Optimizing Cluster Head Selection with Deep Learning-Based Memory Model (DLMM) for Wireless Sensor Networks

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Abstract: Wireless Sensor Networks (WSNs) play an essential role in a variety of applications due to their capacity for data sensing and transmission. Nonetheless, the finite battery power of sensor nodes poses significant challenges to the longevity of these networks. Traditional routing strategies, which frequently rely on multi-hop transmissions and the creation of clusters, can result in high-energy consumption, particularly for Cluster Heads (CHs) responsible for data aggregation and transmission. This study tackles this issue by employing Deep Learning-Based Memory Model (DLMM) to optimize routing and CH selection for improved energy efficiency. By incorporating a mobile sink that travels along a linear trajectory, the approach minimizes energy expenditure by limiting cluster formation and favouring single-hop transmissions. The method strategically selects CHs based on the nodes' residual energy levels, thereby prolonging network life. Experimental findings reveal that this strategy can reduce energy consumption by as much as 22.98% in comparison to traditional multi-hop data transmission with circular path sink movements, ultimately enhancing network longevity by 39.05%. The performance assessment, conducted on a 100-node network with varying sink speeds, yielded an energy efficiency improvement of 16.68% over conventional models.

Keywords: *Wireless Sensor Networks, Cluster Head, DLMM, Mobile Sink, Energy Efficiency.*

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I. INTRODUCTION

Wireless Sensor Networks (WSNs) are increasingly important in various domains, including environmental monitoring, industrial automation, and military surveillance, where the accuracy and reliability of data collection and transmission are crucial. These networks consist of many small sensor nodes that collect environmental data and send it to a central processing unit. As WSNs are increasingly deployed, especially in large-scale applications, effective energy management is becoming crucial for prolonging the network's operational lifespan. Optimizing energy usage not only improves the performance of sensor nodes but also supports the overall sustainability of the network infrastructure. Tackling these energy consumption challenges is vital for the future growth and implementation of WSN technologies, ensuring they can fulfil the requirements of various applications while upholding reliability and efficiency. In wireless sensor networks, the complexities of energy management are shaped by several factors, particularly the multi-hop data transmission process, increased communication overhead, and the varying rates of energy depletion among different nodes. Tackling these issues is essential for enhancing network performance and maintaining sustainable operation over time. [1-3]

When data is transmitted via multiple hops, the reliance on various intermediate nodes for forwarding purposes significantly contributes to increased energy usage. Consequently, this escalation in energy demands can lead to the early deterioration and failure of the nodes that facilitate the data transfer. As a result of this uneven energy usage, the functionality and longevity of the network are compromised. The reliance on CHs for critical data management roles not only accelerates their energy exhaustion but also impacts the network's efficiency and operational stability over time. Additionally, the dynamics of sink node mobility can adversely affect the overall performance of data communication within a network. When sink nodes follow a predictable circular path, it can lead to uneven coverage, leaving some areas inadequately serviced. This situation complicates the network topology by creating unnecessary clusters and also raises the energy costs linked to multi-hop data transfers. The issue of high energy consumption continues to be a challenge across different routing protocols, even with on-going research and

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development focused on improving energy efficiency. Factors contributing to this issue include ineffective clustering strategies, the selection of cluster heads that do not optimize energy use, and a lack of comprehensive planning for data routing paths. [4-7]

Conventional approaches, including LEACH, TEEN and PEGASIS, typically depend on static cluster heads or arbitrary selection mechanisms that fail to account for the varying energy levels of network nodes. Additionally, the implementation of predetermined mobility trajectories for the sink, such as circular routes, often results in certain areas of the network being inadequately serviced. This oversight contributes to energy inefficiencies and diminishes the overall packet delivery rates within the system. The absence of adaptive routing strategies further intensifies the issue of energy depletion during data transmission, ultimately compromising the longevity of the network. By not incorporating intelligent decision-making processes, these traditional methods are unable to optimize energy usage effectively, leading to a significant reduction in the operational lifespan of the network. [16-18].

- The main aim of this research is to create a routing and cluster head (CH) selection strategy that enhances energy efficiency, thereby prolonging the operational lifespan of wireless sensor networks (WSNs) by tackling the shortcomings of current protocols.
- The proposed approach focuses on reducing energy usage throughout the network.
- It seeks to refine CH selection in accordance with the varying energy levels of nodes, decrease multi-hop transmissions through the implementation of mobile sinks, and enhance key performance indicators, including throughput, packet delivery ratio (PDR), and latency.
- The originality of this research lies in developing a Deep Learning-based Learning Model (DLLM) designed to improve routing and cluster head (CH) selection in Wireless Sensor Networks (WSNs). The principal contributions of this study include:
- This mechanism leverages historical data and the energy levels of nodes to optimize the selection of data transmission paths, ensuring enhanced performance and resource utilization within the network.
- By utilizing a DLLM-based strategy for CH selection, the process adapts to the energy status of the nodes, thereby enhancing the longevity of the network. This dynamic selection not only prevents the untimely depletion of individual nodes but also fosters more balanced energy utilization across the entire system.
- By implementing a linear path for mobile sink movement, this approach allows for efficient data transfer, as most nodes are capable of communicating directly without the need for multiple hops, which significantly decreases energy expenditure.
- A thorough assessment of the proposed methodology was conducted in comparison to six established techniques, revealing its enhanced effectiveness in several key areas, including energy efficiency, overall network longevity, and the successful delivery of packets. The evaluation highlights the advantages of the new approach, showcasing its ability to outperform existing methods in critical performance metrics, thereby contributing to improved sustainability and reliability in network operations.

II. LITERATURE REVIEW

The topic of energy-efficient routing and cluster head (CH) selection in wireless sensor networks (WSNs) has been the focus of considerable research, leading to the development of a variety of methodologies over time. These methodologies can be generally classified into three main categories: clustering-based protocols, multi-hop routing protocols, and strategies involving mobile sinks. This examination of various strategies emphasizes the on-going work to optimize energy consumption in Wireless Sensor Networks (WSNs), which is vital for extending the operational life of sensor nodes. By assessing the pros and cons of each method, researchers aim to improve the efficiency and effectiveness of data transmission in these networks, thereby fostering more sustainable and reliable sensor network applications.

The author discusses the use of the Optimizer-Based Clustering Algorithm (OBCA) in Underwater Wireless Sensor Networks (UWSNs), which are gaining popularity for tracking marine life and monitoring underwater environments. OBCA, based on a genetic algorithm, optimizes clustering solutions by using crossover and mutation operators. It offers advantages like speed, scalability, and robustness in dynamic networks, considering factors such as topology, node density, and mobility. Additionally, OBCA adapts to changes in network conditions by adjusting clusters. Widely studied and tested, OBCA is highly recommended for UWSN implementations due to its effectiveness and versatility [8].

The author presents the Low-Energy Dynamic Clustering (LEDC) protocol to improve energy efficiency in query-based wireless sensor networks (WSNs). Unlike traditional clustering protocols, which form clusters without considering query target positions and rely on energy-intensive distributed procedures, LEDC adopts a centralized approach. The key contributions of LEDC include: a prediction-based scheme for efficient and scalable network information maintenance, centralized algorithms for optimal dynamic cluster formation aligned with query target distribution, an energy-aware forwarding strategy to balance energy load in inter-cluster communication, and a parallel processing algorithm to enhance network throughput and reduce query latency. Simulation results show that LEDC significantly reduces node energy consumption and extends the network's lifetime compared to existing protocols [9].

The author presents a model predictive approach aimed at enhancing the evaluation of network lifetime and the selection of cluster heads in wireless sensor networks (WSNs). It utilizes the Smart Mesh IP Power and performance calculator to gather dynamic network parameters, which are then integrated with machine learning techniques to optimize both clustering and routing processes [10]. The other author's work introduces a model aimed at enhancing the energy efficiency and longevity of wireless sensor networks by strategically minimizing the number of active sensor nodes and optimizing the placement of cluster heads (CH). To achieve effective clustering of nodes, the k-means algorithm is utilized, designating one node from each cluster to serve as the representative for that group [11].

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The author presents an innovative approach known as the optimized genetic algorithm-based cluster head election (OptGACHE), aimed at enhancing energy efficiency in Internet of Things (IoT)-enabled wireless sensor networks (WSNs). This approach specifically addresses the critical issue of limited battery life in IoT devices, which are typically non-rechargeable [12]. The other author's work focuses on the critical issue of minimizing energy consumption to prolong the operational lifespan of Internet of Things (IoT) enabled wireless sensor networks (IoT-WSNs). It presents a new algorithm known as the Improved Sunflower Optimization Algorithm (ISFO), which is designed to optimize the selection of Cluster Heads (CHs) within these networks [13]. Another paper introduces the Energy-Efficient Mobility-based Cluster Head Selection (EEMCS) mechanism, designed to enhance the efficiency of cluster head selection in wireless sensor networks. It addresses critical challenges such as inadequate cluster head selection, fixed clustering, and static rounds, which contribute to excessive energy consumption within the network [14].

Recent studies have explored various machine-learning techniques, such as Reinforcement Learning (RL) and Deep Neural Networks (DNNs), to improve routing and Cluster Head (CH) selection in Wireless Sensor Networks (WSNs). Q-routing, which utilizes RL concepts, boosts routing efficiency by learning the best paths adaptively. However, this approach demands considerable computational resources, which may pose challenges for nodes within resource-limited WSN environments. In recent developments, DNN-based strategies have emerged that aim to forecast optimal routing paths by analysing historical data. Although these techniques show considerable potential, they typically necessitate substantial training and computational capabilities, which can be a limiting factor in the context of WSNs. The balance between performance and resource constraints remains a critical consideration in the application of these advanced machine learning techniques [15].

LEACH (Low-Energy Adaptive Clustering Hierarchy) is acknowledged as one of the most popular clustering protocols in wireless sensor networks (WSNs). This protocol operates by randomly selecting cluster heads (CHs) and periodically rotating these roles to balance energy consumption across the network nodes. However, despite its innovative approach, LEACH does not take into account the residual energy levels of nodes during the CH selection process, which can lead to uneven energy depletion and a shorter overall lifespan for the network. Furthermore, the Threshold-sensitive Energy Efficient sensor Network (TEEN) introduced a threshold-based strategy designed to minimize unnecessary data transmissions; however, its design is mainly focused on applications that require timely data delivery, which may limit its effectiveness in situations that demand continuous monitoring [16-17].

PEGASIS, which stands for Power-Efficient GAthering in Sensor Information Systems, employs a chain-based methodology for data transmission. In this framework, nodes interact exclusively with their closest neighbor, while a designated leader node is responsible for relaying the aggregated data to the sink. This strategy effectively minimizes the frequency of transmissions; however, it results in the leader node facing accelerated energy depletion, which can ultimately compromise the stability of the network. The design of PEGASIS aims to enhance energy efficiency in sensor networks by limiting communication to nearest neighbors and centralizing data aggregation through a leader node. Although this approach significantly decreases the overall transmission load, it inadvertently causes the leader node to deplete its energy reserves at a faster rate. Consequently, this rapid energy loss can lead to potential instability within the network, highlighting a critical challenge in maintaining reliable communication in such systems [18].

III. RESEARCH METHODOLOGY

This research introduces the Deep Learning-Based Memory Model (DLMM) method, focusing on two key issues: reliability and energy consumption. These factors are critical in the current landscape of wireless sensor network research. The DLMM method builds upon previous approaches like LEACH, TEEN, and PEGASIS, incorporating additional features that were not present in existing systems for multi-hop wireless networks.

In wireless sensor networks (WSN), the need to retransmit data packets leads to higher energy consumption in sensor nodes compared to standard nodes. When a node's energy runs low, it can no longer participate in communication and cannot serve as a relay node or router. This can significantly shorten the lifespan of the sensor network. The DLMM method aims to tackle this issue by selecting a relay node with a higher energy level and periodically changing which node acts as the relay. This means that each time the sender node retransmits a packet, a different relay node is chosen. This process continues for other relay nodes and includes other sensor nodes in the network.

The Deep Learning-Based Memory Model (DLMM) is suggested as a more effective solution for transmission nodes during data transfer between the sender and receiver in a Wireless Sensor Network (WSN). This approach starts by collecting data on the relay nodes and measuring the distances of all relay nodes between the sending node and the receiving sink node. Whenever the sender wants to communicate with the receiving node, the positions of the relay nodes change dynamically based on the number of hop counts and the packet sequence number. The relay node with the fewest hops and the earliest packet sequence number is chosen to forward the data to the sink node. The DLMM technique enhances the selection process for identifying a node with a higher energy level among the relay nodes, ensuring that the optimized path is both reliable and durable during data transmission.

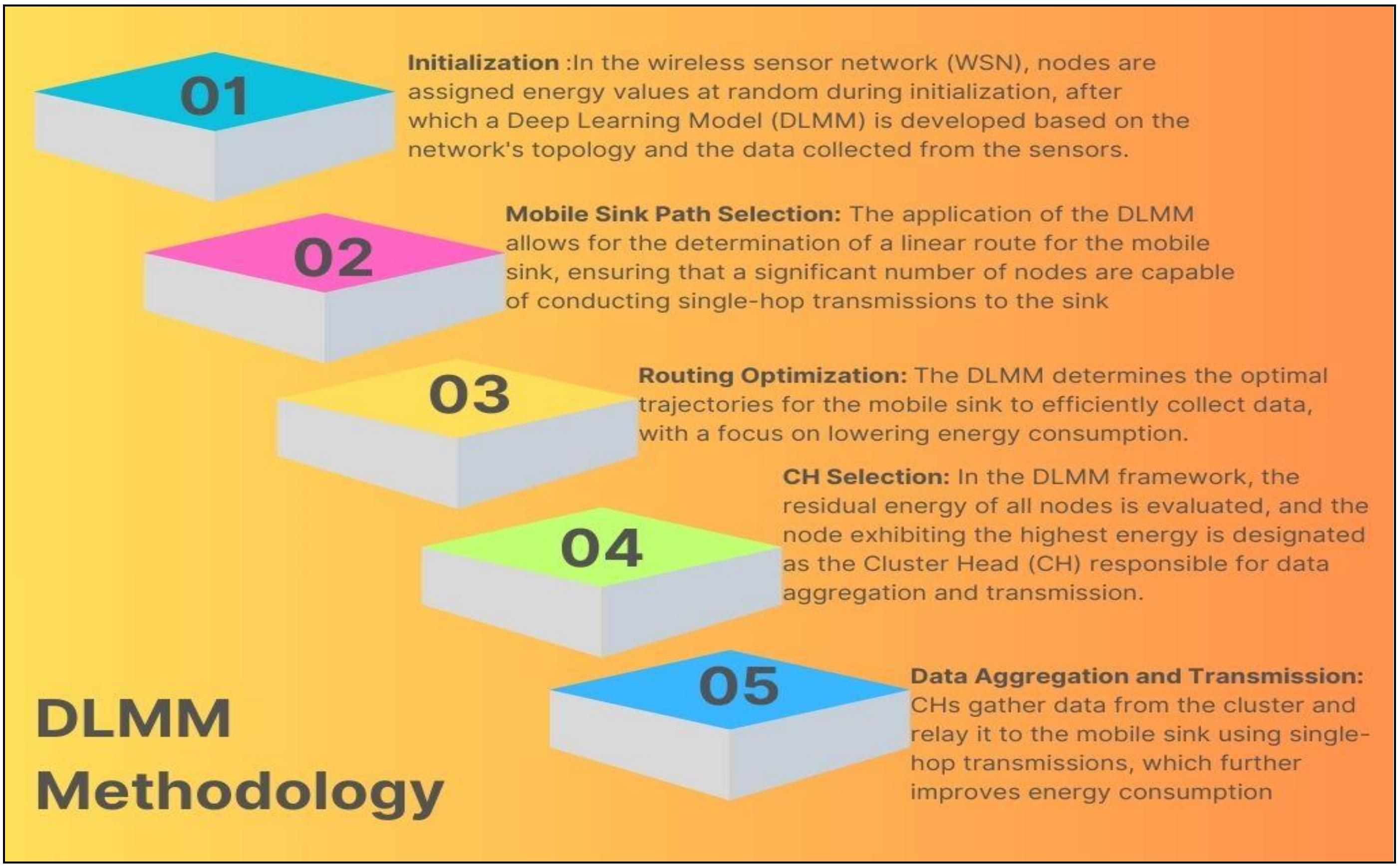

Fig 1 DLMM Methodology

The DLMM technique will be implemented using the Network Simulator 2 simulation tool and compared with the existing LEACH, TEEN and PEGASIS methods. The flowchart of proposed work is shown in figure 1.

The pseudo code algorithm for DLMM method is shown in table 1. This process outlines an energy-efficient routing protocol for wireless sensor networks, aiming to minimize energy consumption using the DLMM algorithm. The inputs include the network topology, sensor node positions, sink node position, initial energy levels, and communication range. The protocol begins with an initialization phase, where all sensor nodes are assigned unique IDs, initialized with their energy levels and positions, and exchange HELLO messages to establish neighbour lists. Next, in the mobile sink path selection phase, each node calculates its distance to the sink and selects a neighbour with the shortest distance as its initial relay node, updating its routing table accordingly. Routing optimization follows, where the DLMM algorithm is used to refine routing paths, adjust transmission power, and schedule transmissions for minimal energy consumption. Data transmission is then carried out, with nodes sending data to their selected relay nodes, which forward it toward the sink node. Periodically, nodes re-evaluate their routes based on factors like remaining energy, hop count, and link quality, ensuring the routing table is updated to maintain efficiency. The protocol also updates energy levels of transmitting and receiving nodes to account for power consumption.

The network is continuously monitored, and when energy levels drop below a threshold, the DLMM energy-saving mechanism is triggered. The process terminates based on predefined criteria, such as a maximum simulation time, a specific number of data transmissions, or a significant drop in overall network energy. This approach dynamically optimizes routing and conserves energy to extend the network's lifespan.

Table 1 Pseudo Code

Input:
- *Network Topology (graph representation)*
- *Sensor Node Positions*
- *Sink Node Position*
- *Initial Energy Levels of Nodes*
- *Communication Range*

Output:
- *Minimum Energy Consumption*

Step 1: Initialization
- *Initialize all sensor nodes with unique IDs.*
- *Initialize all sensor nodes with initial energy levels.*
- *Initialize all sensor nodes with their current positions.*
- *Initialize Sink Node with its position.*

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- Create an empty routing table for each node.
- Each node broadcasts a HELLO message to its neighbors within communication range.
- Each node receives HELLO messages from neighbors and updates its neighbor list.

Step 2: Mobile Sink Path Selection

- Each node calculates its distance to the Sink Node.
- Each node selects the neighbor with the shortest distance to the Sink Node as the initial relay node.
- Each node updates its routing table with the selected relay node.

Step 3: Routing Optimization

- Implement the DLMM algorithm to:
  - Optimize the routing paths.
  - Adjust transmission powers.
  - Schedule data transmissions to minimize energy consumption.

Step 4: Data Transmission

- Each sensor node transmits data to its selected relay node.
- Relay nodes forward data towards the Sink Node based on their routing tables.

Step 5: CH Selection

- Periodically (e.g., every 'T' time units):
  - Each node re-evaluates its route based on:
    - Remaining energy levels of its neighbors.
    - Hop count to the Sink Node.
    - Link quality (e.g., signal strength).
  - If a better route (e.g., with lower energy consumption or fewer hops) is found:
    - Update the routing table accordingly.

Step 6: Energy Consumption Update

- Update the energy level of each transmitting and receiving node based on transmission and reception power consumption models.

Step 7: Data Transmission and Monitoring

- Continue data transmission using the optimized routes and parameters.
- Check the energy levels of all nodes.
- If a node's energy level falls below a threshold, trigger DLMM energy-saving mechanism.

Step 8: Termination

- The algorithm can terminate based on predefined criteria, such as:
  - A maximum simulation time.
  - A certain number of data transmissions.
  - A significant drop in the overall network energy.

➢ *Implementation Steps*

- Create folder named leach and pegasis inside ns-all-in-one folder.
- Include appropriate files like: leach.h, leach.cc, leach_logs.cc, leach_packet.h, leach_rqueue.cc, leach_rqueue.h, leach_stable.cc and leach_rtable.h for LEACH protocol and pegasis.h, pegasis.cc, pegasis _logs.cc, pegasis _packet.h, pegasis _rqueue.cc, pegasis_rqueue.h, pegasis _stable.cc and pegasis _rtable.h for PEGASIS Search Optimization protocol.
- Inside ns-2.35 folder, does necessary and required changes in common, queue, tcl-lib, trace folders and modify packet.h, priqueue.cc, ns-agent.tcl, ns-mobilenode.tcl, ns-packet.tcl, ns-lib.tcl, cmu-trace.h, cmu-trace.cc, makefile and makefile.in files.
- In terminal, re-configure the NS-2 using commands like: make, make clean and sudo make install.
- Implement DLMM method in top of PEGASIS and LEACH protocols and integrate it using above steps.
- Then again re-configure NS-2.
- To run the TCL file use command like: ns filename.tcl

The table 2 outlines the simulation environment setup for evaluating the performance of various routing protocols in a wireless sensor network. The network uses a wireless medium for communication with a two-way ground propagation model. The physical layer serves as the network interface type, and the MAC protocol employed is Mac 802.11. A Drop Tail priority queue is used as the interface queue type, while the link layer is modelled using the LL protocol. An omnidirectional antenna is utilized for communication. The simulation includes varying numbers of mobile nodes (20, 40, 60, 80, and 100) and compares the performance of routing protocols DLMM, LEACH, TEEN, and PEGASIS. Each node starts with an initial energy of 10 joules. The simulation uses UDP as the transmission protocol and CBR (Constant Bit Rate) as the application protocol. The simulation is run until a predefined end time of 1000 seconds to analyse network performance under these configurations.

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Table 2 Simulation Environment Setup

Channel type	**Wireless medium**
radio-propagation model	Two-way Ground model
network interface type	Physical layer
MAC type	Mac 802.11
interface queue type	Queue/DropTail/PriQueue
link layer type	LL
antenna model	Antenna/OmniAntenna
number of mobile nodes	20,40,60,80 and 100
routing protocol methods	DLMM, LEACH, TEEN, PEGASIS
Initial Energy of Nodes	10 joules
Transmission and Application Protocols	UDP and CBR
time of simulation end	1000 seconds

IV. RESULTS AND DISCUSSION

The experimental results show a significant improvement in performance metrics when the proposed DLMM method is compared to existing methods: LEACH, TEEN and PEGASIS. These results are evaluated using metrics like Energy Consumption, Network Lifetime, PDR, Residual Energy, Average Delay, and Throughput over a network of 100 nodes.

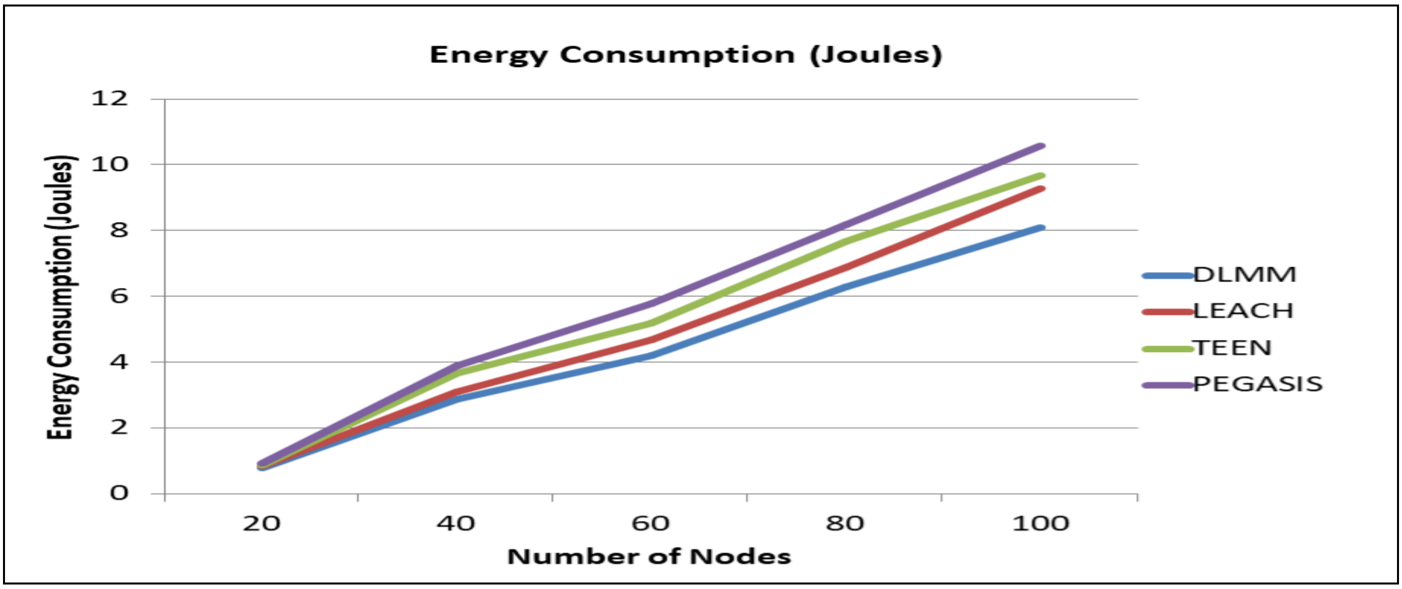

Fig 2 Energy Consumption

The figure 2 represents the energy consumption of Wireless Sensor Network (WSN) nodes for various protocols—DLMM, LEACH, TEEN, and PEGASIS—measured at different node counts (20, 40, 60, 80, and 100). These protocols have been simulated using Network Simulator 2 (NS2) to study their energy efficiency. For all protocols, energy consumption increases as the number of nodes in the network increases. This is expected as more nodes consume more energy for data communication, processing, and transmission. DLMM consistently consumes the least energy among all protocols, indicating it is the most energy-efficient. PEGASIS consumes the highest energy in all cases, suggesting it is less energy-efficient compared to others in this experiment. LEACH and TEEN fall in between, with TEEN consuming slightly more energy than LEACH as the number of nodes increases. At 20 nodes, energy consumption is minimal across all protocols, but the order remains consistent: DLMM < LEACH < TEEN < PEGASIS. At 100 nodes, energy consumption shows a substantial increase for all protocols. PEGASIS reaches 10.6, while DLMM remains at 8.1, indicating a clear efficiency gap. DLMM is the most energy-efficient protocol, likely due to optimized data aggregation, reduced transmission costs, or better clustering techniques. PEGASIS is the least efficient, possibly because of longer communication chains or higher overhead in the protocol's operation. These results are critical for selecting protocols in energy-constrained WSN applications, where minimizing energy consumption is essential to prolong network lifetime.

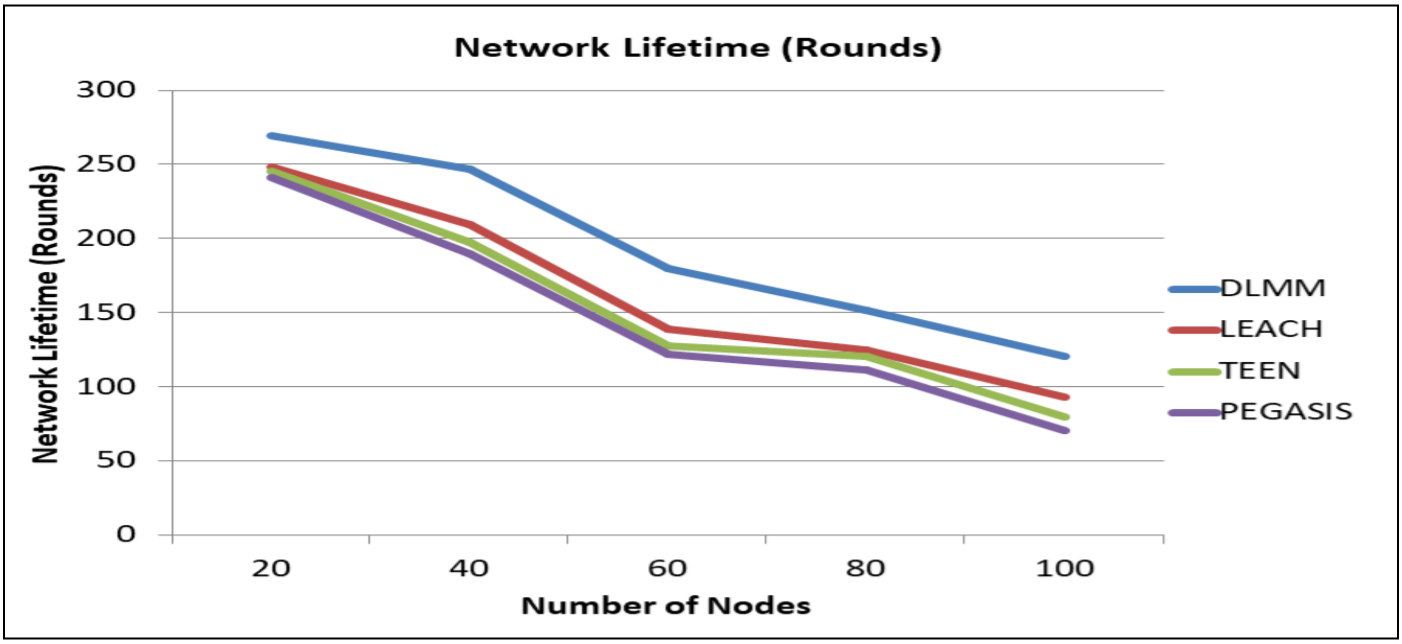

Fig 3 Network Lifetime

The figure 3 represents the network lifetime (measured in rounds) of Wireless Sensor Network (WSN) nodes for four protocols—DLMM, LEACH, TEEN, and PEGASIS—evaluated at different node counts (20, 40, 60, 80, and 100). This data is derived from simulations conducted using Network Simulator 2 (NS2). Across all protocols, the network lifetime decreases as the number of nodes increases. This is expected as larger networks consume more energy, leading to faster node depletion. DLMM exhibits the longest network lifetime for all scenarios, indicating its superior energy efficiency and effective resource management. PEGASIS consistently shows the shortest network lifetime, reflecting higher energy consumption and less efficiency in preserving network longevity. LEACH and TEEN show moderate performance, with LEACH generally outlasting TEEN. At 20 nodes, the network lifetime for DLMM is 270 rounds, while PEGASIS reaches only 242 rounds, showcasing a notable performance gap. At 100 nodes, the network lifetime reduces significantly, with DLMM achieving 121 rounds and PEGASIS dropping to just 71 rounds. The performance gap between DLMM and PEGASIS widens as the network size increases, highlighting DLMM's scalability and adaptability to larger networks. DLMM is the best protocol in terms of prolonging network lifetime, likely due to efficient energy utilization and lower communication overhead. PEGASIS, despite being a chain-based protocol, struggles with energy distribution and scalability, leading to the shortest network lifetime. LEACH and TEEN perform moderately, with LEACH showing better results than TEEN in most cases.

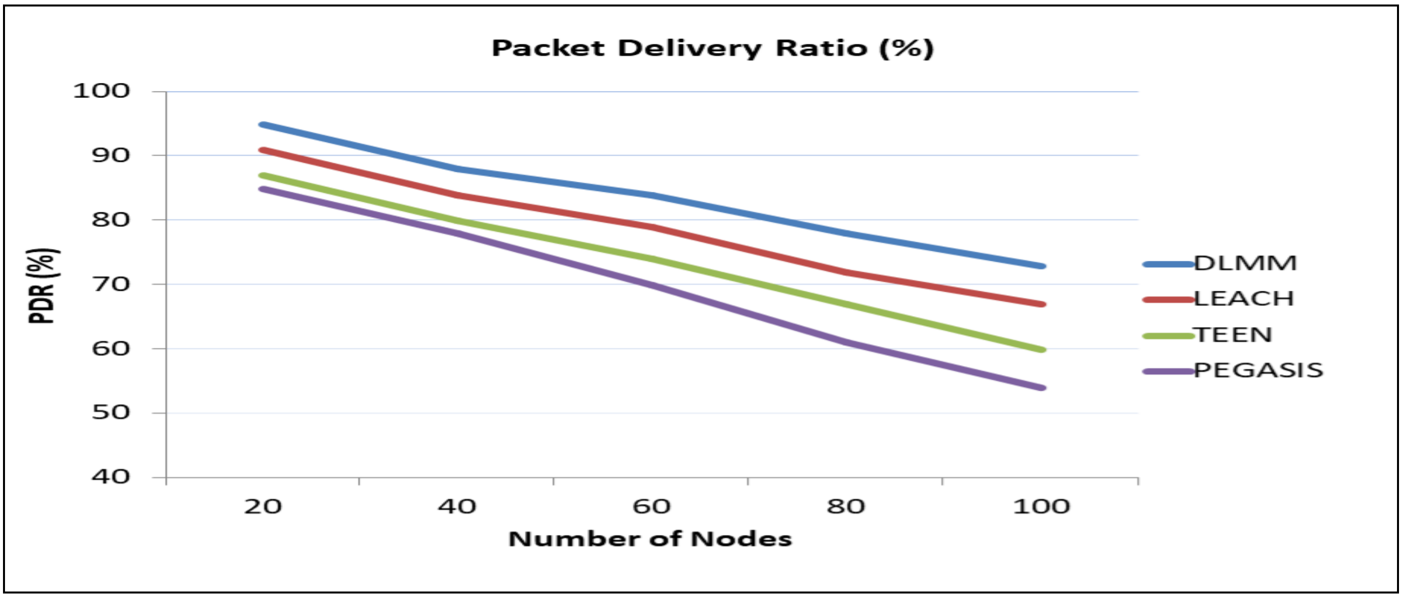

Fig 4 Packet Delivery Ratio

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The figure 4 presents the Packet Delivery Ratio (PDR) (measured in percentage) of Wireless Sensor Network (WSN) nodes for four protocols—DLMM, LEACH, TEEN, and PEGASIS—simulated for varying node counts (20, 40, 60, 80, and 100). This simulation was performed using Network Simulator 2 (NS2). For all protocols, the Packet Delivery Ratio decreases as the number of nodes increases. This reduction is likely due to higher congestion, increased packet collisions, and greater energy depletion in larger networks. DLMM consistently achieves the highest PDR across all node counts, indicating its reliability and efficiency in data transmission. PEGASIS shows the lowest PDR in all scenarios, suggesting it struggles with reliable packet delivery as the network scales. LEACH and TEEN perform moderately, with LEACH generally outperforming TEEN. At 20 nodes, PDR is highest for all protocols, with DLMM achieving 95%, while PEGASIS records the lowest at 85%. At 100 nodes, the performance gap widens significantly. DLMM maintains a PDR of 73%, while PEGASIS drops to just 54%, highlighting its inefficiency in larger networks. The PDR for DLMM consistently exceeds PEGASIS by a significant margin (e.g., 19% at 100 nodes), demonstrating DLMM's superior scalability and robustness in maintaining packet delivery. DLMM is the most reliable protocol, maintaining the highest PDR across all network sizes due to its efficient routing and robust handling of network congestion. PEGASIS struggles with reliable packet delivery, especially as the network size increases, likely due to its chain-based routing leading to increased delays and packet drops. LEACH and TEEN perform moderately, with LEACH showing better results, likely due to its clustering strategy reducing packet loss.

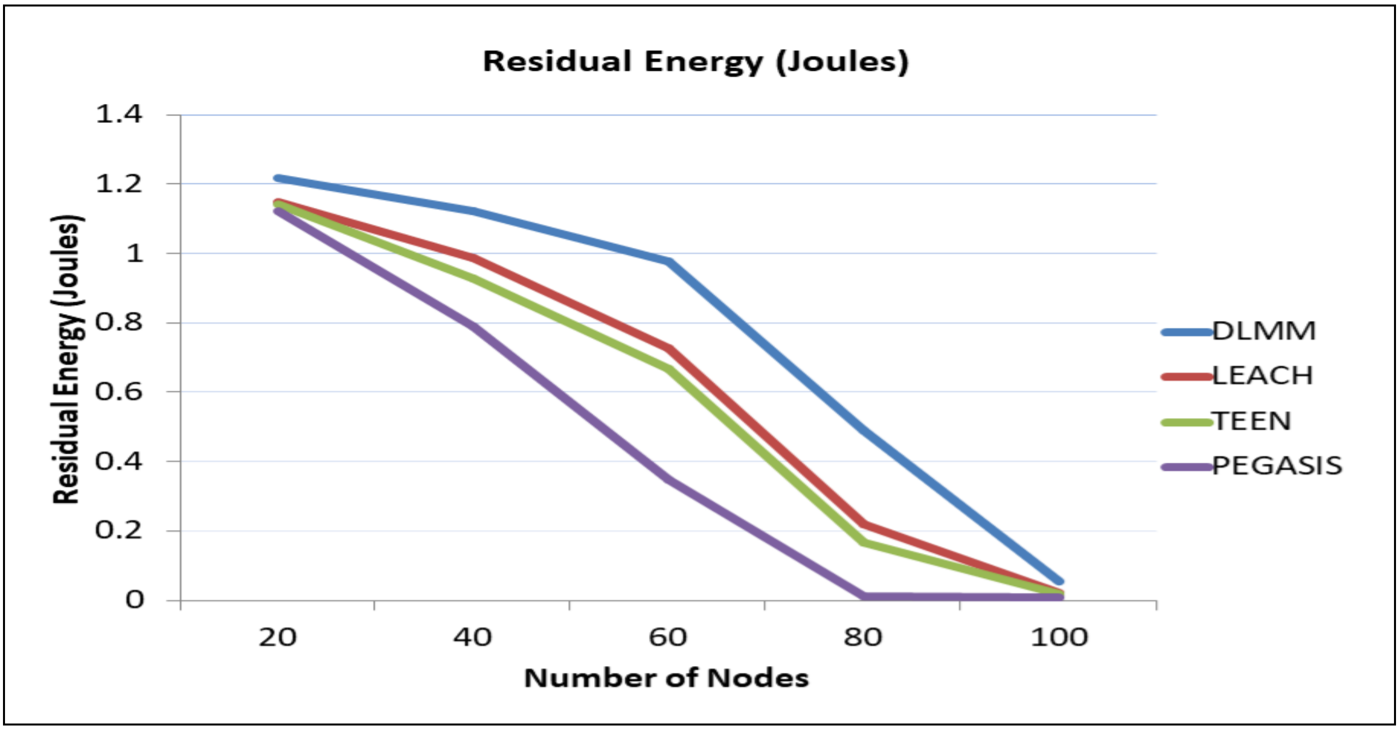

Fig 5 Residual Energy

The figure 5 represents the residual energy (measured in joules) of Wireless Sensor Network (WSN) nodes after operations for various protocols—DLMM, LEACH, TEEN, and PEGASIS—evaluated at increasing node counts (20, 40, 60, 80, and 100). This data is derived from simulations conducted using Network Simulator 2 (NS2). Residual energy decreases as the number of nodes increases across all protocols. This is expected because larger networks typically require more energy for communication, data processing, and routing. DLMM consistently retains the highest residual energy, indicating its energy-efficient operations. PEGASIS shows the lowest residual energy, reflecting its high energy consumption and inefficient energy utilization. LEACH and TEEN have moderate performance, with LEACH slightly outperforming TEEN in most cases. At 20 nodes, the residual energy for DLMM is 1.22 J, while PEGASIS has only 1.124 J, showcasing a small difference in efficiency. As the network grows to 100 nodes, the gap widens significantly: DLMM retains 0.055 J, while PEGASIS has only 0.009 J, indicating substantial energy savings with DLMM. LEACH and TEEN also deplete their energy quickly as the node count increases, with LEACH retaining 0.025 J and TEEN retaining 0.021 J at 100 nodes. The gap between DLMM and the other protocols widens as the network scales, showcasing DLMM's efficiency in preserving energy over extended operations. DLMM is the most energy-efficient protocol, retaining the highest residual energy across all network sizes. This efficiency can be attributed to optimized communication, clustering, and routing techniques. PEGASIS consumes the most energy, leaving minimal residual energy, which could result in quicker network depletion and reduced lifespan. LEACH and TEEN perform moderately, but their energy efficiency is significantly lower than DLMM, particularly in larger networks. Residual energy is a critical metric for evaluating the longevity and sustainability of WSN protocols. Higher residual energy, as demonstrated by DLMM, ensures prolonged network functionality, making it suitable for energy-constrained applications.

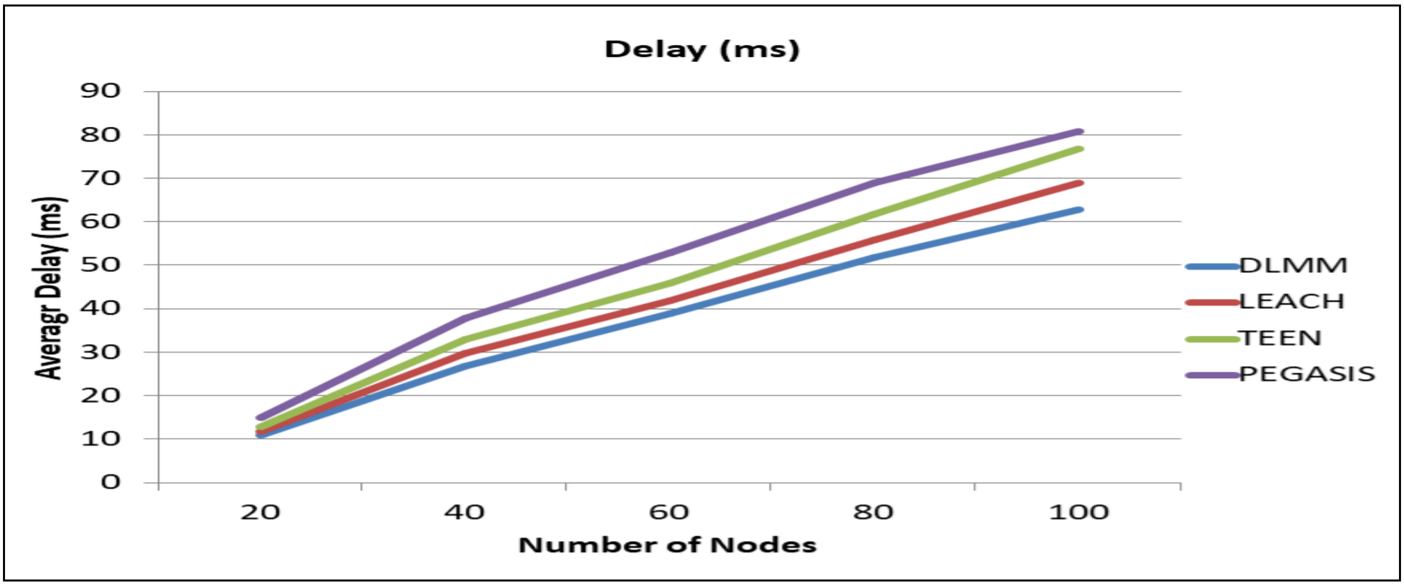

Fig 6 Delay

The figure 6 represents the average delay (measured in milliseconds) of Wireless Sensor Network (WSN) nodes for different protocols—DLMM, LEACH, TEEN, and PEGASIS—evaluated at varying node counts (20, 40, 60, 80, and 100). This data is derived from simulations conducted using Network Simulator 2 (NS2). Average delay increases as the number of nodes in the network increases across all protocols. This is expected as larger networks experience higher congestion, longer transmission paths, and more resource contention. DLMM consistently achieves the lowest average delay, indicating its efficiency in managing network traffic and reducing latency. PEGASIS experiences the highest delay in all scenarios, likely due to its chain-based routing strategy, which introduces additional latency for multi-hop communication. LEACH and TEEN show moderate performance, with LEACH having slightly lower delays than TEEN. At 20 nodes, average delay is minimal for all protocols, with DLMM having 11 ms, while PEGASIS records 15 ms. At 100 nodes, delays increase significantly across all protocols. DLMM achieves 63 ms, while PEGASIS reaches 81 ms, showcasing the challenges of maintaining low latency in larger networks. The delay difference between DLMM and PEGASIS widens as the network size increases, reflecting DLMM's superior handling of network scalability and traffic congestion. DLMM demonstrates the lowest average delay, making it the most suitable protocol for applications requiring low-latency communication, such as real-time monitoring or time-sensitive data transmission. PEGASIS incurs the highest delays due to its sequential communication model, which increases latency with the addition of more nodes. LEACH and TEEN perform moderately, with LEACH slightly outperforming TEEN in minimizing delay.

V. CONCLUSION

This research paper introduces a Deep Learning-Based Memory Model (DLMM) to improve energy efficiency in Wireless Sensor Networks (WSNs). The core innovation lies in using DLMM for optimized cluster head selection and routing, incorporating a mobile sink moving linearly to minimize multi-hop transmissions. This approach strategically selects cluster heads based on remaining node energy and prioritizes single-hop communications, significantly reducing energy consumption and extending network lifespan compared to conventional methods like LEACH, TEEN, and PEGASIS. Extensive simulations demonstrate substantial improvements in energy efficiency, network lifetime, packet delivery ratio, and latency. The DLMM method uses a mobile sink that moves along a linear path, which facilitates direct communication and reduces energy consumption by minimizing multi-hop transmissions. The method also selects CHs based on the nodes' residual energy levels, which further extends network lifespan. Simulation results show that DLMM achieves lower energy consumption, longer network lifetimes, and higher packet delivery ratios (PDR). The paper concludes that the proposed DLMM method is more effective in enhancing the performance of WSNs, particularly in energy-constrained applications.

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