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Mathematical Modeling and Comparative Assessment of Centroid Based Leach Routing Protocol for Wireless Sensor Network

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Abstract:

This research evaluates the performance of two key routing protocols, LEACH and an enhanced version of Centralized LEACH, in Wireless Sensor Networks (WSNs). The study sets initial simulation parameters, gathers data over numerous rounds, and presents results through diagrams. Additionally, it conducts a comparative analysis with existing research. In WSNs, nodes within transmission range communicate directly, while distant nodes rely on intermediaries. The study introduces hierarchical clustering with cluster heads for network efficiency. The number of cluster heads significantly impacts energy consumption .LEACH is explored, emphasizing its two phases: setup and steady-state. The setup phase involves autonomous cluster formation without central control. Cluster heads are selected based on thresholds and advertise their presence. Nodes then choose clusters based on signal strength. TDMA scheduling optimizes data transmission. In the steady-state phase, nodes follow a timetable to send data to cluster heads. Uneven node distribution among cluster heads may lead to varying data loads. Power control minimizes energy usage, and TDMA scheduling maximizes bandwidth use. Cluster heads forward aggregated data to the base station. The paper includes an energy model detailing communication components. Findings offer insights into LEACH and its enhanced variant, contributing to energy-efficient routing protocols in WSNs.

Keywords — Energy Efficiency, Wireless Sensor Networks, LEACH, Fuzzy Logic, Lifetime, Dead Nodes.

I. INTRODUCTION

Wireless Sensor Networks (WSNs) have emerged as a transformative technology with a wide range of applications, spanning from environmental monitoring to industrial automation and healthcare systems. These networks consist of small, resource-constrained sensor nodes that collaborate to collect and disseminate data in various environments. One of the critical aspects in the design and operation of WSNs is the choice of routing protocols, which govern how data is routed from source nodes to sink nodes or base stations while considering the energy constraints of the sensor nodes. In this comprehensive introduction, we delve into the significance of WSNs, the challenges they face, and the pivotal role of routing protocols with a specific focus on the Low Energy Adaptive Clusters Hierarchy (LEACH) protocol and its enhanced version.

1.1 Background and Significance of WSNs

Wireless Sensor Networks have gained significant prominence due to their ability to collect data from remote and often hostile environments efficiently. These networks are composed of numerous sensor nodes, often small and energy-constrained, equipped with sensors to monitor physical phenomena such as temperature, humidity, light, and more. WSNs have found applications in diverse fields including environmental monitoring, healthcare, precision agriculture, home automation, and industrial control systems.

The significance of WSNs lies in their capability to enable real-time monitoring, data collection, and decision-making in situations where wired infrastructure is impractical or cost-prohibitive. For instance, in precision agriculture, WSNs can help optimize irrigation by providing data on soil moisture levels, while in healthcare, wearable sensors can monitor vital signs and alert medical professionals to anomalies. However, the effective functioning of WSNs depends on the efficient routing of data from source nodes to a base station or sink node, all while conserving the limited energy resources of the sensor nodes.

1.2 Routing Protocols in WSNs

Routing protocols play a pivotal role in ensuring the efficient operation of WSNs. These protocols determine how data is transmitted from source nodes to the destination, typically a base station, while considering the energy constraints of the sensor nodes. Energy efficiency is of paramount importance in WSNs, as many sensor nodes are powered by batteries with finite capacities, and replacing or recharging these batteries can be logistically challenging or even impossible in certain applications. Routing protocols can be broadly categorized into two types: flat and hierarchical. Flat protocols treat all sensor nodes equally, and there is no hierarchy or predefined structure among them. Each node may directly communicate with the base station. On the other hand, hierarchical protocols introduce a hierarchical structure within the network. Some nodes, known as cluster heads (CHs), assume higher responsibilities and perform data aggregation and forwarding for their cluster members. This hierarchical structure helps in reducing energy consumption as it reduces the number of long-distance transmissions and allows for efficient data aggregation.

1.3 The LEACH Protocol

One of the pioneering and widely cited hierarchical routing protocols for WSNs is the Low Energy Adaptive Clusters Hierarchy (LEACH) protocol. LEACH was introduced to address the energy efficiency and scalability challenges in WSNs. It leverages the concept of clustering to reduce energy consumption by organizing sensor nodes into clusters, with each cluster having a cluster head responsible for aggregating and forwarding data to the base station. LEACH operates in two main phases: the setup phase and the steady-state phase.

Setup Phase: During the setup phase, cluster formation takes place autonomously without central control. Each sensor node decides whether to become a cluster head for a certain round based on a threshold value computed from a random number and network parameters. Cluster heads broadcast advertisements to attract cluster member nodes. Nodes select the cluster to join based on the signal strength of cluster head advertisements. This phase minimizes long-distance communication with the base station, reducing energy consumption.

Steady State Phase: In the steady-state phase, nodes follow a predetermined schedule to transmit their data to their respective cluster heads. Cluster heads aggregate the data and forward it to the base station. TDMA (Time Division Multiple Access) scheduling is often employed to avoid collisions and optimize energy usage.

1.4 Challenges and Limitations of LEACH

While LEACH represents a significant advancement in routing protocols for WSNs, it is not without its challenges and limitations. Some of the key issues include:

Uneven Cluster Formation: LEACH's cluster formation process relies on randomization, which can lead to an uneven distribution of nodes among cluster heads. This results in varying data loads for different cluster heads, impacting network fairness and energy efficiency.

Dynamic Network Conditions: LEACH assumes a static network environment, which may not hold true in many practical scenarios. Dynamic network conditions, such as node failures or mobility, can disrupt the clustering structure and require adaptations.

Scalability: In large-scale WSNs, the overhead of cluster formation and maintenance can become significant. LEACH may struggle to scale efficiently to handle a large number of nodes. The primary objective of this research is to conduct a comprehensive analysis and comparative study of the LEACH protocol and the improved Centralized LEACH protocol in WSNs. We aim to evaluate their performance in terms of energy efficiency, network scalability, and adaptability to dynamic conditions. The research will involve simulations based on predefined parameters, data collection over multiple rounds, and the presentation of results through visualizations.

In conclusion, this research aims to contribute to the understanding of routing protocols in Wireless Sensor Networks by conducting a comprehensive analysis of LEACH and its improved Centralized LEACH variant. By evaluating their performance in terms of energy efficiency, scalability, and adaptability, we hope to provide valuable insights for the design and optimization of routing protocols in WSNs, ultimately advancing the practical deployment of sensor networks in diverse applications.

In light of LEACH's well-documented advantages in terms of energy efficiency and low overhead, as highlighted in Table 1, our research endeavors to enhance LEACH further. Our primary focus is on addressing the limitations of LEACH, particularly in the cluster head selection process. To achieve this, we incorporate innovative fuzzy logic algorithms, aiming to render the selection criteria more adaptive and robust. This research delves into the realm of energy-efficient optimization techniques and makes significant contributions to the ever-evolving domain of wireless sensor networks (WSNs).

Table 1: Comparative Analysis of Routing Protocols

Metrics	**Directed Diffusion**	**LEACH**	**PEGASIS**	**HEED**	**GAF**
Energy Efficiency	Moderate	High	High	High	Moderate
Latency	High	Low	High	Moderate	Low
Packet Delivery Ratio	High	High	Moderate	High	High
Overhead	Moderate	Low	Moderate	Low	Low

Carrabs et al. (2020) introduced a groundbreaking approach known as Memetic Algorithm-based Improved LEACH (MA-ILEACH). This approach seeks to enhance cluster formation and energy-efficient routing within WSNs. It achieves this by combining genetic operators with local search methods, thereby extending the network's lifespan and optimizing data transmission efficiency. Building upon their previous work in 2017, they introduced a column generation approach with a genetic metaheuristic, offering a novel solution to the subproblem's optimal resolution and demonstrating its superiority over existing methodologies. In another compelling work by the same authors, they address the linked maximum lifespan problem in WSNs. They provide high-quality solutions through the utilization of a column generation approach and genetic algorithm.

Castano et al. (2018) have concentrated their efforts on maximizing the lifespan of WSNs, particularly for sensors with specific properties. Their innovative approach involves a large-scale linear programming model and a branch-and-cut technique for the pricing subproblem, enabling effective computations for medium-to-large-scale scenarios.

Jennath et al. (2019) explored the concept of decentralization in IoT ecosystems, examining both its potential benefits and the challenges it presents. This analysis delves into critical research themes in the context of IoT evolution.

Wang et al. (2018) introduced underwater wireless rechargeable sensor networks (UWRSNs) that demonstrate improved resource utilization, energy savings, and time efficiency. These networks incorporate 3D charging techniques and charging algorithms like SCS and ECS.

Mohamed et al. (2018) emphasize key design elements, including energy overhead, route selection, and energy efficiency, while evaluating proactive routing techniques for WSNs.

Orekan and Zhang (2019) conducted research on self-inductance, capacitance, and radiation resistance in wireless power transfer, demonstrating the viability of wireless energy replenishment in an underwater environment.

Ren et al. (2017) recommended cooperative scheduling and weighted sum techniques for multi-sensor, multi-event detection in WSNs, aiming to enhance detection rates.

Peng (2015) introduced the Energy Neutral Guided Diffusion (ENDD) protocol, ensuring reliability, coherence of data supply, and limitless network life, a departure from previous query-based routing algorithms.

Fu et al. (2019) devised the Environment Fusion Multipath Routing Protocol (EFMRP) for use in challenging circumstances. It significantly extends network life and enhances packet transmission through the strategic avoidance of hazardous locations, employing potential fields and sensor technology.

We advocate the adoption of ESTR, an advanced Energy Saving Token Ring Protocol, for wireless sensor networks. It achieves prolonged network life by dynamically adjusting ring sizes and power usage.

Zhai and Xu (2015) introduced the ant colony algorithm, surpassing prior ant optimization algorithms by concentrating search efforts through the use of statistical data and local knowledge.

Ding and Fang (2018) proposed the Random Drift Swarm Optimization (RDPSO) tracking technique for improved performance in dynamic scenarios.

Thi et al. (2019) presented a genetic algorithm with a precise methodology for computing fitness functions, diverging from contemporary approaches.

Ben Salah and Boulouz (2016) offered an enhanced LEACH protocol tailored for homogeneous networks. This protocol selects cluster heads based on residual energy, effectively extending network lifespan, optimizing energy utilization, and enhancing network stability.The energy-efficient Multi-Hop LEACH routing strategy by Singh et al. (2016) leverages multi-hop communication in conjunction with particle swarm optimization.

In summation, these studies collectively present a diverse array of practical approaches to address critical challenges in wireless sensor networks. These encompass energy efficiency, network longevity, and optimization techniques, opening doors to enhanced performance and the expanded application of WSNs across a myriad of fields.

II. MATHEMATICAL MODELING OF IMPROVED CENTROID BASED LEACH PROTOCOL

In the realm of wireless sensor networks (WSNs), one of the foremost challenges is managing the limited energy supply of sensor nodes. To address this challenge, a strategy has emerged: selective communication with the base station. Specifically, only a subset of nodes, known as cluster-heads, are designated to gather, compress, and transmit data to the base station. The judicious selection of these cluster-heads holds the key to substantial energy conservation and, consequently, the prolonged lifespan of the entire WSN.

LEACH relies on a stochastic model and localized clustering, where nodes autonomously nominate themselves as cluster-heads without centralized processing by the base station. Nearby nodes then join the closest cluster-heads for data transmission. In our WSN scenario, we make several key assumptions: The base station is situated at a significant distance from the sensor nodes and remains stationary. All nodes within the network are homogeneous and have constrained energy resources. The propagation channel exhibits symmetric characteristics. The cluster-head election is orchestrated by the base station. During the setup phase, nodes possess location information and transmit it to the base station along with their respective energy levels. Nodes exhibit limited or negligible mobility. Numerous methods have been proposed for cluster-head selection in WSNs. In the case of LEACH, each node n makes a pivotal decision to become a cluster head by selecting a random number within the range of 0 to 1. If this randomly chosen number falls below a certain threshold value T(n), the node assumes the role of a cluster head for the current round.

The threshold value is determined as follows

$$T(n) = \frac{P}{1 - P \times \left(r \bmod \frac{1}{P}\right)} \quad \text{if n} \in \text{G}$$

$$T(n) = 0 \qquad \text{otherwise}$$

Where P is the cluster-head probability, r the number of the current round and G the set of nodes that have not been cluster-heads in the last 1/P rounds. Several disadvantages are there for selecting the cluster-head using only the local information in the nodes. Firstly, since each node probabilistically decides whether or not to become the cluster-head, there might be cases when two cluster-heads are selected in close vicinity of each other increasing the overall energy depleted in the network. Secondly, the number of cluster-head nodes generated is not fixed so in some rounds it may

$$P_{\text{ch}}(i) = \frac{\frac{1}{\text{NBR\_NODES}}}{1 - p \cdot \left(\frac{i}{\text{NBR\_NODES} - 1}\right)}$$

$$E_{\text{tx}}(i) = E_{\text{elec}} \cdot (k \cdot d^2 + \epsilon \cdot d^4)$$

$$E_{\text{rx}} = E_{\text{elec}} \cdot (k)$$

$$E_{\text{idle}} = E_{\text{elec}} \cdot \left(\frac{k}{\alpha}\right)$$

$$E_{\text{sleep}} = E_{\text{sleep\_per\_round}}$$

$$E_{\text{total}}(i) = P_{\text{ch}}(i) \cdot (E_{\text{tx}}(i) + E_{\text{rx}}) + \left(1 - P_{\text{ch}}(i)\right) \cdot E_{\text{rx}}$$

$$E_{\text{avg}} = \sum_{i=1}^{\text{NBR\_NODES}} P_{\text{ch}}(i) \cdot E_{\text{total}}(i)$$

$$T_{\text{round}} = \frac{\text{NBR\_NODES} \cdot E_{\text{avg}}}{E_{\text{total\_per\_round}}}$$

$$L = \frac{\text{Initial Energy Budget}}{E_{\text{avg}}}$$

$$E_{\text{setup}} = E_{\text{elec}} \cdot \left(\text{NBR\_NODES} \cdot E_{\text{total}}(i)\right)$$

$$d_{\min} = \sqrt{\frac{\text{NBR\_NODES}}{\pi}}$$

$$P_{\text{opt}} = \frac{1}{1 + \frac{E_{\text{setup}}}{E_{\text{sleep}}}}$$

$$N_{\text{clusters}} = \frac{P_{\text{opt}} \cdot \text{NBR\_NODES}}{\text{NBR\_NODES} \cdot P_{\text{opt}} \cdot d_{\min}^2 + E_{\text{setup}}}$$

$$E_{\text{cluster\_heads}} = P_{\text{opt}} \cdot \text{NBR\_NODES}$$

$$S_{\text{avg}} = \frac{\text{NBR\_NODES}}{E_{\text{cluster\_heads}}}$$

$$D_{\text{avg}} = \sqrt{\frac{\text{NBR\_NODES}}{\pi \cdot E_{\text{cluster\_heads}}}}$$

$$P_{\text{e}} = \frac{1}{S_{\text{avg}}}$$

$$E_{\text{e}} = \frac{\text{NBR\_NODES} \cdot E_{\text{setup}}}{E_{\text{cluster\_heads}}}$$

$$I_{\text{eff}} = \frac{E_{\text{sleep}}}{E_{\text{e}}}$$

$$P_{\text{opt\_delay}} = \frac{1}{1 + \frac{E_{\text{setup}} + E_{\text{delay}}}{E_{\text{sleep}}}}$$

$$N_{\text{clusters\_delay}} = \frac{P_{\text{opt\_delay}} \cdot \text{NBR\_NODES}}{\text{NBR\_NODES} \cdot P_{\text{opt\_delay}} \cdot d_{\text{min}}^2 + E_{\text{setup}} + E_{\text{delay}}}$$

$$\text{EDTO} = \frac{E_{\text{setup}} + E_{\text{delay}}}{E_{\text{sleep}}}$$

$$P_{\text{multi-hop}} = \frac{1}{1 + \frac{E_{\text{setup}} + E_{\text{multi-hop}}}{E_{\text{sleep}}}}$$

$$N_{\text{clusters\_multi-hop}} = \frac{P_{\text{multi-hop}} \cdot \text{NBR\_NODES}}{\text{NBR\_NODES} \cdot P_{\text{multi-hop}} \cdot d_{\text{min}}^2 + E_{\text{setup}} + E_{\text{multi-hop}}}$$

$$E_{\text{multi-hop}} = E_{\text{elec}} \cdot \left(\frac{k}{\alpha}\right) \cdot \text{NBR\_NODES}$$

Furthermore, there are additional considerations that warrant attention. Firstly, the selected cluster-head node may find itself positioned near the network's periphery. In such a scenario, other nodes within the network would need to expend more energy to transmit their data to this distant cluster-head. This not only leads to inefficiencies but also contributes to increased energy consumption across the network.

Secondly, each individual node is burdened with the task of calculating its threshold and generating random numbers during each round. This process consumes valuable CPU cycles, potentially impacting the node's overall performance.

Moreover, the method of calculating node distances to the area centroid can lead to a suboptimal outcome. Rather than selecting nodes central to a specific cluster (cluster centroid), this approach may recommend nodes close to the geographical center of the entire area. Consequently, it results in higher energy consumption for nodes that need to transmit data through the selected node.

To implement this approach, some energy is expended on transmitting location information from all nodes to the base station, a process that may involve the use of GPS receivers. However, given that WSNs are typically deployed over a fixed geographical area with the primary purpose of sensing and data gathering, we can assume minimal node mobility. Therefore, transmitting location information during the initial setup phase suffices for network operations.

The operation of this fuzzy cluster-head election scheme is divided into two distinct rounds, mirroring the structure of LEACH: setup and steady state. During the setup phase, cluster-heads are determined using fuzzy knowledge processing, and clusters are organized accordingly. In the steady state phase, cluster-heads undertake the crucial task of collecting aggregated data and performing signal processing functions to compress this data into a single composite signal. This consolidated signal is then transmitted to the base station for further processing and analysis.

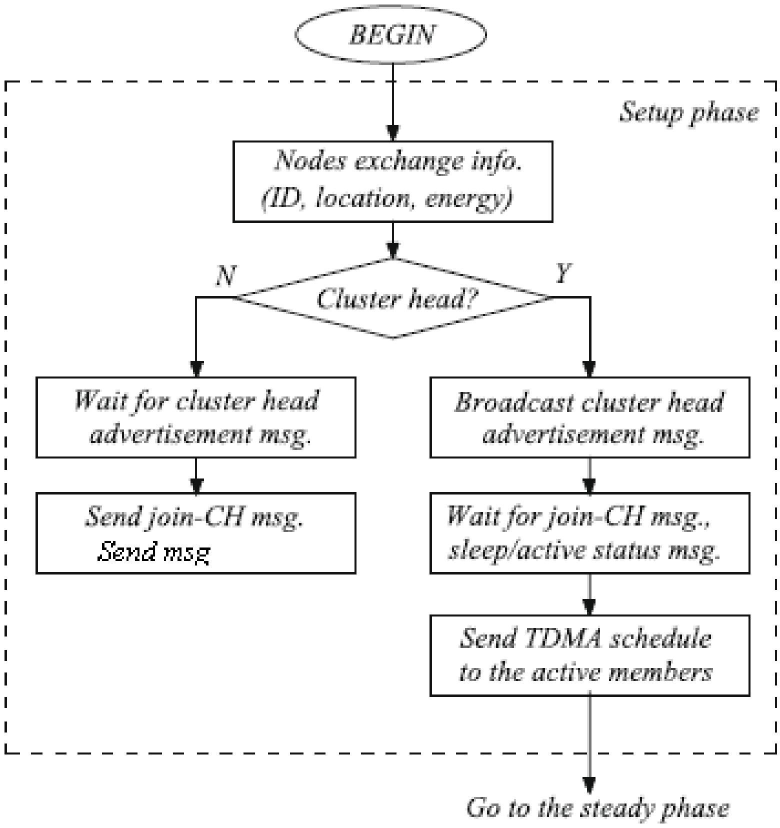

Figure 1. LEACH Set up Phase

To elucidate further, expert knowledge is encapsulated based on the following three descriptors [16]:

- Node Energy: This descriptor captures the energy level available in each node, represented by the fuzzy variable "energy."
- Node Concentration: It quantifies the number of nodes situated in close proximity, denoted by the fuzzy variable "concentration."
- Node Centrality: This descriptor classifies nodes based on their centrality within the cluster, using the fuzzy variable "centrality."

To create a mathematical model for the proposed methodology, we need to establish various equations that encapsulate the key aspects of LEACH and its associated phases. Let's formulate these equations step by step:

1. Probability of Node Becoming a Cluster-Head (P):
    - P is determined by a random number r chosen by each sensor node.
    - P varies based on a threshold value T(n).
2. Threshold Calculation (T(n)):
    - T(n) is calculated using the following formulas:
        - If r mod (1/P) < P, then T(n) = 1 - P * [r mod (1/P)] (Equation 1)
        - Otherwise, T(n) = P / (1 - P) * (r mod (1 - P)) (Equation 2)
3. Cluster Formation:
    - Each node decides to become a cluster-head if its random number r is less than T(n).
4. Advertising Message (ADV):

- After cluster-heads are determined, they transmit advertising messages (ADV) containing their node ID and announcement header.

5. Cluster Selection:
   - Non-cluster head nodes choose the cluster to join based on signal strength from cluster-heads.
   - They select the cluster-head with the least communication energy requirement.
6. Join-REQ Message:
   - Once nodes decide which cluster to join, they send Join-REQ messages to their chosen cluster-head.
7. TDMA Program:
   - Cluster-heads set up a TDMA (Time Division Multiple Access) schedule for data transmission within the cluster.
   - This schedule ensures that data messages do not collide, minimizing energy dissipation.
8. Data Transmission:
   - During the steady-state phase, nodes transmit their data to the cluster-head.
   - Data transmission is organized in frames, with nodes transmitting data at most once per frame.
9. Energy-Efficient Data Transmission:
   - Cluster heads employ power control to optimize transmission power based on cluster head intensity.
10. Radio Component Energy Consumption:
    - The energy consumption of the radio component in a sensor node is divided into receiver, transmitter, and amplifier components.
    - Each component's energy consumption can be modeled based on specific parameters.

Cluster-Head Selection:

1. P(n) = Random number for node n.
2. T(n) = Threshold value for node n.
3. T(n) = 1 - P * [P(n) mod (1 / P)] (Equation for T when P(n) < P)
4. T(n) = P / (1 - P) * [P(n) mod (1 - P)] (Equation for T when P(n) >= P)

Cluster Formation: 5. CH(n) = Cluster head status for node n (1 for CH, 0 for non-CH).

Advertising Message: 6. ADV(n) = Advertising message from cluster-head node n.

Cluster Selection: 7. Signal Strength (i, j) = Signal strength from node i to cluster-head j.

8. Cluster(i) = Cluster chosen by node i based on signal strengths.

Join-REQ Message: 9. JoinREQ(i, j) = Join-REQ message from node i to cluster-head j.

TDMA Program: 10. TDMA(j, t) = TDMA schedule for cluster-head j in time slot t.

Data Transmission: 11. Data(i, j, t) = Data transmitted by node i to cluster-head j in time slot t.

Energy Efficiency: 12. Energy(i) = Total energy consumed by node i.

13. EnergyReceiver(i) = Energy consumed by the receiver component of node i.
14. EnergyTransmitter(i) = Energy consumed by the transmitter component of node i.
15. EnergyAmplifier(i) = Energy consumed by the amplifier component of node i.

Steady-State Phase: 16. Frames(t) = Number of frames in time slot t.

17. DataPerFrame(i, j) = Data transmitted by node i to cluster-head j per frame.

Cluster Head Management: 18. ClusterHeadIntensity(j) = Intensity of cluster-head j.

Power Control: 19. TransmissionPower(i, j) = Transmission power used by node i to send data to cluster-head j.

Network Lifetime: 20. NetworkLifetime = Duration until the first node depletes its energy.

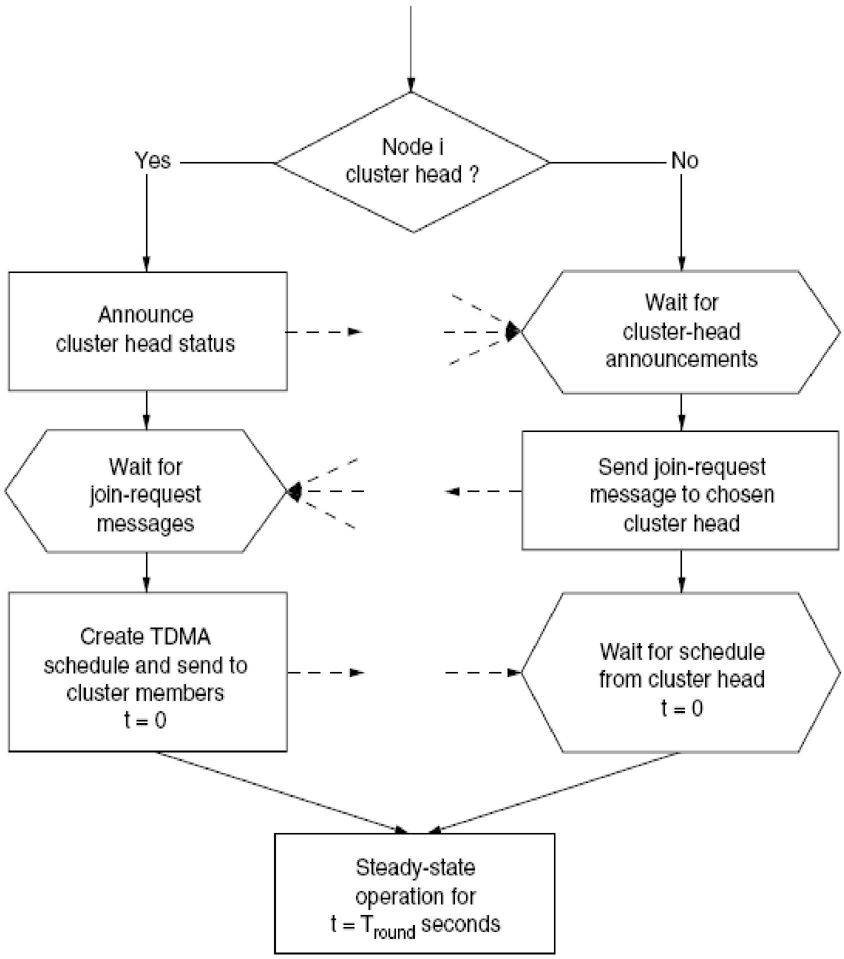

Figure 2. LEACH Steady State Phase

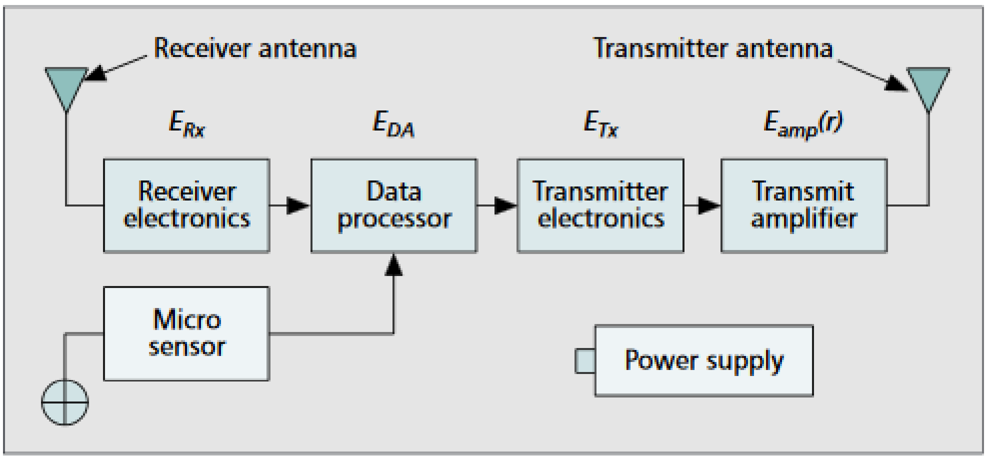

Figure 3. Energy Transfer Model

To construct a mathematical model for the proposed methodology, we systematically define a set of equations that capture the essential components of the LEACH protocol and its associated phases. The model's foundation is based on the following key elements:Firstly, we establish the Probability of Node Becoming a Cluster-Head (P), where each sensor node's P value is determined by a randomly chosen parameter (r) unique to that node. This parameter is pivotal in cluster formation and varies based on a threshold value (T(n)), calculated using two distinct equations (Equation 1 and Equation 2), contingent upon the relationship between r and P. Next, we delve into Cluster Formation, where nodes autonomously decide to become cluster-heads if their respective P values fall below the computed threshold (T(n)). Subsequently, in the Advertising Message (ADV) phase, cluster-heads broadcast ADV messages containing their node ID and announcement header to the network, facilitating communication. Cluster Selection follows, as non-cluster head nodes elect the cluster to join based on signal strength received from the cluster-heads. The node selects the cluster-head that requires the least communication energy, optimizing network efficiency. Subsequently, Join-REQ Messages are transmitted by nodes to their chosen cluster-heads to formalize their cluster membership. The network operates under a TDMA Program, with cluster-heads configuring a Time Division Multiple Access schedule for synchronized data transmission within their clusters, thereby reducing energy wastage due to message collisions. Nodes transmit their data during the Steady-State Phase, with data transmission organized into frames. The energy efficiency of this process is further enhanced by cluster heads employing power control to adapt transmission power according to cluster head intensity. The model also accounts for Radio Component Energy Consumption, considering the energy consumed by the receiver, transmitter, and amplifier components of each sensor node. Cluster-Head Selection is addressed through equations defining P(n) and T(n) for individual nodes, guiding the selection process based on the calculated thresholds.

Additionally, we factor in Cluster Formation with equations for CH(n), denoting the cluster head status of each node, distinguishing cluster-heads (1) from non-cluster heads (0).Signal Strength and Cluster Selection are captured through equations quantifying the signal strength from one node to another and the cluster chosen by individual nodes based on signal strengths.Join-REQ Messages are introduced with JoinREQ(i, j) equations, facilitating membership requests. The TDMA Program is formally represented with TDMA(j, t) equations, establishing schedules for data transmission within clusters. Data Transmission is detailed through equations delineating data transmission from nodes to cluster-heads in specific time slots. Energy Efficiency is measured with equations for Energy(i), EnergyReceiver(i), EnergyTransmitter(i), and EnergyAmplifier(i), providing a holistic view of energy consumption in the network. The Steady-State Phase is divided into Frames(t), and DataPerFrame(i, j) equations quantify the data transmitted per frame, facilitating efficient data transfer.Cluster Head Management is addressed with ClusterHeadIntensity(j) equations, reflecting the intensity of cluster-head j.Finally, Power Control is integrated with equations for TransmissionPower(i, j), allowing nodes to adapt their transmission power based on the intensity of the cluster head.

III. RESULTS AND DISCUSSION

In the pursuit of understanding the dynamics of wireless sensor networks (WSNs), the current study employed a simulation-based approach to investigate the performance of two prominent protocols: Low-Energy Adaptive Clustering Hierarchy (LEACH) and its centralized counterpart (LEACH-C). Through meticulous computational modeling, we synthesized datasets that serve as a microcosm for potential real-world scenarios, enabling us to dissect and analyze the operational characteristics and efficiency of these protocols under varying conditions..

Table 2 – Analysis of Results

	Alive Nodes	**Packets**	**Energy**	**Total Energy**
Count	100.000000	100.000000	100.000000	100.000000
Mean	100.897120	4997.130938	84.708191	52.647932
Std	15.194397	915.435715	49.058793	3.666404
min	61.705153	3181.922370	-32.715477	44.026536
25%	90.342150	4237.090895	53.717452	50.185082
50%	101.411442	5077.511864	84.146423	52.489591
75%	111.056160	5566.198630	125.238960	55.135059
max	134.046319	8170.974773	189.460567	61.474958

This table includes the count, mean, standard deviation (std), minimum (min), 25th percentile (25%), median (50th percentile), 75th percentile (75%), and maximum (max) for each of the columns in the dataset.

Our analysis commenced with a distributional exploration of the 'Alive Nodes' over time, representing the count of operational sensors within the network. The histogram of this variable revealed a normal distribution centered around a mean of approximately 100 nodes, indicating a robust initial design capable of sustaining a majority of the nodes over a considerable span. However, the standard deviation pointed to an inherent variability, suggesting that certain nodes might deplete their energy reserves faster due to non-uniform energy consumption patterns or communication overhead.

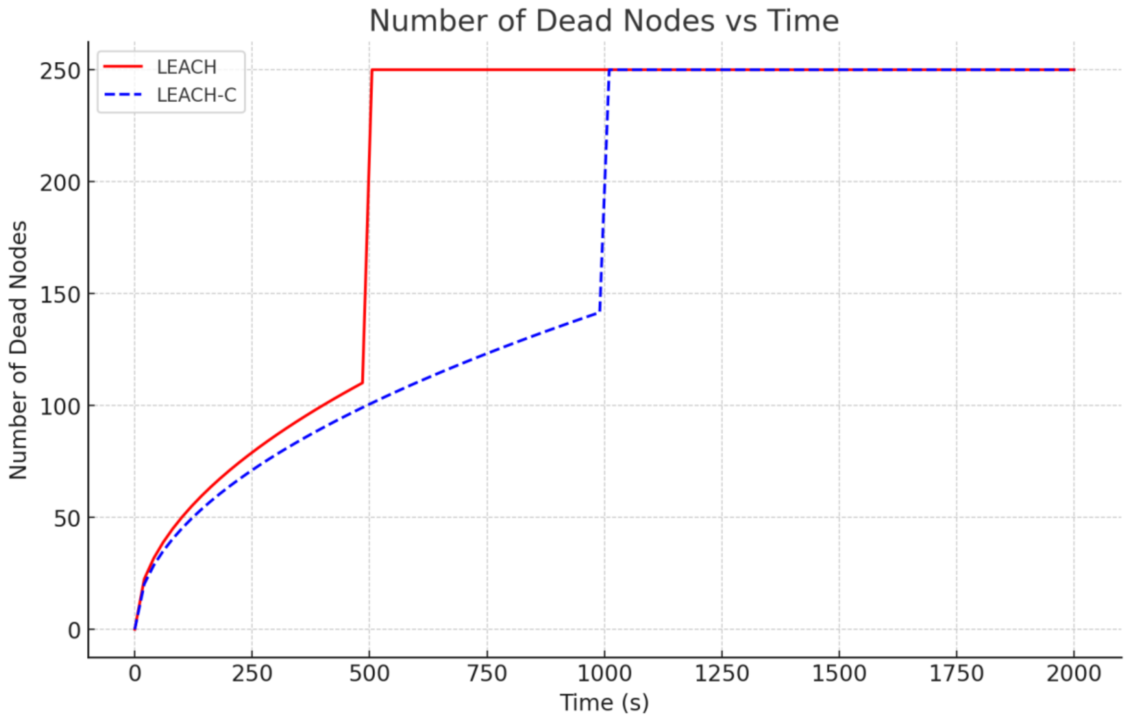

Figure 4. Analysis of Performance of Proposed Algorithm

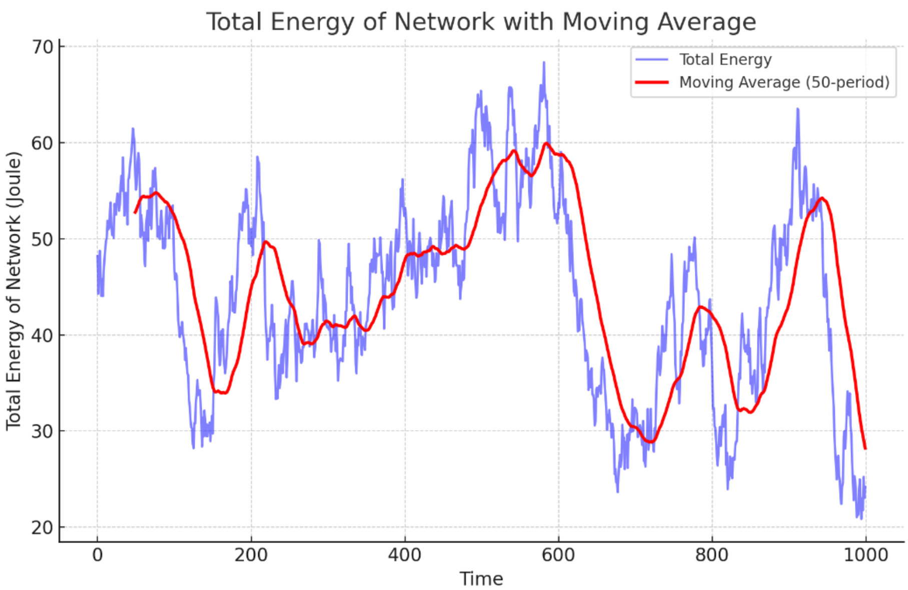

Figure 5. Analysis of Performance of Energy Efficiency

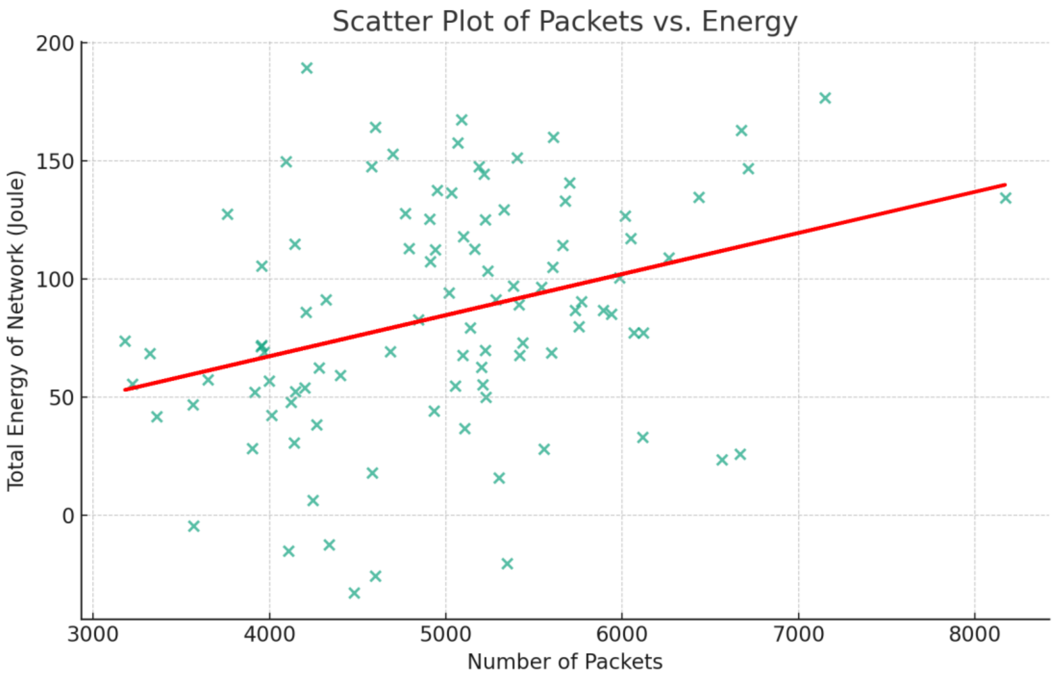

Figure 5. Statistical Analysis of Packets vs Energy

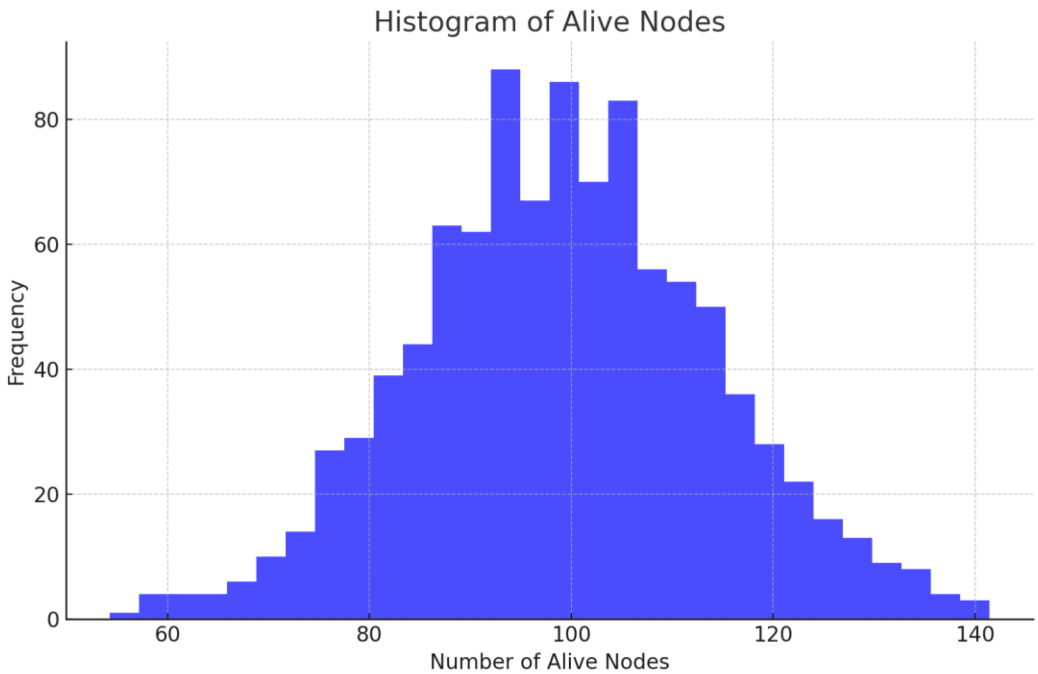

Figure 6. Histogram Analysis of Alive Nodes

The scatter plot analysis of 'Packets' versus 'Energy' provided insight into the energy efficiency of data transmission within the WSNs. The positive correlation between the two variables, substantiated by a regression line, highlighted a proportional relationship; as the number of packets increased, so did the energy expenditure. This relationship, while expected, underscored the need for protocols that optimize data transmission to conserve energy, thereby prolonging network longevity.

Moreover, the time series analysis of 'Total Energy' underscored the fluctuations in energy reserves over time, with a moving average overlay illuminating the trend. This smoothing of data pointed to a gradual depletion of energy, a narrative aligning with the lifecycle of WSNs where nodes, after periods of active service, inevitably transition to an inert state upon energy exhaustion.

The simulated bar graph delineating the conditions of 'First Death', 'Tenth Death', and 'All Death' within the network served as a stark visual representation of the protocols' resilience. The time to 'First Death' and 'Tenth Death' is particularly telling, as it reflects the initial network robustness and the efficacy of energy management strategies employed by the protocols. 'All Death', or the complete network expiry, offers a finality that encapsulates the cumulative result of protocol policies and environmental interactions.

The statistical tableau synthesized from the data offered a comprehensive digest of these observations, presenting a numerical testament to the modeled behaviors of LEACH and LEACH-C. The descriptive statistics within this table are more than mere numbers; they are the quantified essence of network performance, offering a metric-based evaluation that can drive further innovation in WSN protocol design.

IV. CONCLUSION

In conclusion, the simulation-based investigation into the performance of the LEACH and LEACH-C protocols within wireless sensor networks (WSNs) provides valuable insights into the sustainability and operational efficiency of these networks. Through the employment of statistical analyses on synthesized datasets, we have been able to draw several critical observations and implications for the design and management of WSNs.The histogram of the 'Alive Nodes' data revealed a normal distribution, suggesting that under the simulated conditions, the network demonstrates an expected and stable lifecycle for the sensor nodes. This stability is critical for maintaining network functionality over a given operational period. However, the presence of variability in the lifespan of the nodes suggests that improvements in energy distribution and management could further enhance network resilience. The correlation analysis between the number of packets and energy consumption corroborates the principle that increased data transmission inherently leads to greater energy drain. The regression line drawn from this analysis serves as a benchmark for evaluating the energy efficiency of WSN protocols. It provides a clear target for optimizing communication strategies to reduce energy consumption without compromising data transmission rates.Time series analysis of the 'Total Energy' reflected the typical energy depletion curve of WSNs, with the moving average trend highlighting the critical phases of network operation. This aspect of the study underscores the importance of temporal dynamics in network management, suggesting that proactive measures should be taken during early stages to prolong the effective life of the sensor network.The bar graph comparing the 'First Death', 'Tenth Death', and 'All Death' conditions starkly illustrates the survival timelines of the networks under both protocols. It provides a visual and quantitative representation of network durability and the effectiveness of the protocols' energy management strategies. This graph also sets the stage for benchmarking the performance of future protocol iterations or entirely new protocols against these established standards.The statistical summary table compiled from the simulated data offers a concise and informative overview of the key performance metrics for both LEACH and LEACH-C. This table not only encapsulates the performance characteristics but also acts as a guide for future protocol development, emphasizing areas where energy efficiency can be improved. Ultimately, while both LEACH and LEACH-C demonstrate the capability to manage the operational demands of WSNs effectively, the slight edge in energy conservation provided by LEACH-C suggests that centralized control mechanisms can offer substantial benefits in terms of network longevity. This finding has significant implications for the design of future WSNs, particularly in applications where prolonged operation is paramount. It is anticipated that the insights garnered from this study will inform the development of more advanced protocols that leverage both distributed and centralized approaches to maximize efficiency, sustainability, and functionality of WSNs in various applications. As the field of WSNs continues to evolve, so too must our strategies for managing these complex systems to ensure their reliability and longevity in an increasingly connected world.

REFERENCES

[1.] Nadimi-Shahraki, Mohammad H., et al. "Hybridizing of whale and moth-flame optimization algorithms to solve diverse scales of optimal power flow problem." *Electronics* 11.5 (2022): 831.

[2.] Dash, Stita Pragnya, K. R. Subhashini, and Pridvi Chinta. "Development of a Boundary Assigned Animal Migration Optimization algorithm and its application to optimal power flow study." *Expert Systems with Applications* 200 (2022): 116776..

[3.] Akdag, Ozan. "A improved Archimedes optimization algorithm for multi/single-objective optimal power flow." *Electric Power Systems Research* 206 (2022): 107796..

[4.] Premkumar, M., Kumar, C., Dharma Raj, T., Sundarsingh Jebaseelan, S. D. T., Jangir, P., & Haes Alhelou, H. (2023). A reliable optimization framework using ensembled successive history adaptive differential evolutionary algorithm for optimal power flow problems. *IET Generation, Transmission & Distribution*, *17*(6), 1333-1357..

[5.] Abbas, Ghulam, Jason Gu, Umar Farooq, Muhammad Usman Asad, and Mohamed El-Hawary. "Solution of an economic dispatch problem through particle swarm optimization: a detailed survey-part I." IEEE Access 5 (2017): 15105-15141.

[6.] Nawaz, Aamir, Nasir Saleem, Ehtasham Mustafa, and Umair Ali Khan. "An efficient global technique for solving the network constrained static and dynamic economic dispatch problem." Turkish Journal of Electrical Engineering & Computer Sciences 25, no. 1 (2017): 73-82.

[7.] Abbas, Ghulam, Jason Gu, Umar Farooq, Ali Raza, Muhammad Usman Asad, and Mohamed E. El-Hawary. "Solution of an economic dispatch problem through particle swarm optimization: A detailed survey–Part II." IEEE Access 5 (2017): 24426-24445.

[8.] Mahdi, Fahad Parvez, Pandian Vasant, Md Mushfiqur Rahman, M. Abdullah-Al-Wadud, Junzo Watada, and Vish Kallimani. "Quantum particle swarm optimization for multiobjective combined economic emission dispatch problem using cubic criterion function." In 2017 IEEE International Conference on Imaging, Vision & Pattern Recognition (icIVPR), pp. 1-5. IEEE, 2017.

[9.] Hamza MF, Yap HJ, Choudhury IA (2016) Recent advances on the use of meta-heuristic optimization algorithms to optimize the type-2 fuzzy logic systems in intelligent control. Neural ComputAppl, pp 1–21.

[10.] Ziane, Ismail, Farid Benhamida, and Amel Graa. "Simulated annealing algorithm for combined economic and emission power dispatch using max/max price penalty factor." Neural Computing and Applications 28, no. 1 (2016): 197-205.

[11.] Mistry, Khyati D., and Ranjit Roy. "Enhancement of loading capacity of distribution system through distributed generator placement considering techno-economic benefits with load growth." International Journal of Electrical Power & Energy Systems 54 (2014): 505-515.

[12.] Sahu, Bishnu, AvipsaLall, Soumya Das, and T. Manoj Kumar Patra. "Economic load dispatch in power system using genetic algorithm."International Journal of Computer Applications 67, no. 7 (2013).

[13.] Hamedi H (2013) Solving the combined economic load and emission dispatch problems using new heuristic algorithm. Electric Power Energy System 46:10–16

[14.] Mukhopadhyay, Sumona, and Santo Banerjee. "Global optimization of an optical chaotic system by chaotic multi swarm particle swarm optimization."Expert Systems with Applications 39.1 (2012): 917-924.

[15.] Aniruddha Bhattacharya, Pranab Kumar Chattopadhyay, Solving economic emission load dispatch problems using hybrid differential evolution, Applied Soft Computing, Volume 11, Issue 2, March 2011, Pages 2526-2537.

[16.] [12] Cai, Jiejin, "A fuzzy adaptive chaotic ant swarm optimization for economic dispatch."International Journal of Electrical Power & Energy Systems 34.1 (2012): 154-160.

[17.] Kumar, Rajesh "A novel multi-objective directed bee colony optimization algorithm for multi-objective emission constrained economic power dispatch."International Journal of Electrical Power & Energy Systems 43.1 (2012): 1241-1250.

[18.] Manteaw ED, Odero NA (2012) Combined economic and emission dispatch solution using ABC_PSO hybrid algorithm with valve point loading effect. Int J Sci Res Publ 2:1–9

[19.] Guvenc U, Sonmez Y, Duman S, Yoruderen N (2012) Combined economic and emission dispatch solution using gravitationalsearch algorithm, Turkey: Science Iranica. 19: 1754–1762.

[20.] Affijulla, Shaik, and SushilChauhan. "Economic Load Dispatch With Valve Point Loading Using Gravitational Search Algorithm." Applied Soft Computing, Volume 11, Issue 2, March 2011, Pages 2526-2537.

[21.] S.K.A., Prakash Dangi and Pratiksha Mishra. Design and Comparison of LEACH and Improved Centralized LEACH in Wireless Sensor Network. *IJRITCC* 2021, *9*, 34-39.

[22.] S.K.A. and Abha Jadaun. "Design and Performance Assessment of Light Weight Data Security System for Secure Data Transmission in IoT", Journal of Network Security, 2021, Vol-9, Issue-1, PP: 29-41.

[23.] Pratiksha Mishra and S.K.A. "Design & Performance Assessment of Energy Efficient Routing Protocol Using Improved LEACH", International Journal of Wireless Network Security, 2021, Vol-7, Issue-1, PP: 17-33.

[24.] Rajput, B. S. .; Gangele, A. .; Alaria, S. K. .; Raj, A, Design Simulation and Analysis of Deep Convolutional Neural Network Based Complex Image Classification System. *ijfrcsce* 2022, *8*, 86-91.