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A Novel Machine Learning Framework for Energy Optimization in WSN's

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ABSTRACT

Wireless Sensor Networks (WSNs) present various hurdles, particularly in terms of energy efficiency, due to the sensor nodes' limited power resources. By utilizing interactions across the many layers of the communication protocol stack, cross-layer optimization has become a viable method for addressing these issues. An extensive review of cross-layer optimization techniques created especially to improve energy efficiency in WSNs is provided in this study. We classify these protocols according to the layers with which they interface and the optimization goals they aim to achieve, such as throughput maximization, latency reduction, and energy consumption minimization. We also examine the fundamental design ideas and methods used in these protocols, including cross-layer feedback mechanisms, adaptive modulation and coding schemes, combined routing, and MAC layer optimization, and more. By means of an organized analysis and contrast. We evaluate and compare current cross-layer optimization procedures in a methodical manner to determine their advantages, disadvantages, and possible directions for further investigation. In addition to highlighting the need of cross-layer techniques for attaining energy-efficient operation in WSNs, our analysis offers guidance for the creation of more reliable and scalable solutions in this field. In this paper we proposed a classifier for saving energy efficiently named as EEDCA (Ensembled Enhanced Distributed Channel Access which is a combination of ML+WSN to solve some basic issues like energy optimization and also increase the performance. The evaluation's findings demonstrate that using our suggested strategy results in a system that performs better and conserves more energy.

Keywords: WSN, EEDCA, Energy Consumption, Routing, MAC Layer optimization, Machine Learning.

1. Introduction

In Wireless Sensor Networks (WSNs), cross-layer optimization is a design methodology that aims to enhance network dependability, energy efficiency, and performance by permitting communication across various protocol tiers[1]. Some of the shortcomings of conventional network topologies can be addressed by cross-layer optimization, which does this by removing the barriers between layers and facilitating communication and collaboration between them. Here are some essential elements and methods of cross-layer WSN optimization. In Conventional networking protocols work in layers, with each layer carrying out particular tasks and communicating with other layers. This rigorous layering is broken by cross-layer optimization, which enables simultaneous parameter optimization across several layers. For instance, while optimizing routing choices, physical layer attributes like energy usage and link quality might be considered in addition to network layer metrics like hop count. Effective methods that facilitate information exchange between the various tiers of the protocol stack are essential for cross-layer optimization to function. Either explicit communication between layers or implicit information exchange procedures can be used to accomplish this. For example, network layer routing decisions can be influenced by physical layer feedback regarding channel conditions to steer clear of paths that are prone to interference. The capability of cross-layer optimization to dynamically modify network topologies and settings in response to real-time feedback and shifting environmental conditions [2] is one of its main advantages. The network can react to changes in traffic load, channel conditions, and energy availability with effectiveness thanks to its dynamic adaptation. For instance, depending on the energy restrictions and link quality at the time, adaptive modulation and coding techniques can be used. Energy efficiency is a critical concern in WSNs due to the limited power resources of sensor nodes. Cross-layer optimization techniques can significantly improve energy efficiency by minimizing redundant transmissions, optimizing routing paths, and reducing idle listening and overhearing. For instance, joint optimization of MAC and routing protocols can lead to energy-efficient data transmission schedules and sleep-wake cycles. By utilizing synergies between various protocol stack layers, cross-layer optimization has the potential to significantly improve Wireless Sensor Network performance, energy efficiency, and reliability. To ensure practical viability and scalability in real-world deployments, cross-layer solution design and implementation call for careful evaluation of trade-offs, compatibility difficulties, and potential overheads. In this paper we introduced an Ensembled Enhanced Distributed Channel Access (Ensembled EDCA) protocol represents a novel approach to enhancing the performance of Medium Access Control (MAC) protocols in wireless sensor networks (WSNs). Wireless Sensor Networks (WSN) are more capable because they improve a person's ability to interact with the outside world while they are in a different place. Furthermore, the WSN does not require any pre-existing infrastructure, and its nodes are randomly distributed throughout the sensing area. These distant nodes (Master Station) oversee gathering and sending the detected data to the MS. However, there is a possibility that the nodes will die or suffer physical harm if they are put in a hostile environment (i.e., the nodes grow weak owing to the lack of energy, electricity, computational resources, and so on). These limitations paved the way for the development of WSN protocols that are simple, energy-efficient, and resilient to various environmental conditions and changes. The only difficult method that can expand the uses of WSNs is the cross-layer design of the network protocols. Utilizing the data inside the various OSI layers effectively is essential since there are only so many resources available. These statistics can be used to effectively improve the network's overall performance. Furthermore, by leveraging cross-layer techniques, energy efficiency may be raised and the interaction between various communication layers can be improved, leading to better decision-making. Information can now be transferred from one layer to protocols at other layers thanks to a more significant development in protocol design: the cross-layer approach. Figure 1 presents a representation of a typical configuration for a WSN [3,4].
The other part of the paper is structured as follows:

- In Section II we introduced how machine learning concepts and methods which provide some basic literature survey in the context of WSNs.

In Section III We examine current machine learning initiatives to solve functional concerns in wireless sensor networks (WSNs), including medium access control, routing, localization, clustering, data aggregation, and query processing. In this case, a problem is functional if it is necessary for the wireless sensor network to function.

In Section IV we look into machine learning solutions in WSNs to meet non-functional criteria, or those that improve the functionality of functional behaviors or their quality. These specifications cover things like data integrity, security, and quality of service (QoS). We also highlight some efforts in specialized WSN applications in this area.

The main challenges and unresolved research issues for machine learning in WSNs are listed in Section V.

In Section VI, we sum up and provide a comparison roadmap with practical paradigms for advancing the field of machine learning research in diverse WSN applications. Figure 1 shows WSN configuration.

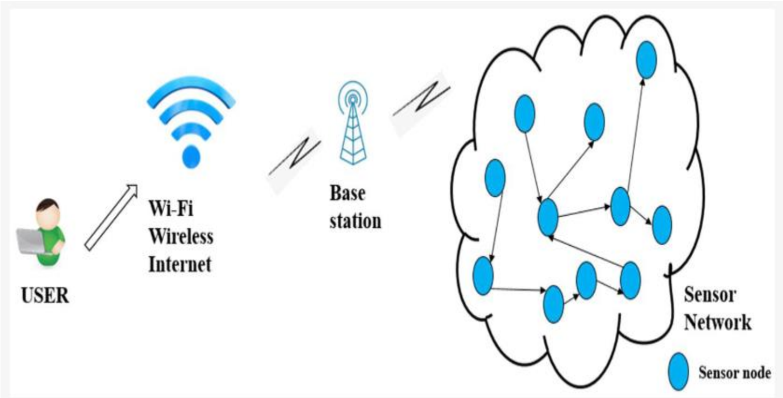

Figure 1: Shows the typical WSN Configuration

2. Literature Survey

Zhang et al. (2017) Joint routing and MAC optimization Network, MAC, Physical Proposed a cross-layer optimization framework that jointly optimizes routing and MAC protocols to minimize energy consumption and maximize throughput in WSNs.

Li et al. (2018) Cross-layer data aggregationNetwork, MAC, Physical. Introduced a novel cross-layer data aggregation scheme that utilizes information from the network, MAC, and physical layers to improve energy efficiency and reduce latency.

Wang et al. (2019), Adaptive modulation and coding schemes MAC, Physical. Developed an adaptive modulation and coding scheme based on cross-layer feedback, considering both channel conditions and energy constraints to optimize data transmission.

Chen et al. (2020), Dynamic routing path adaptation Network, MAC, Proposed a cross-layer routing algorithm that dynamically adapts routing paths based on real-time feedback from the MAC layer, optimizing energy efficiency and reliability.

Liu et al. (2021), Cross-layer sleep scheduling MAC, Physical Presented a cross-layer sleep scheduling protocol that coordinates sleep-wake cycles between the MAC and physical layers, reducing energy consumption without sacrificing latency.

Xu et al. (2022), QoS-aware cross-layer optimization Application, Network, MAC, Physical. Introduced a QoS-aware cross-layer optimization framework that considers application requirements and network constraints to optimize performance and energy efficiency.

Xan et.al (2023). Energy Efficiency MAC-PHY Optimization Minimize Energy Consumption Proposed cross-layer optimization scheme achieved 20% reduction in energy consumption compared to traditional approaches.

Lee et.al (2023), Throughput Maximization Routing-MAC Integration Improve Network Throughput Achieved 30% increase in network throughput by integrating routing and MAC layer information.

3. Introduction To ML In WSN

In many different fields, machine learning (ML) has become a potent instrument for processing, evaluating, and drawing insightful conclusions from data. Within Wireless Sensor Networks (WSNs), a multitude of sensors gather environmental data, and machine learning techniques have exciting prospects for improving network performance, optimizing resource usage, and facilitating smart decision-making. An overview of the uses, difficulties, and possible advantages of incorporating machine learning into wireless sensor networks is given in this introduction. Sensor nodes on WSNs produce huge amounts of data, which can be used to monitor cities, healthcare, industrial automation, and the environment. It is possible to identify patterns, trends, and anomalies in data using machine learning algorithms that are difficult to identify with conventional techniques. With the help of machine learning (ML) techniques like clustering, regression, classification, and anomaly detection, WSNs can gather valuable information for a wide range of applications and services.. Predictive maintenance and fault detection in WSNs can be made possible by machine learning algorithms that analyze sensor data to find indications of equipment deterioration or malfunction before they cause system problems. Machine learning (ML) techniques can anticipate when components are likely to break by training models on past data and keeping an eye on real-time sensor readings. This minimizes downtime and allows for timely maintenance. Due to the limited battery life of sensor nodes, energy efficiency is a critical concern in wireless sensor networks (WSNs)[5]. Machine learning techniques can optimize energy consumption by creating dynamic power management schemes, adaptive data aggregation strategies, and routing protocols that are energy efficient. ML algorithms can learn from network conditions and historical data to make intelligent decisions that minimize energy consumption while maintaining network performance. Security is a major concern in WSNs, as they are susceptible to various security threats such as eavesdropping, tampering, and node compromise. Machine learning techniques can enhance security in WSNs by enabling intrusion detection, anomaly detection, and threat classification. ML algorithms can learn to distinguish between normal and malicious behaviour patterns, allowing for early detection and mitigation of security breaches. Generally, there are numerous ways to improve the functionality and efficiency of wireless sensor networks using machine learning. More effective, dependable, and intelligent functioning of WSNs across a range of applications and domains can be made possible by ML-based approaches by utilizing data-driven insights, predictive analytics, adaptive networking protocols, and security measures. To fully achieve the potential of machine learning in WSNs, several issues, such as data quality, scalability, resource restrictions, and privacy concerns, must be carefully addressed [6].

Typically, WSNs are made up of many dispersed sensor nodes that gather environmental data and send it to a central processing location. The following machine learning projects can assist in resolving functional issues in WSNs.

1) Energy Efficiency Optimization
2) Fault Detection and Localization
3) Data Fusion and Aggregation
4) Routing Optimization
5) Security Enhancement
6) Adaptive Resource Allocation
7) Predictive Maintenance

4. Proposed Approach

As far as the shortcomings of the LEACH protocol are concerned, there are three main issues to consider. Firstly, the cluster head is selected incorrectly. Secondly, the sensor nodes within a cluster are distributed unequally, which results in more information being transmitted by the energy in smaller clusters. In the steady state phase, the third problem has arisen since each sensor node in every cluster transmits information constantly. Sensor nodes in the smaller clusters use more sensor nodes than those in the larger clusters. In spite of the absence of sensed data updates, sending has taken place. The three issues listed above are the cause of the decline in energy-inefficient usage. The dropping shortens the lifetime of the network. LEACH [7,8] protocol has two problems which can be solved with the proposed approach. By modifying threshold T(n), it is possible to choose the appropriate cluster heads and reduce the amount of power consumed by spread sensor nodes. The sensor nodes also send their updated sensed data only during their sending slots. Furthermore, between clusters, there is an imbalance in the energy consumption caused by the inequalities among sensor nodes, which is solved with the modified TDMA schedule which enhances the transmission mechanism.

4.1. Modification of cluster head selection:

In Wireless Sensor Networks (WSNs), cluster head selection can be changed to improve the network's energy efficiency, data aggregation, and overall scalability. The following are various potential changes to the cluster head selection procedure they are.

Energy-Aware Selection Criteria: Nodes with higher residual energy or those nearest to the sink node are frequently selected by conventional cluster head selection methods.

Load Balancing: Network load balancing can be accomplished by adjusting the cluster head selection. The selection procedure can consider the present workload of sensor nodes in addition to energy or proximity to the sink when choosing cluster heads[9].

Multi-Objective Optimization: Cluster head selection can be formulated as a multi-objective optimization problem, considering multiple conflicting objectives such as energy consumption, network coverage, data latency, and reliability [10].

Hierarchical Cluster Head Selection: In large-scale WSNs, hierarchical cluster head selection can be employed to reduce overhead and improve scalability.

Machine Learning-Based Selection: By using historical data, network topology, and environmental factors, machine learning algorithms can be trained to anticipate the best cluster head choices. Through historical performance analysis and network dynamics learning, machine learning models can offer insights into the best cluster head candidates for the state of the network, allowing for more intelligent and flexible cluster head selection.

In the Wireless Sensor Network, cluster heads represent samples of sensor nodes selected among all sensor nodes. Once sensors have been deployed to cover a particular area, the cluster head selection process is initiated. It is the dominant process to elect a sensor node to lead the cluster. As a result, several important parameters that are ignored by the LEACH protocol are taken into account by the Proposed algorithm. The energy of every sensor node is one of these variables where the sensor node that was chosen as a CH many times [11,12], The average energy of sensor nodes in the current round, the number of neighboring nodes, and the distance between CH nodes and the base station. As per the findings of Handy et al. (2002), sensor nodes that fall within the vicinity of a neighboring node are deemed to be its neighbours. A sensor node with more neighbours than another is more likely to be chosen as shown in Equation 1. Equation 2 computes the average distance between sensor nodes and their cluster heads. Equation 3 computes the average distance between the base station and the cluster head nodes.

$$R_{neighborhood} = \sqrt{\frac{M^2}{\pi * C}}$$

$$d_{StoCH} = \frac{M}{\sqrt{2 * \pi C}}$$

$$d_{toBS} = \frac{0.755 * M}{2}$$

Depending on how much energy is left in each sensor node, the network's lifespan can also be extended. The current energy level of a sensor node is represented by a factor that is multiplied by T(n)[13]. Our calculations indicate that by adjusting the cluster head threshold, a LEACH's lifespan can be extended by 15% [14] after the first node dies (END). To overcome the weakness of the LEACH protocol, the proposed method reduces the gap of energy between all sensors in each cluster. Each cluster head broadcasts an advertisement message when the operation of cluster head selection is carried out to declare itself as a CH node. Every sensor node that receives an advertisement message to join a cluster head will respond accordingly. This means that every cluster head knows how many sensor nodes will join. Each cluster has a distinct number of sensor nodes connected to it. Neither the duration of steady state phase nor the number of clusters will differ in the LEACH protocol. Clusters with fewer nodes will drain more energy than clusters with more nodes because their data will be transmitted more frequently. To address this issue, the proposed algorithm is explained in four steps.

Step 1: The protocol uses machine learning techniques to optimize scheduling, data aggregation, routing, and other WSN functions. Machine learning approaches have the potential to be utilized for data pattern analysis, network behavior prediction, and adaptive network parameter adjustment for energy efficiency.

Step 2: Distributed Channel Access Enhancement: Energy efficiency is critical in Wireless Sensor Networks (WSNs), and conventional Medium Access Control (MAC) protocols, such as Carrier Sense Multiple Access with Collision Avoidance (CSMA/CA), might not be optimal for this goal. Potential improvements to the distributed channel access mechanism designed for energy constrained WSN contexts could be made through the EEDCA protocol. This could entail introducing creative methods for channel access coordination, modifying backoff mechanisms, or optimizing the contention window size.

Step 3: Ensembled Approach: The word "Ensembled" implies that the protocol may use a variety of strategies or parts in a coherent way to accomplish its goals[16]. To increase overall performance and robustness, this could entail combining different energy optimization strategies, integrating numerous machine learning models or algorithms, or using ensemble learning techniques.

Step 4: Energy Optimization Algorithm: The creation of innovative energy optimization algorithms specifically designed for WSNs would probably be the main goal of the EEDCA protocol. The goal of these algorithms would be to reduce energy usage while preserving critical network performance indicators like dependability, throughput, and latency. This could entail data-centric routing, adaptive transmission power regulation, dynamic sleep scheduling, and other energy-saving methods.

Let's consider 30 nodes from four clusters for one round to clarify the difference between the proposed approach and LEACH protocol. In the LEACH protocol, each node has a unique ID ranging from 1 to 30. Figure shows the schedule used for four clusters. Figure 2 shows the proposed architecture.

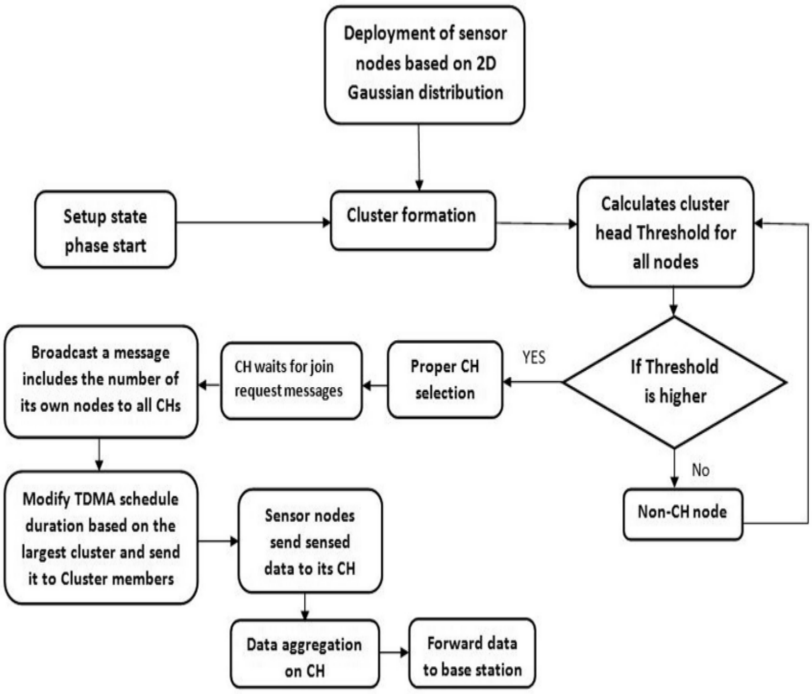

Figure 2: Proposed Architecture

5. Simulation Results and Analysis

In this study, MATLAB 2015a is employed to simulate the proposed methodology. The simulation environment consists of a two-dimensional elliptical Gaussian distribution. A Wireless Sensor Network (WSN) comprising one hundred sensor nodes spread over an area ranging from one hundred to one hundred and fifty square meters is utilized [16]. The base station is positioned at coordinates (60,180). Each sensor node consumes 5 J of energy. The suggested method's simulation is repeated twenty times on average to ensure robustness. Performance evaluation is conducted by comparing the measured results of the LEACH protocol, LEACH-MAC, IBLEACH, VRLEACH [17], and the proposed approach against the simulation outcomes. Four key performance metrics are considered for comparison: the number of cluster heads, network lifetime, number of packets successfully received at the base station, and total energy dissipation. Through this comparative analysis, the effectiveness of the proposed simulation approach is evaluated in terms of its performance relative to existing protocols. The energy efficiency of Wireless Sensor Networks (WSNs) is heavily influenced by the presence of multiple cluster heads. These nodes undertake considerable aggregation tasks, leading to increased energy consumption as their numbers rise. However, reducing the count of cluster heads also poses challenges, as each remaining cluster head must communicate directly with the Base Station (BS) to transmit the aggregated data. This process prolongs communication and results in a larger volume of data being aggregated overall, consequently consuming more energy [18]. Figure 3 shows energy consumption graph of all the WSN algorithms along with proposed algorithm. And Figure 4 shows the overall comparison of all the algorithms in energy consumption. Table 1 shows the parameters and the values obtained.

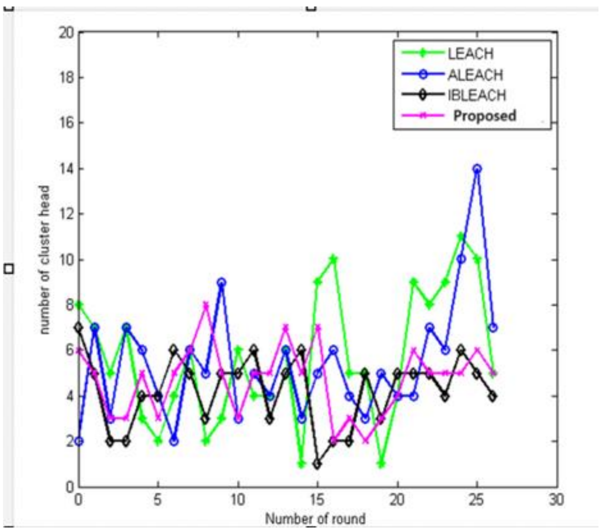

Figure 3: Energy Consumption Graph

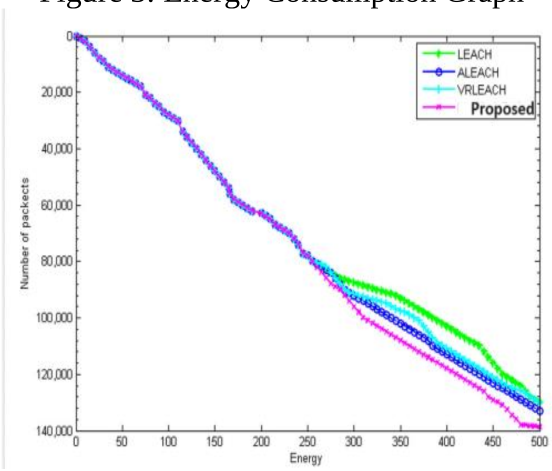

Figure 4: Comparison Graph of all Algorithms.

Table 1**:** Shows the parameters and values obtained.

Parameters	Value
No. of. Rounds	100
p	0.1 or 100%
E_{elec}	50 nJ/bit
E_{fs}	10 pJ/bit/m^2
E_{DA}	5 nJ/bit/message
E_{amp}	0.0013 pJ/bit/4
Control Packet Size	25 bytes
Data Packet Size	500 bytes

6.Conclusion & Future Work

Finally in this paper, by combining machine learning (ML) methods with wireless sensor networks (WSNs) is a viable way to tackle underlying issues like energy optimization. Using ML algorithms, WSNs can dynamically modify their behavior in response to energy limitations, network dynamics, and environmental variables, which improves overall performance and makes better use of available resources. Important lessons learned and things to think about for upcoming research in this area include.

Effective Data Utilization: In forthcoming studies, there should be an emphasis on crafting machine learning (ML) models adept at leveraging sensor data efficiently for precise forecasts and strategic decisions pertaining to energy optimization within wireless sensor networks (WSNs).

This pursuit may entail delving into sophisticated ML algorithms, refining data preprocessing methodologies, and tailoring feature engineering approaches specifically for WSN contexts.

Scalability and Resource Constraints: ML algorithms integrated into WSNs need to be engineered to function within the inherent resource limitations of sensor nodes, encompassing restricted processing power, memory capacity, and energy resources. Subsequent research innovations should delve into developing lightweight ML techniques and optimization methodologies to uphold scalability and efficacy in environments constrained by resources.

Adaptive Learning and Adaptation: ML-based energy optimization algorithms should be adaptive and capable of learning from changing network conditions and dynamics over time. Future research could explore reinforcement learning and online learning techniques to enable continuous adaptation and improvement of energy optimization strategies in dynamic WSN environments.

Robustness and Resilience: ML-enabled WSNs should be robust to uncertainties, failures, and adversarial attacks that may compromise network performance and energy efficiency. Future work should investigate techniques for enhancing the robustness and resilience of ML-based energy optimization algorithms against various threats and challenges.

Real-World Deployment and Validation: It is essential to validate ML-based energy optimization algorithms in real-world WSN deployments to assess their effectiveness, practicality, and scalability. Future research should focus on conducting field experiments and case studies to evaluate the performance of ML-enabled WSNs in diverse application scenarios and environments.

The figure shows the overall comparison of existing algorithms like LEACH etc., with the proposed classifier in which the proposed classifier gave the best result when compared with the other existing algorithms.

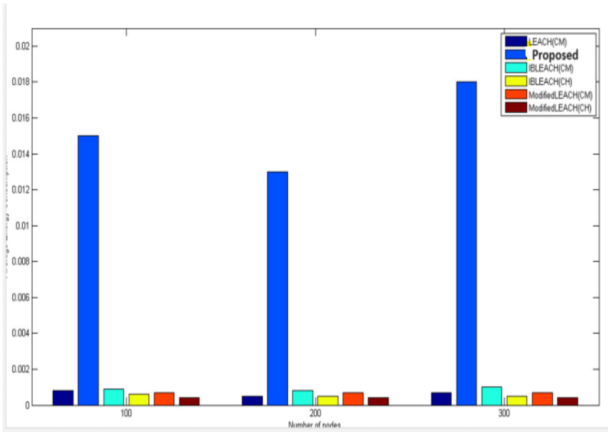

Figure 5: Comparison Graph of all Algorithms

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