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CLUSTERING OPTIMIZATION BASED ON FUZZY LOGIC FOR WIRELESS SENSOR NETWORKS

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Master’s Thesis

Supervisor

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DEDICATION

I would like to dedicate this work to my first teacher, my mother, my first supporter and role model, my father and my companion throughout the journey. Without you, this dream would never come true and to my brother and my sister who stood with me in order to achieve my dream.

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ABSTRACT

CLUSTERING OPTIMIZATION BASED ON FUZZY LOGIC FOR WIRELESS SENSOR NETWORKS

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Clustering is a powerful technique that organizes the process of the system to confirm network scalability, reduces the consumed energy, as well as realizes the network lifetime extension. The clustering routing algorithm is commonly utilized within wireless sensor networks (WSNs) due to its high-energy efficiency and scalability. The energy source in WSNs may be restricted to the battery's ability of the sensor nodes. As transmission energy is proportional to the distance that exists separating a sender to receiver, clustering in WSN can assist reduce energy usage. Data may be sent from any sensor node to corresponding Cluster Head (CH) for efficient information gathering. There is a need for maximizing the WSNs lifetime, optimization of network operation is crucial. The suggesting clustering algorithm is applied to enhance the lifetime of WSNs by selecting cluster heads (CHs) and forming clusters.

Researchers have developed Fuzzy Logic (FL) to address the issue of overburdening Cluster Head (CH) during cluster formation in WSN. FL focuses on the CH efficiency, distributing load between sensor nodes for enhancing lifetime of network. The proposed protocol fuzzy logic based-clustering (FLB-CLS) outperforms FD-LEACH and OC-FCM, regarding network lifetime and throughput, also improving advance for networks that have higher node density. Each sensor node calculates the probability of CH using a distributed fuzzy inference system. For various network sizes and topologies, the results of simulation specify enhancements in energy efficiency as a result of network lifetime along with consumed energy balancing across sensor nodes. with concerning to first node dead along with total node dead, results demonstrate an average improvement.

Keywords: FD-LEACH, Cluster Head, FD-LEACH, CHs, OC-FCM.

ÖZET

KABLOSUZ SENSÖR AĞLARI İÇİN BULANIK MANTIK TEMELLİ KÜMELEME OPTİMİZASYONU

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Kümeleme, ağ ölçeklenebilirliğini doğrulamak, tüketilen enerjiyi azaltmak ve ağ ömrünü uzatmak için sistemin sürecini düzenleyen güçlü bir tekniktir. Kümeleme yönlendirme algoritması, yüksek enerji verimliliği ve ölçeklenebilirliği nedeniyle kablosuz sensör ağlarında (KSA'lar) yaygın olarak kullanılır. KSA'lardaki enerji kaynağı, sensör düğümlerinin pil kapasitesiyle sınırlı olabilir. İletim enerjisi, bir göndericiyi alıcıya ayıran mesafeyle orantılı olduğundan, KSA'lardaki kümeleme enerji kullanımını azaltmaya yardımcı olabilir. Veriler, verimli bilgi toplama için herhangi bir sensör düğümünden karşılık gelen Küme Başına (CH) gönderilebilir. Kablosuz Sensör Ağlarının ömrünü en üst düzeye çıkarma ihtiyacı vardır, ağ operasyonunun optimizasyonu çok önemlidir. Önerilen kümeleme algoritması, küme başlarını (CH'ler) seçerek ve kümeler oluşturarak Kablosuz Sensör Ağlarının ömrünü artırmak için uygulanır.

Araştırmacılar, Kablosuz Sensör Ağlarında (WSN) küme oluşumu sırasında Küme Başının (CH) aşırı yüklenmesi sorununu ele almak için Bulanık Mantık (FL) geliştirdiler. FL, yükü sensör düğümleri arasında dağıtarak ağın ömrünü artırmak için CH verimliliğine odaklanır. Önerilen protokol bulanık mantık tabanlı kümeleme (FLB-CLS), ağ ömrü ve verimi açısından FD-LEACH ve OC-FCM'den daha iyi performans gösterir ve ayrıca daha yüksek düğüm yoğunluğuna sahip ağlar için ilerlemeyi iyileştirir. Her sensör düğümü, dağıtılmış bulanık çıkarım sistemi kullanarak CH olasılığını hesaplar. Çeşitli ağ boyutları ve topolojileri için, simülasyon sonuçları, ağ ömrü ve sensör düğümleri arasında tüketilen enerji dengelemesi sonucunda enerji verimliliğindeki iyileştirmeleri belirtir. İlk düğümün ölümüyle birlikte toplam düğüm ölümüyle ilgili olarak, sonuçlar ortalama bir iyileşme göstermektedir.

Anahtar Sözcükler: FD-LEACH, Küme Başı, FD-LEACH, CH'ler, OC-FCM.

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INTRODUCTION

1.1 INTRODUCTION

Clustering Clustering optimization in Wireless Sensor Networks (WSNs) considers a significant problem to address for efficient data gathering and network management. Fuzzy logic can be employed as a technique to optimize clustering in WSNs.

WSNs have appeared as a prominent technology related to wide range application, covering environmental monitoring, surveillance, healthcare, and industrial automation. In WSNs, huge numbers of sensor nodes are positioned in a geographical area to collectively sense, process, and transmit data from the monitored environment. However, due to the restricted resources of sensor nodes, such as energy, handling capability and bandwidth, efficient data gathering and network management become critical challenges.

In this kind of network, the development of clusters or networks aids in the decrease of energy consumption throughout data transmission, particularly when considering sustainability and resilience [1]. For a result, when clustering is performed easily, the network self-sufficient lifetime (no need to replace the nodes' batteries) may be increased. A node within a cluster known as a Cluster Head (CH), it considers in charge for communicating with any additional CHs or the Base Station. The node collects all data from the nodes in its cluster, aggregates it, then sends it to the base station (BS). Based on the data, a base station or sink chooses what to do. The BS may decide centrally that certain nodes are the CHs, or the sensor nodes may decide in a distributed manner. As more information may be employed to effectively generate the clusters, centralized clustering algorithms have shown to have better behaviour than their distributed counterparts [2].

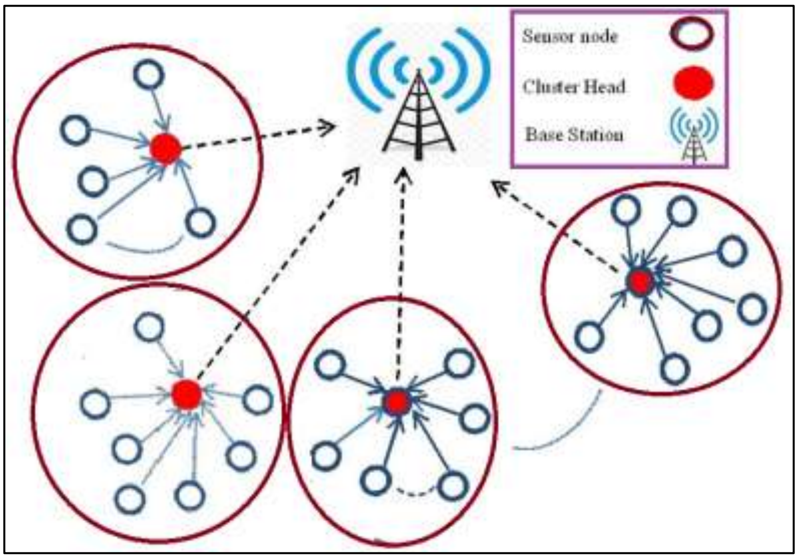


Figure 1.1: General Structure Of Wsns.

The duration for which the cluster structure will be maintained is a crucial clustering-related topic. Initial recommendations for clustering algorithms stated that new clusters should arise on a regular basis. They choose to decide on the CHs in each round, in particular. The temporal unit into which the network lifespan is split is known as a round. Sending the measurements to the BS involves sequential inter-cluster communication, data collection, and intra-cluster communication. As a result, the first concepts (such as LEACH-C [3]) had the CHs being determined at the start of each cycle.

Clustering is an effective technique employed in WSNs to enhance network performance by organizing sensor nodes into groups or clusters. In a clustered WSN, one or more sensor nodes are selected as cluster heads have a responsibilty for collecting data related to cluster participants so as to transmit it to the sink node. Clustering offers several advantages, including reduced energy consumption, improved scalability, efficient data aggregation, and enhanced network lifetime.

However, reaching optimal clustering within WSNs considers a complex task due to various factors such as node heterogeneity, dynamic network conditions, and the need for balancing consumed energy through the network. Clustering optimization aims to further enhance the performance of WSNs by optimizing the selection and formation of clusters. The goal is to determine the optimal configuration of clusters that maximizes network efficiency, minimizes energy consumption, and achieves other desired objectives. Traditional clustering algorithms, like LEACH (Low-Energy Adaptive Clustering Hierarchy) and HEED (Hybrid Energy-Efficient Distributed), use heuristics or randomization techniques for 8y the most efficient clustering scheme.

So as to overcome these limitations, intensive efforts have been given in the literature toward clustering optimization and a interest of research focused on employing some optimizers like fuzzy logic algorithm for improving network cluster members concerning WSNs. Fuzzy Set Logic offer an efficient framework to cope with uncertainty and imprecision, rendering it a successful means for clustering optimization in WSNs [4]. Fuzzy theory is an option to add linguistic variables and fuzzy rules for the management of that specific decision in cluster formation. Fuzzy logic traits makes it possible to model more subtle relationships between the input parameters and desired clustering outcomes, leading to an easier way of handling piece-wise cluster optimization results.

This thesis seeks to examination the application of fuzzy logic for optimization in WSNs. We depict a fuzzy logic approach to achieve high adaptability and effeciency using various factors including node density, remnaing energy, communication distance etc... along with network topology. The proposed approach for optimizing fuzzy logic clustering will be evaluated, compared with existing algorithms on several performance metrics like network lifetime, energy consumed and rate of data aggregation.

To sum up, the objective of this dissertation is to investigate and exploit a novel method for cluster head optimization by utilizing fuzzy logic for wireless sensor networks. Insights derived from these experimental results may be valuable for designing and developing the better clustering mechanisms that can operate more efficiently in adaptive manner, which will go on to improve the overall performance of WSN applications.

In WSNs, clustering is a well known effectiveness technique used for addressing many issues. The method in which sensor nodes are classified with the help of a technique known as clustering, In this sense one node among them is selected and it will act like Cluster Head (CH) to collect data from member nodes within that cluster. It reduces energy consumption, improves network scalability and data aggregation efficiency while extending the life of the network.

This investigating and proposing of a clustering optimization approach utilizing fuzzy logic for WSNs is targeting this thesis. We aspire towards building a fuzzy logic controlled decision making framework that shall improve clustering performances for efficient data communication, power consumption and network lifetime. Multiple parameters will be considered in the proposed approach and incorporate an optimization algorithm to search for near-optimal clustering configurations. The suggested approach's performance will be assessed through simulations and also compared through many remaining clustering algorithms.

1.2 BACKGROUND

Recently, WSNs have gained significant attention owing to their potential to enable pervasive monitoring and data collection in various domains. It involved of a huge tiny numbers, resource-constrained sensor nodes organizing in a targeted area for monitoring environmental and physical conditions. These nodes collaborate to accumulate data, process, then transmit to a essential base station or sink node.

Clustering is a fundamental technique applied in WSNs for bring together all sensor nodes into logical groups or clusters. Each one typically involves cluster head (CH) serves as a director for the cluster and handles communication through base station [5]. It collects and aggregates data from the member nodes, performs data fusion or compression, and transmits an aggregated data toward base station, so decreases the overall communication overhead in the network.

Clustering offers several advantages in WSNs [6]. First, it helps in balancing their energy consumed among sensor nodes by selecting heads that consider responsible for data fusion and transmission, while other nodes can conserve their energy by communicating only with the CH. Second, clustering provides a hierarchical structure that improves network scalability, as data from many nodes will be efficiently collected and transmitted to the base station. Third, it enables spatial and sequential correlations among sensor data, which have been exploiting for efficient data processing, event detection, and decision-making.

Various clustering algorithms have been planned with WSNs, for example LEACH, HEED, and PEGASIS . These algorithms typically rely on heuristics or predefined thresholds to select cluster heads, often established at issues of residual energy, proximity of base station, or node density. However, these traditional approaches may not consider the dynamic nature of the network, individual node characteristics, or the trade-off between different performance metrics.

To address the limitations of traditional clustering algorithms, there is a growing interest in leveraging optimization techniques to enhance clustering in WSNs. Optimization aims to discover the greatest promising solution from a set of feasible solutions, considering multiple objectives and constraints. The process of optimization, in fact it has to balance between discovering the optimal solution within a set full of viable ones and multiple objectives along with constraints. Among these algorithms, optimization-based clustering solutions seek near-optimal configurations for each given metric: Neworks lifetime maximization [7], energy consumption minimization or network coverage and load balance positioning anlaysis[.

Fuzzy logic is one of the most important optimization method with several pragmatic issues like wsn etc. Fuzzy logic allows reasoning with uncertainty, imprecision based on using linguistic variables and fuzzy rules. Clustering optimization using fuzzy logic techniques can be applied for WSNs to gain the advantages of intelligent decision-making based on a wide range of parameters (residual energy levels, node density, communication distance-network topology). Finally, fuzzy logic-based clustering optimization aims to find an optimal or nearly optimal cluster configurations that minimize energy consumption while maximizing network lifetimeand global networks performance.

Due to the merits and features of fuzzy logic-based clustering in WSNs optimization, this dissertation is set out to explore a new methodology which applies fuzzy logic techniques for optimizing cluster formation in WSNs. The envisioned solution will take into account different contexts, design relevant membership functions and fuzzy rules; then combined with optimization algorithms to explore for optimal or near-optimal clusters configurations. Afterward through simulations, its performance is checked by comparing with already available clustering algorithms and proving that it can improve the network efficiency and utilization of resources.

1.3 PROBLEM STATEMENT

Wireless Sensor Networks (WSNs) have to meet various requirements like energy efficiency, perfect scalability and data aggregation. Clustering is an efficient approach to solve these problems in which sensor nodes are grouped together or combined with them. But, the traditional clustering algorithms uses simple methods for CH selection without considering dynamic nature of network or nodal properties. Such a situation leads to non-optimal clustering configurations that in turn negatively affect the energy consumption, network lifetime and over all network performance.

In order to cope up with these limitations, it is necessary to improve the process of clustering in WSNs by using multiple parameters as input and applying intelligent decision-making techniques. Considering that fuzzy logic is an established soft computing approach showing capabilities of adaptability and flexibility in decision-making tasks across different sectors, it deserves attention as another potential alternative for clustering optimization within WSNs. Nevertheless, there is any research gap in the area of using fuzzy logic based et al. for cluster optimization and WSNs [9].

Besides, traditional clustering algorithms cannot deal with the uncertainty and imprecision in WSNs. A more intelligent and adaptive approach for cluster formation: A lot of decision-making is involved in forming clusters and selecting the CH Finding out suitable CRs which can turn into a good cluster head, takes place on certain parameters fixed static or dynamically based upon network conditions [10].

Consequently, the addressing issue addressed in this text is a way for clustering to be optimal among deployments of WSNs while on fuzzy logic. Objective: The objective of this study is to design a fuzzy logic-based decision-making framework for the efficient clustering in WSNs and which results in better energy consumption, energy efficiency as well the network life time. Challenge ready to be addressed are like:

a. The selection of cluster heads by the existing clustering algorithms is mostly based on some predefined criteria or heuristics that may not be able to accommodate changing node capabilities and network conditions correctly. Flexibility and thought should be combined to formulate a comprehensive yet thoughtful mechanism in cluster head election considering communication distance, node density as well as the remaining energy within each sensor.

b. Lack of Adaptability and Flexibility: Many traditional clustering methods apply fixed parameters or thresholds that are not suitable for diverse WSN scenarios. The challenge is to construct a clustering optimization strategy that adapts according to the network conditions, node attributes and application requirements.

c. Energy Unequal Distribution and Short Network Lifetime: Poor clustering may lead to a distribution of energy sources among the nodes within., by draining more rapidly than others. It has the challenge to develop an optimization strategy that maximizes data collection efficiency and balances energy consumption in a network extending its life.

d. On account of variable environmental conditions and sensor readings, the WSNs suffer uncertainties which affect decision-making processes. The challenge lies in how to establish a fuzzy logic rule based on clustering so as to reflect the modeling of uncertainties into decision-making, i.e. optimization for cluster result.

These challenges can be solved which results in more efficient clustering to improve energy utilization, network lifetime, data aggregation and performance of the overall WSN. The proposed optimization method that is based on fuzzy logic will offer a versatile and adaptive base for clustering in WSNs, supporting simultaneous parameters as well with network conditions to actualize the best cluster formations along with optimal CH selections.

Therefore, the problem addressed in this thesis is:

How can clustering optimization in WSNs be improved using fuzzy logic-based decision-making techniques?

This problem encompasses the following sub-questions:

a. How can fuzzy logic be utilized to model uncertainties and optimize clustering decisions in WSNs?

b. Which parameters should be considered for clustering optimization, and how can their relevance be captured using fuzzy membership functions?

c. How can fuzzy rules be formulated to determine form of the cluster in addition to choose the cluster head founded in the input parameters?

d. How can an optimization algorithm be integrated with the fuzzy logic-based approach to search for near-optimal clustering configurations?

e. What are the performance implications of the proposed fuzzy logic-based clustering optimization approach compared to existing clustering algorithms?

By attempting to solve questions, this thesis purposes to contribute to the development of an intelligent clustering optimization approach using fuzzy logic for WSNs. The effectiveness and efficiency of the planned approach may be evaluated through simulations, and then a performance comparison made with existing clustering algorithms. Ultimately, there is an improvement in energy efficiency, network scalability, and WSNs network lifetime through intelligent clustering optimization using fuzzy logic.

1.4 THESIS ORGANIZATION

The rest of this thesis is prepared as follows: Chapter 2 provides an overview of WSNs, highlighting the importance of clustering in these networks. It introduces fuzzy logic and its application in WSNs. Chapter 3 discusses the challenges and existing techniques for clustering optimization in WSNs. This work investigates optimization algorithms particularly suited for the proposed fuzzy logic based clustering load-balanced framework and outlines our approach in algorithm design. In this chapter, the way of realization is proposed and detailed; then about experiment settings are described followed by result analysis on top. Lastly, Chapter 5 wraps up the thesis summarizing its contributions and opening avenues for further research.

2. LITERATURE SURVEY

2.1 INTRODUCTION

The clustering optimization, in WSNs, is an active research topic to enhance the network performance, energy efficiency and scalability by organizing sensor nodes into clusters. These clusters, which are made in the network formation phase of AMRIT framework help in data aggregation and routing as well as resource management during networking.

Some are K-means Algorithm, Hierarchical Clustering Technique, Density-based Clustering Methods (DBSCAN etc), Genetic Algorithms(GA), Particle Swarm Optimization(PSO) algorithm for optimization in clustering scenarios as well Ant Colony Optimization and Simulated Annealing techniques which belong to swarm intelligence concept. These algorithms focus on cluster head creation and selection, nodes energy conservation while balancing it with other mechanisms of data aggregation.

Energy-Efficient Clustering attempts to minimize the power consumed from nodes by choosing cluster heads, increasing them and data aggregation techniques. It is achieved based on the following elements: Residual energy, communication cost and proximity of node. Cluster Head Selection Advanced Data Aggregation improves data aggregation in cluster so as to minimize chained transmission, energy depletion and network scalability.

In all the above scenarios, when WSNs are formed to clusters; EN have observed that node heterogeneity in energy levels along with processing and sensing capabilities considered instead of homogeneous nodes forming a cluster treated as Heterogeneous WSN. Cross-layer Optimization is the combination of this clustering process with other layers in the protocol stack so that it adapts feature at different layer for improved resource utilization and better performance in heterogeneous networks. Key QoS aspects are:QoS-Aware Clustering-application-specific requirements related to the data stream can be a factor in how and where clusters form. Load Balancing-the node or cluster head is balanced through workload distribution throughout to avoid network congestion, enhance overall quality of service(qos). These all-together approaches with the objective of cluster optimization in WSN to boost network performance and efficiency.

In the rest of this paper, only several key methods and aspects should be kept track while clustering is optimized for WSNs. Researchers are still investigating on state-of-the-art effective little techniques and algorithms to meet the challenges, constraints of the WSNs along with who is able to develop up-to-date scalability, energy efficiency methods/techniques.

2.2 RELATED WORKS CLUSTERING OPTIMIZATION IN WSNS SURVEY

Optimizing the way in which clusters are assigned is a challenging issue for WSNs that has been widely investigated within network optimization and wireless communications. Zero or more works related to WSN clustering optimization exist such as that of a number of studies, reviews and surveys.

Riaz M., Qayyum A. and Ali S.B: "An Energy-Efficient Clustering Algorithms in Wireless Sensor Networks: A Survey". This paper provides a detailed survey on several energy efficient clustering algorithms in the context of WSNs (2018) [11]. It explains several objectives used to optimize the WSNs, including improvement of network lifetime, energy consumption reduction and equalization concerning nodes in sensor networks. It speaks about all sort of clustering techniques available there and where a technique is suitable or not.

The study of WSN and its variations has grown significantly in recent years. Researchers from all across the world are working to create a routing protocol that is both energy-efficient and offers a sufficient degree of security for data exchange. Clustering of the sensor network is one of the methods used by the researchers. Given that each node has a specific purpose to complete during data transfer, this method naturally uses less energy. A comparison of these protocols created at parameters like heterogeneity, clustering technique, cluster size, etc. has been offered after a survey of 35 clustering algorithms and protocols.

A Literature Survey of Clustering in Wireless Sensor Networks is explained by S. p Kaur et al (2016) [12]: This early survey paper focuses on clustering algorithms in WSNs and provides a classification of existing techniques depend on their objectives, cluster formation criteria, and cluster maintenance. It discusses various issues related to clustering, such as cluster formation, cluster head selection, data aggregation, and energy efficiency.

Increased request for Wireless Sensor Networks (WSN) in a variety of applications had made this a popular area of research. Among the tests presented are energy conservation, possibility of expansion, and restricted network resources, among others, with energy conservation considered the most crucial. Clustering enhances efficiency of the energy with designating high-power nodes by means of cluster chiefs (CHs), thereby decreasing the likelihood of node energy reduction. Scalability, defect tolerances, data collection, and energy efficiency were a few of clustering's primary goals. This paper discusses the challenges associated with clustering and the methods or techniques that have been devised to surmount them. Several prominent Quality of service (QoS) centred clustering routing protocols related to WSN may be recognized after a summary of clustering techniques. Several parameters are used to compare and contrast these methods and protocols.

Singh Er et al. (2017) [13] presented a comprehensive survey on energy-efficient hierarchical clustering techniques in WSNs. This paper specifically focuses on hierarchical clustering techniques in WSNs. It discusses various energy-efficient algorithms, including LEACH and its variants, HEED, and SEP (Stable Election Protocol). The survey provides a comparative analysis of these algorithms based on their advantages, disadvantages, and performance metrics.

A survey paper presented by Amin Shahraki et al. (2020) [14], a arrangement of clustering algorithms for WSNs then identifies open issues and challenges in the field. It categorizes clustering algorithms into hierarchical and flat approaches, and discusses their characteristics, advantages, and limitations. The survey also highlights emerging trends and future research directions in WSN clustering optimization.

WSNs are flexible ad-hoc networks with thousands of resource-constrained sensors. Network management is a challenge due to deployment size and quality concerns. Topology management, particularly clustering, is used to manage nodes and execute tasks. This paper reviews existing WSN clustering techniques, focusing on 215 most important ones depend on clustering purposes and network features like flexibility and heterogeneity. The review provides insights for designing effective clustering techniques in WSNs.

Wohwe Sambo D et al. (2019) [15] illustrated a WSNs are increasingly utilized in areas like ecological field in addition to smart cities, where huge of sensor nodes were implemented.

Hierarchical approaches improve network performance and lifetime, with clusters led by Cluster Heads. However, traditional clustering is not efficient. Recent research on Machine Learning and Computational Intelligence has developed optimized clustering algorithms for WSNs created on ecological actions. These algorithms outperform traditional ones. The choice of appropriate clustering paradigm remains a challenge due to the diversity of WSN applications. This paper reviews proposed optimized clustering solutions and compares them based on 10 parameters. Swarm Intelligence paradigm considered extra suitable designed to applications with low consumed energy, big data rate, or high possibility of expansion, while Fuzzy Logic-based solutions are suitable for applications requiring fewer nodes.

A Review of Clustering Algorithms for WSNs presented by Benabdellah, A.C. et al. (2019) [16]. This review paper provides an overview of clustering algorithms in WSNs, through a attention on their application to Internet of Things (IoT) systems. It discusses different clustering techniques, including LEACH, LEACH-C, PEGASIS (Power-Efficient Gathering in Sensor Information Systems), so many others. The review highlights the key features, performance metrics, and challenges associated with each algorithm.

A research offers a comprehensive review at standard and leading-edge clustering approaches in data mining by Pitafi S. et al. (2023) [17] focusing on computer and data sciences, pattern recognition, AI artificial intelligence, besides machine learning. It discusses open contests in clustering, for instance computational complexity, cluster enhancement, convergence quickness, data dimensions, usefulness, data object demonstration, evaluation procedures, and information removal. This review serves as a benchmark for scientists and professionals to develope the state-of-the-art within clustering methods.

These are just a few examples of related work illustrated in table 2.1, reviews, and surveys on clustering optimization in WSNs. The field of WSNs is dynamic, and new research is constantly emerging.

Table 2.1: Related Work For Fuzzy Logic Clustering Optimization On WSN.

Year	Authors	Literature	Main Contributions
2010[1]	*V. Katiyar et al.*	"Clustering Algorithm for Heterogeneous WSNs : A Survey"	• Argument on 10 clustering protocols
2011[2]	*V. Kumar, Ganjeev J., Sudarshan Tiwari*	"Energy Efficient Clustering Algorithms in Wireless Sensor Networks : A Survey"	• Argument on 22 clustering protocols and different variants of LEACH • Comparison of the protocols discussed
2012[3]	*Dipak Wajgi et al.*	"Load Balancing Algorithms in Wireless Sensor Networks"	• Argument on 13 clustering protocols • Comparison of the protocols discussed
2013[4]	*D.J. Dechene et al.*	"A Survey of Clustering Algorithms for Wireless Sensor Networks"	• Argument on 12 clustering protocols • Division of Protocols in terms of Heuristics, Hierarchical, Weighted and Grid Schemes
2014[5]	*B. Revathy et al.*	"Latest Algorithms in Wireless Sensor Networks for Energy Conservation : A Survey"	• Discussion on 03 clustering protocols • Pseudo code of the protocols were elaborated
2015[6]	*Gaurav Kumar Nigam et al.*	"A Survey on Protocols and Routing Algorithms for Wireless Sensor Networks"	• Discussion on 13 clustering protocols • Advantages & disadvantages of each protocol of each protocol were specifically mentioned
2015[7]	*Mohini Kumrawat et al.*	"Survey on Clustering Algorithms of Wireless Sensor Networks"	• Discussion on 10 clustering protocols • Discussed protocols were divided on the basis of connectivity, mobility, identification and combined weight.

2.3 CLUSTERING OPTIMIZATION

In recent years, clustering optimization in WSNs became the subject of much research. Numerous methods and strategies have been put forth to raise the effectiveness and performance of WSN clustering algorithms. A few important articles and sources that cover clustering optimization in WSNs are as follows:

Dong M., et al. (2016) [18] introduced a survey for the energy-efficient routing methods thru QoS constraint for WSNs. While this survey focuses on routing techniques, it covers several clustering-based approaches for energy efficiency in WSNs and provides insights into their integration with routing protocols.

Rostami, A et al. (2017) [19] provides an updated overview of clustering algorithms in WSNs, discussing various optimization techniques, challenges, and future directions. Wireless sensor networks (WSNs) use clustering methods for optimization energy consumption, data collected, and increasing network lifetime. However, challenges like selecting a sensor by means of a cluster head (CH) remain. In clustering, nodes were allocated into clusters, with CHs selected as head. Nodes sense the surrounding then send data to CHs, which aggregate and transmit it to the base station. Clustering offers advantages like scalability, energy effectiveness, and reduced routing delay. they studies various clustering methods, focusing on homogenous and heterogeneous networks, comparing their advantages and disadvantages.

P. Y. Kong et al. (2022) [20] explained the distributed sensor clustering by artificial neural network based on resident information. IoT has led to the deployment of numerous sensors across large geographical areas, enabling efficient communication. Distributed sensor clustering is more scalable, avoiding traffic congestion, and avoiding single-point failure. However, global information may create more clusters. This article proposes using artificial neural networks (ANN) to summarize centralized clustering experiences and transfer this knowledge to distributed decision makers. Secondary local information is used to compensate for global loss, achieving a similar clustering solution with a 5% error probability.

Mohan P et al. (2022) [21] proves that Energy consumption be a significant concern in wireless underwater sensor networks (WUSNs), as data transfer requires higher transmission powers. Clustering, a procedure for separating networks within groups with resident base station, can improve network energy efficiency. An original protocol termed distance- and energy-constrained k-means clustering system (DEKCS) is proposed for cluster head assortment, updating residual energy thresholds and selecting optimal clusters based on network size. The proposed scheme outperforms conventional LEACH by over 90% besides optimized LEACH form centred on k-means clustering by 42%.

A. Latha et al. (2019) [22] proposed a Trust Assisted-Energy Efficient Aggregation (TA-EEA) arrangement for Wireless Sensor Networks (WSN) to improve aggregation precision, reduce neighbor reliability constraints, and minimize energy utilization. The three-fold process confirms reliable neighbor assortment, duty cycle-based energy management, and reactive congestion controllimg for seamless transmission, maximizing energy consumption and achieving a higher packet delivery ratio.

To begin an investigation into clustering optimization in WSNs, a using of these sources as a stepping off point. One may learn more about the particular subjects and have a thorough grasp of the state of research in this field by reading the citations and related work that are referenced in these publications.

2.4 K-MEANS CLUSTERING ALGORITHM

The It is an unsupervised learning technique that is used for clustering problems. K-Means Clustering It helps us for grouping the data into distinctive categories and supplying a convenient method of independently identifying the category types in an unlabelled dataset without necessity to need training. Better ways of finding the initial cluster centroids have been suggested. We will introduce a some of them in this section.

D. Wohwe Sambo, et al; Relative K-means Clustering Algorithm: An Experimental Evaluation in The Context of WSNS in 2019 [23]

Designing cluster-based routing protocols necessitates clustering approach in WSNs. K-means is an attractive algorithm for the task of organizing sensor nodes, but it has drawbacks. In this paper, we tackle these weakness-points and suggest proper tactics for enhancing K-means results. The solution is the energy-saving solutions for sensor nodes, in order to enhance long reporting life of WSNs. Since the present review reveals an impressive lack of studies on limitations of K-means that is basically why we have attempted to motivate our work.

Ran X. et al. (2021) [24] new K-means clustering algorithm for detecting urban hotspots using a noise-based approach. Overpopulation in metro cities is a problem - but the most important solution to this issue lies right under our feet. The K-means clustering algorithm has been able to help for decades when the number of clusters and initialization centers need to be determined. With noise algorithm data attribution will respond itself randomly and out the result of clustering, number of clustersAinitial cluster. Four unsupervised evaluation indexes are implemented to evaluate the clustering results, and we leverage a nonparametric Wilcoxon statistical method for verification. The proposed noise K-means clustering algorithm will be experimented on five taxi GPS datasets to assess its performance (denoted as IsolationK) against the following baseline techniques: Fuzzy C-Means, K-Means and Plus which we refer hereafter simply by CKM,K,(++) respectively.

Ali A. Hassan et al. However, (2019) [25] said the clustering is important in many areas such as machine learning and WSNs which announced it. This organizes sensor nodes along with an appropriate cluster, in which energy is stored and network lifetime will be prolonged. Although fuzzy c-means (FCM) is very popular in WSNs, it sometimes generates unbalanced clusters because the nodes are randomly deployed. It could be suggested that a new clustering manner named FCM-CM to enhance the well-known fuzzy c-method (FCM) algorithm through incorporating it with crucial mechanism(CM). The planned technique when tested for various new parameters gives better results and generates balanced clusters with high intra-distance balancing which ultimately preserves the energy efficiently thus increases the network lifetime.

Zhao, L. et al. In [26], Tang et al. present a modified version of K-means clustering algorithm for WSNs to increase energy efficiency and data transmission reliability.

An improved clustering-based algorithm for selecting cluster-heads of LEACH (LEACH-M) has been proposed to overcome the drawbacks such as randomly selected, and energy-consumption high discussed above in WSN. The cluster-head threshold equation was optimized by taking into account residual energy and network addresses of nodes using ZigBee's distributed address assign mechanism (DAAM). And under the cluster-head competing mechanism, LEACH-M solved the energy load balancing of network in essence and effectively improved energy efficiency.

A result of simulation via NS-2.35 demonstrate that a presented algorithm is able to extend the network lifetime, reduce consumed energy, improved the quantity of receiving data at the BS, regardless of whether the region is 100 $100m^2$ or 300 $300m^2$.

Qiong Z. Y. et al. (2016) [27] explains the implementation of the k-means algorithm for the LEACH protocol. They proposed the KDUCR algorithm, an arrangement of the k-Means with Dijkstra algorithms. K-means is utilized to seperate SN within k clusters and allocate CH for the initial round, whereas the Dijkstra algorithm can be applied to determine the straight route between CH and BS. A result indicate that KDUCR overtakes LEACH and LEACH-C in terms of energy consumption. The sink node implements the K-means clustering algorithm then generates the entire clustering procedure. This permits the network as a whole to consume less energy, but causes the sink node's energy to deplete quicker.

T. N. Viet et al. (2021) [28] introduced an integration of the k-means algorithm with the slime mold algorithm (SMA). SMA-LEACH, the proposed routing algorithm, is preferable to PSO--LEACH and BAA-LEACH, which use (PSO) and the bat algorithm (BAA), respectively, to enhance LEACH. They presented a hybrid clustering algorithm which integrates the K-means algorithm and the LEACH protocol for energy-efficient routing in WSNs, considering both energy consumption and network coverage. Analysis of simulations demonstrates that SMA-LEACH decreases network consuming energy along with enhances the WSNs lifetime. These algorithms operation (SMA to CH selection and k-means to clustering) operate independently, and the analysis of the method's assistances restricted to the living nodes number, no additional information provided concerning the energy consumption.

R. Sharma et al. (2023) [29] explained the Modified-Invasive Weed Optimization Based Clustering Algorithm (M-IWOCA) is an evolutionary approach-based clustering protocol for WSNs aimed at energy conservation and network life duration. The algorithm selects the rightest node to be a cluster head, enhancing network lifetime and minimizing energy utilization. A fuzzy inference model evaluates fitnesses of any network nodes. The simulation results illustrate a substantial reduction within dead nodes per round and improved network stability by 45% in related to the Artificial Bee Colony (ABC) protocol besides 18% to the Quantum Artificial Bee Colony (QABC) protocol.

D. Lubin Balasubramanian et al. (2023) [30] presents an energy-aware hybrid clustering algorithm which merges the K-means algorithm and the Genetic Algorithm (GA) for improved energy efficiency in WSNs.

This work introduces a cluster-based routing approach in (WSNs) using a hybrid seagull rock swarm & opposition-based learning (HSROBL) algorithm. The approach selects cluster heads (CHs) using optimization algorithms, focusing on distance, safeness, delay, and energy. Results show an overall performance improvement of about 28.50% compared to existing algorithms, demonstrating the importance of optimal CH selection in efficient routing.

2.5 OPTIMIZATION TECHNIQUES IN WSNS

J. Amutha et al. (2021) [31] focused on clustering methods in WSNs, focusing on classical, optimization, and machine learning techniques. Wireless Sensor Networks (WSNs) are gaining interest from academics, engineers, also technology societies owing to such fields like energy effectiveness, communicated data, and network lifetime. They are seeking economical attitudes for enhancing existing solutions and discover fresh schemes, approaches, and algorithms. It provides performance metrics and parameters for each category, discussing aspects like cluster head selection, routing protocols, reliability, security, and unequal clustering. The study also discusses advantages, limitations, applications, research gaps, challenges, and directions, motivating further research in cluster-based WSNs.

Sharmin, S. et al. (2023) [32] purposes to enhance the energy efficiency and network endurance of (WSNs) by combining hybrid PSO (HPSO) and improved low-energy adaptive clustering hierarchy (HPSO-ILEACH). This HPSO-ILEACH algorithm determines the cluster head (CH) node, the cluster's member nodes separation area, besides the remaining nodes energy. It then minimizes energy spending through the clustering procedure with altering the CH. This HPSO-ILEACH algorithm have been appropriately performed utilized to data aggregation and it saves energy, simulation studies showed this is able to improved network lifetime by 55% of the nodes survive whereas consuming only 28%of engaged in other algorithms. This method is very important to prolong the lifetime of WSNs reducing energy costs.

Rao, P.C.S. et al. originated a super-efficient protocol to Conway's 13-state decoder (to achieve maximal savings on energy conservation) in the regime of vanishing losses. In (2016) [33], an Enhanced PSO-Based Clustering Optimization Energy (EPSO-COE) algorithm is presented. Pso clustering and head selection for reducing power consumption Wireless Sensor Networks (WSNs) are simple networks with sensor elements installed and used for observing physical entities in certain fields. These networks typically have self-supported battery power for efficient operations and communication. The metrics of Performances were assessed and associated to competitive clustering algorithms for confirming the decrease in consuming energy.

Vellaichamy, J. et al. (2023) [34] proposed a multi-criteria clustering and optimal bio-inspired routing algorithm to improve network lifetime and operational time of WSN-based applications. The method uses multi-standards clustering for chosing the peak cluster head (CH) and uses moth flare and slap swarm optimization algorithms for analyzing the quality path for information transmitted. WSNs were increasingly utilized for scoring and transmitting data from the physical environment. However, a limited energy consumption of the sensing element is a significant issue. The proposed method minimizes energy consumption by 18.6% and increases lifetime by 6% associated to further routing protocols.

Yan, X. et al. (2022) [35] presented an algorithm of game theory-based energy- effective clustering (GEC) for WSNs, any sensor node considers a game player, adopting favorable strategies based on idle listening time. A penalty mechanism is announced to prevent selfish behavior. Simulation results illustrate the GEC efficiently saves consuming energy and increases network data transmission, thereby prolonging the network lifetime. The goal is to save energy and increase data transmission, thus enhancing the efficiency of wireless sensor networks.

Verma S. et al. (2023) [36] presented a genetic algorithm- created optimization approach for energy-efficient data aggregation in WSNs, aiming to minimize energy consumption while maximizing network lifetime.

The Genetic Algorithm-based Optimized Clustering (GAOC) protocol for optimizing CH assortment in heterogeneous WSN. In its fitness function, it incorporates parameters including residual energy, drain’s distance, and node density. Wireless Sensor Network (WSN) longevity and potential have been hindered by sensor node battery limitations. MS-GAOC is proposed to reduce communication distance and resolve the Hot-Spot issue. Simulation analysis demonstrates that GAOC and MS-GAOC are superior to advanced protocols concerning stability period, network lifetime, inactive nodes, through-put, and network remaining energy. It is anticipated that these protocols will be useful for monitoring hostile applications like forest fire detection and volcanic eruptions.

3. RESEARCH METHODOLOGY

3.1 INTRODUCTION

WSNs Wireless sensor networks (WSNs) consist of massive number of small, energy-constrained sensors modularized units that collaboratively monitor and collect various data. Clustering is one of the primary techniques used in WSNs to group a set of sensor nodes called clusters, which include some type of cluster head responsible for data aggregation and transmission to BS. Using more sophisticated techniques like fuzzy logic, clustering optimization tries to improve over network performance and energy efficiency of the networks in lifetime.

Fuzzy logic is a mathematical framework for dealing with imprecision and fuzziness in decision-making. You can see it working efficiently in different fields including WSNs for real-world data and parameters that are inherently imprecise. WSN clustering optimization with fuzzy logic makes cluster construction and node assignment more adaptable, robust and flexible.

In this chapter, the material and methodology used in designing the fuzzy logic based clustering optimization for WSNs are discussed. Although details of the proposed method are presented, it was a non-technical description which outlined its main components, how they interact/benefit from each other and overall operations.

3.2 FUZZY LOGIC-BASED CLUSTERING OPTIMIZATION

A Fuzzy clustering optimization framework (FLCOF): A fuzzy logic based cluster optimizing scheme. This framework is an attempt to enhance modern clustering algorithms using fuzzy logic principles [37] So this blog defines the basic elements and ideas of a Fuzzy Logic-Based Clustering Optimization Framework :

Clustering Algorithms Clustering: is a Data Analysis Technique used to combine similar data points together. This is achieved using a multitude of algorithms like k-means, hierarchical clustering, DBSCAN and many more. Cluster size, distance metrics and initialization techniques are parameters which these algorithms requires.

Membership functions: Membership Functions allude that in clustering synergy, each data point gets a certain degree of membership to every cluster. These degrees represent the point that a data goes for a specific cluster. Fuzzy logic permits progressive transitions between cluster memberships, thereby capturing overlapping or ambiguous clusters.

Objective Function: The objective function quantifies clustering results' quality. It considers aspects such as compactness (distance between nodes within a cluster) and separation (distance between clusters). The objective is to identify a clustering configuration that optimizes this function.

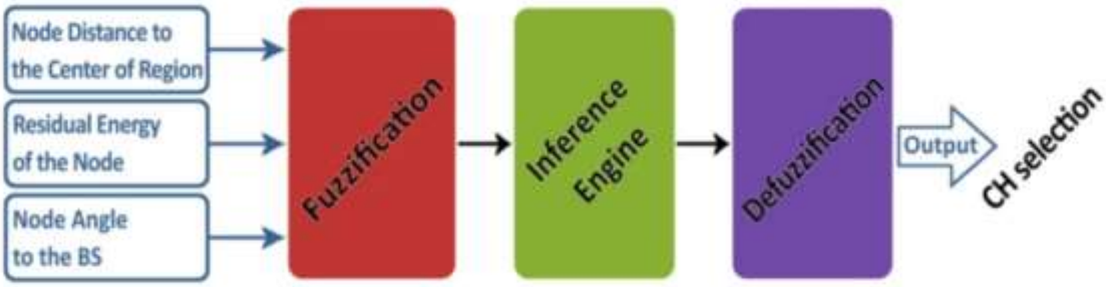
In order to fine-tune clustering parameters, fuzzy logic-based clustering optimization frameworks frequently employ optimization algorithms. Evolutional algorithms, GE algorithms, PSO, in addition to other optimization techniques were frequently utilized to optimize cluster assignment parameters.

Hybrid Methodologies: Some frameworks may combine fuzzy logic with other optimization or machine learning strategies to obtain superior outcomes. For example, integrating fuzzy logic with neural networks or reinforcement learning to adjust clustering parameters dynamically.

Validation and Evaluation: The efficacy of the FLCOF is typically evaluated using inner authentication metrics (such as silhauette score and Devis-Bouldin indeces) and the other one is the external (like modify Randi index and standardised common information) to determine the quality of the clusters obtained.

FLCOFs may be applied with variety of clustering-based presentations, comprising pattern recognition, image segmentation, customer segmentation, and anomaly detection. The fuzzy logic aspect helps to manage scenarios in which data point transitions between clusters are incremental.

Therefore, a Fuzzy Logic-Based Clustering Optimization Framework is intended to improve clustering algorithms by introducing fuzzy logic concepts to more effectively capture data uncertainty and optimize clustering parameters. This strategy can lead to enhanced cluster designation in situations where strict, distinct cluster boundaries are inappropriate.



3.2.1 Fuzzy Sets With Association Utilities

Fuzzy Sets and association utilities consider introductory concepts in fuzzy logic, an approach of mathematics concerning imprecision as well as uncertainty. With difference to traditional binary logic, that categorizes elements as either absolutely (1) denotes true or absolutely (0) which denotes false, FL permits degrees of truth or set membership between 0 and 1 [38].

a. Fuzzy Sets: In conventional sets, elements are either included or excluded. In fuzzy sets, an element's grade at set affiliation is quantified with value more than 0 and less than1. A membership values denote the likelihood that a constituent is a member of the set. For instance, if an imprecise set of "tall people" has a membership value of 0.8 for a person's height, this indicates that the individual is 80% tall.

b. Membership Function: A membership function is a mathematical function that specifies an element's degree of membership in an ambiguous set. It associates each constituent with its membership value. Membership functions can be as like triangular, trapezoidal, or even sigmoidal, among other shapes. A membership selected function is dependent upon an applied features with problem domain characteristics.

Consider the "Temperature" fuzzy set by means of a membership feature representing the warmth degree. The membership function could be triangular with its maximum at a pleasant 25 degrees Celsius. The membership value decreases as the temperature deviates from 25 degrees, indicating the level of comfort or warmth.

Control schemes, administrative, design recognition, and AI are among the many disciplines in which fuzzy logic is widely employed. Fuzzy logic enables systems to handle and process uncertain or ambiguous information more effectively, making them more robust and adaptable in real-world situations where obtaining precise values is frequently difficult [39].

Fuzzy Sets and association utilities as a membership are important components of FL systems, providing a basis for reasoning and inference based on degrees of truth, which can be especially useful when precise logic is inadequate to represent the complexity of the problem domain.

3.2.2 Membership Function's Design

Membership functions consider a fundamental concept in fuzzy logic that characterize the membership element degree within specific fuzzy set. They map input values from the problem domain to a range of membership values between 0 and 1 indicating a measure of an element's affiliation with the the fuzzy set. Typically, in FL, a membership meaning may be associated with a linguistic variable that represents a particular attribute or characteristic of the problem domain. Membership functions are crucial for transforming precise (numerical) input values into fuzzy values, enabling fuzzy logic systems to deal with uncertainty and imprecision.

Designing membership functions is a crucial stage in the implementation of fuzzy logic, particularly in contexts such as Fuzzy Logic-Based Clustering Optimization Frameworks. Membership functions play a crucial role in representing uncertainty and gradation in data by defining a degree concerning component goes to specific ambiguous set. A design of these functions begins with a thorough comprehension of the problem domain and data characteristics. It is crucial to determine fuzzy sets quantities, which is comparable to the cluster numbers. The selection of membership function forms, like triangular, may be sigmoidal, depends at characteristics of the data distribution. Adjusting these functions for optimal data fit is the next step in parameter optimization.

It is essential to balance the overlap between membership functions in order to convey the nuanced uncertainty in data assignments without excessively complex functions. After devising the functions, it is essential to validate the data and clustering results [40]. For evaluating class of clusters created by the fuzzy logic method, internal validation metrics examples silhouette score can be used. When the initial results are not good enough, follows a process of iterative refinement where parameters and shapes get tweaked to match better data.

Integration of domain knowledge and expert insights into the development of membership function enriches this process. This approach is multi-faceted, and incorporates multiple methods (data analysis inputs expert input lessons learned iterative adjustment) to create the best membership functions that reflects accurately of their uncertainties in raw data relations. The ultimate goal is to give clustering some dynamics by harnessing the power of fuzzy logic in order to make it more applicable for scenarios where sharp boundaries may not suffice.

3.2.3 Formulation Of Fuzzy Rules

The Fuzzy sets and membership functions are used to represent the degree of a sensor node or nodes being members of specific clusters/roles corresponding linguistic variables.

Fuzzy inference system(FIS) is generated to build rules and decision-making processes for cluster head, on 2 feature understandings like -A. Cluster formation-B., Node assignments

Fuzzy Sets vs. Membership Functions The basic concepts of fuzzy logic theory, for solving problems where fuzziness and uncertainty appear are Fuzzy sets instead of (i.e., as opposed to) scientific numbers. Main functions Unlike classical binary logic which defines things either absolutely true or false as 1 or 0 respectively, fuzzy set theory assigns a degree of truth from just below zero to one.

a. Fuzzy Sets: An element in a conventional set is each a part in a set, may be it is not. Instead, with fuzzy sets, a degree element of set membership can be expressed as a number between 0 and 1. The amount of truth whether an element belongs to the set is indicated by its membership value. For instance, a person is 80% tall if they belong to a fuzzy set of "tall people" and their membership value for height is 0.8.

b. Membership Function: it is a function with mathematical expression creates the level element related to the fuzzy assortment membership. Every element is mapped to the relevant membership value. There are several types of memberships, including sigmoidal, triangular, , and trapezoidal. An application and the features of the issue domain determine which membership function is best.

As an illustration, let us take a fuzzy set called "Temperature" and its membership function, which denotes the degree of warmth. A triangle function with a peak at the cozy temperature of 25 degrees Celsius might represent the membership function. The membership number drops when the temperature goes below 25 degrees, signifying a loss in warmth or comfort.

Fuzzy logic (FL)enables systems to manage and analyze imprecise or uncertain data more skillfully, increasing their robustness and adaptability to real-world scenarios where it is frequently difficult to acquire accurate values. A basis for understanding and inference that relies on degrees of truth is provided by fuzzy sets and membership functions, which are important elements of FL systems. These can be especially helpful when crisp logic is unable to adequately capture the complexity of the issue domain.

To depict the extent of a sensor node's membership in various roles or clusters, linguistic variables as well as membership functions are utilized, they can be used in WSNs to express an extent to which sensor nodes be a part of certain roles or clusters within the network. With this method, node attributes may be represented in a more flexible and descriptive way, which facilitates improved decision-making when it comes to cluster formation or role assignment. The application of both can be summerized as:

a. Linguistic Variables: An attribute or feature of the sensor nodes represented as concepts in natural language are termed as linguistic variables. For example, in clustering or job assignment scenarios these linguistic variables may refer to the properties like "energy level", " base station distance" OR even more sophisticated ones such as"The sensed data quality". Instead of exact numerical values, linguistic variables use descriptive terms such as "low", "medium" and high to represent different amounts these traits.

b. Membership Functions Membership functions define the degree to which a value belongs to a particular linguistic (for example high, medium and low). They also expose methods and connect numerical values with linguistic phrases that measure the degree of correspondence between a certain value, its description in language. While membership function can be of triangle, trapezoidal, Gaussian or sigmoidal shape based on the type of linguistic variable.

One example for the membership function with a linguistic variable being energy level, would be a triangle like function centered around some value of an energy. Nodes closer to the interior value of energy introduce more than a bit with 1, whereas nodes further outside will do so less.

Using linguistic variables and membership functions, the characteristics of sensor nodes can be described in more understandable human terms. Be used for decision making process in clustering or job assignment. As a result, by utilizing fuzzy logic and reasoning, the ambiguity and imprecision that is closely associated with real-world sensor node characteristics can be addressed which enhances more flexibility for WSN clustering/role allocation algorithms

The three main parts of linguistic variables in fuzzy logic are [41]:

a. Variable Name: This is the variable name, which in this case as mentioned above will be or should be equal to label. We post to indicate by adjective the property of interest as an example, a weather forecasting system might deduce the linguistic variable types are "temperature" or "humidity".

b. Linguistic Terms: The terms to describe different levels of an attribute are known as linguistic terms. The natural language strings are application and locale dependent, and they generally describe temperatures as qualitative (e.g., "Low", "Medium", or 'High') categories but can be more detailed ('Hot', 'Warm' vs. Membership Function:

c. Membership Function: Each linguistic term's degree of membership for a given value is defined by the membership function. It measures how well a given value fits the linguistic description by mapping the attribute's numerical values to the relevant membership degree. Membership functions are frequently shown visually as triangles, trapezoids, or sigmoid curves. They can also be discrete or continuous.

Take into consideration, for instance, the linguistic variables "Temperature" and the phrases "Cold," "Mild," and "Hot." Each term's membership function may be described as follows:

a. The membership function known as "Cold" is a triangle with a center of 10 degrees Celsius.

b. The membership function labeled as "mild" is a triangle with a center of 20 degrees Celsius.

c. "Hot" membership function: Triangle-shaped function with a 30-degree Celsius center of gravity.

It may express its thoughts regarding temperature readings in a more human-interpretable way with the use of this language variable and its membership functions, enabling more adaptable and flexible decision-making at applications including climate control, fuzzy logic-based systems, and systems that support decisions.

In actual applications, the fuzziness along with uncertainty of the issue domain are correctly represented by membership functions that are created according to expert knowledge or data analysis. The design of the membership functions is an essential stage in the construction of fuzzy systems since their parameters and shape have a substantial impact on the behavior and functionality of the fuzzy logic system [42].

3.2.4 Network Parameters

Node density, energy levels, remaining energy, communication cost, and node proximity are a few examples of criteria to include.

Actually, a performance and optimisation of WSNs heavily depends upon network parameters [43]. These variables affect the network's overall dependability, longevity, and efficiency.

Node Density: The quantity of sensor nodes placed in a given region is referred to as node density. Although a high node density can improve coverage and data accuracy, it also raises energy and transmission costs. Data accuracy may suffer and coverage gaps may arise from low node density. Optimizing the network lifetime requires maintaining a balance between node density. While too low a node density might result in coverage gaps and decreased network performance overall, an excessively high node density can cause early energy depletion and rapid node death.

Energy Levels and Residual Energy: Because the energy supply of all sensor nodes within a WSN vam be finite, it is indispensable for monitoring both residual energy and energy levels in order to maintain network longevity. To avoid network splits, particularly in the presence of nodes a power threshold away from complete battery depletion Intermediary handling for dying and low energy manifests may be necessary. The energy level is the total amount of power at first available in each sensor nodes. Nodes get very quickly exhausted; being activated, this means running out of energy by performing tasks (processing, communicating and sensing). Network issues due to the energy fatigue,

Communication Cost: It is the energy consumed in transferring data from one node to another. It is dependent on factors like data packet size, signal strength and distance. Besides improving the overall network performances, minimizing the communication cost is critical for energy saving.

Multiple strategies such as data aggregation, duty cycling the nodes (i.e., switching them ON only for their usage time) and energy efficient communication protocols along with optimization of network topology in term of hop length reduction can be employed to reduce cost associated with communications. For wireless sensor networks, good network performance results from the optimal use of communication costs and residual energy so as to reach a balance between functional continuance in the network on one hand, and power-saving ability or vitality support for nodes on another hand.

Distance between nodes: How far away the nodes are from one another affects both signal strength and how well communication channels work for example, remote nodes may consume higher energy to transport the data than nearer ones due better communication links.

Network Coverage: This represents the region that is being watched by the sensor nodes. You want to make sure that things happening in or around the deployment area are getting detected and reported, so you have good coverage. Availability is an important metric for evaluating the perception, tracking and collection of environmental data by a WSN. Successful coverage is essential for the network to function properly and data completeness.

Data Accuracy: the data accuracy simply refers to how accurately and precisely we can extract the essential information from sensor nodes. The type of information obtained from the network is important to make worthy and effective decisions.

Data Aggregation: This is the process of combining and reducing data from several nodes previous to transmitting it via a base station. Efficient information gathering can save energy and reduce the cost of transport.

Cluster size and Head Selection: In WSNs, nodes are often grouped together for representation of efficient data collection to transmit by utilizing clustering. Therefore, how to balance energy usage and network load with the respect of cluster size (K) as well as selection of Cluster Head becomes an issue.

Optimization of these network characteristics is therefore achieved by using algorithms, protocols and methodologies aligned for the respective goals and constraints associated with WSN application. However, these properties should be balanced in order to maximize energy efficiency and network lifetime prolongment while not degrade overall performance of WSNs.

3.3 CLUSTER FORMATION CRITERIA

Cluster formation criteria is a series of rules or conditions on why sensor nodes will cluster together in WSNs. Clustering is just a fundamental methodology used to perform data aggregation, save the energy and handle communique in WSNs [5]. When clusters form, nodes elect cluster chiefs to manage intra-cluster communication and data aggregation. Clusters need to be formed and include tied nodes as cluster heads so that network performance is optimized and the resource usage. It gives up the resources to select cluster heads and considers network load, energy consumption as well node's distance.

As being one general criterion for cluster formation, the network clustering that consists of nodes from a predefined distance lead to proximity-based criteria where each node is in same community if their distances are less than certain threshold [44]. Proximity-based criteria often rely on a predefined communication distance. Such nodes are then capable of communicating directly with each other and join in the same cluster. A more intelligent way is to use energy level as a criterion (nodes having more/remaining energy have higher chances of being selected cluster heads). This guarantees the prolongation of lifetime, and at the same time balancing energy consumption by selecting nodes with surplus power for additional burden.

The same holds for data fusion and aggregation criteria as well; nodes that sense the similar phenomenon or collect resembling fields belong together in a cluster due to incentives. This way, nodes are able to merge their data right beforehand of transmission and it reduces the communication overhead. To reduce the total energy consumption, cluster formation criteria were also optimised according to communication cost. This means that nodes which are closest to the data sink/base station with lower communication costs can be selected as cluster leaders.

Furthermore, needs for coverage, connection and reachability, node capabilities, load balancing, and dynamic changes to shifting network circumstances can all serve as guidelines for cluster formation criteria. Certain cluster creation methods dynamically modify the cluster structure to preserve network performance in response to changes in network circumstances, which include failures of nodes or energy depletion.

Depending on the particular application, network architecture, energy limitations, and performance goals, different cluster formation criteria will be used. To maximize cluster formation in WSNs, various clustering algorithms may be expanded, including HEED, TEEN, and LEACH [45]. WSNs can achieve increased overall performance, well network structure, and increased efficiency of the energy with carefully choosing the cluster formation criteria.

3.4 FUZZY LOGIC-BASED CLUSTER HEAD SELECTION

3.4.1 Fuzzy Rule Base

To decide which nodes are suitable to lead a cluster, establish a set of fuzzy rules that consider network characteristics. A key element of fuzzy logic-based systems, such as those utilized in head choicing FL-based clusters, is the rule based of fuzzy. A rules of if-then stand for collection of that encodes the logic used to make decisions about whether sensor nodes are suitable to lead a cluster. Every rule connects the output (cluster head candidacy) to the input linguistic factors (like node energy, base station distance, and data aggregation capabilities).

The fuzzy if-then rules that make up the fuzzy rule base are divided into two primary components: the antecedent and the consequent. Depending upon the linguistic factors and their linguistic expressions, an antecedent lays down the requirements or standards. It explains the input circumstances that cause the rule to become active. The output action or conclusion that the output linguistic variable and its linguistic words reflect is stated in the consequent, on the other hand.

Natural language statements are a common format for fuzzy rules. In the case of cluster head selection, an example of a fuzzy rule might be: "When a node energy be great as well as a range for base station is small, then the node has a great cluster head candidacy." A rules number besides a selection of linguistic factors and terms are determined by the complexity of an administrative procedure and the factors taken into consideration to choose cluster head. Such a case, "high" and "short" are the linguistic terms of the input variables "node energy" and "range toward base station," respectively, a "high" is the linguistic term of the output variable "cluster head candidacy." To properly assess each node's cluster head eligibility, the rule base should be carefully developed to capture the pertinent linkages and interactions among the input criteria.

The FL rule base may utilized in the fuzzy inference process to assess the extent to which the supplied data satisfies each rule. Fuzzy logic operators (AND, OR) are used to combine the activation strengths of the rules in order to get the overall cluster head candidacy value for each node. Cluster heads can be chosen based on their candidacy values after the defuzzification procedure transforms o/p of the fuzzy to a crisp result which denotes a node's final cluster head candidacy score.

The performance and flexibility of the FL-based cluster head choice system are significantly influenced by the efficacy and strength of the fuzzy rule basis. Having domain experience, data analysis skills, and expert knowledge are essential for creating a rule basis that works well and can make wise judgments in a range of application scenarios.

3.4.2 Fuzzy Inference Process:

Determine the degree of membership of every node as a possible cluster head by evaluating the fuzzy rules and input parameters employing fuzzy logic operations, which include fuzzy AND, fuzzy OR, as well as fuzzy aggregation techniques.

A key component of fuzzy logic-based systems, such as those utilized in FL-based clustering head choice for WSNs, is a fuzzy inference procedure. While the the procedure of converting clear input data into fuzzy standards is Fuzzification [46]. There are equivalent membership functions for each input language variable, including node energy, base station distance, and data aggregation capabilities, which translate the crisp values into the relevant linguistic phrases. The membership functions describe the imprecision and uncertainty inherent in the data by defining a membership's degree or belongingness inputs related for linguistic word.

The fuzzy rules in a fuzzy rule base are assessed using the fuzzified input data. A collection of if-then rules that embody the decision-making logic may be found in the fuzzy rule base. An antecedent (conditions) and a resulting (output) create each rule. Every rule has an antecedent that lists fuzzy sets of the linguistic which are input and cause the rule to activate. The extent to which the input data meets the requirements described in the antecedent determines the activation intensities of the rules.

Since several rules might be substantially activated by the incoming data, their activation intensities may overlap. Fuzzy logic operators, such as AND and OR, are utilized for combining the activation strengths of principles with common inputs in order to address this. The OR operator, for instance, combined the activation strengths of many rules that share an input variable, indicating the combined effect of these rules on the system.

The total fuzzy output is then obtained by averaging the activation intensities of all the fuzzy rules through the fuzzy inference process. The sum total of the entire parameters affects on the output linguistic variables are represented by this so called aggregated output. The final step of this fuzzy inference process is referred to as "defuzzification" which transforms the output into corresponding crisp value. Many defuzzification techniques are like a centroid, maxima mean or weighted average which is used to produce the crisp value of output. This simple value represents some final decision or outcome of the system. It can be used to differentiate between classes in many machine learning problems, like spam filter example (spam/non-spam), medical generalization (example: sickness/sick free) etc.

Fuzzy logic system of cluster head selection: The fuzzy inference process using the logical methodology based on input-in-output type can make an intelligent decision to choose a more suitable node taking into consideration many criteria and uncertainties, this choice is done precisely by performing effective coordination through the use arbitrary level numbers. This technique will make the decision-making process flow-based, adaptable and context-aware that suits best to dynamic non-deterministic environment such as WSNs. Accordingly, the system is capable of dealing with uncertain/vague data and achieving intuitive decisions on selecting cluster head for WSN that enhances network scheduling efficiency as well resource utilization.

3.4.3 Defuzzification

A defuzzification stage is required in fuzzy logic-based systems (like the one employed to select cluster heads for WSNs based on a fuzzy approach). A fuzzy value is obtained based on the output linguistic variable, representing a degree of membership to each linguistic word through use of the Fuzzy Inference. For instance, we may define a set of linguistic terms indicated by suitable phrases for the output language variable corresponding to cluster head selection as "cluster head candidacy," with appropriate terms being low, medium and high.

This crisp value outcome can be extracted from the fuzzified output with some defuzzification techniques and it is an easy to understand result. There are different types of techniques available for defuzzify the output of fuzzy logic system such as weighted average method, mean-of-maxima function and centroid (weighted-sum) method. The weighted average of the membership values of all linguistic words is the centroid, or center of gravity, of the merged fuzzy set, as determined by the centroid technique. It uses output to create a realistic value’s crisp.

As an alternative, the mean of maxima approach determines which phrases in the language have the highest membership values and then finds the mean of the values that go along with those terms. The fuzzy output's most significant linguistic words are taken into account. The weighted average approach is an additional choice that allocates weights to the linguistic words according on how much of the fuzzy output they include. The weighted average of the crisp values connected to each phrase is then determined [48].

The process of defuzzification yields a single, sharp value that is the fuzzy logic-based system's ultimate output. This crisp number represents each sensor node's level of head candidacy within a situation of WSN choice of cluster head. Higher candidacy score nodes are chosen to be cluster chiefs, in charge of overseeing data aggregation and communication inside their own clusters.

Defuzzification makes guarantee that the fuzzy logic-based system produces an output that is both comprehensible and useful. It makes simple decision-making possible and makes it easier to use fuzzy logic practically in diversity related to real-world situations, including WSNs. Information kind required from the fuzzy output and the particular needs of the application determine the defuzzification approach to use. Defuzzification makes it possible to use fuzzy logic-based systems in WSNs effectively and efficiently to maximize resource management and network performance by extracting crisp values from fuzzy outputs.

3.5 DEFINITION AND ORIGINATION OF MODEL SYSTEM

The structure of the system involves several sensor nodes and one base station (BS). There are double nodes categories: typical one as well as nodes to be chosen clustering head. Monitoring an environment and transmitting sensor data to the chosen head one considers among a responsibilities of shared nodes. This shared nodes could be used to choose a head one in a methodical manner. Data from common nodes is received via a head, who aggregates and sends it dirctly toward BS.

An energy model considers first-order radio type, and the consumed energy be with communication step. An overall energy use is an amount of the dissipated energy which produced by the transmited data, reception, in addition to aggregation. Equation (3.1) may be utilized for computing the consumed energy through sending data, whereas Equation (3.2) utilizes to measure the consumed energy during data reception [49].

$$E_{TX}(L,d) = (E_{elec} + \varepsilon_{amp})L \tag{3.1}$$

$$E_{RX}(L) = E_{elec}L \tag{3.2}$$

The energy used while a transmitting of an L -bit data is denoted by $E_{TX}(L, d)$, while the energy used during the data receipt can be denoted with $E_{RX}(L)$. An amplifier's consuming energy throughout the transmission phase may be found using equation (3.3), where amp represents the amplifier's energy consumption.

$$\varepsilon_{amp} = \begin{cases} \varepsilon_{fs} d^2 \text{ if } d \leq d_0 \\ \varepsilon_{mp} d^4 \text{ if } d > d_0 \end{cases} \tag{3.3}$$

The free-space propagation concept will be implemented in sensor node if d is less than or equal to d0. On the other hand, Equation (3.4) may be used to determine the value of d_0 whether the system utilizes a multi-path fading channel that utilizes the $\mathcal{E}_{fs}$ and $\mathcal{E}_{mp}$ denotes to energy element at network.

$$d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}} \tag{3.4}$$

Expanding the lifetime besides the efficiency of energy in WSN requires careful consideration of cluster heads amount within every cycle. Equation (3.5) can be used to estimate an ideal cluster size kopt [33].

$$k_{opt} = \sqrt{\frac{\varepsilon_{fs}}{\pi(\varepsilon_{mp} d_{toBS}^4 - E_{elec})}} M\sqrt{N} \tag{3.5}$$

where M and N stand for the system's total nodes quantity as well as covered area, respectively. Where the base is defined by BS.

3.5.1 Cluster Head Election

The formation of cluster is permanent, with just the cluster topology altering every round if necessary. This applies to the whole network operation. Both Fuzzy sets with fuzzy rule base are used to determine the likelihood that any working SN at the cluster will turn into a CH. For the upcoming rounds, a node having highest potential value may be elected to be new CH. To choose a CH in each cluster, two fuzzy input factors are used: the intra-cluster communication cost besides a remaining energy at supernova. Each input variable's discrete values are obtained as a normalized form with regard to the members of its cluster. The subsequent formulation may be utilized for getting the normalized residual energy related to every SN in the cluster:

$$NorE(i) = \frac{E(i) - E_{\min}}{E_{\max} - E_{\min}} \tag{3.6}$$

The residual energy of the i_{th} supernova within clusters is denoted by E(i). The remnant energies in the present cluster with the lowest and largest values, respectively, are called E_{min} and E_{max}. The fuzzy membership function and linguistic values for residual energy are shown in Fig. 1.

Total cost of data transmission to CH associated to active cluster followers is known as intra-cluster communication cost. Based on the member's strength to the distance from nodes of CH, it is exactly proportionate, for the i_{th} SN in the cluster, gives a normalizing amount of the intra-cluster rate.

$$Distance(i, j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{3.7}$$

where the Euclidean distance between double SNs within cluster having (xi, yi) and (xj, yj) coordinates, respectively, is represented by Distance (i, j) in Eq. (3.7).

$$Cost(i) = \sum_{j=1}^{n} Distance(i, j)^{\beta} \tag{3.8}$$

The rate of intra-cluster communication, represented by cost(i) in Eq. (3.8) is derived from the summing the distances for ith SN with linked cluster followers raised to power β. For Distance (i, j), the value of β is assumed to be 2 unless otherwise specified 4.

$$NorCost(i) = \frac{Cost(i) - \min Cost}{\max Cost - \min Cost} \tag{3.9}$$

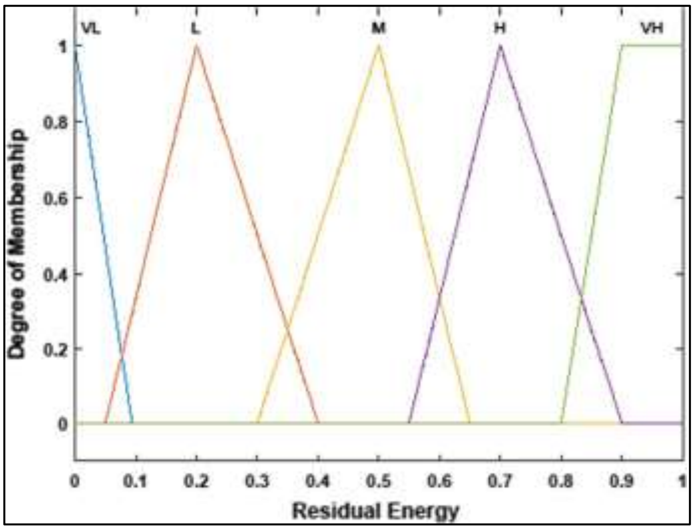


Figure 3.1: Membership Function Vs Residual Energy.

The overall quantity of cluster nodes that are members is n. In Eq. (3.9) a normalizing cost of ith SN, representing by min as well as max are denoted by NorCost(i). Cost represents the cluster's lowest and highest intra-cluster communication costs, respectively. Fig. 2 displays the language values for the fuzzy membership function and Intra Cluster Communication Cost.

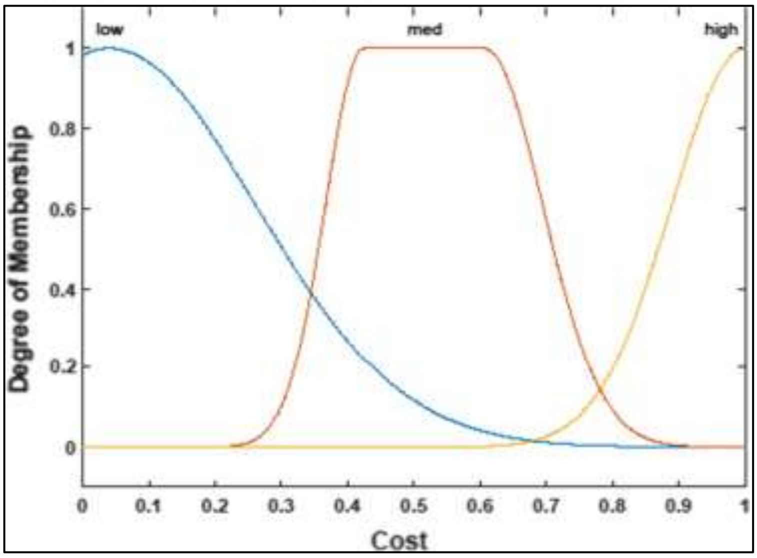


Figure 3.2: Membership Function Vs Intra Cluster Communication Cost.

The fuzzy criteria reported in Table 3.1 are utilized to determine the chances rate related to ith SN for becoming CH. Fig. 3 displays the linguistic standards of variables opportunity with corresponding fuzzy set. Using a Center of Area (COA) defuzzification approach, a crisp value Probability is obtained [50].

Table 3.1: Fuzzy Procedures To CH Election.

S. nos.	Residual energy	Cost	Possibility
1	Very low (VL)	Low	Very low (VL)
2	Very low (VL)	Medium	Very low (VL)
3	Very low (VL)	High	Very low (VL)
4	Low (L)	Low	Low (L)
5	Low (L)	Medium	Low (L)
6	Low (L)	High	Very low (L)
7	Medium (M)	Low	High (H)
8	Medium (M)	Medium	Medium (M)
9	Medium (M)	High	Low (L)
10	High (H)	Low	Very high (VH)
11	High (H)	Medium	High (H)
12	High (H)	High	Low (L)
13	Very high (VH)	Low	Very high (VH)
14	Very high (VH)	Medium	High (H)
15	Very high (VH)	High	Medium (M)

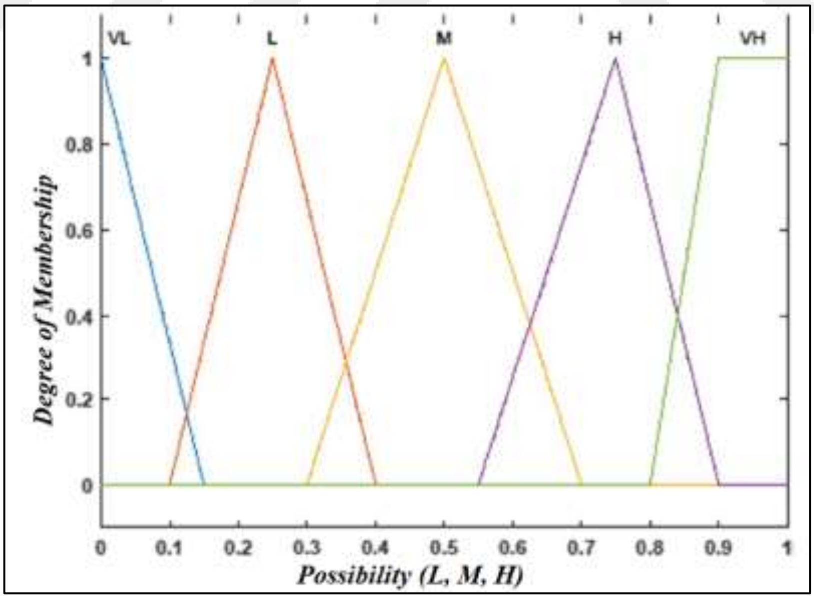


Figure 3.3: Membership Function Vs Possibility.

3.5.2 Bases Of Fuzzy Rules

They are fundamental component of fuzzy logic-based systems, including those used in various applications, such as cluster formation and node assignments in WSNs. It involves set of if-then rules which encode expert knowledge, heuristics, and decision-making logic in a linguistic and intuitive form. These rules help guide the system's behavior by mapping input & output variables_using fuzzy logic principles.

Each rules in fuzzy represents a specific condition and its corresponding action. The condition is referred to as the antecedent, while the action is called the consequent. The antecedent contains the input linguistic variables and their linguistic terms, defining the conditions under which the rule is activated. The consequent consists of the output linguistic variables and their linguistic terms, representing the desired output or decision linked input procedures.

The rules in the fuzzy rule base reflect domain-specific knowledge and expertise, and they are designed to capture both input and output variables dealings. These rules can be expressed in natural language, creating them simply explanation with humans and domain specialists. The language of the rules captures some uncertainties (imprecision) associated with real-world information via linguistic terms.

This fuzzy inference processing is heart of the fuzzy based systems, which include many applications in real world like formation cluster and maintain node assignments etc. as applied on WSNs. It is the process by finding-out a rating of how much an output linguistic variable should belong to each and all its respective terms, based on where in between which input our raw membership level falls.

Here's how the fuzzy inference process works:

Fuzzification: The process begins with fuzzification, where crisp (numerical) input values can be recorded to an equivalent linguistic terms using membership functions. Each input linguistic variable has membership functions that define the level of membership (a value ranging from 0 to a. of the input to any linguistic time. These utilities capture the uncertainty and imprecision associated with the input data.

Fuzzy Rule Bases: They comprise if-then sets which encode the decision-making logic. To each rule links the input linguistic terms to the output one linguistic terms. The rules capture the relations amid the inputs & outputs and are designed for signifying expert knowledge and domain-specific heuristics.

Rule Evaluation: The fuzzified input values are used to evaluate each fuzzy rule in the fuzzy bases. These rules involving antecedent (input situations) with a following outputs. The antecedent specifies fuzzy sets of the input linguistic variables that activate the rule. The activation strength of each rule is determined by the degree to which the input values satisfy the conditions specified in the antecedent.

Fuzzy Logic Operators: The activation strengths of multiple rules may overlap, as multiple rules can be partially activated by the input data. To handle this, fuzzy logic operators (e.g., AND, OR) are used to combine the activation strengths of rules with shared inputs. For example, in the case of multiple rules with the same input variable, the OR operator combines the activation strengths of these rules, representing their combined influence on the system.

Rule Aggregation: The fuzzy inference process aggregates the activation strengths of all the fuzzy rules to obtain the overall fuzzy output. This aggregated output represents the combined effects of all the rules on the output linguistic variable.

Defuzzification: The final step in the fuzzy inference process denotes defuzzification, its a fuzzy output that changed to a crisp value. Defuzzification approaches, like centroid, mean of maxima, besides weighted average, can be utilized for calculating crisp values from fuzzy output. This crisp value represents the system's final decision or output.

By applying a fuzzy inference processing, a system of fuzzy logic-bases can make intelligent decisions based on the fuzzy input data, considering multiple criteria and uncertainties. This process for flexible, adaptive and context-aware decision-making is very appropriate to dynamic environment with uncertain. E. g., those encountered in WSNs. The system allows to manage vague and uncertain data that provides recommendations based on available knowledge for a wide range of WSNs applications, as well in other fields.

3.6 FUZZY LOGIC BASED CLUSTERS ALGORITHMS FOR WSN (FLB-CLS)

Fuzzy logic-based cluster formation and node assignments: It is an intelligent way of organizing SNs into clusters in which roles or responsibilities to the nodes are assigned based on rhetoric fuzzy logic principles. They use the capacity of fuzzy logic to deal with vague and uncertain information in order to take well-founded decisions, keeping those methods applicable for dynamic resource-constrained environments.

During the fuzzy-logic based cluster formation, nodes judge for them self to be a good candidate of CH using fuzzy inference. Furthermore, fuzzy logic takes nearly into account multiple criteria (input linguistic variables such as node energy, communication range and connectivity). Each linguistic variable has linguistic terms, and membership functions describe memberships degree of a node to each term based on its characteristics. Fuzzification converts crisp input data, such as node energy levels and communication range, into fuzzy values using membership functions. Then, fuzzy rule bases, consisting (if-then) procedures, encodes expert knowledge and domain-specific heuristics to determine cluster head candidacy. The rules define the conditions under which the node may be more likely becoming a CH based on its fuzzy input values.

The fuzzy inference process combines the rules' activation strengths to determine the overall cluster head candidacy of each node. The activation strengths represent a degree where each rule can be fulfilled centred on node's characteristics. The fuzzy inference process aggregates the rules' activation strengths using fuzzy logic operators (e.g., AND, OR) to obtain a fuzzy output representing the cluster head candidacy. Finally, defuzzification converts the fuzzy output into crisp cluster head candidacy values, allowing nodes to be ranked based on their candidacy.

Once the cluster head candidacy values are obtained, nodes with higher candidacy scores are selected as cluster heads. The fuzzy logic-based approach allows for a flexible and context-aware selection of cluster heads, considering multiple criteria and uncertainties. When the cluster heads are selected, all other regular nodes join in a cluster whose head is its closest and most capable. Fuzzy logic - fuzzy sets to assign roles or responsibilities for each node in the clusters. For example, the cluster can be formed in a way where specific nodes are assigned tasks like those which have better residual energy or advanced sensing capabilities.

Fuzzy-logic-based cluster formation and node assignments, therefore, possess an important feature of being able to dynamically adjust in response to changes for the network. This may be due to node failure; energy levels of nodes are different or environmental changes have occurred. The system checks and rechecks cluster head candidates in a fuzzy logic fashion, continuously updating the structure of clusters with nodes joining when their interests coincide. This adaptable change model allows the network to remain robust, energy-efficient and sensitive according to new conditions.

Summary: Fuzzy logic-based cluster formation and node assignments provide an intelligent adaptive method for WSNs organization. They use fuzziness as a method for intuitive scaling and adaptiveness in the heterogonous large-scale dynamic systems of WSN. They help in improved optimization of resources, enable energy efficient behaviors and also provide high level network performance for developing and managing WSNs.

3.7 OPTIMIZATION OBJECTIVES

Optimization Optimization objectives in the context of WSNs are for example associated with network, efficiency and resource utilization performances to be realized. In fact, these objectives provide the foundation for designing algorithms, protocols and mechanisms (albeit with trade-offs) to fulfil end system needs in WSNs. Design of the optimization objective collections are made based on application-specific needs, network features as well because difficulties combated in your installation atmosphere. Popular Types of Optimization Functions in WSNs

Prolonging Network Lifetime: This is one of the most significant optimization goal. Since energy depletes at nodes, the lifetime of a WSN can be extended to an 9acceptable level by judiciously managing the scarce resource and utilizing it properly among different tasks/nodes.

Throughput: When an application moves a big volume of data per second, it is absolutely necessary for the software to do as much transferrable (transmitted) effective network traffic in any time (padding or real transmitted). Is in generating High-Throughput which includes efficient data collect, aggregation and telemetry strategies.

Reliability and Fault Tolerance: Providing reliable communication and fault tolerance is crucial in WSNs, for example with harsh or dynamic environments. The goals of optimization could be to design efficient routing methods and/or data recovery mechanisms for if nodes fail in ensuring that all the generated information reaches its destinations.

Data Accuracy: When it comes to applications that need accurate data sensing and reporting, then Data accuracy is one of the most crucial optimization goals. It is essential to minimize the errors and uncertainties from data error, so as optimal use of smart fusion techniques that have been developed using soft computing for aggregation of data.

The number of nodes/traffic Data: The scalability and optimization of the network should be handled so that as new services are integrated into edge deployments, this upgrade does not bring down operational efficiency in securing traffic throughout the system. Efficiency - Large-scale WSN deployments imply scalable algorithms and protocols.

Latency and Delay: Optimizing the time required for submitting, processing APIs and returning responses is a critical component when executing services that need to be timely delivered. Also, routing paths and transmission schedules can help to reduce the delays in data travel from sensors through fog gateways.

Load Balancing: Load balancing is intended to distribute blank energy and communication load across the network. This avoids the premature energy depletion in some nodes and extends to the overall network lifetime.

Deciding which of these optimization objectives to select and what are the orders based on different system requirements is application specific, as well balancing among several performance metrics. Academic and Engineers are continuously evolved innovative algorithms, protocols which can be used for directing such optimization objective as well for improving overall efficiency, performance of WSNs in many application domains.

3.7.1 Energy Efficiency

To level nodes while consuming energy for scaling expensive between few clusters and assignment of notes to the cluster in a way that maximizes network life. Energy efficiency has been regarded as one of the major optimization goals in WSNs due to various a priori resource constraints of sensor nodes such as limited battery capacity and impracticality for having regular change or recharging batteries especially when deployed at inaccessible areas. Maximizing energy efficiency may be necessary for extending lifetime of networks and ensure sustainable operation. Various techniques are employed to achieve energy efficiency in WSNs.

One approach to enhancing energy efficiency be situated on development of such protocols. These protocols aim for getting the best energy-efficient paths for data transmission, avoiding long-distance communications and reducing the number of hops between nodes. By minimizing the consuming energy through the transmitted data, a route of energy-efficient protocols help extend the network's overall lifetime.

Data aggregation and fusion are another important aspect of energy efficiency in WSNs. As an alternative of straight transmitted raw sensor data to the BSs, nearby nodes can collaboratively aggregate and compress data before forwarding it. It saves the energy as it reduces the network data transfer volume. Data fusion mechanisms aggregate repetitive data coming from several nodes, further containing and saving energy spent on traffic due to these additional transmissions.

To improve energy efficiency, clustering algorithms are employed. In clustering, sensor nodes are organized into groups and CHs may be elected to represent these clusters. These head nodes now take responsibility for collecting information from cluster members integrated in it say relays the same data back to base station. This hierarchical method leads to the reduction of communication overhead as nodes do not have any need to forward data directly at BS, since they can easily transmit it through their cluster head.

In WSNs, dynamic adaptation is one of the main approaches to realize energy efficiency. The network topology and properties could change with time due to link failures, environmental changes (such as atmospheric absorption), or mobility. By leveraging adaptive algorithms and mechanisms that adjust the network's operation according to real-time conditions -energy expenditure can be optimized. This includes putting nodes with low energy to sleep so that they can conserve their energy, and re-routing the communication paths in order to avoid areas where some of the nodes have completely run out of power.

Energy saving functionalities in hardware and communication protocols contribute to the overall energy efficiency in WSNs, alongside with algorithmic approaches. Low power radio communication protocols that are widely used for minimizing the energy-consumed from wireless data transmission as ZigBee and Bluetooth Low Energy (BLE). Additionally, the advent of energy harvesting techniques enables nodes to scavenge power from nature sources (e.g., solar, wind or vibration) and replenish their battery along with enhancing efficiency.

Through energy efficiency the WSNs are designed and operated in a way that they can save as much energy resources as possible for other applications scenarios.

3.7.2 Load Balancing

Avoid the problem of congestion of network clusters and Increase scalability to share tokens evenly between cluster heads across nodes.

Also Load Balancing is one among the key optimization objective catered in WSNs which aims to reduce energy and communication load evenly throughout the network. Load balancing ensures that no nodes are overburdened with traffic rendering them useless after running out of battery, reduced performance and their network being susceptible to failure. Load balancing is intended to balance the loads such that resources are used effectively and network life span is maximised.

Load balancing can be tackled from different ways. One side is energy load balancing: introduced for the first time as ensuring that consuming of sensor nodes evenly distributed their energy. Data packets routed to the sink are fed by available energy sources with higher residual levels while data traffic traverses preferentially through lower energy consuming paths via Energy-aware routing protocols. This makes the load balancing problem non-symmetric in terms of energy and is not appropriate because it can put some nodes to sleep faster than others, which raises major concerns; given that power supplies are scarce which could easily endanger lifetime at one shot.

Load balancing in SMC refers to the efficient distribution of computational tasks and data processing between sensor nodes. Nodes with higher processing power can be assigned more work and nodes with shallow resources are distributed light works. In doing so, the network does not burden a single node with all processing thus guarantee optimal use of computational resources in the network.

In WSNs, another important issue is communication load balancing. Its goal is to evenly distribute the data transmission workload on all networks. Relays with stronger communication may act as intermediate options for nodes that are further away from the base station or have weaker links. The method decreases the hop numbers for data transmissions and also minimizes communication energy used.

Another common load balancing approach is Cluster-Based Load Balancing that is used in WSNs. This class of algorithms implements load balancing as a clustering algorithm by forming clusters with an equal amount of energy and communication capacities. Dynamic selection of cluster-heads based on their residual, communication ranges and computational capabilities. It groups together the nodes that are unevenly distributed through into clusters and then for cluster level data can be collected which helps to reduce communication overheads and also distribute the load evenly among these cluster heads.

Load balancing strategies focus around the ability to dynamically adapt load. Load balancing mechanisms should be able to adapt dynamically when network changes happen e.g. node failures, environmental conditions change or new nodes are added [3]. The key is that the load changes are always made in a dynamic way so as to keep some balance in the network whilst it evolves its topology and operating conditions.

Load Balancing in WSNs has been considered as a challenging task due to the dynamic and resource-constrained sensor node natures. This sometimes involves complex algorithms, decentralized decision-making and instant feedback of the demand on its part to manage network loads effectively. Good load balancing can improve the energy consumption, performance of network and resource utilization, thus improving network efficiency significantly in a variety of WSN applications.

3.7.3 Quality-Of-Service (Qos) Considerations

In WSNs, it is important to consider Quality-of-Service (QoS) which ensures that a network satisfies the requirement of applications running in this. QoS means a collection of performance metrics and criteria that must be provided to achieve an acceptable level of system operation as needed for reliable data delivery. QoS topics cover different aspects related to WSN design and management in order not only support a certain quality of service, but also incorporate the demands coming from many application domains.

Quality of the Data - Reliability and Accuracy: This is one (not all) common concern for applications. In addition, we need to implement error detection and correction mechanisms for QoS considerations in which data transmitting from sensor nodes through the base station are authentic and error free.

Latency and Delay: Time-critical applications such as real-time monitoring (control) systems require short delay in data transmission apart from expectedly low latency. QoS and consider the optimization of routing protocols, communication schedules to reduce communications latency while ensuring data delivery in a timely manner.

Throughput and Data Rate: This is important to applications where a lot of data is generated, or the comments need to be updated very often Choice of communication protocols and data aggregation mechanisms at the RPL routing layer also influence QoS.

Energy Efficiency & The Network Lifetime: Although energy efficiency is the major optimization goal in WSNs, QoS constraints refrain it from adopting potentially significant methods if network lifetime and service quality may be for limited. However, balancing such energy efficiency with the QoS requirements to keep accurate and reliable network performance over a long time is necessary.

Security and Privacy - A subset of QoS considerations are measures to improve network security as well as data privacy. However, to guard the specific confidentiality of information and safeguard network integrity right through these layers' robust encryption (coupled with certificates), verification, as well as gateway appliances do continue being essential.

Dynamic Adaptation: When the nodes are failure, environmental changes (e.g. sunlight being blocked by a large vehicle) or mobility which means QoS consideration include the network's capability of dynamically adjusting itself for varying conditions hostile and friendly environment. Assert Null Dynamic adaptation mechanisms ensure that QoS metrics are always satisfied, even under uncertain and dynamic nature of the environment.

3.8 CLUSTERING IN WSNS

3.8.1 Benefits Of Clustering In Wsns

Clustering is a fundamental method in WSNs, and it forms SN into clusters. Clustering is more energy efficient, scalable and supports data aggregation/fusion as well as load balancing in WSNs. The concept is that cluster formation minimizes energy consumption as the sensor nodes function in a bulky group and send data to sink node by compressing at the level of cluster head, which consists from among on these sensors.

While implementing clustering into WSNs, we need to consider a few points:

a. Cluster Formation Criteria: The most important part is selection of the cluster heads. Selection of one method to another in this situation depends on features like level of node energies, proximity via sink, communication cost and other capabilities that you consider for a sensor network.

b. Cluster Head Selection: need effective algorithms and methods to dynamically choose the cluster head. It helps selecting energy-rich nodes or specific capacity in cluster heads so that better network performance can be achieved.

c. Clustering Setting & Maintenance - After the selection of cluster heads, next task is to allot clusters members. The cluster creation and maintenance here needs to be dynamic such that in case of node status change, failure or mobility the algorithm should take care.

d. Communication Protocols: Clustering mandates design and implementation of Communication protocols for intra-cluster communication between different nodes, as well as inter -cluster communications to exchange messages across systems. These protocols are required to route data in an efficient manner between cluster heads, member nodes and the sink node while considering energy efficiency and based on network limitations.

e. Cluster Head Replacement: Cluster heads have some extra task compared to member nodes, result of that is the energy consumption on cluster head level happens more rapidly compare as other node so they required replacement periodically. There should be proper mechanism that a cluster head loses half of its energy at time when it is close to the lifeline, so new CHs can replace them and hence availability should not ends up there.

f. Algorithm - Clustering algorithms should have fault tolerance mechanisms when processing a node failure while the network continues uninterrupted. Redundancy, cooperative clustering or cluster structure reorganization accomplishes this goal.

g. Security Issues: Clustering brings security issues since cluster heads are the most critical nodes for data aggregation and transmission. Secure communication, authentication and data confidentiality in clusters Of course sensitive information must be well protected with secure channels between apps.

Then, clustering plays a vital role in WSNs by allowing energy-efficient data aggregation-enhancing scalability and fostering load balancing.

Energy Efficiency: Clustering decreases the consuming energy of SNs via establishing a hierarchical structure. Cluster heads, selected from among SNs, consider in charge of aggregating and processing data from cluster members, thereby minimizing the energy expended in long-distance transmissions to the sink node.

Scalability: WSNs often encompass a large number of sensor nodes. Clustering allows for efficient management and communication by dividing the network into smaller, manageable clusters. This enhances scalability and simplifies network control and maintenance.

Data Aggregation and Fusion: Data aggregation and fusion are assisted by clusters. Cluster heads assemble data from member nodes, make aggregating it, then transfer an aggregated data to the SNs. This reduces redundant transmissions, conserves energy, and facilitates efficient data processing and analysis.

Load Balancing: Clustering distributes the network traffic and processing load across multiple cluster heads, preventing congestion and ensuring a more balanced utilization of network resources. This improves overall network performance and extends network lifetime.

Considerations in Clustering WSNs: Several considerations should be taken into account when implementing clustering in WSNs:

a. Cluster Formation Criteria: Determining the criteria for selecting cluster heads is crucial. Features like a level of node energies, proximity via sink, communication cost, and node capabilities should be considered in the selection process.

b. Cluster Head Election: Efficient algorithms and mechanisms are required to select cluster heads dynamically. This ensures that energy-rich nodes or nodes with specific capabilities are chosen as cluster heads to maximize network performance.

c. Cluster Formation and Maintenance: Once cluster heads are selected, member nodes need to be assigned to appropriate clusters. Dynamic cluster formation and maintenance algorithms should be employed to handle changes in node status, failures, or mobility.

d. Communication Protocols: Clustering requires the design and implementation of communication protocols to facilitate intra-cluster and inter-cluster communication. These protocols should efficiently route data between cluster heads, member nodes, and the sink node while considering energy efficiency and network constraints.

e. Cluster Head Replacement: As cluster heads consuming additional energy because of some additional responsibilities, their energy levels may deplete faster than member nodes. Effective mechanisms should be in place to replace cluster heads when their energy falls below a certain threshold, ensuring the stability and continuity of the clustering process.

f. Fault Tolerance: Clustering algorithms should incorporate fault tolerance mechanisms to handle node failures and maintain network connectivity. This can be achieved through redundancy, cooperative clustering, or reconfiguration of cluster structures.

g. Security Considerations: Clustering introduces new security challenges, as cluster heads become critical nodes for data aggregation and transmission. Ensuring secure communication, authentication, and data confidentiality within clusters is essential to protect sensitive information.

In summary, clustering shows a dynamic part in WSNs by enabling energy-effictive data aggregation, improving scalability, and facilitating load balancing. By carefully considering cluster formation criteria, cluster head election, communication protocols, and fault tolerance mechanisms, effective clustering strategies can be designed and implemented in WSNs to optimize network performance, enhance energy efficiency, and prolong network lifetime.

3.8.2 Importance Of Clustering Optimization

Clustering is important in WSNs, and it provides a lot of advantages; hence It optimization needed to ensure good clustering. In this section we explore the importance of clustering optimization in WSNs.

a. Energy Efficiency: Clustering optimization improves energy efficiency in WSNs by an order of quadratic dimension [22]. A network layer can structure sensor nodes in clusters that capitalize on spatial and temporal data correlations, which will radically cut down redundant transmissions. Key to this approach is the use of local processing within cluster heads for data aggregation, reducing the energy spent in long-range communications all the way back to sink nodes.

b. Most notably, as soon as more network lifetime relates to Efficient clustering optimization techniques for WSNs. The energy utilization is fairly balanced among the sensor nodes by reducing consumed energy when transmitting and processing data locally.

c. Scalability: Scalable performance for large scale WSNs Post clustering optimization.Encode the output. In this way, network complexity and management as well as communication overhead is reduced by breaking the network into smaller clusters. This also allows for an efficient resource allocation, routing and data processing - important to support the increasing SNs number at a network.

d. Network Performance and QoS: Enhancing the performance of Network-Quality of Service (QoS) with efficient clustering techniques. Clustering optimization handles the way data flows, and resource utilization is optimized with communication paths to avoid network congestions achieving better efficiency in delivering the content.

e. High Fault Tolerance and Efficient Network Resilience: Clustering optimization techniques can lead to increased fault tolerance abilities, while supporting resilience mechanisms in WSNs. Clustering also provides redundancy and alternate communication paths by breaking up functionality into cluster heads and member nodes that create an overlay network.

Clustering optimization plays an essential role in WSNs as well due to its significant influence on energy efficiency, network lifetime, scalability data aggregation, general network performance except fault tolerance and resilience. Through these clustering optimization techniques, WSNs can provide improved resource utilization and data management for sustainability as well as efficient operations in the sensor networks.

4. IMPLEMENTATION AND PERFORMANCE ANALYSIS

4.1 INTRODUCTION

Wireless Sensor Networks (WSNs) have recently emerged as an important technology for monitoring applications to capture data from various environments, and are used in several areas such retail, industrial research or ecological measurements. Application deployment in the real-world requires designing clustering algorithms which not only ensures a higher network performance but also reduces energy wastage. In this chapter, we demonstrate the implementation and evaluation of novel fuzzy-based clustering optimization method in WSNs.

As discussed in earlier chapters, WSNs still face the same difficulties: energy saving mechanisms to extend network long life and reduce information redundancy. One popular way of organizing nodes is clustering, in which sensor nodes are divided into clusters where a leader node typically presides over each cluster. This organizational structure allows data aggregation at the cluster head which in turn reduces long distance communication and hence helps increasing network life simulation.

The existing researches mainly concentrated on the efficient management of clustering in WSNs. Despite numerous clustering algorithms exist, a newer promising approach of including fuzzy logic in the optimization process could help to enhance cluster formation, adaptability and resource allocation. Thus, the need for this chapter arises in order to bridge the gap between theoretical foundations derived throughout chapters and practical implementations and empirical evaluations of the proposed clustering optimization using fuzzy logic.

4.2 WSN SIMULATION ENVIRONMENT

Wireless Sensor Networks (WSN) simulators: In WSN, different scenarios and challenges like clustering optimization algorithm effectiveness can be tuned while testing to get accurate results. This section details our simulation environment and components, which are used as the basis for our empirical evaluation.

4.2.1 Simulation Software: Matlab

MATLAB, as a general-purpose numerical computing environment is used to model and analyze the behavior of our Wireless Sensor Network (WSN) making it the simulation software of choice for this study. We chose to use MATLAB due to its flexibility and robustness in simulating WSNs, such that our work group could explore the characteristics of clustering optimization algorithm we designed under controlled conditions.

We performed comprehensive validation of our MATLAB-based simulations to guarantee the accuracy and reliability. As and when possible, we validated these results by comparing simulation outcomes with closed-form analytical expressions or confirming our results against empirical data from published reports on actual WSN deployments.

The wireless sensor network topology is one of the most important factors that define how sensors nodes behave and interact in simulations with Wireless Sensor Networks (WSN). Choosing an Appropriate Topology. The first step in this process is to select a suitable topology that enables our experiments to reflect the real-world deployment scenarios as closely as possible.

4.2.2 Topology Selection

For our research, they selected a specific network topology (a grid-based one), as this type of network model was more relevant with the reality based scenarios we wanted to address.

The chosen topology is known for being a realistic one, generally reflecting the typical structures and connectivity patterns present in WSN deployments. Since grid-based topology is scalable by definition, we run these experiments on different network sizes and node densities. This topology allows representing static and dynamic moving scenarios, incorporating the effect of different mobility speeds on sensor nodes.

This topology has sensor nodes that are scattered within the coverage area of this network. Communication links are created between nodes in the grid-based topology oriented toward their physical distance and a connected network is formed. It might be hierarchical with some nodes taking on roles such as cluster leader or data aggregator. This hierarchy is in line with the clustering optimization algorithm that had to be discover during analysis. For such settings, this means that with the grid based topology it is possible to keep node movement while preserving connectivity for our research question which moves around mobility patterns from various mobile sensor nodes.

A grid-based topology selection for our fuzzy logic based cluster optimization algorithm evaluation is motivated by its salient features that enable a practical and less structured testing infrastructure. By its adaptive to different, network sizes, node densities and mobility scenarios our explorations are used in a considerable range of real-world situations.

4.2.3 Network Size And Density Of Nodes

We set the scale of network in experiements, we configure more number of sensor nodes at differently sized area. The proximity of nodes was affected by the node density, which is fixed in our settings. The values of these parameters were changed, to assess the performance of the algorithm at different network scales.

In last, our WSN simulations will run over a grid-based structure abstracting network topology to be realistic, scalable and adaptable. Empirical evaluations of the clustering optimization algorithm in several WSN scenarios are based on this topology together with simulation software described above. Additional simulation parameters, settings and the algorithm deployed in a chosen network topology will be detailed on subsequent sections.

4.3 EXPERIMENTAL METHODOLOGY

This experimental methodology explains the procedure that has been carried out to scrutinize over the efficiency of fuzzy logic based clustering optimizing algorithm in WSN. Experimental Design This section explains how we design the experiment to verify if our algorithm works effectively and its data acquiring process, as well as shows you where they evaluated their algorithms.

4.3.1 Experimental Design

Experimental design is the one that selects the conditions and parameters under which we evaluate a given clustering optimization algorithm This paper, in turn tells you about the assessment made for a clustering optimization algorithm having predefined inputs and parameters. One particular scenario generator is more significantly adapted out design using some unique experiments and there are applying special proposals for other network sizes, node densities or mobility patterns. They are built as control groups to benchmark against and utilize popular clustering algorithms or other traditional methods. This randomization technique is used to give minimum bias and make sure that all the parameters are randomized within these fixed levels. Repeats experiments (for statistical significance) The experimental methodology is based on the collection of empirical data from sensor measurements, simulation logs and real-world deployment traces. A collection of sensor nodes that monitor network performance (energy consumption, data transmission, cluster formation and node health). Design/methodology/approach Simulation records are produced by using the MATLAB methods, and then they will be used as a model to validate simulation results in deployment with real world data regarding mobile sensor nodes.

4.4 PERFORMANCE METRICS

In our work on Clustering Optimization Using Fuzzy Logic in Wireless Sensor Networks, we need to give the performance metrics which you employ for checking how efficient your algorithm is. These are objective metrics to assess how well (or bad) your algorithm is doing. A few of the most commonly used performance metrics research codes are:

4.4.1 Network Lifetime

The network life time refers to the amount of time span a wireless sensor Network can work out before first node goes in drained energy. It is considered a key metric in evaluating the durability and persistence of the network. The network lifetime is the time of creation a network in which at least one node can not take part on such activities as long as its energy level falls below that predetermined threshold.

The network lifetime is an essential performance metric in Wireless Sensor Networks (WSNs) and represents how long the sensors are able to work so that this also considers important role of evaluating the sustainability and longevity of a WSN. It denotes the lifetime until which WSN can function before the first sensor node of network loses all its energy. Extending the lifetime of a network is usually an important goal since it influences directly on how useful and efficient are the network as a whole. The network lifetime is usually represented in time based units such as hours, days and years or rounds according to the domain of the experiment/simulation.

Many aspects such as the energy consumption, initial levels of energy and also techniques for gathering the energy are priorities in network lifetime. A critical system architecture abbreviation was formulated to reduce the energy consumption and extends life with respect of a network, efficient algorithm. Sensor nodes that have more initial energy in v probably can keep the network functions longer. The node energy in a WSN can be restored by means of power sources, such as solar or kinetic energy harvesting [4], which could prolong network lifetime.

These are typically long-duration monitoring applications, like environmental sensing, surveillance and infrastructure monitoring where energy efficiency is important to maximize network lifetime. Extending the life of network can reduce maintenance costs and improve WSN practicability in harsh or remote environments.

Fuzzy set logic based clustering optimization algorithms attempt to achieve network lifetime extension by closely organizing sensor nodes into clusters, thereby conserving energy in long range communications and balancing typical battery usages among the deployed note. To be sure, whether or how much the clustering optimization affects on network lifetime is an important component to evaluate the performance of algorithm in WSNs.

4.4.2 Energy Consumption

An essential performance metric in Wireless Sensor Networks (WSNs) is energy consumption which determines how efficient and sustainable a network can be. It measures how fast the energy resource gets consumed by a sensor node performing different task in the network. Energy consumption should be managed wisely and attention has to put in optimizing it since prolonging the network lifetime, robust operational dependability are important features.

Energy (such as power or watt-hours converted to joules in this paper) represents the energy consumed by a single sensor node and the entire network during various tasks, like for example sensing on-board data transmission receiving processing communication etc.

Energy Consumption Measurements:- It can be used to measure how original or efficient a clustering optimization algorithm is. These metrics: Average Node Energy, residual Energy and Energy Consumption Rate in average are used to check the distribution of energy amongst all sensors nodes. Several factors affect the energy consumption of sensor nodes in a Wireless Sensor Network (WSN) These factors include transmission distance, data rate, methods of aggregating the data together once gathered at a central point (mining), when and how often sensors are actively gathering information from specimen they monitor for changes in physical way points calling frequency; as well power saving strategy's utilised by nodes to make most out time not nessasary spent being energy wastefully. The transmission of data over a long period consumes more energy because the sender has to send strongly enough for the receiver to perceive it. As beds, the fuel consumption by percentage via network traffic will also be larger with higher data rates. The next technic used is data aggregation which helps in combining the local processed data and then transmit them, will minimize transmission power consumption.

The measurements of energy consumption in the experiments or simulations can be expressed at many levels, depending on their contexts. Standard units are joules (or millijoules) per node-level measurements and watt-hours for aggregated, network wide measures.

In WSNs, saltatory energy consumption is a serious issue because sensor nodes are typically battery powered and have limited energy source. The use of energy with relevance in reducing deployment frequency, battery change or recharge need and continuous monitoring at remote maintenance free area is important for networks to live longer.

For example, fuzzy logic based clustering optimization algorithms target minimization of energy consumption for WSNs by optimizing communication pattern and/or clustering nodes or DBL sleep-wakeup schedule. This sort of algorithms are meant to balance the energy consumption among nodes and can dramatically increase network lifetime while increasing its global efficiency. A critical aspect of the effectiveness evaluation for practical WSN deployments is to evaluate how cluster optimization reduces energy consumption.

4.4.3 Latency

Wireless sensor networks (WSNs) stand emphasis on the performance metric known as latency, which is defined for measuring time consumed in transmitting data from source to destination node within a network. Applications that demand real-time, consistent data delivery thereby short latency are unequivocally non-starters without low latency. Latency is defined as the time required for data to travel from one source node to a destination on the network. If you are running anything in real-time, it will be better to have lower latency for the application.

Latency is the measurement of how long it takes from when I initiate data and to where that data reaches successfully utilizing another node. It's normally measured in milliseconds (ms) or microseconds (μs). Components include propagational delay, transmission delay and procession delay Latency is a unit of time, usually milliseconds (ms) or microseconds (μs), and it tells us how fast can we get the response after an application submits requests.

The latency in WSNs is a sophisticated procedure that includes propagation delay, transmission holdup, processing time and queuing caveats. Propagation Delay - Time taken for signal to travel from source point and reach destination, depending on the distance between both ends of link through electromagnetic speed. Transmission delay: Time it takes to physically transmit the data bits through a cable, affected by factors such as date rate and channel conditions. Processing delay - time data sits in queues on intermediate nodes before getting forwarded to next hop;

Low latency is particularly important in applications where data needs to be delivered from its point of origin to a client device as quickly possible with minimal delay--for example, in environment monitoring systems; health care and surgery robots; the internet-of-things space (e.g., industrial automation); or emergency response and disaster-recovery services. It also makes higher-performing timely environmental change detection, immediate patient tracking and faster control of industrial processes. Knowing this also assists emergency response or disaster recovery decisions.

Some strategies like efficient routing, cluster head or intermediate node data aggregation [7], QoS aware protocols giving priorities to real-time traffic and local processing at sensor nodes can be used in such networks. The measures are to eliminate the pseudo coding gray codes with low Hamming Distance within each group, and encode all-new groups of data packets individually at a time on order to avoid long encoding delays in WSNs.

The cluster optimization algorithms like fuzzy logic create latency in WSN. These algorithms work groups the sensor node, and also optimize communication patterns which in return reduce the number of hops (thus packet delays).

4.4.4 Throughput

Throughput is an important performance metric, which defines the amount of data to be delivered from source nodes to sink node (or base station) that as well within a network. It measures the amount of data that your network can transfer and is a basic measure for how well reliable or efficient you are. Throughput is defined as the rate of data successfully delivered from source nodes to sink node or base station. This is usually measured in bits per second (bps) or packets per second (pps).

Throughput is usually quantified in bits-per-second (bps) or packets per second and reflects how much data source nodes relayed to the destination (sink) node during some specified duration of time. Inferred Available Bandwidth - provides a measure of the network's data-carrying capacity and its ability to handle traffic. We use conventional data rate units (bps or pps) as defined throughput based on the timing granularity of application.

Optimised channel management may include optimisation of routing, QoS (Quality of Service) handling as well as data aggregation aiming at improving the throughput in WSNs. Shorter path lengths lead to lower number of hops and, thus reduced bottlenecks allows for efficient routing over the network; Quality Management: Critical data traffic can be prioritized with QoS management which is essential especially in time sensitive applications. Pulling in all this data, like the CDRA models or security alerts wherever you can sustain that kind of thing yourself and then feeding down nock on effects which create congestion... so another mode at collection time is to aggregate. Adaptive data rate that changes on the fly as network conditions warrant.

Abstract Throughput has been an important performance metric for evaluating the efficiency and effectiveness of a wireless sensor network (WSN), especially in applications that require timely delivery and high data throughput.

4.4.5 Packet Loss Rate

It is usually represented as a percentage - the rate of lost packets or dropped on all sent at that time. Traffic allows us understand both the health of the network and how well we are delivering data. Packet loss rate (PLR) is an important performance measurement for Wireless Sensor Network (WSN) as well as other communication systems. This is a measurement of how many data packets are lost in transit to their destination, for example due ot network congestion, interference or errors. Packet loss is disruptive to the dependable of high-fidelity data transfer, and thus Packet Loss makes it a vital metric for tracking & operating. Packet loss rate: it is the proportion of data packets lost in transmission Packet loss is a plague the does terrible things to your precious data and so anything that we can do to minimize this evil from eating our bits cannot be underplayed.

It can also be computed as the packet loss rate using this formula.

Packet Loss Rate (%) = ((Total Packets Sent - Number of Received Back) / Total Packets Sent)* 100

The packet loss rate is expressed in percentage (%), and it describes the ratio / proportion of all packets sent; then what fraction was lost.

Packet loss ratio is an important performance indicator in the area of Wireless Sensor Networks (WSNs) and communication systems for data integrity, quality of service (QoS), as well as network health. The high packet loss would cause the data of sensor nodes collected incomplete or inaccurate, and impair reliability. With many applications having strict QoS requirements or sometimes, bidding to control their timing (e.g., real-time monitoring and control systems), packet loss becomes a very sensitive issue. Examining packet loss rate offers an indication on the stability & quality of a network.

Maintaining data reliability and Network Performance in Wireless sensor Networks critically depends on the packet loss rate. This may include increasing robustness of the network by using error correction techniques like Forward Error Correction (FEC) or Automatic Repeat reQuest (ARQ), increased redundancy in case of critical data packets through multiple copies, prioritization and maintenance grace periods for important traffic along with appropriate resource allocations to reduce congestion at crucial points as well as optimization over communication links via efficient routing algorithms among other such modifications. These mechanisms can be used to reduce the chances of packets being lost and thus make a network more resilient.

4.4.6 Network Coverage

In Wireless Sensor Networks (WSNs), a basic performance parameter is the network coverage. It determine how well the sensor nodes in network are spread to observe and sense a particular area or region of interest Network coverage is a novel concept that reflects the degree of sensor nodes observing monitoring area and it plays an important role in many applications, such as surveillance, environmental observation and intrusion detection. Network coverage is the measure of a spatial distribution on sensor nodes and it evaluates that quota which, monitored region shares by these senor nodes. This may be shown as a percentage of the total area monitored. Coverage Metrics: Coverage metrics measure how well the sensor nodes cover all of the monitored area. It is in % of area coverage or Redundancy levels.

The methods of calculating network coverage based on the application, and what is conceived of as being covered. It includes both types of coverage such as cell-based and node based: Area-Based Coverage is under reference which consider division of monitored area into grid cells for checking individual sensors covering the respective region or remaining field unused, Node Based makes measurements on sensor nodes based measurement. If a part of the sensing range is overlapped with other nodes, then that region is called as coverage.

How to Investigate Network Coverage in a WSN (Wireless Sensor Network) Objective: Obtain some measurement during the deployment or simulation, calculate coverage metrics according to the chosen criteria and methodology, visualize results by graphs/plots/maps regarding of network coverage level / degree/ map view... then check variations under different scenarios where nodes are placed with some simple spread rule depending on existing analysis module using MATLAB as an analytical tool.

4.5 DATA CHARACTERISTICS USING FCM

This part distinguishes an enquiry to find out the outcomes & elaborates their findings in detail Our Clustering Process Using FCM Throughout the study of clustering, we obtained data and performed analysis through applying...medium.com These results signal the capstone to our studies, revealing overarching findings and trends elicited from our research.

We most of all want to ensure you have the full picture on what our results mean and how important they may or may not be in this summary of some of the factors we observed. This middle section sets the ground for a detailed analysis and interpretation of data, giving back some context, piecing together tropical threads, making sense or questions to relationships perhaps addressing initial research questions or hypotheses. This section is designed to provide a coherent picture of the major insights followed by an extended discussion, which will include consideration about implications. It will also discuss the results with regard to prior work and, where relevant, clarify unexpected or otherwise interesting findings.

By thoroughly examining each of our results, followed by discussion we aim also to contribute a new knowledge to the literature in our discipline and highlight an understanding that is substantial. Furthermore, we also invite our readers to engage with the information provided through comments and feedback which allows for a positive discussion forum where all parties can share their thoughts and contribute further knowledge in studying research fields. Generating random data points and assign them to a cluster. In Clustering in Fuzzy logic based is rand function used. After that it simply define the cluster centres as random points and enter a loop to do clustering by updating clusters assignments centre from each other. Figure 4 is used to plot the data points and cluster centers using scatter function.

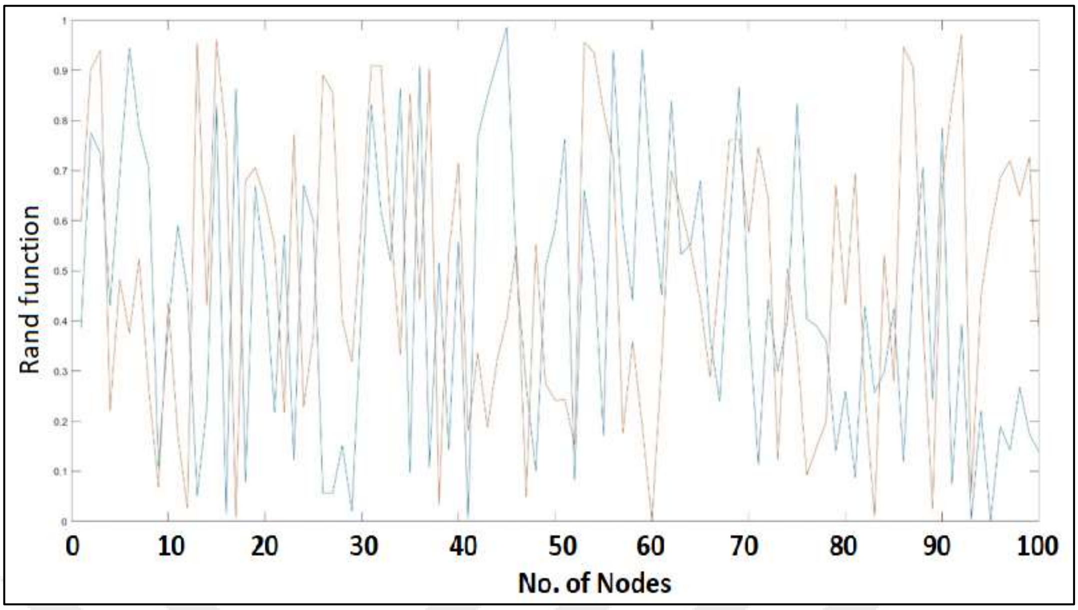


Figure 4.1: Show The Random Data Point For Fuzzy Logic Clustering.

In fuzzy logic-based clustering, the input data need to be clustered is generally taken as random data points. In general, these include one or more features that provide a description of the information associated with an observation and can also be used in classification. Description of Random Data points used in fuzzy logic clustering

A random data point will have a set of attributes or features. Some dimensions, measurements or properties may be described by these attributes. As an example, when aggregating consumer preferences data for a recommendation system with distinct attributes and type-levels-such as age or income,product purchase of history etc.-these can be used in your S3 object store. Fuzzy Logic Clustering : In fuzzy logic clustering is carried out on the basis uncertain memberships of data points to a variety of clusters. The data point belongs to various degree nais, pointing in fuzzy logic where a single hard clustering will be part of. Membership degrees of these data points to every cluster are considered, allowing for the possibility that a data point may belong to more than one group.

When data points are represented as coordinates in a multidimensional space, each attribute is mapped to its own dimension. For example, if aggregating customer data using such attributes as age and income would have a two-dimensional space with one axis for age and another for income. Each data point in this space is specified by its coordinates, and that coordinate describes the position of it w.r.t. other points. In fuzzy logic clustering, figure 5 indicates that initial fuzzy membership degrees to clusters may be assigned to data elements. These assignments may be random, or could be chosen based on some possibly application-dependent algorithm.

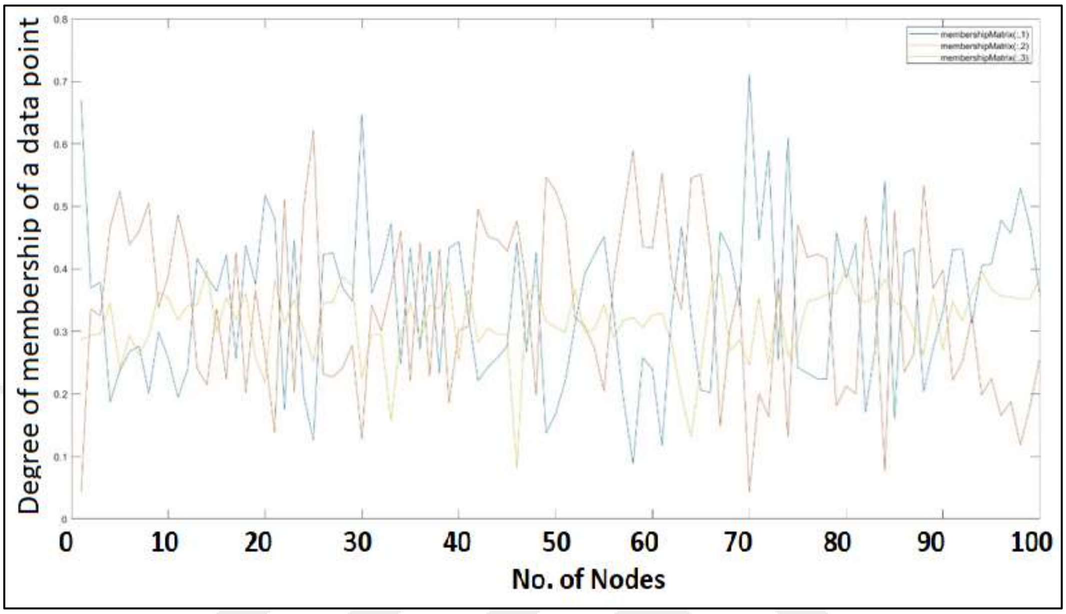


Figure 4.2: Fuzzy Membership Matrix.

Initial Fuzzy Membership shown in figure 4.2, it is fuzzy membership matrix at the beginning of this algorithm that produce using rand function, Every entry in the fuzzy membership matrix signifies how well a data point belongs to that particular cluster.

Primarily, we build a fuzzy membership matrix by using the rand function to generate random values (which could be thought of as degrees) on how much a data point belongs to you different clusters. Generally speaking, this matrix has row data elements and the number of columns depends on how many clusters are there. From one feature space distribution of arbitrary data points, to another it may be significantly different. They can be perfect clusters, a mix of overlapping or nearly-overlapping various individual documents near their average dates. The distribution of the data has an impact on how difficult clustering will be. In fuzzy logic clustering, cluster centroids the points where clusters will be centred. Based on the fuzzy memberships and data point coordinates, centroids are calculated. Data points that are closer to the centroid have higher membership degrees.

These are fuzzy logic based clustering algorithms for which random data points have been passed as i/p & these show the diversity and complexity of actual data. Fuzzy logic clustering aims to cluster these data points in a way which captures the uncertainty and fuzziness found within this data, thus making more flexible and sophisticated regarding conventional or crisp cluster assignments as illustrated in figure 6.

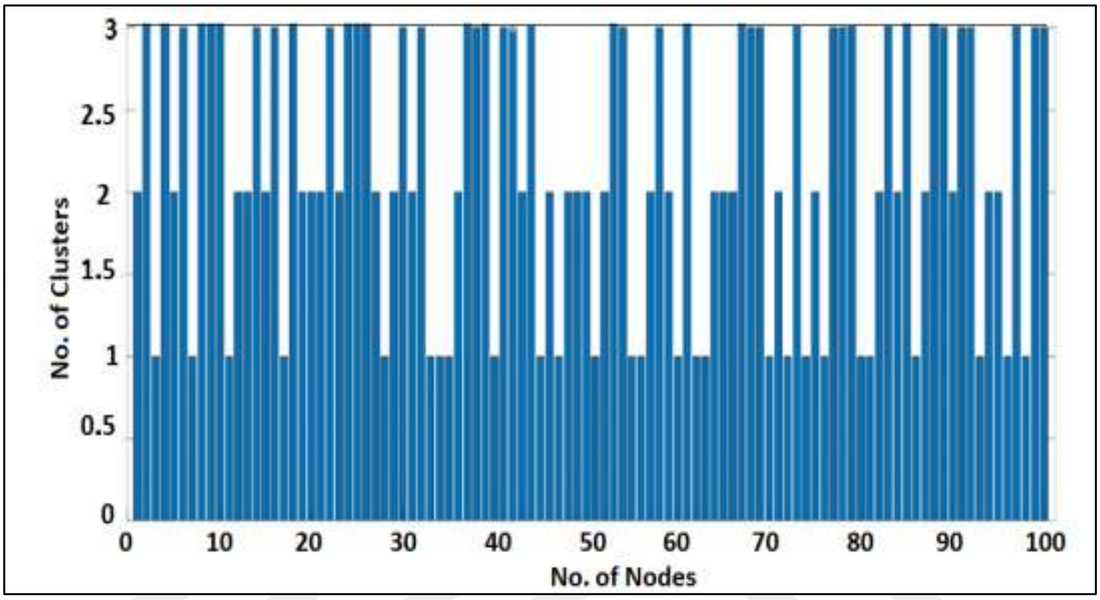


Figure 4.3: Cluster Assignments.

Let us explain how to generate such an initial imprecise membership matrix in more detail: 1. The first step is to define the parameters: – You need to know the number of data points and clusters in your dataset. – You need to define the possible random membership values range – it is a number from 0 to 1 inclusively when 0 means no membership in the cluster, and when 1 means full membership in the cluster. Step 2 is to Initialize Fuzzy Membership Matrix. You need to create an empty matrix, where is the number of data points and is the number of clusters. Step 3 is to Generate Random Values: – You need to iterate through every matrix cell, i.e., through the membership value of each data point in each cluster. – You need to generate a random number between 0 and 1 inclusively.

For example, we can do it in a MATLAB-like pseudocode:

for = 1:N for = 1:K = rand

end

end

Step 4 is to Normalize Membership Values. In order to ensure that every data point’s sum of membership values is 1 which indicates 100% membership in every cluster, you need to normalize the values by dividing each value by a row sum.

Example pseudo-code: for = 1:N = sum(i, :) =
end
end

As a result, after this process, you will obtain an initial imprecise membership matrix, where every element represents the degree to what the data point belongs to the cluster. In accordance with the fuzzy logic principle of partial membership in different clusters, the normalization process ensures that each data point’s sum of membership is 1 . This matrix can be further used by such iterative clustering algorithms as Fuzzy C-Means based on the data and membership values to assign clusters.

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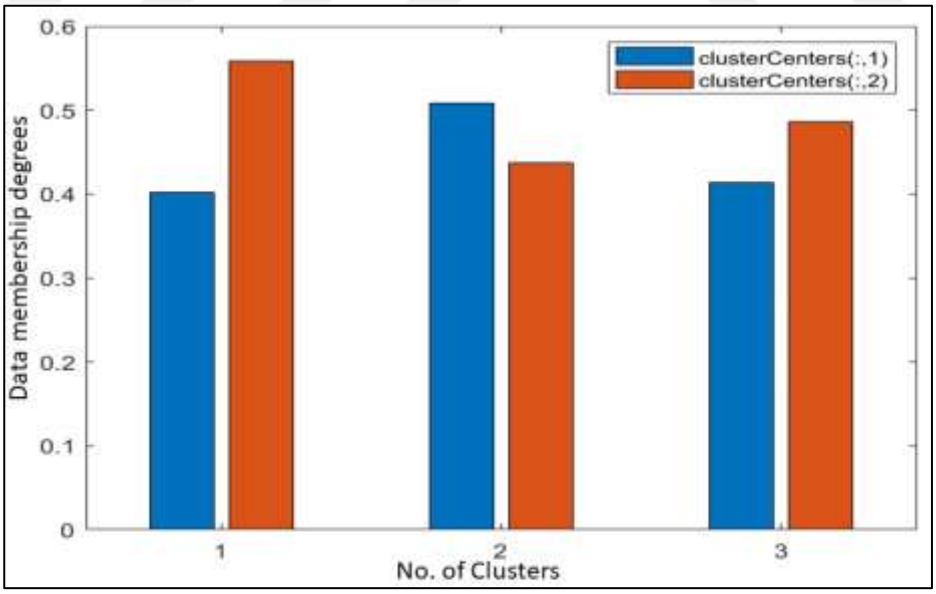

Figure 4.4: The Cluster Center For 3 Clusters.

These methodologies calculate the cluster centroids (in this case, three clusters) based on fuzzy membership degree of data points to get appropriate partition strength in Fuzzy logic-based clustering algorithms like Fuzzy C-Means or also termed as ours. This is a simple description of how cluster centers can be calculated.

Initialize Cluster Centers in Step 1

a. Initiate the cluster centers to begin. Depending on the specific clustering algorithm and your needs, you can either initialize them with a random value or use another method.

Calculate the Cluster Centers in Step 2

b. Iterate over each cluster and calculate the cluster center for each cluster based on the imprecise membership degrees of the data points. The cluster center is determined by calculating a weighted average of the data points, where the membership degrees serve as weights.

For the i-th cluster (where i ranges from 1 to the number of clusters, in this case, 3):

a. Initialize variables to store the sum of membership-weighted data point coordinates: sum_x_i, sum_y_i, etc., depending on the dimensionality of your data.

b. Iterate through all data points:

a. For each data point, calculate its contribution to the weighted sum based on its membership degree for the i-th cluster. For example, if you're dealing with 2D data (x, y), you'd do something like this:

   sum_x_i += membership_i_j * x_j

   # x_j is the x-coordinate of data point j

   sum_y_i += membership_i_j * y_j

   # y_j is the y-coordinate of data point j sum_x_i += membership_i_j * x_j

   # x_j is the x-coordinate of data point j sum_y_i += membership_i_j * y_j

   # y_j is the y-coordinate of data point j

c. After iterating through all data points, divide the weighted sums by the sum of the membership degrees for the i-th cluster to obtain the cluster center's coordinates:

center_x_i = sum_x_i / sum_membership_i

center_y_i = sum_y_i / sum_membership_i

d. Repeat this process for each cluster (i-th cluster), and you'll obtain the cluster centers for your 3 clusters.

The cluster centers represent the locations central to each cluster in the feature space. They are computed using the fuzzy membership degrees to account for the partial membership of data points in multiple clusters shown in figure 8, a key feature of fuzzy logic-based clustering algorithms such as FCM.

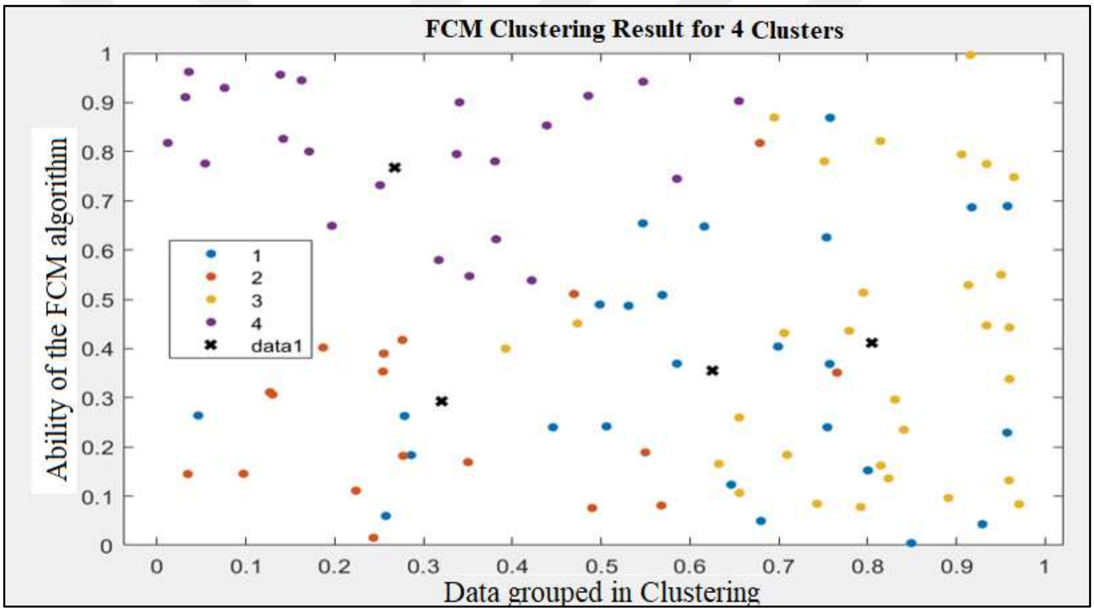

Figure 4.5: Fuzzy Logic Clustering.

The final figure (figure 4.5) after the application of (fuzzy logic clustering), where the figure depicts the data point's random distribution with cluster centers, also the ability of the algorithm to determine the locations of the cluster centers of the data points, as depicted by the black symbol (X) in the figure above.

The algorithm takes into account the random distribution of data points and the initial placement of cluster centers following the implementation of fuzzy logic clustering. It then uses fuzzy logic principles to determine the locations of the cluster centers in relation to the data points. Here is a summary of the procedure:

Distribution of Data Points at Random: Initially, the data points in your dataset are distributed at random across the feature space, with each data point being characterized by its attributes or features. So these random positions echo the inherent diversity and challenge of your data with some individual points not taking a clear position within one cluster.

Starting with Initial Cluster Center Placement: The initial cluster center placement is the first thing that this algorithm starts up working on. Technically for a given data and number of clusters these first initial centers are decided with random initialization or other techniques. Commonly these centers are not situated very well initially in this feature space, they are an inaccurate representation of true data cluster centroids.

Fuzzy logic clustering algorithms, such as Fuzzy C-Means (FCM), implements fuzzy membership degrees for representing the degree to point that each data point have its place to each cluster. The algorithm refines these membership degrees iteratively and, as a result, modifies the positions of the cluster centers.

During each iteration, the algorithm computes the new coordinates of the cluster centers using weighted averaging. This is accomplished by calculating a weighted average of the data point coordinates, with the weights being determined by the fuzzy membership degrees. Data points with higher membership degrees for a particular cluster exert a greater influence on the new cluster center position.

The iterative procedure proceeds until a convergence criterion is satisfied. Typically, this criterion is based on a measurement of how much cluster centers shift between iterations. When the algorithm converges, the cluster centers have reached relatively stable positions and the ambiguous membership degrees have stabilized.

ultimate Cluster Center Locations: The coordinates of the cluster centers at convergence represent their ultimate locations with respect to the data elements. Having in mind that unlike before the labels were not available, and since each data point is partly a member of different clusters (cluster assignment) at last we optimize these centers to most appropriately represent our input space. Essentially, the algorithm has learned where clusters are in feature space.

To sum up, fuzzy logic clustering algorithms calculate the positions of cluster center in random distribution of data points with adaptively. By iteratively refining membership degrees and weighting averages, the algorithm converges to cluster centers that better represent the true data structure than e.g. k-means alternative, allowing for more flexible and precise clustering in some scenarios where a sample can belong partially to several clusters regions.

4.6 SIMULATION SETUP

The proposed protocol has been simulated and experimented for network size of 200 nodes. The CH is elected based on FLB-CLS Model based on fuzzy descriptors such as Remaining Battery power, Distance to base station and Concentration.

A network of 200 nodes has been used to simulate and test the suggested protocol. The fuzzy description is used to elect the CH using the fuzzy logic based-clustering (FLB-CLS) proposed model. These 200 static sensor nodes are placed at random over the 200 m x 200 m monitoring region for a WSN simulation setup. The monitoring area at position (100, 250) is maintained clear of the BS. Every sensor node is initially provided with 0.5 J of energy. As a result, the network's total starting energy is 50 J. The standard data packet size for exchanging sensed data is 4000 bits. The observation region is split up into 10 m x 10 m equal-sized granules. Control packet overhead that happened during path establishment in the network is disregarded for simplicity's sake. The energy model presented in Section 3 has been employed to assess the network's energy usage. Eelec and EDA have parameter values set to 100 nJ/bit and 10 nJ/bit/signal, respectively. The experimental simulations were carried out for 200 WSN deployments in order to guarantee the accuracy and fairness of the outcomes. The average results from these deployments were then utilized to offer a comparative account of the procedures. Changing the clusters number K from one to ten allows for the experimental determination of Kopt's value. For every value of K, the average amount of energy utilized per round is computed. K = 10 is the lowest energy usage each round on average. Kopt = 10 is then determined.

Table 4.1: Simulation Parameters.

Type	Parameters	Value
Network	Network Size	200 x 200m
	No. of Nodes	200
	Expected no. of Clusters	4
	BS Location	50x50m
	Node distribution	Uniform
	Channel	Wireless
	Channel type	Bidirectional
	Energy Model	Battery
	Start Up Energy	1J
Radio lassical	ETx elec/ERx ϵfs ϵmp	50nJ/bit 10pJ/bit/m2 0.0013pJ/bit/m4
Application	Simulation time & Round time	100s & 20s
	Packet Header Size	24 bytes
	Data Packet Size	24bytes

200 sensor nodes are evenly distributed among the regions of (x=0, y=0) and (x=200, y=200) in this experiment. At (x=100, x=100) is where BS location can be implemented. Four clusters are guaranteed by the cluster formation process, and CH periodically rotates during each cycle. Every round lasts for thirty seconds. A data packet is said to be 24 bytes in size. A basic energy model is taken into account.

The total energy used by each node during typical network operation is determined by adding up the energy used for data transmission, reception, and aggregation. Figure 4.6 displays a comparison graph of the total energy consumption in percentage terms vs rounds for all procedures that are being tested and the protocol that is being suggested.

Figure 4.6 illustrates how much less energy is used overall in the suggested methodology when compared to FD-LEACH and OC-FCM. Furthermore, as the image illustrates, while the suggested protocol FLB-CLS used up 50% of the network energy, FD-LEACH and OC-FCM used up 70%, and the network in FD-LEACH stopped working entirely. Because FD-LEACH picks CHs using probabilistic techniques, the distribution of CHs in WSN is not uniform, and intra-cluster distances have grown. Consequently, even with the use of fuzzy sets and judgments during multi-hop route building, it used more network energy.

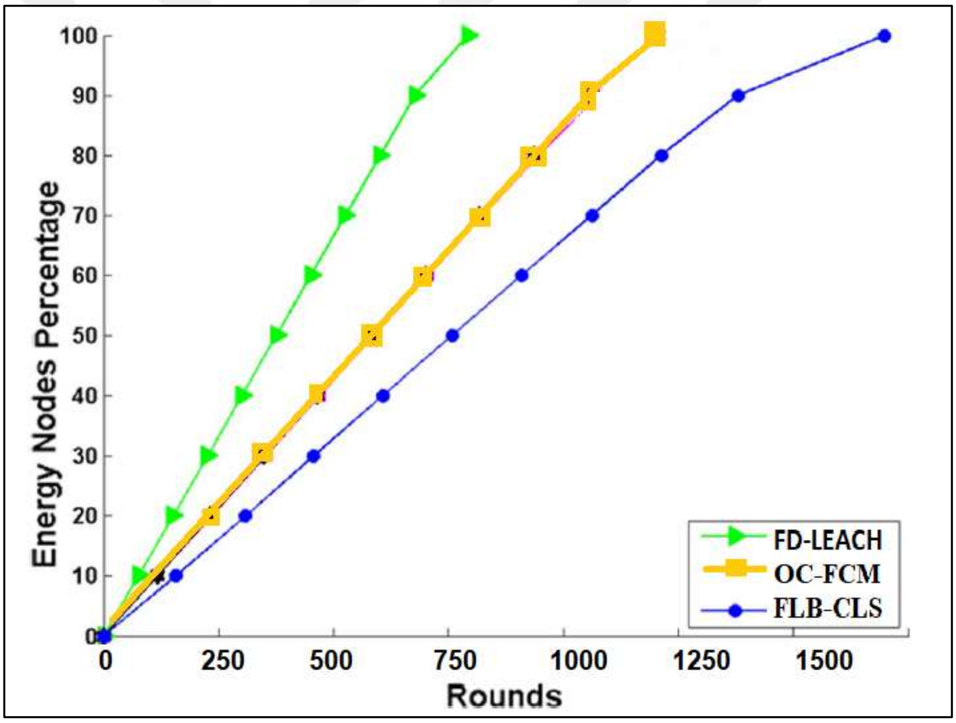

Figure 4.6: Energy Consumed Vs Rounds Percentage For WSN With N = 200.

As seen in Fig. 4.7, long-distance transmissions are decreased in the network to a greater extent due to optimum cluster formation utilizing FCM, fuzzy CH selection, and multi-hopping with gateway nodes. This results in low energy usage per sensor node. In light of this, the suggested algorithm FLB-CLS balances energy load and uses a lot less energy than the other protocols that are being tested.

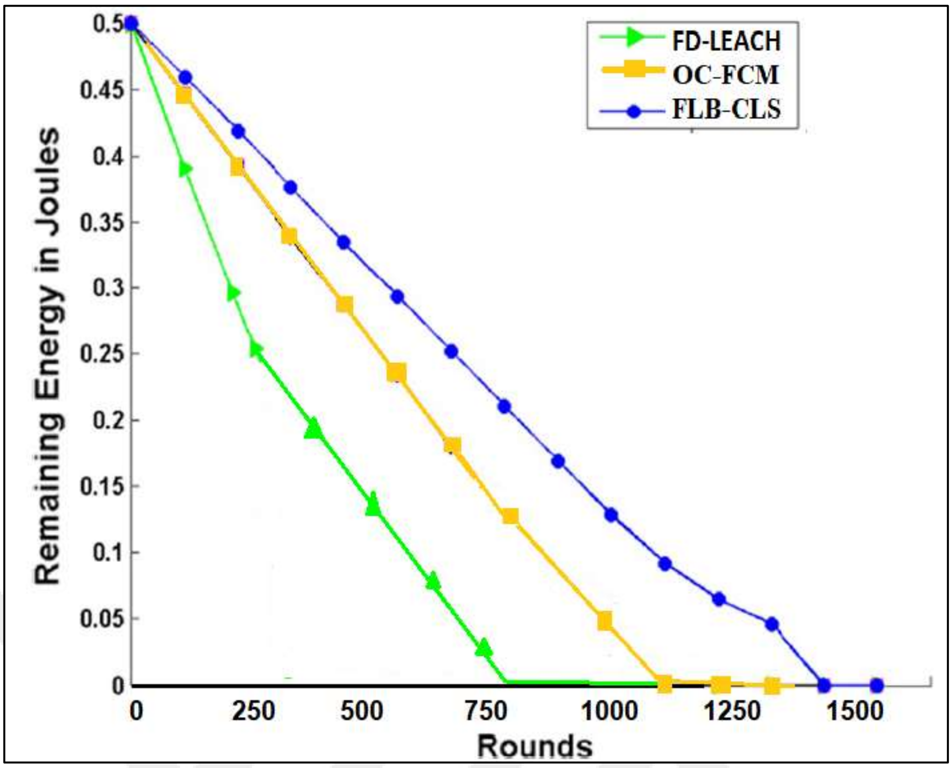

Figure 4.7: Average Energy Consumption Per SN With N =200.

When a sensor node within the network has 0% residual energy, it is regarded as dead. As the number of nodes that have died in the network rises, so does the network's operating capacity. As a result, network performance is directly impacted by the mortality rate of sensor nodes. Figure 4.8 shows a plot of the three protocols' respective network operating abilities. As can be seen from the figure, the suggested protocol FLB-CLS has a far slower rate of sensor node degradation than the other three protocols that are being tested. Based on the figure, it can be noted that FD-LEACH and OC-FCM nearly vanished when the suggested protocol only caused 10% of the network's nodes to die. Thus, it can be said that over the course of the network's lifetime, the suggested protocol FLB-CLS performs significantly greater than FD-LEACH and OC-FCM.

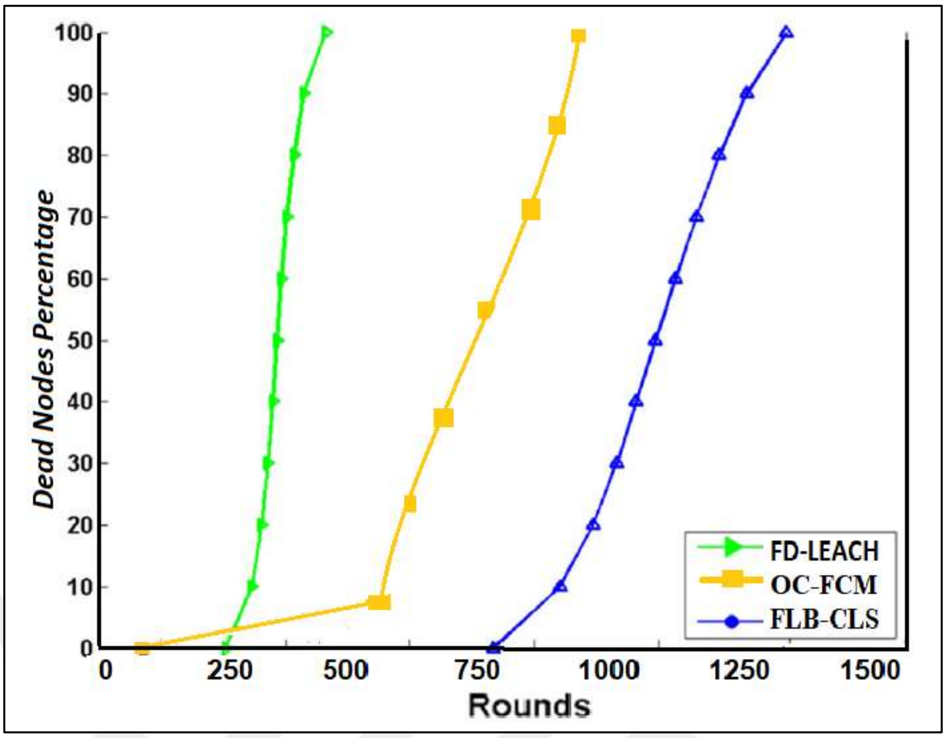

Figure 4.8: Dead Nodes Versus Rounds Percentage With N = 200.

Throughput is calculated using this formula given in equation 4.10:

$$Throughput = \frac{No.of\ Packets\ delivered * Packet\ size}{time} \tag{4.1}$$

The total number of identical data packets delivered for every cycle is used to determine the network's throughput. In Figure 4.9, throughput for each of the three protocols is displayed. Figure 4.9 shows how many packet generations in OC-FCM and FD-LEACH reach saturation at around 1084 and 1050 rounds, respectively. A total of 94,293 and 96,135 data packets are created in the OC-FCM and FD-LEACH protocols, respectively. Comparing FLB-CLS to FD-LEACH and OC-FCM, the total number of data packets produced increases by 25% and 30%, respectively. Compared to the FLB-CLS suggested protocol, FD-LEACH and OC-FCM produce less data from the monitoring region since their nodes last shorter periods of time. As a result, the throughput of the suggested approach is significantly higher. Figure 4.9 shows the total number of packets transmitted from source node to BS that includes control packets, retransmitted packets etc.

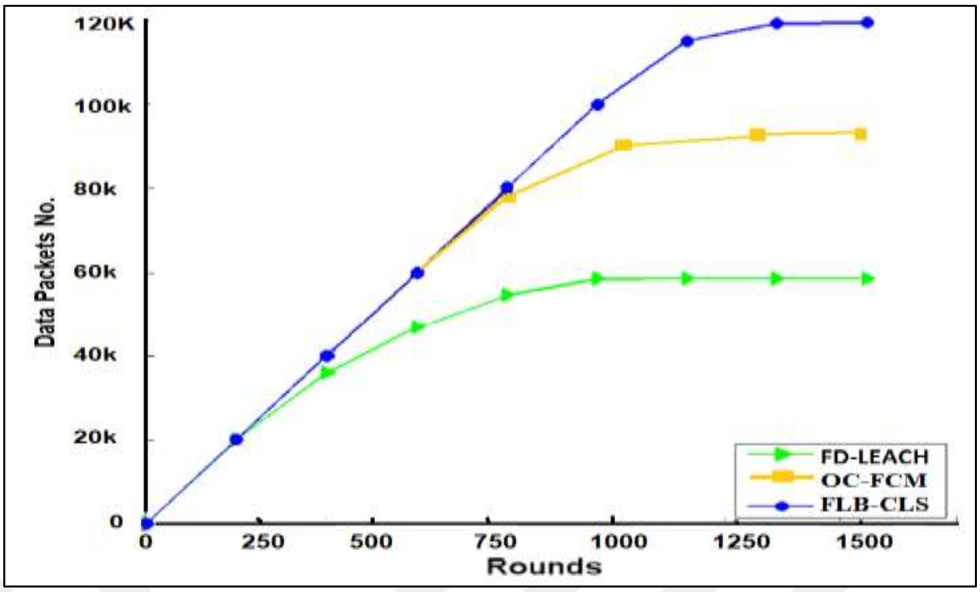

Figure 4.9: Data Packets Vs Number Of Rounds.

Enhancing the adaptability and robustness of WSNs clustering algorithms may be achieved through the use of fuzzy logic, a computational paradigm inspired by human thinking. Unlike traditional binary logic, fuzzy logic is capable of handling imprecise and uncertain input, mimicking the decision-making processes of people. Principles of fuzzy logic allow clustering algorithms to make sophisticated and context-aware judgments, resulting in further intelligent and energy-efficient network activities.

Our objective is to optimize the network's cluster creation and maintenance by using the inherent flexibility of fuzzy logic. Fuzzy logic approaches should lead to advances in data aggregation, routing protocols, and cluster head selection. These enhancements should provide more reliable communication, increase network durability, and improve data accuracy.

In this study, we investigate the theoretical underpinnings of fuzzy logic and its performance in WSNs. We use extensive simulations and real-world experiments to evaluate the effectiveness optimization of fuzzy logic-based clustering algorithms against traditional techniques. The findings of this research have the potential to advance academic understanding of fuzzy logic and offer practical suggestions for enhancing the resilience and efficacy of WSNs under challenging and unpredictable circumstances.

We are getting closer to the realization of seamless, trustworthy, and sustainable IoT ecosystems thanks to this study, which opens the way for more intelligent, flexible, and energy-efficient WSNs. It accomplishes this by looking at how fuzzy logic ideas are incorporated into WSN clustering methods.

5. CONCLUSIONS AND FUTURE WORK

5.1 INTRODUCTION

For various network sizes and topologies, simulation findings indicate improvements in energy efficiency as a result of network lifetime as well as consumed It is advised that every parameter affecting the energy efficiency of the WSN routing protocol be used to get the best potential outcomes of energy-efficient routing protocols in WSN. Furthermore, it is advised that they be integrated in a fashion that indicates the amount to which each influences the WSN's energy efficiency. We presented the fuzzy logic based-clustering (FLB-CLS) approach to create energy-efficient routing protocols. In addition, we presented an efficient fuzzy logic for this clustering technique's CH selection. This fuzzy logic uses five criteria to estimate the likelihood of any sensor being a CH. These characteristics are as follows: the remaining energy of the given sensor node, the distance of sensor nodes from the BS, the density of other surrounding sensor nodes around the candidate CH, node compaction surrounding the sensor node, and the average of the local spent energy.

Our findings reveal the fact that the fuzzy logic-based strategy enhanced overall network performance by extending network lifetime, lowering energy usage, and improving data accuracy. Fuzzy logic's capacity to deal with imprecise and unreliable information has proven useful in the setting of WSNs, wherein sensor readings are frequently influenced via noise and environmental influences.

For various network sizes and topologies, simulation findings indicate improvements in energy efficiency as a result of network lifetime as well as consumed for throughput, energy efficiency, and network longevity, the suggested protocol was compared against FD-LEACH, and OCM-FCM.

When compared to FD-LEACH and OC-FCM, FLB-CLS increased network lifetime by 30% and 35%, respectively. When compared to FD-LEACH and OC-FCM has a 24% higher throughput. According to the findings, FLB-CLS energy load distribution among all sensor nodes is more efficiently balanced than the other three protocols. The suggested protocol's performance is further improved for increasing network node density. As a result, it is established that the suggested protocol is appropriate for WSN applications. This work may be expanded further by include trust value as a fuzzy parameter during CH selection and constructing multi-hop links to make the protocol appropriate for secure networks.

5.2 FUTURE WORK

For various network sizes and topologies, simulation findings indicate improvements in energy efficiency as a result of network lifetime as well as consumed While our study has achieved significant advances in employing fuzzy logic to optimize clustering in WSNs, there are various options for future investigation:

Advanced Fuzzy Logic Models: Look into more complicated and adaptable fuzzy logic models, such as neuro-fuzzy systems, to improve decision-making accuracy in uncertain and dynamic contexts.

Machine Learning Integration: Investigate the use of machine learning techniques such as deep learning and reinforcement learning in conjunction with fuzzy logic to create intelligent and self-learning clustering algorithms for WSNs.

Real-World Deployments: Perform real-world deployments and field testing to evaluate the fuzzy logic-based clustering optimization method under a variety of environmental situations, providing a more thorough knowledge of its performance in realistic settings.

Energy Harvesting Techniques: Look into combining energy harvesting techniques like solar or kinetic energy harvesting with fuzzy logic-based clustering to create self-sustaining WSNs that can operate for lengthy periods of time without external power sources.

Enhancements to security: Investigate and create fuzzy logic-based security techniques to guard against new risks and assaults, while also assuring the confidentiality, integrity, and authenticity of data sent within clustered WSNs.

We may further enhance and extend the capabilities of fuzzy logic-based clustering optimization algorithms by tackling these areas in future research, opening the way for the broad deployment of efficient and reliable Wireless Sensor Networks in diverse sectors.

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