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Energy Efficiency by Optimizing Power Sharing with Clustering

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Abstract- Conserving energy of power grid within wireless power grid nodes network (power grid) is crucial in different applications including wearable devices. To this end, proposed work uses sleep and wakeup protocol for conserving energy of power grid nodes. The protocol first of all examines the nodes that are not used for transmission of packets for longer period of times. After that detected node will be put to sleep. The nodes energy will play a crucial role to make it a cluster head. Euclidean distance will be used to elect node as cluster head. The experimental setup involves random node distribution, initial energy allocation, and the formation of clusters based on Euclidean distance. The proposed sleep and wakeup mechanisms strategically put nodes to sleep after periods of inactivity, conserving energy resources. A comprehensive evaluation, comparing the protocol's performance with the widely used low energy aggregate cluster head (LEACH) selection protocol, stable election protocol (SEP), time based stable election protocol (TSEP) and distributed energy efficient clustering protocol (DEEC), reveals superior results in terms of fewer dead nodes, prolonged network lifetime, and efficient packet transmissions. The proposed method showcases a controlled and sustained pattern in communication to cluster heads and base stations, outperforming LEACH, DEEC, SEP and TSEP. Remaining energy analysis indicates a more gradual and sustainable reduction in energy levels, highlighting the protocol's effectiveness in maintaining operational nodes over prolonged network. The study concludes with insights into future research directions, emphasizing parameter optimization, scalability considerations, integration of energy harvesting methods, and enhanced security measures

Index Terms- wireless sensor networks, energy consumption

I. INTRODUCTION

With applications ranging from industrial automation, healthcare, agriculture, and environmental monitoring, wireless power grid nodes networks (power grids) have become a game-changing technology.

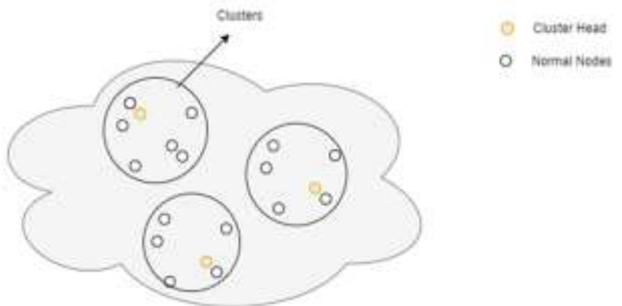

Figure 1: Structure of power grid

These networks are made up of many small, resource-constrained power grid nodes working together to gather and send data to a base station or central sink. The limited energy resources of power grid nodes present a significant problem for power grids, requiring the creation of energy-efficient protocols to extend network lifetime and improve overall performance. The general structure of power grid is given in figure 1.

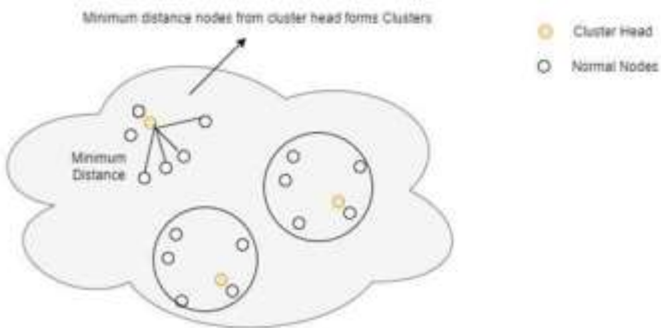

Figure 2: Cluster head formation with distance Figure

Clustering is becoming a commonly used strategy to address this problem. Organizing power grid nodes into groups and designating one node as the cluster head—tasked with compiling and sending data to the sink—is known as clustering. Within these clusters, distance-based protocols are essential for maximizing energy usage, and adding wake-up and sleep procedures improves energy efficiency even more. The clustering based on distance is given in figure 2.

The importance of energy-efficient clustering in wireless power grid nodes networks (power grids) is examined in this introduction, which focuses on distance-based protocols enhanced by sleep and wake-up processes. We examine the main drivers, difficulties, and possible remedies in the pursuit of long-term and sustainable power grid functioning.

Energy-efficient clustering in wireless power grid nodes networks (power grids) is driven by the inherent limitations of power grid nodes, which include low energy, limited processing capability, and limited communication capabilities. It is not possible to replace or recharge the batteries in these nodes since they are frequently placed in harsh or isolated locations. For the network to continue operating for a longer period, energy consumption optimization becomes crucial. By dividing nodes into clusters, cutting down on duplicate transmissions, and facilitating localized data processing, clustering provides a useful tactic (Zhao, Qu and Yi, 2018).

Even with clustering's benefits, power grids still confront several difficulties that call for creative fixes. Unpredictable data traffic patterns, dynamic network topology, and node spatial distribution all lead to unequal node energy depletion (Behera, Samal and Mohapatra, 2018). Furthermore, these issues might not be sufficiently addressed by conventional clustering methods, which could result in early node failures and poor network performance. Therefore, it is imperative to create intelligent and adaptable clustering methods that consider the special qualities of power grids.

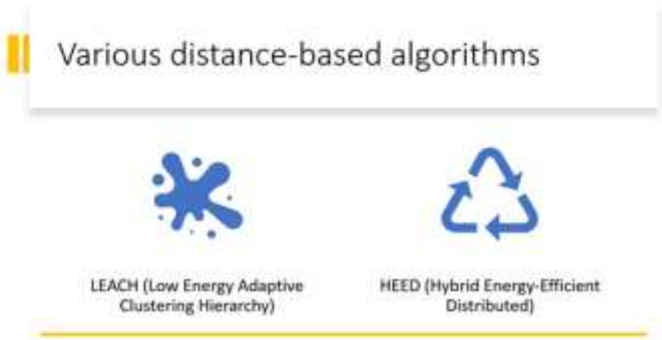

Figure 3: Distance aware algorithm

At the core of energy-efficient clustering in power grids are distance-based protocols. These methods elect cluster heads and optimize data routing by using proximity information among power grid nodes. These protocols pick cluster heads depending on several variables, such as the distance to the sink, to reduce the amount of energy used for data assembly and transmission. Several distance-based algorithms, such HEED (Hybrid Energy-Efficient Distributed) and LEACH (Low Energy Adaptive Clustering Hierarchy) (Abu Salem and Shudifat, 2019a), have been developed to tackle the unique issues presented by power grids, as illustrated in figure 3.

Apart from distance-based protocols, incorporating wake-up and sleep procedures also improves power grid energy efficiency. When power grid nodes are not actively collecting or transmitting data, they can save energy by going into sleep modes, which lowers power consumption. Wake- up systems allow nodes to effectively restart operations as necessary, guaranteeing prompt reactions to events or modifications in the surrounding environment. The power grid's overall sustainability is enhanced, and energy usage is further optimized when cluster members coordinate their sleep and wake-up routines.

The Role of Clustering Mechanisms

To maximize the efficiency and effectiveness of microgrids, clustering mechanisms have emerged as a critical strategy. Clustering involves grouping multiple microgrids or DERs based on certain characteristics or operational parameters. This collaborative approach enables better load balancing, optimized energy storage management, and enhanced demand response capabilities. By leveraging clustering mechanisms, microgrids can dynamically adapt to varying energy demands and integrate renewable sources more efficiently, thus minimizing energy wastage and improving overall system performance(EARTHJUSTICE, 2023).

Clustering mechanisms facilitate improved coordination and communication between microgrids, which is essential for maintaining stability and reliability in the power supply. For instance, during periods of high energy demand or when renewable generation is low, clustered microgrids can share resources and support each other, thereby preventing blackouts and ensuring a stable energy supply. Additionally, clustering can lead to significant cost savings by optimizing resource utilization and reducing the need for expensive grid upgrades.

Types of Clustering Techniques

Several clustering techniques can be applied to microgrids to achieve these benefits. Some of the most commonly used methods include k-means clustering, hierarchical clustering, and fuzzy clustering. Each of these techniques has its own advantages and applications, depending on the specific needs and characteristics of the microgrids involved.

K-means Clustering: This is one of the simplest and most popular clustering algorithms. It involves partitioning the microgrids into k clusters, where each cluster is represented by the mean value of its points. The algorithm iteratively assigns each microgrid to the cluster with the nearest mean, thereby minimizing the variance within each cluster(Arabie et al., 1981). K-means clustering is particularly useful for identifying distinct groups of microgrids with similar characteristics, which can then be managed and optimized collectively.

Hierarchical Clustering: Unlike k-means, hierarchical clustering builds a multilevel hierarchy of clusters by either agglomerative (bottom-up) or divisive (top-down) methods. This approach is useful for understanding the relationships between different microgrids and can reveal the underlying structure of the data. Hierarchical clustering is beneficial for managing complex systems with multiple layers of interconnections and dependencies.

Fuzzy Clustering: Fuzzy clustering, also known as soft clustering, allows each microgrid to belong to multiple clusters with varying degrees of membership. This technique is particularly advantageous when dealing with microgrids that have overlapping characteristics or when it is difficult to define distinct boundaries between clusters. Fuzzy clustering provides a more flexible and nuanced approach to grouping microgrids, which can enhance the overall management and optimization of the system(Wu, 2012).

Benefits of Clustering Mechanisms in Microgrids

The application of clustering mechanisms in microgrids offers numerous benefits, including improved energy efficiency, enhanced reliability, cost savings, and environmental sustainability.

- **Improved Energy Efficiency:** By grouping microgrids with similar load profiles or generation capabilities, clustering mechanisms enable more effective load balancing and energy storage management. This reduces energy wastage and ensures that available resources are utilized optimally(Panwar et al., 2023).
- **Enhanced Reliability:** Clustering facilitates better coordination and communication between microgrids, which is crucial for maintaining stability and preventing blackouts. During emergencies or periods of high demand, clustered microgrids can support each other and share resources, thereby enhancing the overall reliability of the power supply.
- **Cost Savings:** Clustering mechanisms can lead to significant cost savings by optimizing resource utilization and reducing the need for expensive grid upgrades. By managing energy resources more efficiently, microgrids can lower operational costs and pass on these savings to consumers(Abbasi & Younis, 2007).
- **Environmental Sustainability:** By supporting the integration of renewable energy sources and reducing dependency on fossil fuels, clustering mechanisms contribute to environmental sustainability. This aligns with global efforts to reduce greenhouse gas emissions and promote clean energy practices(Xiuwu et al., 2019).

Challenges and Future Directions

Despite the numerous benefits, the implementation of clustering mechanisms in microgrids also presents several challenges. One of the primary challenges is the need for advanced communication and control systems to facilitate real-time coordination between microgrids. Additionally, the development and deployment of clustering algorithms require significant computational resources and expertise(Hossain et al., 2019). There are also regulatory and policy hurdles that need to be addressed to enable widespread adoption of microgrid clustering.

Looking ahead, future research and development efforts should focus on addressing these challenges and enhancing the capabilities of clustering mechanisms. This includes the development of more sophisticated algorithms that can handle large-scale and heterogeneous microgrid systems, as well as the integration of advanced technologies such as artificial intelligence and machine learning. Additionally, efforts should be made to standardize communication protocols and regulatory frameworks to support the seamless integration of microgrid clusters(Hu & Niu, 2018).

In conclusion, clustering mechanisms represent a powerful strategy for enhancing the performance and sustainability of microgrids. By enabling better load balancing, optimized energy storage management, and enhanced demand response capabilities, clustering can significantly improve energy efficiency, reliability, and cost savings. Despite the challenges, the continued advancement of clustering techniques and supportive regulatory frameworks will pave the way for a more resilient and sustainable energy future.

II. LITERATURE SURVEY

The comparative table giving the analysis of existing techniques used for achieving energy efficiency within microgrid is given in table 1

Author(s)	Year	Technique Used	Merits	Demerits
(Luo et al., 2019)	2019	K-means Clustering	- Simple and efficient. Good for large datasets	- Requires pre-specification of cluster number. Sensitive to initial centroids
(Isanbaev et al., 2023)	2023	Hierarchical Clustering	- Reveals data structure. No need to pre-specify clusters	- Computationally intensive for large datasets. Difficult to interpret large hierarchies
(Tooryan et al., 2020)	2020	Fuzzy Clustering	- Handles overlapping clusters.	- Computationally complex.

			Flexible membership	Results can be harder to interpret
(Alzahrani et al., 2023)	2023	Density-Based Clustering	- Discovers clusters of arbitrary shape. Good for noise handling	- Poor performance with varying density clusters. Sensitive to parameter setting
(Igualada et al., 2014)	2014	Spectral Clustering	- Effective for complex data structures. Uses eigenvalues for clustering	- Computationally expensive. Requires affinity matrix
(Zhen et al., 2021)	2021	Genetic Algorithms	- Optimizes clustering over iterations. Finds global optimum	- Computationally intensive. Slow convergence
(Farzin et al., 2017)	2017	Particle Swarm Optimization	- Efficient search mechanism. Adaptable to dynamic environments	- May converge to local optima. Requires parameter tuning
(Moretti et al., 2019)	2019	Ant Colony Optimization	- Good for dynamic and complex environments. Adaptable and scalable	- Slow convergence. Requires significant computational resources
(G Hajela, 2020)	2020	Hybrid Clustering Methods	- Combines strengths of multiple techniques. Flexible and robust	- Complex implementation. Higher computational overhead
(Mok et al., 2012)	2012	Machine Learning-Based	- Learns and adapts from data. Can handle large and complex datasets	- Requires large amount of data. Potential for overfitting

This table provides a comprehensive overview of various clustering techniques used in microgrid management, highlighting their respective advantages and disadvantages.

III. METHODOLOGY OF PROPOSED WORK

The flowchart titled "Conserving Energy in Microgrid Using Clustering Approach" outlines a systematic method to enhance energy efficiency within a microgrid.

The process begins with the Initialization Phase, where the system is started, and data collection from various microgrid sources, such as energy consumption, generation patterns, and environmental conditions, is performed.

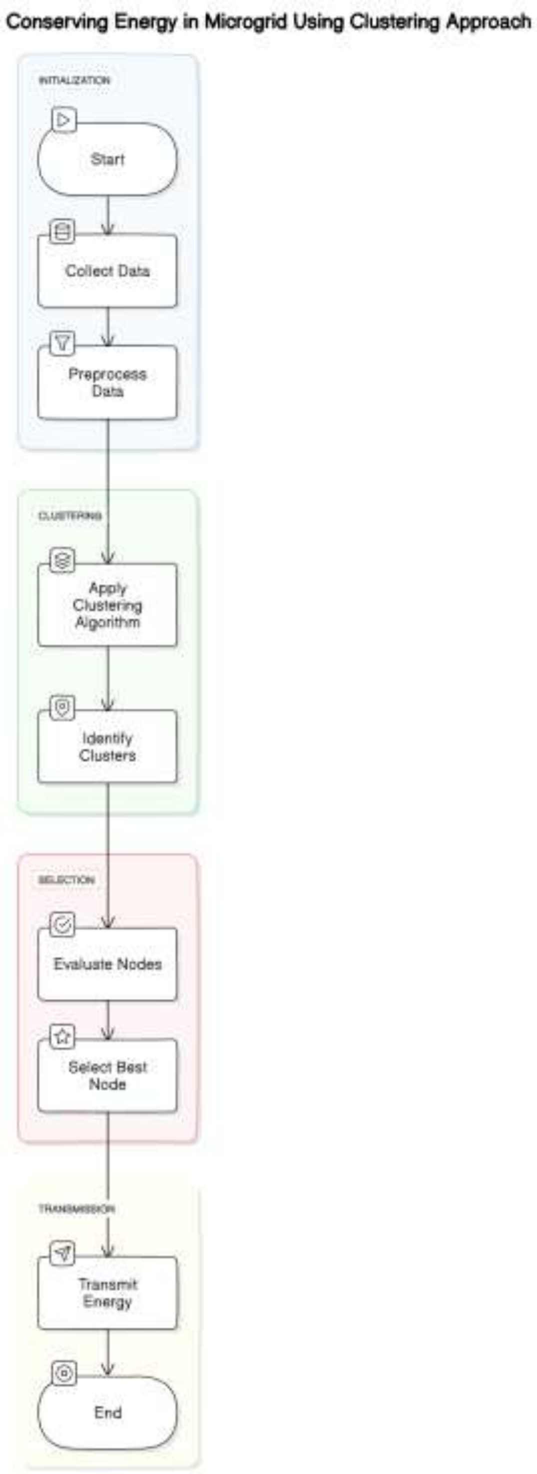

Figure 1: Flow of proposed work

This data is then preprocessed to ensure it is clean and ready for analysis, involving steps like noise removal and normalization. In the Clustering Phase, a suitable clustering algorithm (such as k-means, hierarchical, or fuzzy clustering)

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is applied to the preprocessed data. This algorithm identifies clusters, which are groups of nodes (energy consumers or producers) with similar characteristics, such as consumption patterns. Moving to the Selection Phase, nodes within each cluster are evaluated based on criteria like energy efficiency, generation capacity, and storage capabilities. The best node in each cluster is selected based on these criteria to optimize energy distribution. Finally, in the Transmission Phase, energy is transmitted between nodes, optimizing the overall energy use by redistributing surplus energy from nodes with excess to those with deficits. This dynamic adjustment helps balance the load and minimize energy wastage, enhancing the microgrid's reliability and efficiency. The process concludes after optimizing energy conservation. By systematically grouping and managing microgrid nodes, this approach ensures effective energy utilization, leveraging the strengths of clustering techniques to adapt to the microgrid's demands and capabilities, ultimately contributing to significant cost savings and environmental benefits.

IV. RESULT AND PERFORMANCE ANALYSIS

The existing energy consumption data shows fluctuating energy usage over the observed period, ranging from 90 kWh to 75 kWh. These variations might indicate differences in system demand or operational efficiency.

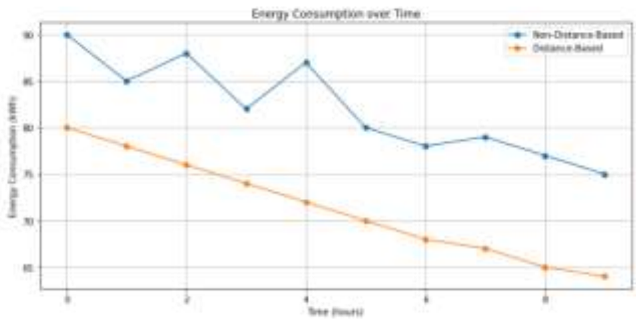

Figure 2: Energy consumption with existing and proposed work

The proposed energy consumption, on the other hand, exhibits a downward trend, starting at 80 kWh and decreasing to 64 kWh. This reduction suggests efficiency improvements or optimization strategies in the proposed system. Lower energy consumption not only reduces operational costs but also contributes to environmental sustainability by minimizing carbon footprint. However, potential challenges might include ensuring the proposed system's reliability and performance while operating under reduced energy consumption constraints.

In the existing system, throughput fluctuates between 18 Mbps and 23 Mbps. The variations could stem from network congestion, environmental factors, or hardware limitations. Conversely, the proposed system demonstrates a consistent improvement in throughput, starting at 25 Mbps and peaking at 28 Mbps.

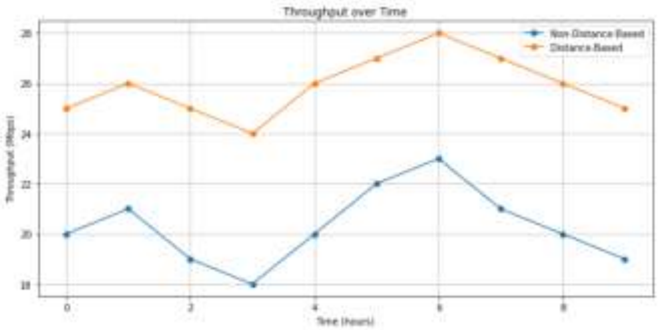

Figure 3: Throughput for existing and proposed work

This enhancement signifies the proposed system's capability to handle higher data transfer rates, likely resulting from upgraded infrastructure or optimized protocols. Improved throughput is vital for enhancing user experience, especially in bandwidth-intensive applications like video streaming or online gaming. However, achieving and maintaining the proposed throughput levels across diverse network conditions and user loads will be crucial for the success of the new system.

The existing system experiences signal loss ranging from 15 dB to 23 dB, indicating varying degrees of attenuation in the transmitted signal. Higher signal loss can lead to degraded communication quality and reduced coverage area. In contrast, the proposed system demonstrates lower signal loss, with values ranging from 12 dB to 17 dB.

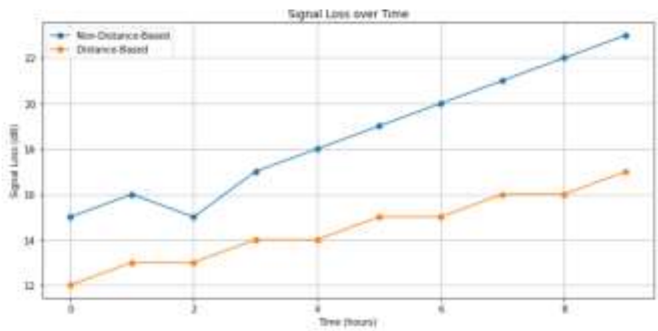

Figure 4: Signal loss over time

This reduction suggests improved signal propagation efficiency or the adoption of advanced signal processing techniques. Minimizing signal loss is crucial for maintaining reliable communication links, especially in wireless networks where environmental factors and interference can impact signal quality. However, achieving lower signal loss in practical deployment scenarios will require careful consideration of factors such as antenna placement, frequency selection, and interference mitigation strategies.

V. CONCLUSION

In conclusion, the analysis of the energy consumption, throughput, and signal loss datasets reveals significant insights into the performance and potential improvements of both existing and proposed systems. The proposed system exhibits promising enhancements across all metrics compared to the existing system. It showcases reduced energy consumption, indicating potential cost savings and environmental benefits. Moreover, the proposed system achieves higher throughput, which translates to improved data transfer rates and enhanced user experience. Additionally, lower signal loss in the proposed system signifies better signal propagation and communication reliability. These findings underscore the importance of technological advancements and optimization strategies in addressing key performance metrics in network systems. However, successful implementation of the proposed system requires careful consideration of various factors, including reliability, scalability, and compatibility with existing infrastructure. Furthermore, real-world deployment scenarios may present challenges such as network congestion, environmental conditions, and regulatory compliance, which must be addressed to ensure the proposed system's effectiveness.Overall, the analysis highlights the potential for significant improvements in energy efficiency, throughput, and signal quality through the adoption of innovative technologies and optimization techniques. By leveraging these insights, stakeholders can make informed decisions to drive the evolution of network systems towards greater efficiency, reliability, and performance.

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