 was used to select the CHs for the next round. The algorithm was written in Python for the purpose of creating clusters, and it was run on Linux using a Python Jupiter notebook (Version: 3). In the first simulation round, all nodes sent their data to BS, which was implemented by Network Simulator 2 (NS2) to determine the values of all parameters. We have now implemented our proposed algorithm (Lifetime Extension algorithm) to extend the life time of WSNs given below.

Lifetime extension algorithm:

Step 1**:** 96 number of nodes has been positioned randomly over $(100,100)\text{m}^2$ area with BS $(50,170)$ coordinates.

Step 2: The CHs chosen by Cluster Head selection algorithm will forward the information to the BS for the second and following rounds.
Step 3: Continue steps 4 through 10 until none of the nodes' remaining energy is being reduced.
Step 4: The counter is raised when the node's value surpasses that of every other node in the cluster based on a comparison of each node's residual energy to the other nodes.
Step 5: The counter is raised when the node's value surpasses that of every other node in the cluster when comparing each node's distance from the BS to the other nodes.
Step 6: A counter is raised when the SNR value of a node surpasses that of every other node in the cluster after comparing each node's value to those of the other nodes.
Step 7: Each node's data accuracy value is compared to all other nodes in the cluster, and when a node's value is higher than all other nodes', the counter is raised.
Step 8: The CHs for the following round are the nodes with the highest counter values.
Step 9: If a cluster has fewer than three nodes, nodes will be added to the closest cluster based on each cluster's reliability.
Step 10: Jump to next round.
Step 11: Stop.
C++ was used to code the WSNs lifespan extension algorithm, and Python was used to implement the outcome. The remaining energy of every node has been found to decrease after 2132 rounds. An illustration of the scenario is shown in Figure 5.

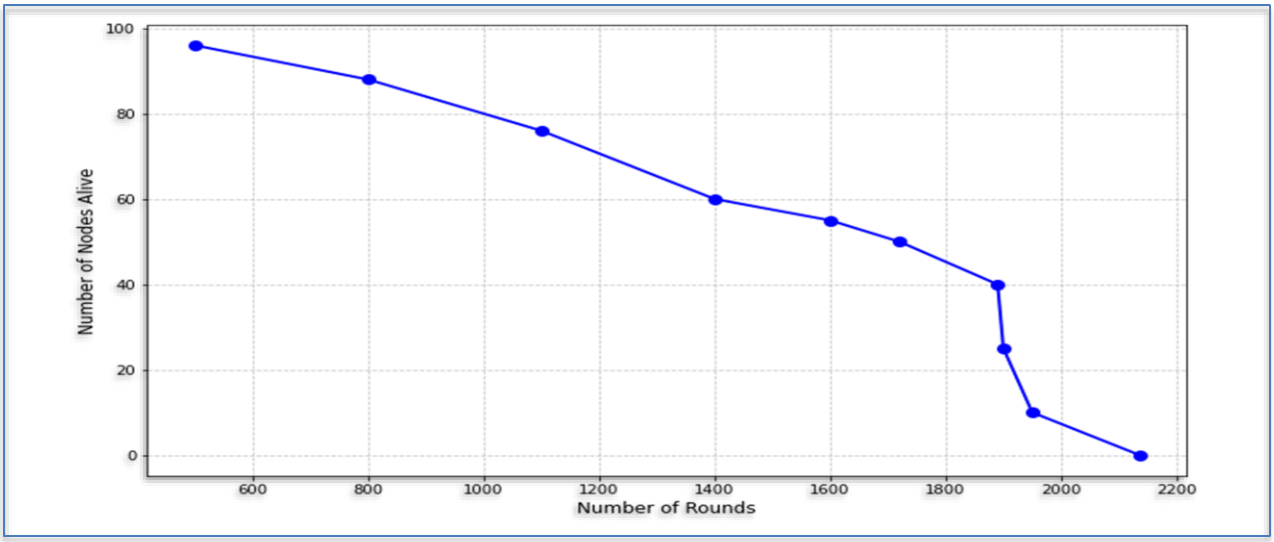

Figure 5: Number of Rounds vs. Number of Nodes alive

LEACH-FC (LEACH-Fuzzy Clustering) [36] and LEACH are two key protocols in Wireless Sensor Networks (WSNs) designed to enhance energy efficiency and extend network lifetime. While LEACH serves as the foundational protocol using probabilistic cluster head selection, LEACH-FC introduces significant improvements by integrating fixed cluster heads and fuzzy logic-based decision-making The main improvements in Leach-C include (a) Fixed Cluster-heads (b) Fuzzy Logic-based Cluster Head Selection (c) Reduced Energy Consumption (d) Increased Data Transmission Efficiency. In this study it has been found that our proposed approach shows greater network lifetime as compare with LEACH and LEACH-FC protocol. Our proposed approached shows 21% and 10% more network lifetime with respect to LEACH and LEACH-FC protocol which has been demonstrated in Figure 5.

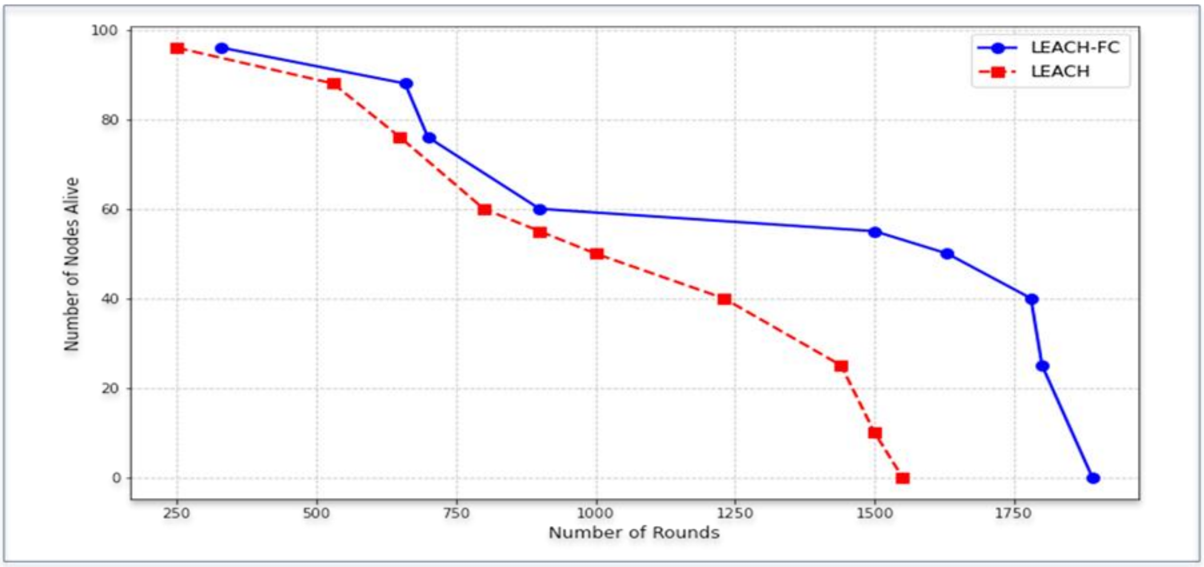

Figure 5: Number of Rounds vs. Number of Nodes alive

Therefore, the overall time complexity of the algorithm is approximately $\Theta(OP_{cl}K^2 + \xi_1)$ or simplified as $\Theta(OP_{cl}K^2)$.

We conducted a statistical hypothesis test using the following hypotheses in order to validate the results:

Null Hypothesis (H_0): The average number of simulation runs falls between 1990 and 2230, which is the 95% confidence interval.

Alternate Hypothesis (H_1): The number of simulation iterations Lies outside the 95% Confidence Interval.

We set the significance level at $\alpha_1 = 0.05$, and T represents a random variable following the t-distribution. The 95% confidence interval is [1990, 2230]. The simulation was repeated 50 times, and the average result obtained was 2130. Using statistical calculations, we have determined T–$Score$ is 0.4219 and p (the probability of T being greater than 0.4219) is 0.7968.

Since ($p > \alpha_1 = 0.05$), we do not have sufficient evidence to reject the null hypothesis (H_0).Hence, it can be deduced that the average number of simulation iterations lies within the 95% confidence interval.

4. Conclusions

In this research, the studies on the selection of entropy weight CHs on WSNs that concentrate on cluster formation with appropriate CHs have produced encouraging findings. The fitness function, which takes into account factors like (i) residual energy, (ii) distance from the sink, (iii) SNR, and (iv) average distance, has established the importance of particular nodes within the network. The weight of each parameter that constitutes the fitness function is determined by applying the entropy-weighted technique. This novel approach makes it possible to choose a dependable cluster while preserving the network's stability, efficient data transfer, and energy efficiency. The results demonstrate that this strategy greatly increases the network's lifespan, providing a noteworthy 20% and 10% increase over conventional LEACH and contemporary LEACH-FC methods, as illustrated in Figure 5. This methodology can be used to real-world situations because it is also designed to be easily understood. The node location was considered to be two dimensions in this study [37], however it is actually multidimensional and not covered in this work. Only few factors have been considered in the selection of CHs, ignoring several others that might affect the network's lifetime. When there is an obstruction between two nodes, the lifespan extension algorithm that selects the distance from the sink as a crucial parameter will not function correctly. It is necessary to implement a new algorithm that takes into account the obstruction between the two nodes. In order to increase the network's lifetime, the proposed method may be used in subsequent studies to discover CHs utilizing multi-criteria decision making. The algorithm that was suggested in this study could be the subject of future research because of its very high level of complexity. In this proposed research only free path propagation model has been chosen someone can use other model for propagation.

References

1. Ayaz, M., Ammad-Uddin, M., Sharif, Z., Mansour, A. and Aggoune, E.H.M., 2019. Internet-of-Things (IoT)-based smart agriculture: Toward making the fields talk. IEEE access, 7, pp.129551-129583.
2. Pachauri, G. and Sharma, S., 2015. Anomaly detection in medical wireless sensor networks using machine learning algorithms. Procedia Computer Science, 70, pp.325-333.
3. Moreno Escobar, J.J., Morales Matamoros, O., Tejeida Padilla, R., Lina Reyes, I. and Quintana Espinosa, H., 2021. A comprehensive review on smart grids: Challenges and opportunities. Sensors, 21(21), p.6978.
4. Du, R., Chen, C., Yang, B., Lu, N., Guan, X. and Shen, X., 2014. Effective urban traffic monitoring by vehicular sensor networks. IEEE transactions on Vehicular Technology, 64(1), pp.273-286.
5. Al-Fuqaha, A., Guizani, M., Mohammadi, M., Aledhari, M. and Ayyash, M., 2015. Internet of things: A survey on enabling technologies, protocols, and applications. IEEE communications surveys & tutorials, 17(4), pp.2347-2376.
6. Palan, N.G., Barbadekar, B.V. and Patil, S., 2017, January. Low energy adaptive clustering hierarchy (LEACH) protocol: A retrospective analysis. In 2017 International conference on inventive systems and control (ICISC) (pp. 1-12). IEEE.
7. Priyadarshi, R., Singh, L. and Singh, A., 2018, February. A novel HEED protocol for wireless sensor networks. In 2018 5th international conference on signal processing and integrated networks (SPIN) (pp. 296-300). IEEE.
8. Ye, M., Li, C., Chen, G. and Wu, J., 2005, April. EECS: an energy efficient clustering scheme in wireless sensor networks. In PCCC 2005. 24th IEEE International Performance, Computing, and Communications Conference, 2005. (pp. 535-540). IEEE.
9. Lindsey, S. and Raghavendra, C.S., 2002, March. PEGASIS: Power-efficient gathering in sensor information systems. In Proceedings, IEEE aerospace conference (Vol. 3, pp. 3-3). IEEE.
10. Manjeshwar, A. and Agrawal, D.P., 2001, April. TEEN: ARouting Protocol for Enhanced Efficiency in Wireless Sensor Networks. In ipdps (Vol. 1, No. 2001, p. 189).
11. Sen, S., Sahoo, L., Tiwary, K., Simic, V. and Senapati, T., 2023. Wireless Sensor Network Lifetime Extension via K-Medoids and MCDM Techniques in Uncertain Environment. Applied Sciences, 13(5), p.3196.
12. Kabashkin, I., 2019. Reliability of cluster-based nodes in wireless sensor networks of cyber physical systems. *Procedia computer science*, *151*, pp.313-320.
13. Park, S.J., Vedantham, R., Sivakumar, R. and Akyildiz, I.F., 2007. GARUDA: Achieving effective reliability for downstream communication in wireless sensor networks. *IEEE Transactions on Mobile Computing*, *7*(2), pp.214-230.
14. Chen, Z., Ma, M., Liu, X., Liu, A. and Zhao, M., 2017. Reliability improved cooperative communication over wireless sensor networks. Symmetry, 9(10), p.209.

15. Bogatyrev, V.A., Bogatyrev, S.V. and Sivov, V.V., 2023, March. Reliability of a Cluster of Duplicated Computer Systems with the Criticality of Functional Requests to Waiting. In *2023 International Russian Smart Industry Conference (SmartIndustryCon)* (pp. 136-140). IEEE.
16. Jin, S., Xie, Y., Gao, Y., Zhou, G., Zhang, W., Tang, S. and He, W., 2021. Data Reliability Analysis of Wireless Sensor Nodes considering Perturbation. Journal of Sensors, 2021, pp.1-15.
17. Zou, W., Ahn, C.K. and Xiang, Z., 2020. Fuzzy-approximation-based distributed fault-tolerant consensus for heterogeneous switched nonlinear multiagent systems. *IEEE Transactions on Fuzzy Systems*, *29*(10), pp.2916-2925.
18. Rathee, G., Khelifi, A. and Iqbal, R., 2021. Artificial Intelligence-(AI-) Enabled Internet of Things (IoT) for Secure Big Data Processing in Multihoming Networks. *Wireless Communications and Mobile Computing*, *2021*(1), p.5754322.
19. Xu, X., Tang, J. and Xiang, H., 2022. Data Transmission Reliability Analysis of Wireless Sensor Networks for Social Network Optimization. Journal of Sensors, 2022, pp.1-12.
20. Yao, J.S. and Wu, K., 2000. Ranking fuzzy numbers based on decomposition principle and signed distance. Fuzzy sets and Systems, 116(2), pp.275-288.
21. Chen, C.H., 2020. A novel multi-criteria decision-making model for building material supplier selection based on entropy-AHP weighted TOPSIS. Entropy, 22(2), p.259.
22. Sahoo, L., Sen, S.S., Tiwary, K., Moslem, S. and Senapati, T., 2024. Improvement of wireless sensor network lifetime via intelligent clustering under uncertainty. *IEEE Access*, *12*, pp.25018-25033.
23. Welvaert, M. and Rosseel, Y., 2013. On the definition of signal-to-noise ratio and contrast-to-noise ratio for fMRI data. PloS one, 8(11), p.e77089.
24. Papadopoulos, P., Tsiartas, A., Gibson, J. and Narayanan, S., 2014, May. A supervised signal-to-noise ratio estimation of speech signals. In 2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP) (pp. 8237-8241). IEEE.
25. Zhan, J., Gurung, S. and Parsa, S.P.K., 2017. Identification of top-k nodes in large networks using katz centrality. Journal of Big Data, 4(1), pp.1-19.
26. Sharkey, K.J., 2017. A control analysis perspective on Katz centrality. Scientific reports, 7(1), p.17247.
27. Heinzelman, W.B., Chandrakasan, A.P. and Balakrishnan, H., 2002. An application-specific protocol architecture for wireless microsensor networks. IEEE Transactions on wireless communications, 1(4), pp.660-670.
28. Li, T., Rezaeipanah, A. and El Din, E.M.T., 2022. An ensemble agglomerative hierarchical clustering algorithm based on clusters clustering technique and the novel similarity measurement. Journal of King Saud University-Computer and Information Sciences, 34(6), pp.3828-3842.
29. Patel, S., Sihmar, S. and Jatain, A., 2015, March. A study of hierarchical clustering algorithms. In 2015 2nd international conference on computing for sustainable global development (INDIACom) (pp. 537-541). IEEE.
30. Haghir Chehreghani, M. and Haghir Chehreghani, M., 2020. Learning representations from dendrograms. Machine Learning, 109(9-10), pp.1779-1802.
31. Liu, Y., Li, Z., Xiong, H., Gao, X. and Wu, J., 2010, December. Understanding of internal clustering validation measures. In *2010 IEEE international conference on data mining* (pp. 911-916). Ieee.
32. Sahoo, L., Sen, S., Tiwary, K., Samanta, S. and Senapati, T., 2022. Modified floyd–warshall's algorithm for Maximum connectivity in wireless sensor networks under uncertainty. Discrete Dynamics in Nature and Society, 2022.
33. Khan, P., Konar, G. and Chakraborty, N., 2014, December. Modification of Floyd-Warshall's algorithm for Shortest Path routing in wireless sensor networks. In 2014 Annual IEEE India Conference (INDICON) (pp. 1-6). IEEE.
34. Sen, S., Sahoo, L. and Ghosh, S.L., 2024. Lifetime extension of wireless sensor networks by perceptive selection of cluster head using K-means and Einstein weighted averaging aggregation operator under uncertainty. *J. Ind. Intell.*, *2*(1), pp.54-62.
35. Sahoo, L., Sen, S., Tiwary, K., Samanta, S. and Senapati, T., 2022. Optimization of data distributed network system under uncertainty. *Discrete Dynamics in Nature and Society*, *2022*(1), p.7806083..
36. Lata, S., Mehfuz, S., Urooj, S. and Alrowais, F., 2020. Fuzzy clustering algorithm for enhancing reliability and network lifetime of wireless sensor networks. IEEE Access, 8, pp.66013-66024.
37. Sen, S., Sahoo, L., Tiwary, K. and Senapati, T., 2023, October. Entropy Weighted TOPSIS Based Cluster Head Selection in Wireless Sensor Networks under Uncertainty. In *telecom* (Vol. 4, No. 4, pp. 678-692). MDPI.