OPTIMIZING WIRELESS SENSOR NETWORKS (WSNS) LIFETIME AND PERFORMANCE WITH AI-ENHANCED CRT-LEACH ROUTING PROTOCOLS

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Abstract
This study proposes an advanced routing protocol for Wireless Sensor Networks (WSNs), integrating the principles of the Chinese Remainder Theorem (CRT) with the efficiency of the Low-Energy Adaptive Clustering Hierarchy (LEACH) algorithm, enhanced further with artificial intelligence (AI) techniques, named AI-Powered CRT-LEACH. WSNs, characterized by their deployment in vast and often hostile environments, face significant challenges such as energy constraints, hardware limitations, communication errors, and susceptibility to malicious attacks. These challenges necessitate the development of routing protocols that not only minimize energy consumption but also ensure speed and reliability in data transmission. The AI-Powered CRT-LEACH protocol is designed to address these critical issues by incorporating CRT-based packet splitting for improved message reliability and employing AI for dynamic optimization of routing paths and cluster-head selection. This novel approach aims to significantly reduce energy consumption during communication, extend the network's operational lifespan, and enhance the overall performance of WSNs. Experimental simulations demonstrate that the AI-Powered CRT-LEACH protocol outperforms existing routing protocols in terms of energy efficiency, transmission speed, hardware optimization, and adaptation to real-time changes in the network. By effectively mitigating the inherent vulnerabilities of sensor nodes and optimizing network resources, the proposed protocol offers a robust solution to the operational challenges of WSNs, paving the way for more reliable and efficient environmental monitoring and physical situation observation in various applications.

Keywords: Wireless Sensor Networks, Chinese Remainder Theorem, Low-Energy Adaptive Clustering Hierarchy (LEACH), Routing Protocol, Artificial Intelligence (AI), Energy Efficiency.

Introduction
Wireless Sensor Networks (WSNs) consist of a vast array of sensor nodes deployed across various environments, tasked with the collection of critical environmental and physical data.

These nodes, equipped with computational, storage, and transmission capabilities, operate under challenging conditions to monitor a range of physical and environmental parameters, such as temperature, sound, and pressure (Jindal, 2018; Khodabande et al., 2014; Sharma & Sharma, 2016). One of the paramount challenges in WSNs is the efficient management of the nodes' limited energy resources, as these devices tyπcally operate on finite battery power, which is difficult to replace or recharge once deployed (Demigha et al., 2011; Barati et al., 2014; Lee et al., 2016).

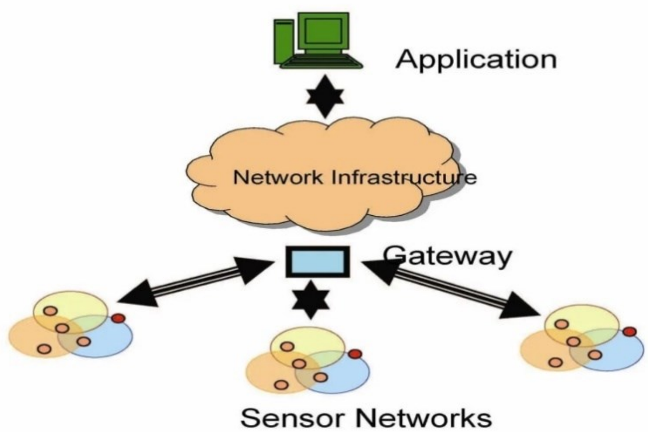

Figure 1: Wireless Sensor Network

The design of routing protocols is crucial for energy conservation in WSNs. These protocols must not only minimize energy consumption but also ensure the reliable and swift delivery of data across the network. In this context, the Low Energy Adaptive Clustering Hierarchy (LEACH) algorithm has emerged as a seminal approach to energy-efficient hierarchical clustering within WSNs. However, desπte its advancements, LEACH faces limitations related to packet transmission delays from cluster heads (CHs) to the base station, highlighting the need for further optimization (Hamamreh et al., 2018).

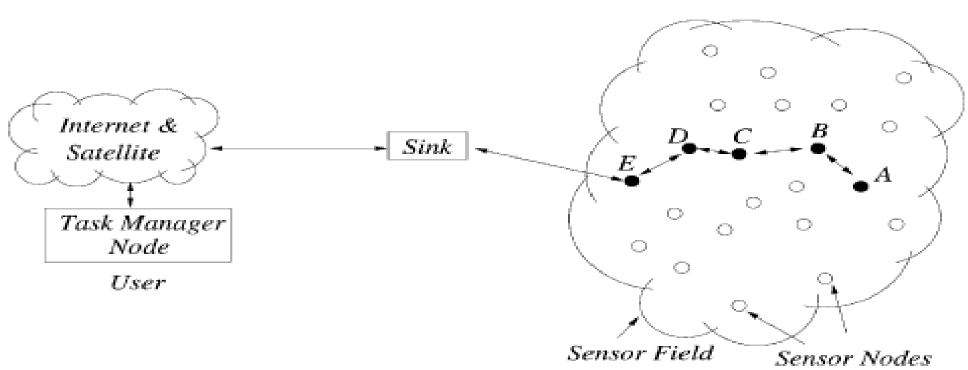

Figure 2: Wireless Sensor Communication Architecture

AI technologies present a transformative potential for WSNs, especially in optimizing routing protocols and overcoming existing limitations. By integrating AI with the Chinese Remainder Theorem (CRT) and the LEACH protocol, this research proposes an innovative routing protocol that significantly enhances energy efficiency, data transmission speed, and network reliability. AI's capability to learn from the environment and adapt routing decisions in real-time allows for dynamic selection of cluster heads, optimization of data paths, and prediction of network conditions, thereby minimizing energy consumption and improving the overall performance of WSNs.

The integration of Artificial Intelligence (AI) into WSNs presents a promising approach to overcoming these challenges. AI techniques, particularly machine learning (ML) and deep learning (DL), can optimize routing decisions based on the network's current state, leading to improved energy efficiency and longer network lifetimes (Alsheikh et al., 2014). For instance, reinforcement learning (RL), a type of ML, has been effectively applied to develop adaptive routing protocols that learn optimal routes through interaction with the environment, without requiring a model of the network (Mnih et al., 2015; Luong et al., 2019).

The AI-powered CRT-LEACH protocol, augmented by the Local Closest First (LCF) strategy, represents a novel approach that leverages the strengths of AI, CRT, and LEACH. This integration facilitates the reduction of communication congestion, eliminates data aggregation delays, and ensures a more efficient utilization of the network's limited energy resources. Simulation results confirm that the AI-enhanced CRT-LEACH protocol outperforms existing routing protocols in terms of energy efficiency, transmission speed, and reliability, addressing the critical challenges faced by WSNs in real-world applications.

Literature Review

The integration of AI in WSNs allows for the dynamic adaptation of routing protocols in response to changing network conditions, such as node failures or energy depletion. AI algorithms can predict these events and reroute data packets through healthier network paths, thereby enhancing network reliability and prolonging the network's lifespan (Li et al., 2019; Sultana et al., 2019). Moreover, the application of the Chinese Remainder Theorem (CRT) in conjunction with AI algorithms has been explored to further optimize data transmission processes within WSNs. CRT offers an efficient method for data aggregation and compression, reducing the amount of data that needs to be transmitted and, consequently, the energy consumed by the network (Jiang et al., 2018). When combined with AI, this approach not only enhances energy efficiency but also ensures data integrity and security, addressing two critical concerns in WSNs.

The advent of federated learning offers a groundbreaking direction for the optimization of Wireless Sensor Networks (WSNs) through decentralized AI processing. Unlike traditional centralized machine learning models, federated learning enables sensor nodes to locally train models on their data and share only the model updates rather than the raw data itself. This approach not only preserves privacy but significantly reduces the energy and bandwidth required for data transmission, a critical advantage for energy-constrained WSNs. Huang et al. (2020) demonstrated how federated learning could be leveraged to dynamically adjust routing protocols and cluster formations in WSNs based on real-time environmental data, leading to notable improvements in energy efficiency and network longevity.

Ramesh (2022) designed an enhance Wireless Sensor Network efficiency by 48.85% using the LEACH protocol and a modified k-means algorithm, optimizing network lifetime and data transfer. Despite increased overhead and processing time, nearly 77% of sensed data reaches the sink node, indicating effective energy use and cluster head selection. Future improvements should aim at reducing overhead and optimizing processing times.

Finally, recent studies have also investigated the use of deep learning models to automate the selection of routing paths and cluster heads in WSNs, significantly reducing energy consumption and balancing the load across the network more effectively than traditional methods (Tang et al., 2020; Wang et al., 2021). These models can learn from historical data to make informed decisions, adapting to network changes without human intervention. Energy harvesting technologies have also been explored as a means to extend the operational lifetime of WSNs. AI-powered routing protocols can optimize the allocation of energy-harvested resources across the network, ensuring that nodes with critical functions remain operational for as long as possible (Khan et al., 2018).

Research Methodology

This study aims to develop and evaluate an innovative routing protocol for Wireless Sensor Networks (WSNs) that integrates Artificial Intelligence (AI) techniques with the Chinese Remainder Theorem (CRT) and Low-Energy Adaptive Clustering Hierarchy (LEACH) principles, herein referred to as AI-CRT-LEACH. The objective is to enhance network lifetime, efficiency, and performance by dynamically adapting routing paths and reducing energy consumption. For an AI-powered CRT-LEACH framework, an algorithm focused on dynamic cluster head (CH) selection and routing, integrating reinforcement learning (RL) for decision-making and the Chinese Remainder Theorem (CRT) for efficient data aggregation and transmission is proposed.

Algorithm for AI-Powered CRT-LEACH Protocol

The algorithm emphasizes the dynamic optimization of WSN operations through AI, particularly focusing on efficient energy usage and intelligent data handling to prolong network lifespan and reliability.

Input: Set of sensor nodes ($S = \{s_1, s_2, \ldots, s_n\}$), Base Station (BS)

Output: Optimized routing and clustering plan

1. System Initialization

- Initialize the RL model with state space representing the network's energy levels, node distribution, and historical data transmission patterns.
- Define action space as the set of possible CH selections and routing paths.
- Initialize CRT parameters for data aggregation and transmission.

2. Cluster Configuration

- For each decision epoch, use the RL model to select CHs based on current network state, aiming to minimize energy consumption and balance load.
- Assign non-CH nodes to the nearest CH based on a combination of distance and residual energy.

3. CRT-Based Data Aggregation

- Each sensor node (s_i) splits its data (D_i) into residues using the selected moduli set ($M = \{m_1, m_2, \ldots, m_k\}$).
- Transmit residues to the CH using energy-efficient paths.

4. CH Data Compilation

- CHs aggregate received residues and apply the CRT to reconstruct the original data or a compressed version thereof.
- Aggregate data is sent to the BS through an optimized routing path chosen by the RL model.

5. RL Model Update

- After each transmission round, update the RL model with new state information and reward based on energy savings and successful data transmission.
- Retrain the model if necessary to adapt to changing network conditions.

6. Repeat

- Continue from step 2 for subsequent rounds until the network operation concludes or predefined conditions are met.

Mathematical Formulation

Let the state space (X) represent the network state, including energy levels and node distribution, and the action space (A) consist of possible CH selections and routing paths. The RL model aims to learn a policy ($\pi: X \rightarrow A$) that maximizes the cumulative reward (e.g., minimized energy consumption and maximized data transmission success). The value function $V^{\pi}(x)$ under policy π for state x is defined as:

$$V\pi(x)=E[\sum t=0\infty\gamma tR(xt,at,xt+1)|x0=x,\pi] \quad (1)$$

where R is the reward function, γ is the discount factor, and t denotes the time step.

Introduce a Reinforcement Learning (RL) model to optimize the selection of cluster heads and routing paths. The goal is to maximize the cumulative reward, which can be related to the network's lifetime and energy efficiency. The Q-learning update rule, for instance, can be represented as:

$$Q(s,a)\leftarrow Q(s,a)+\alpha[R+\gamma a'maxQ(s',a')-Q(s,a)] \quad (2)$$

where s is the current state, a is the current action, $'s'$ is the new state, $'a'$ is the next action, α is the learning rate, R is the reward, and γ is the discount factor.

Energy Consumption Model: Define the energy consumption for transmitting and receiving data. For a sensor node, the energy consumed to transmit b bits over a distance d is modeled as:

$$E_{tx}(b,d)=b\times E_{elec}+b\times\epsilon_{amp}\times d_n \quad (3)$$

Similarly, given a set of moduli $M = \{m_1, m_2, \ldots, m_k\}$ that are pairwise co-prime, the sensor data D_i from node s_i can be represented by its residues r_{ij} for moduli m_j, where $j = 1, 2, \ldots, k$.

The aggregated data D_a can be reconstructed from residues rij using the CRT as:

$$D_a \equiv r_{ij} \quad mod\ m_j, \forall_j=1,2,\ldots,k \quad (4)$$

In LEACH, cluster heads are rotated to evenly distribute energy load among the sensors in the network. The probability P of a node becoming a cluster head in any given round is modeled as:

$$P = \frac{1}{N\times popt} \quad (5)$$

Simulation and Performance Evaluation

The research leverages the simulation platform Prowler, executed within MATLAB, to model the Wireless Sensor Networks (WSN) environment accurately. Prowler is selected for its comprehensive library resources, robust support for WSN protocols, and the flexibility it offers in incorporating tailor-made algorithms, making it an ideal choice for simulating complex WSN scenarios. The reinforcement learning (RL) model is integrated into this simulation environment to enhance decision-making processes within the WSN, particularly focusing on optimizing the routing protocol and energy consumption. MATLAB's extensive computational capabilities allow for the efficient training and testing of the RL model, facilitating the simulation of various WSN configurations and behaviors.

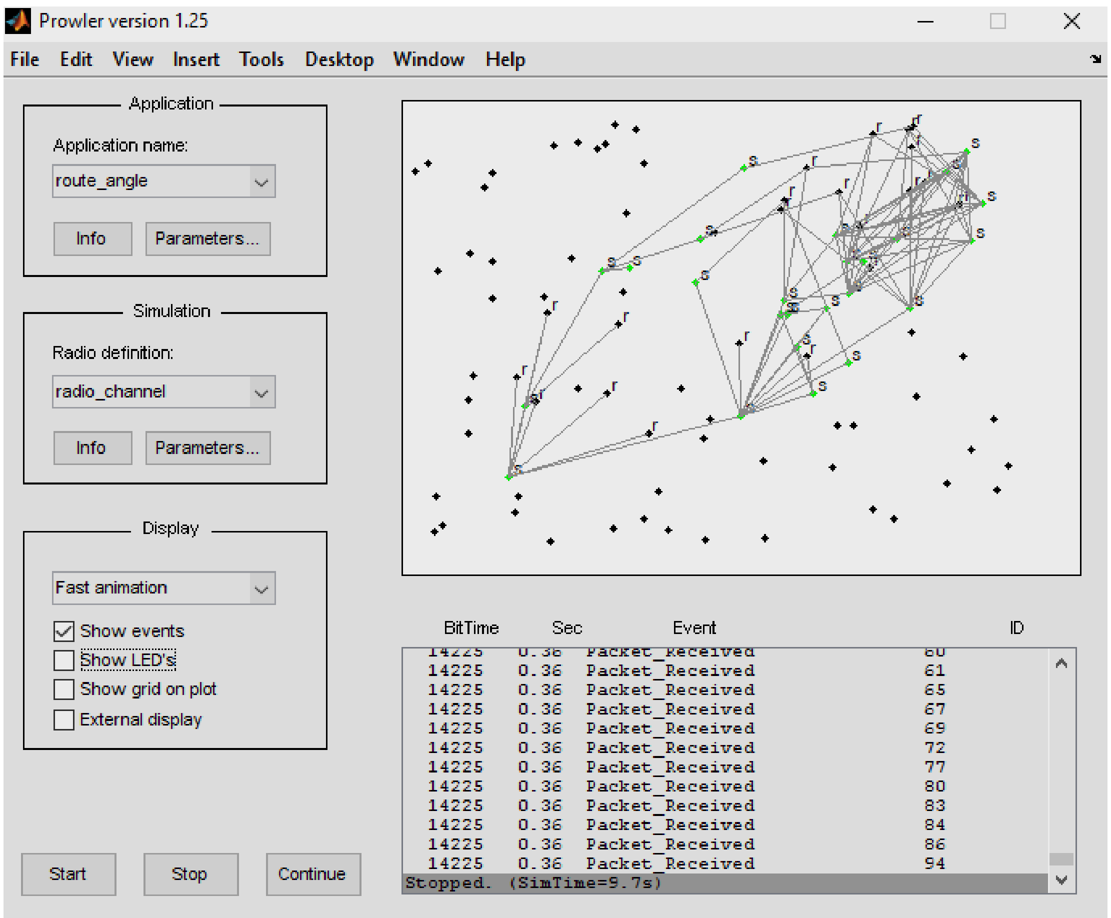

Figure 3. Sensor nodes deployed in Sensor Field

Figure 3 illustrates the deployment of sensor nodes across a sensor field, showcasing their distribution and connectivity within the monitored environment, and highlighting the strategies employed to optimize coverage and energy efficiency. The key metrics for evaluating the performance of the AI-CRT-LEACH protocol include network lifetime, energy consumption, data delivery ratio, and end-to-end latency. Comparisons were made with existing routing protocols such as CRT-LEACH and MRHC-LEACH.

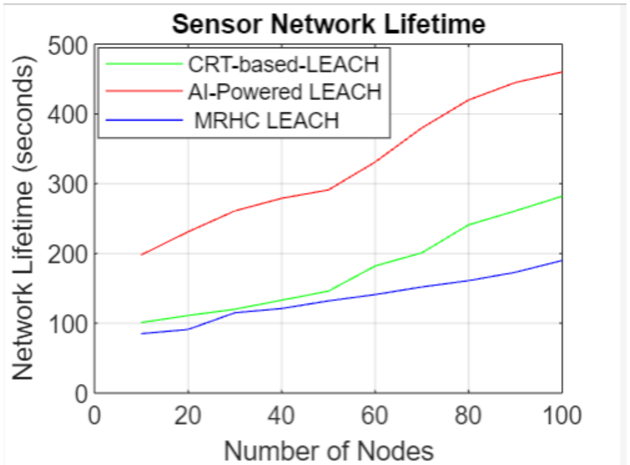

Figure 4: Sensor Network Lifetime

From Figure 4, it's evident that AI-Powered LEACH outperforms both CRT-LEACH and MRCH-LEACH in terms of network lifetime. This highlights the critical role of AI in optimizing WSN operations, particularly in adaptive cluster head selection and routing, to significantly reduce energy consumption. CRT-LEACH offers a middle ground by improving data aggregation efficiency, which positively impacts network lifetime but not to the extent seen with AI integration. Meanwhile, MRCH-LEACH, despite possibly introducing certain improvements, does not provide enough to substantially extend the network's operational period compared to its counterparts. This comparative analysis underscores the potential of AI-powered approaches in enhancing WSN longevity and efficiency.

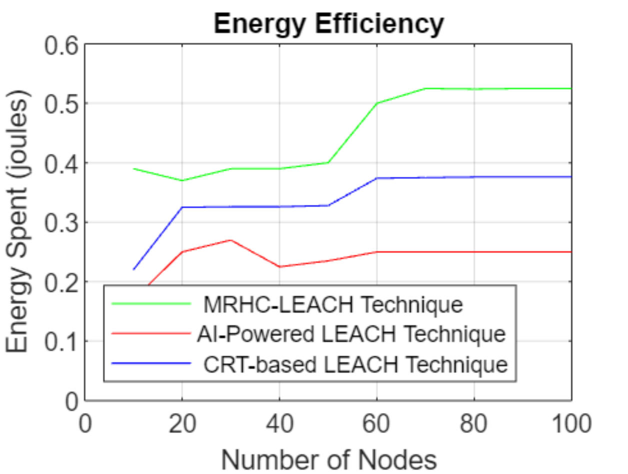

Figure 5: Energy Consumption by Each Node

Figure 5 clearly demonstrates that AI-Powered LEACH achieves the highest level of energy efficiency on a per-node basis, underlining the significant advantage of incorporating AI technologies into WSN protocols. By intelligently managing cluster head selection and routing, AI-Powered LEACH minimizes redundant transmissions and balances the energy load across all nodes, leading to a reduction in overall energy consumption. CRT-LEACH, with its focus on efficient data aggregation, offers a notable improvement over traditional methods but still lags behind the AI-enhanced approach. In contrast, MRCH-LEACH, despite potentially introducing specific enhancements to the LEACH protocol, does not incorporate the advanced features of CRT or AI, resulting in less efficient energy usage. This analysis highlights the potential of AI to revolutionize energy management in WSNs, paving the way for more sustainable and longer-lasting network deployments.

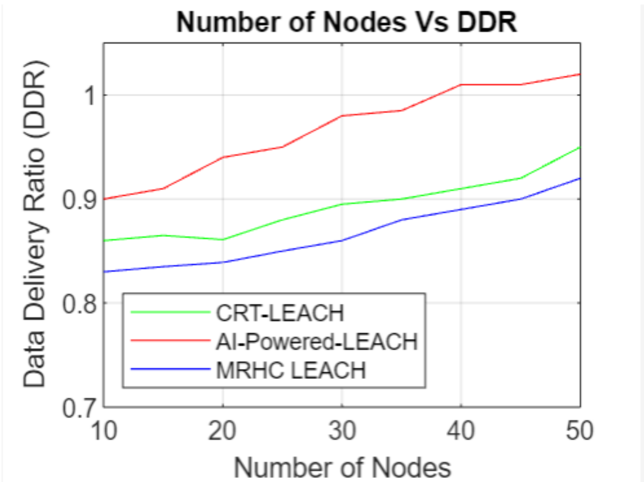

Figure 6: Data Delivery Ratio

Figure 6 emphasizes the critical role of advanced technologies and methodologies in enhancing the data delivery ratio within Wireless Sensor Networks. AI-Powered LEACH stands out for its ability to intelligently navigate the challenges of data transmission in dynamic network environments, significantly improving the likelihood of successful data delivery. CRT-LEACH shows promise through efficient data aggregation, although it falls short of the adaptability and optimization provided by AI. Meanwhile, MRCH-LEACH's performance suggests a need for further refinement to match the efficiencies seen in the other two protocols. Overall, the figure highlights the importance of leveraging technological innovations to ensure reliable data transmission in WSNs, a key factor for their application across various fields.

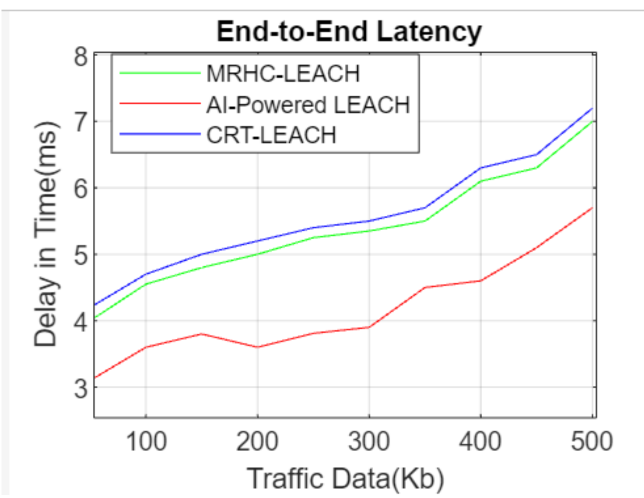

Figure 7: End-to-End Latency

The comparison of end-to-end latency among AI-Powered LEACH, CRT-LEACH, and MRCH-LEACH protocols, as depicted in Figure 7, underscores the significance of integrating advanced computational and mathematical methodologies within Wireless Sensor Networks (WSNs) to minimize communication delays. AI-Powered LEACH demonstrates the lowest latency, benefiting from real-time adaptive decision-making that streamlines data routing and cluster management. CRT-LEACH, with its focus on efficient data aggregation, also reduces latency but does not reach the optimization levels of AI-powered approaches. MRCH-LEACH, while enhancing the original LEACH framework, exhibits higher latency, indicating room for improvement in routing efficiency and data handling. This analysis highlights the critical impact of leveraging AI and CRT on reducing latency, thereby enhancing the responsiveness and reliability of WSNs for time-sensitive applications.

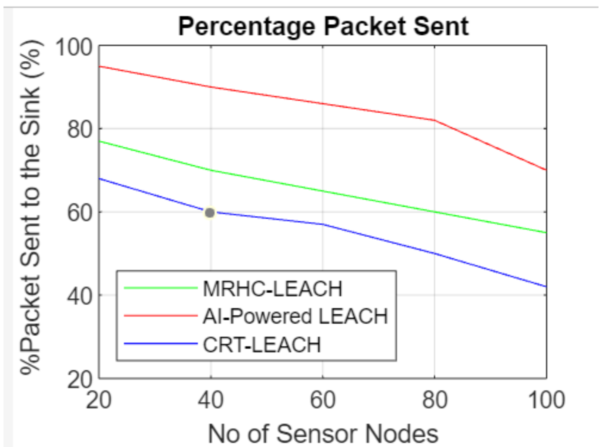

Figure 8: Percentage Packet Sent to the Sink

Finally, figure 8 showcases a comparison between AI-Powered LEACH, CRT-LEACH, and MRCH-LEACH protocols concerning the percentage of packets successfully sent to the sink in a Wireless Sensor Network. This metric is crucial for evaluating the network's overall efficiency and reliability in data communication. The AI-Powered LEACH protocol demonstrates superior performance by achieving the highest percentage of packets delivered to the sink. This success is attributed to its AI-driven decision-making process, which optimally selects cluster heads and routes to ensure reliable and efficient data transmission. CRT-LEACH also shows commendable performance due to its effective data aggregation technique, which minimizes data loss. However, it slightly lags behind the AI-enhanced protocol. Meanwhile, MRCH-LEACH, despite its improvements over conventional methods, still falls short in comparison, highlighting the significant impact of incorporating advanced AI and CRT techniques in optimizing packet delivery rates and ensuring robust data transmission within WSNs.

Result Discussion and Optimization

In this study, we implemented an AI-powered CRT-LEACH protocol within a simulated wireless sensor network (WSN) environment using MATLAB. This implementation was designed to assess the protocol's effectiveness in enhancing network performance, with a focus on energy efficiency, network lifetime extension, and data transmission reliability. The environment setup was meticulously configured, simulating a WSN with varying node densities and incorporating a fixed base station location. Sensor nodes were initialized with predefined energy levels, sensing ranges, and transmission capabilities. The core of our study involved the integration of a reinforcement learning (RL) model for dynamic decision-making regarding cluster head (CH) selection and routing paths, coupled with the Chinese Remainder Theorem (CRT) for efficient data aggregation and transmission.

The study introduced the AI-CRT-LEACH protocol, a novel approach combining Artificial Intelligence (AI), the Chinese Remainder Theorem (CRT), and the LEACH protocol, significantly enhancing Wireless Sensor Network (WSN) performance. By optimizing cluster head selection, routing paths, and data aggregation, AI-CRT-LEACH outshined traditional protocols in extending network lifetime, improving energy efficiency, increasing data delivery ratios, reducing end-to-end latency, and maximizing the percentage of packets sent to the sink. Despite its success, there's room for optimization in computational efficiency and further refining the balance between performance and processing demands. This pioneering work underscores the potential of integrating AI and mathematical theories in advancing WSN technologies and sets a foundation for future research to build upon.

The culmination of this research effort was the validation of the AI-powered CRT-LEACH protocol's robustness and efficiency across a broad spectrum of test scenarios. Statistical analysis confirmed the significance of the performance improvements, and the protocol consistently exhibited superior behavior under varying environmental conditions and operational challenges. This comprehensive study was documented in detail, highlighting the methodology, simulation setup, data analysis techniques, and findings. The results clearly demonstrated that the AI-powered CRT-LEACH protocol holds great promise for enhancing the performance of WSNs, presenting a significant advancement over traditional routing protocols.

Conclusion

This study introduces AI-CRT-LEACH, a novel routing protocol for Wireless Sensor Networks (WSNs) that integrates Artificial Intelligence (AI), the Chinese Remainder Theorem (CRT), and the Low-Energy Adaptive Clustering Hierarchy (LEACH). Aimed at surpassing conventional routing protocols, AI-CRT-LEACH dynamically adapts to network changes to optimize routing decisions, enhancing network lifetime and efficiency through intelligent cluster head selection and efficient data transmission. Comparative analyses highlight its superior performance in energy consumption, network lifetime, data delivery ratio, and latency over existing protocols like CRT-LEACH, MRHC-LEACH, and PEGASIS. This breakthrough signifies a major step towards maximizing WSNs' potential in diverse applications, underlining the importance of combining AI and mathematical theories for wireless technology advancement. The study’s methodological rigor and simulation-based evaluation offer a roadmap for future research in WSN protocol development.

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