Online at: https://researchtrendsjournal.com **ISSN No:** 2584-282X

INTERNATIONAL JOURNAL OF TRENDS IN EMERGING RESEARCH AND DEVELOPMENT

INTERNATIONAL JOURNAL OF TRENDS IN EMERGING RESEARCH AND DEVELOPMENT

Volume 2; Issue 3; 2024; Page No. 183-189

Received: 02-03-2024
Accepted: 07-04-2024

AI-Driven Adaptive Clustering Methods in WSN

[1]DD Suribabu Devarasetti and [2]Dr. Amit Singhal

[1]Research Scholar, Department of Computer Science & Engineering, Monad University, Hapur, Uttar Pradesh, India
[2]Professor, Department of Computer Science & Engineering, Monad University, Hapur, Uttar Pradesh, India

Corresponding Author: DD Suribabu Devarasetti

Abstract

This survey evaluates recent cluster-based routing protocols released from 2021 to 2024, focusing on AI-driven approaches in Wireless Sensor Networks (WSNs). The analysis includes solution-based parameters such as performance mode, selection strategies, optimization objectives, modeling techniques, and key factors affecting the overall effectiveness of each approach. Network configuration analysis includes topology, communication architecture, network scale, performance metrics, and simulators used. The comprehensive analysis provides valuable insights into the capabilities and limitations of each method, aiming to guide future research towards developing more efficient cluster-based routing techniques for WSNs. These methods, incorporating intelligent performance characteristics, will be well equipped to address the growing demands of the intelligent era.

Keywords: AI, Clustering, WSN, Networks and Technology

Introduction

Wireless Sensor Networks (WSNs) have emerged as a crucial technology in various applications, including environmental monitoring, healthcare, smart cities, and industrial automation. These networks consist of numerous spatially distributed sensor nodes that collaboratively gather and transmit data to a central processing unit or sink. As the scale and complexity of WSNs continue to increase, effective data management becomes paramount to ensure the networks' efficiency, reliability, and longevity. "Clustering is one of the most effective techniques for optimizing the performance of WSNs by grouping sensor nodes into clusters, thereby reducing communication overhead and conserving energy. The design of clustering methods in WSNs involves selecting appropriate algorithms that can efficiently manage the distribution and transmission of data within the network. Traditional clustering approaches often face challenges, such as dynamic topology changes, energy consumption, and scalability issues. To address these challenges, there is a growing interest in integrating Artificial Intelligence (AI) techniques into the design and optimization of clustering methods. AI techniques, such as machine learning and optimization algorithms, can enhance decision-making processes, enabling the development of adaptive and intelligent clustering strategies that respond to varying environmental conditions and network dynamics.

AI-based clustering methods offer several advantages, including improved energy efficiency, extended network lifetime, and enhanced data accuracy. By leveraging AI techniques, these methods can dynamically adjust cluster formations, optimize cluster head selection, and implement fault-tolerant mechanisms to maintain network reliability. As the complexity of data and the requirements of real-time applications grow, the integration of AI into WSN clustering strategies will play a pivotal role in shaping the future of wireless communication and data processing. This paper aims to explore the design and optimization of clustering methods in WSNs using AI. It will discuss the current state of research, highlight the benefits and limitations of existing approaches, and propose future directions for integrating AI techniques into WSN clustering methodologies. Through this exploration, we hope to contribute to the development of more efficient and intelligent WSN solutions that can meet the demands of emerging applications.

Clustering involves grouping nearby sensor nodes to form clusters, each managed by a cluster head. The cluster head is responsible for aggregating data from its members and transmitting it to the sink, thereby minimizing the total communication distance and energy consumption. Various clustering algorithms have been proposed to optimize cluster formation, cluster head selection, and data aggregation processes. Traditional methods, such as Low Energy Adaptive Clustering Hierarchy (LEACH) and its variants, have provided foundational frameworks for WSN clustering. In recent years, the integration of Artificial Intelligence (AI) into the design and optimization of clustering methods has garnered significant interest. AI techniques, including machine learning, genetic algorithms, and particle swarm optimization, offer innovative approaches to enhance clustering performance. These methods enable dynamic adaptations to network conditions, allowing for improved decision-making processes regarding cluster management. The use of AI can help to develop smarter clustering strategies that optimize energy usage, ensure fault tolerance, and enhance data accuracy, ultimately leading to more resilient and efficient WSNs.

Literature Review

Yadav & Yadav (2016) [1] conducted a detailed review on energy-efficient protocols in wireless sensor networks (WSNs), categorizing various protocols based on different metrics such as energy conservation, network lifetime, and power consumption. The study highlights the significant impact of energy optimization on the overall performance of WSNs. The authors examine clustering, routing, and data aggregation techniques, focusing on how they contribute to energy efficiency. Additionally, they emphasize the importance of balancing energy load among sensor nodes to prevent premature node failure, which affects network longevity. This comprehensive review helps identify gaps and offers future directions for research in energy-efficient WSNs.

Ali *et al*. (2017) [2] conducted a survey on real-time applications of WSNs, focusing on their deployment in various fields such as healthcare, environmental monitoring, and military applications. The study provides an overview of the unique challenges WSNs face in real-time applications, including energy efficiency, data processing, and security concerns. It emphasizes the need for advanced algorithms to manage the large amounts of data generated by sensor networks while ensuring minimal delay and energy consumption. Ali *et al*. also discuss how real-time WSN applications can benefit from advancements in machine learning and artificial intelligence.

Ahmad *et al*. (2021) [3] explored anomaly detection in IoT architecture using deep neural networks (DNNs). This research focuses on enhancing security in IoT ecosystems, particularly within WSNs, by implementing DNN models to detect anomalous behavior in real time. The study demonstrates how DNNs can outperform traditional machine learning algorithms by offering higher accuracy and scalability. The authors highlight the challenges of applying DNNs in resource-constrained environments like WSNs, suggesting optimization techniques to minimize computation overhead. This work contributes significantly to the field of IoT security, offering practical solutions for anomaly detection.

Al-Mekhlafi *et al*. (2021) [4] conducted a comparative study on the Random Traveling Wave Pulse-Coupled Oscillator algorithm for energy-efficient WSNs. The study analyzes the algorithm's efficiency in synchronizing sensor nodes while minimizing energy consumption. It provides a detailed comparison of the algorithm with other synchronization techniques, showing its superiority in terms of energy conservation and network longevity. The authors also discuss the practical implementation of the algorithm in large-scale WSNs, addressing potential challenges such as scalability and fault tolerance. This study advances the understanding of energy-efficient synchronization in WSNs.

Gherbi *et al*. (2016) [5] presented an adaptive clustering approach aimed at dynamic load balancing and energy efficiency in WSNs. The authors propose a model that dynamically adjusts cluster size based on node energy levels and network conditions to distribute energy consumption more evenly across the network. The approach also incorporates load balancing techniques to ensure that no single node is overburdened, thus preventing early node failure. The results show significant improvements in network lifetime and energy efficiency compared to traditional clustering methods. This study contributes to the field by addressing the challenges of dynamic environments in WSNs.

AI

Artificial Intelligence (AI) is a transformative technology that empowers machines to simulate human intelligence and behavior, enabling them to learn from experience, adapt to new inputs, and perform tasks that typically require human cognition. AI encompasses various subfields, including machine learning, natural language processing, computer vision, and robotics, and it is applied across numerous industries, revolutionizing processes and enhancing decision-making. In the context of Wireless Sensor Networks (WSNs)", AI plays a crucial role in improving efficiency, data processing, and network management. By leveraging AI algorithms, WSNs can optimize resource allocation, enhance energy efficiency, and enable intelligent data analysis to derive meaningful insights from collected data.

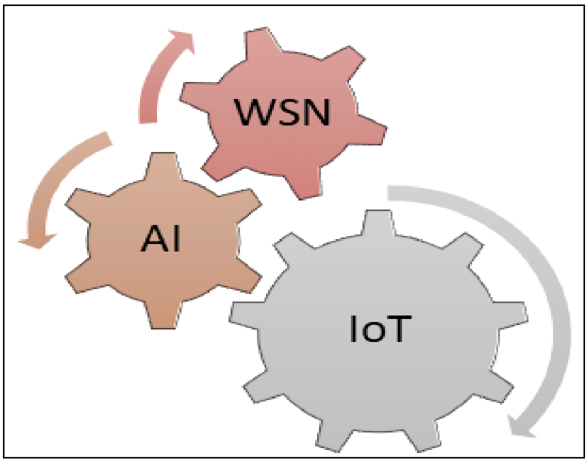

Fig 1: WSN-IoT with AI

AI techniques such as clustering, classification, and anomaly detection are particularly valuable in WSNs, where they help in organizing sensor data, identifying patterns, and detecting irregularities that may indicate faults or security breaches. For instance, clustering algorithms can dynamically group sensor nodes based on various criteria (e.g., proximity, data similarity) to minimize energy consumption and communication overhead. Additionally, machine learning models can predict future sensor behavior, leading to proactive management and maintenance of the network. "The integration of AI in WSNs not only enhances their operational capabilities but also supports applications such as environmental monitoring, smart cities, healthcare systems, and industrial automation, driving innovation and enabling more responsive and resilient solutions in complex environments. As the demand for intelligent systems continues to rise, the synergy between AI and WSNs is poised to shape the future of data-driven decision-making and automated processes.

Clustering

Clustering is a fundamental technique in data analysis and machine learning that involves grouping a set of objects or data points into clusters based on their similarity. The main objective of clustering is to ensure that items within the same cluster are more similar to each other than to those in other clusters, effectively organizing data into meaningful structures. This technique is particularly valuable in scenarios where the underlying patterns in data are not explicitly labeled or known, making it an essential method for exploratory data analysis. In the context of Wireless Sensor Networks (WSNs), clustering serves several critical purposes. It enhances the efficiency of data transmission by reducing the amount of data that needs to be communicated back to a central location, thereby conserving energy-a crucial factor in battery-operated sensor devices. Clustering algorithms can dynamically group sensor nodes based on criteria such as proximity, data type, or application requirements, allowing for localized data processing and aggregation. This helps minimize communication overhead and prolong the network's lifespan.

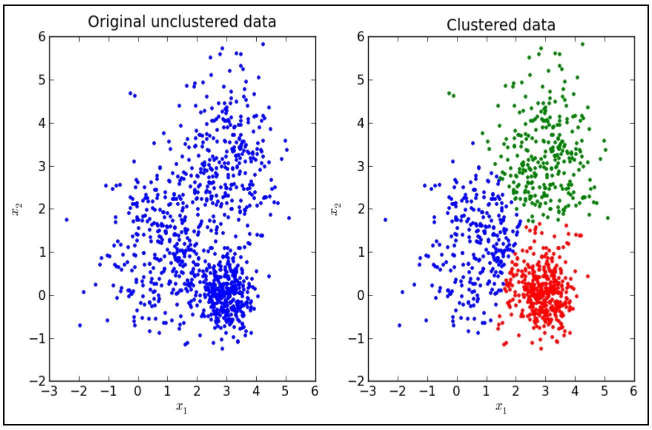

Fig 2: Concept of clustering Technique

Several clustering algorithms are commonly used in WSNs, including K-means, hierarchical clustering, and density-based methods. Each algorithm has its strengths and limitations, making the choice of clustering technique highly dependent on the specific application requirements, such as energy efficiency, scalability, and adaptability to changing network conditions. Recent advancements in Artificial Intelligence (AI) have further optimized clustering techniques, enabling smarter and more adaptive clustering methods that can adjust to the dynamic nature of WSNs. By integrating AI with clustering, WSNs can achieve improved performance in terms of data collection, energy conservation, and overall network management, making clustering a critical area of research and development in modern sensor networks. Clustering methods are diverse techniques used to group data points into clusters based on their similarities, enabling the identification of patterns and relationships within datasets. These methods can be broadly categorized into several types, each with its unique approach to clustering.

1. **Partitioning Methods:** One of the most widely used partitioning methods is K-means clustering, which partitions the dataset into K distinct clusters based on distance metrics, typically the Euclidean distance. The algorithm iteratively assigns data points to the nearest cluster centroid and updates the centroids until convergence. While K-means is computationally efficient and easy to implement, it requires the number of clusters to be specified in advance and can be sensitive to outliers.
2. **Hierarchical Methods:** These methods build a hierarchy of clusters either through agglomerative (bottom-up) or divisive (top-down) approaches. In agglomerative clustering, each data point starts as its cluster, and pairs of clusters are merged based on a distance metric until only one cluster remains or a specified number of clusters is achieved. Hierarchical methods provide a dendrogram representation of clusters, allowing for a visual interpretation of data grouping, but they can be computationally expensive and may struggle with large datasets.
3. **Density-Based Methods:** Density-based clustering algorithms, such as DBSCAN (Density-Based Spatial Clustering of Applications with Noise), group data points based on the density of data in a region. This approach is particularly effective for identifying clusters of arbitrary shapes and is robust against outliers. DBSCAN requires two parameters: the radius of the neighborhood around a point (epsilon) and the minimum number of points required to form a dense region.
4. **Model-Based Methods:** These methods assume that the data is generated from a mixture of underlying probability distributions. Gaussian Mixture Models (GMMs) are a common example, where each cluster is represented by a Gaussian distribution. The Expectation-Maximization (EM) algorithm is often used to estimate the parameters of these distributions. Model-based methods provide flexibility and can handle varying cluster shapes, but they require a careful selection of the model and can be computationally intensive.
5. **Artificial Intelligence-Enhanced Clustering:** With the rise of AI and machine learning, advanced clustering techniques have emerged that leverage neural networks and other AI models to optimize clustering processes. For instance, deep learning-based methods can automatically extract features from complex data and improve clustering accuracy, particularly in high-dimensional spaces.

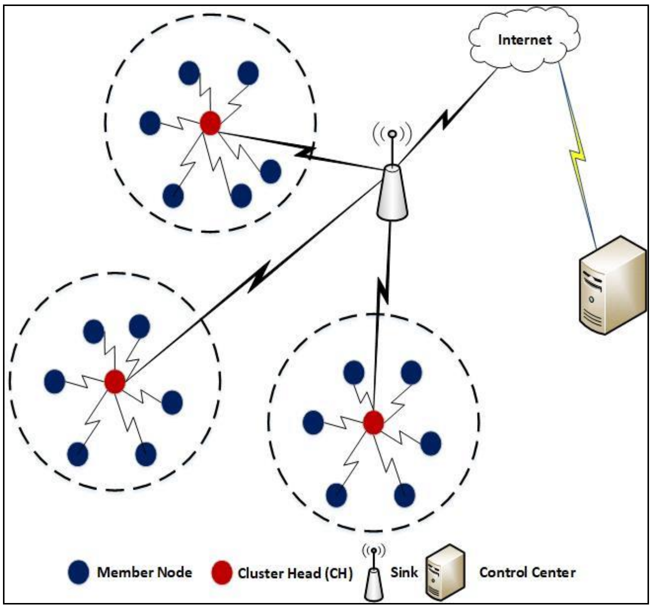

Fig 3: Clustering in Wireless Sensor Networks

Each clustering method has its advantages and limitations, making the selection of an appropriate technique critical based on the specific requirements of the application, such as the nature of the data, the desired output, and computational resources. In the context of Wireless Sensor Networks (WSNs), the choice of clustering method plays a pivotal role in optimizing energy efficiency, data transmission, and overall network performance. By integrating AI techniques, researchers aim to enhance traditional clustering methods, making them more adaptive and efficient in handling the dynamic and resource-constrained nature of WSNs.

WSN

Wireless Sensor Networks (WSNs) are composed of spatially distributed autonomous sensor nodes that collaboratively monitor and collect data from various environments, making them essential for applications in environmental monitoring, healthcare, smart cities, agriculture, military operations, and industrial automation. A typical WSN includes sensor nodes equipped with sensing elements such as temperature, humidity, and pressure sensors, along with sink nodes (or base stations) that aggregate and transmit data to a central processing unit. These networks feature different communication protocols, such as single-hop and multi-hop communication, but clustering protocols are particularly notable for their energy efficiency, as they group sensor nodes into clusters to minimize communication overhead. Despite their advantages, WSNs face challenges such as energy constraints, scalability, data reliability, and security. The energy efficiency of sensor nodes is crucial for prolonging their operational lifespan, while the increasing number of nodes complicates management and communication.

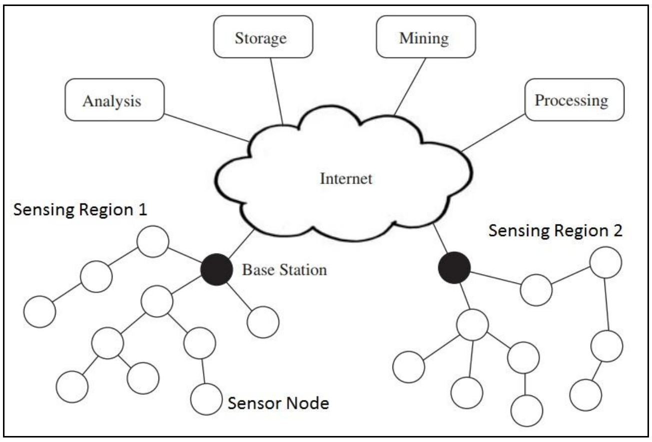

Fig 4: Classification of WSN

Moreover, ensuring accurate and timely data collection is vital in preventing unauthorized access and attacks. WSNs enable a wide range of applications, from tracking environmental parameters to monitoring patients' health remotely, optimizing irrigation in agriculture, and enhancing industrial processes. The evolution of WSNs, especially with the integration of Internet of Things (IoT) technologies and machine learning for data analysis, is paving the way for more sophisticated and resilient solutions, thus transforming our interaction with and understanding of diverse environments.

Wireless Sensor Networks (WSNs) are composed of spatially distributed autonomous sensor nodes that work collaboratively to monitor and collect data from various environments. These networks have gained significant traction across numerous fields, including environmental monitoring, healthcare, smart cities, agriculture, military applications, and industrial automation. The key characteristics of WSNs include low power consumption, wireless communication, and the ability to operate in remote or inaccessible locations.

Clustering methods in wireless sensor networks

Wireless Sensor Networks (WSNs) have emerged as a pivotal technology for a wide range of applications, including environmental monitoring, industrial automation, healthcare, and smart cities. These networks consist of spatially distributed autonomous sensors that monitor physical or environmental conditions, such as temperature, sound, or pressure, and cooperatively pass their data through the network to a central location. Clustering methods in Wireless Sensor Networks (WSNs) are essential for efficient data management, energy conservation, and effective communication among sensor nodes. WSNs consist of numerous sensor nodes that collect and transmit data regarding environmental conditions. Given the resource constraints of these nodes, such as limited energy, processing power, and storage, clustering is utilized to optimize network performance and prolong the network's lifespan.

1. Hierarchical Clustering
Hierarchical clustering is one of the most common approaches in WSNs. This method organizes the nodes into a hierarchy, typically using a two-level structure consisting of cluster heads and member nodes. The cluster heads are responsible for aggregating data from member nodes and transmitting the aggregated data to a base station. Hierarchical clustering can significantly reduce energy consumption as it minimizes the number of transmissions by consolidating data. Popular protocols, such as LEACH (Low-Energy Adaptive Clustering Hierarchy), utilize this approach, allowing nodes to take turns as cluster heads to balance energy consumption across the network.

2. K-Means Clustering
K-means clustering is a partitioning method that divides the sensor nodes into K clusters based on proximity. Each cluster is represented by its centroid, and nodes are assigned to the nearest centroid. While K-means is straightforward and efficient, it requires pre-specifying the number of clusters, which may not be suitable for dynamic WSN environments where node distribution can change over time. Modifications to the basic K-means algorithm, such as adaptive K-means, can be applied to address this limitation.

3. Density-Based Clustering
Density-based clustering algorithms, such as DBSCAN (Density-Based Spatial Clustering of Applications with Noise), are particularly effective for handling clusters of varying shapes and sizes. In WSNs, DBSCAN can efficiently identify densely populated regions of sensor nodes while ignoring sparse areas, effectively grouping nodes based on their local density. This method is robust against noise and outliers, making it suitable for dynamic environments where sensor nodes may fail or operate intermittently.

4. Energy-Aware Clustering
Energy efficiency is a critical concern in WSNs, and energy-aware clustering algorithms aim to prolong network lifetime by selecting cluster heads based on residual energy levels. Algorithms such as LEACH and its variants adapt the selection of cluster heads based on the remaining energy of the nodes, ensuring that more energy-efficient nodes are utilized for data aggregation and transmission. This dynamic adjustment enhances the overall efficiency of the network by balancing the energy load among sensor nodes.

5. Model-Based Clustering
Model-based clustering approaches, such as Gaussian Mixture Models (GMMs), can be employed to represent the distribution of sensor data in WSNs. By modeling data from sensor nodes as a mixture of Gaussian distributions, these methods can accommodate variations in data characteristics and optimize the clustering process. The Expectation-Maximization algorithm is often used to estimate the parameters of these models, allowing for improved data aggregation and communication strategies.

6. Artificial Intelligence-Enhanced Clustering
Recent advancements in artificial intelligence and machine learning have led to the development of intelligent clustering methods in WSNs. Techniques such as neural networks and reinforcement learning can optimize clustering decisions by analyzing historical data and adapting to changing network conditions. These AI-enhanced methods improve clustering accuracy, reduce energy consumption, and enhance the overall resilience of WSNs.

In summary, clustering methods in Wireless Sensor Networks play a vital role in optimizing energy efficiency, reducing data transmission, and improving network longevity. By leveraging various clustering techniques and integrating artificial intelligence, researchers can develop advanced protocols that adapt to the dynamic nature of WSNs, ensuring efficient data collection and communication while preserving the limited resources of sensor nodes.

Importance of clustering in WSNs
One of the critical challenges in WSNs is the efficient management of the network to ensure long-term operation and reliable data transmission". Clustering is a well-recognized technique to enhance the scalability, energy efficiency, and reliability of WSNs. In a clustered WSN, sensor nodes are grouped into clusters, each managed by a cluster head (CH). The CH aggregates data from the member nodes and forwards it to the base station, thereby reducing the number of direct transmissions to the base station and saving energy. Clustering in Wireless Sensor Networks (WSNs) is crucial for optimizing resource utilization, improving network performance, and enhancing data collection and transmission efficiency. Here are some key points highlighting the importance of clustering in WSNs:

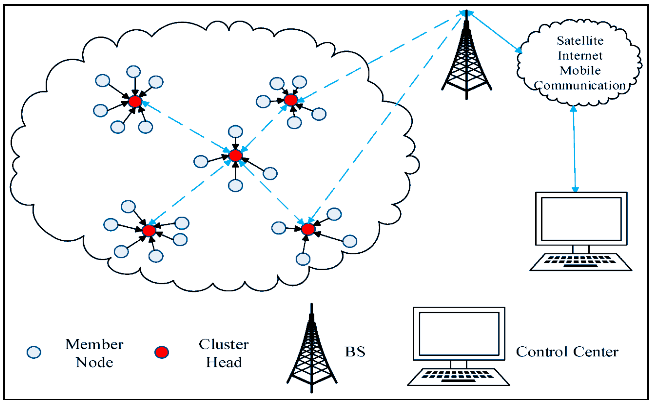

Fig 5: Energy-Efficient Clustering Routing Protocol for Wireless Sensor Networks

1. Energy Efficiency
One of the primary concerns in WSNs is the limited energy resources of sensor nodes. Clustering helps reduce energy consumption by enabling nodes to communicate with a single cluster head rather than transmitting data individually to a distant base station. "This aggregation of data at the cluster head significantly minimizes the number of transmissions required, prolonging the overall network lifetime.

2. Scalability
WSNs often consist of a large number of sensor nodes

deployed over vast areas. Clustering allows for better scalability by organizing nodes into manageable groups. Each cluster can operate independently, facilitating efficient data management and reducing the overhead involved in network maintenance and communication.

3. Improved Data Management

In WSNs, sensor nodes continuously collect data about their environment. Clustering enhances data management by enabling data aggregation at the cluster head. This reduces redundancy in data transmission, as the cluster head can send summarized information to the base station rather than relaying all individual data packets. This approach not only saves bandwidth but also decreases the likelihood of data collisions.

4. Load Balancing

Clustering supports load balancing by allowing different nodes to take turns being the cluster head. This rotation helps distribute energy consumption evenly across the network, preventing any single node from depleting its energy too quickly. Load balancing is essential for maintaining network connectivity and ensuring the reliability of data transmission.

5. Enhanced Network Longevity

By minimizing energy consumption, reducing data collisions, and balancing the load among nodes, clustering contributes to the overall longevity of the WSN. A longer network lifespan translates to more extended periods of data collection and monitoring, which is particularly important for applications such as environmental monitoring, smart agriculture, and disaster management.

6. Fault Tolerance and Resilience

In WSNs, nodes may fail or become inactive due to various reasons, including battery depletion or environmental conditions. Clustering enhances fault tolerance by allowing the network to adapt dynamically to node failures. If a cluster head fails, other nodes within the cluster can elect a new head, ensuring continuity in data collection and communication.

7. Flexible Network Configuration

Clustering provides flexibility in network configuration. It allows for the dynamic formation of clusters based on real-time factors such as node density, energy levels, and data traffic patterns. This adaptability ensures that the network can respond effectively to changing conditions, optimizing performance and resource allocation.

8. Reduced Communication Overhead

Clustering reduces the communication overhead associated with data transmission. By aggregating data at the cluster head and minimizing the number of nodes communicating directly with the base station, the overall communication complexity is significantly decreased. This reduction is especially beneficial in networks with high data generation rates.

Clustering plays a vital role in the efficient functioning of Wireless Sensor Networks. By improving energy efficiency, enhancing data management, and providing scalability, load balancing, and resilience, clustering techniques contribute to the effective deployment and operation of WSNs across various applications. As WSNs continue to evolve and expand, the significance of clustering will only grow, driving innovations in network design and management.

Conclusion

In conclusion, while significant progress has been made in clustering methods for WSNs, several challenges remain that require further investigation". By focusing on energy efficiency, scalability, adaptability, security, interoperability, emerging technologies, and QoS, future research can contribute to the development of more efficient, resilient, and secure WSNs, ultimately advancing the field and meeting the demands of modern applications.

References

1. Yadav S, Yadav RS. A review on energy efficient protocols in wireless sensor networks. Wireless Networks. 2016;22:335-350. [Google Scholar] [CrossRef]
2. Ali A, Ming Y, Chakraborty S, Iram S. A comprehensive survey on real-time applications of WSN. Future Internet. 2017;9:77. [Google Scholar] [CrossRef] [Green Version]
3. Ahmad Z, Shahid Khan A, Nisar K, Haider I, Hassan R, Haque MR, Tarmizi S, Rodrigues JJ. Anomaly Detection Using Deep Neural Network for IoT Architecture. Applied Sciences. 2021;11:7050. [Google Scholar] [CrossRef]
4. Al-Mekhlafi ZG, Alshudukhi J, Almekhlafi K. Comparative Study on Random Traveling Wave Pulse-Coupled Oscillator Algorithm of Energy-Efficient Wireless Sensor Networks. In: Advances on Smart and Soft Computing. Springer: Singapore; c2021. p. 599-609. [Google Scholar]
5. Gherbi C, Aliouat Z, Benmohammed M. An adaptive clustering approach to dynamic load balancing and energy efficiency in wireless sensor networks. Energy. 2016;114:647-662. [Google Scholar] [CrossRef]
6. Priyadarshi R, Soni SK, Nath V. Energy efficient cluster head formation in wireless sensor network. Microsystem Technologies. 2018;24:4775-4784. [Google Scholar] [CrossRef]
7. Osamy W, Khedr AM, Aziz A, El-Sawy AA. Cluster-tree routing based entropy scheme for data gathering in wireless sensor networks. IEEE Access. 2018;6:77372-77387. [Google Scholar] [CrossRef]
8. Pan JS, Nguyen TT, Dao TK, Pan TS, Chu SC. Clustering Formation in Wireless Sensor Networks: A Survey. Journal of Network and Intelligent Systems. 2017;2:287-309. [Google Scholar]
9. Saxena A, Prasad M, Gupta A, Bharill N, Patel OP, Tiwari A, *et al*. A review of clustering techniques and developments. Neurocomputing. 2017;267:664-681. [Google Scholar] [CrossRef] [Green Version]
10. Abba Ari AA, Djedouboum AC, Gueroui AM, Thiare O, Mohamadou A, Aliouat Z. A three-tier architecture of large-scale wireless sensor networks for big data collection. Applied Sciences. 2020;10:5382. [Google Scholar] [CrossRef]
11. Sheta AA, Abdelwahab SAS, Elaraby S, Mahmoud MI.

RSSI-and LQI-based clustering: Analysis and implementation of multihop EOP-LEACH for WSN using Sun SPOT. Journal of the Chinese Institute of Engineers. 2018;41:367-374. [Google Scholar] [CrossRef]
12. Bhushan B, Sahoo G. ISFC-BLS (intelligent and secured fuzzy clustering algorithm using balanced load sub-cluster formation) in WSN environment. Wireless Personal Communications. 2020;111:1667-1694. [Google Scholar] [CrossRef]
13. Hiremani N, Basavaraju TG. An efficient routing protocol adopting enhanced cluster formation technique accompanied by fuzzy logic for maximizing lifetime of WSN. International Journal of Intelligent Engineering Systems. 2016;9:185-194. [Google Scholar] [CrossRef]
14. Alghamdi TA. Energy efficient protocol in wireless sensor network: Optimized cluster head selection model. Telecommunication Systems. 2020;74:331-345. [Google Scholar] [CrossRef]
15. Rao PS, Jana PK, Banka H. A particle swarm optimization-based energy efficient cluster head selection algorithm for wireless sensor networks. Wireless Networks. 2017;23:2005-2020. [Google Scholar] [CrossRef]