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Artificial Intelligence Driven Power Optimization in IOT-Enabled Wireless Sensor Networks

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Abstract: - The widespread use of Wireless Sensor Networks (WSN) in Internet of Things (IoT) causes energy efficiency issues. This paper proposes an AI-based solution to this problem. The propose an AI-Driven Power Optimization framework for IoT-enabled WSN using Deep Q-Network (DQN) and Dynamic Voltage and Frequency Scaling (DVFS). These techniques can adapt to changing network conditions and reduce power consumption when used together. Sensor nodes provide environmental parameters, battery status, and network behavior data to the AI-driven framework DQN is implemented after data preprocessing to learn and make power management decisions using reinforcement learning. Neural network-driven agent operates in a state and action space. It optimizes energy use with rewards. Real-time hardware power adjustment is done using DVFS. DVFS precise control and AI-driven decision-making create a comprehensive power optimization strategy. AI adapts to new challenges and optimizes network lifespan by improving its power management policies. Experimental implementations of the proposed framework show significant energy savings, network lifespan extension, and QoS improvements. AI-Driven Power Optimization in IoT-enabled WSN is proven effective and flexible. This study shows the potential of AI, specifically DQN and DVFS, in IoT-enabled WSN. This AI-Driven Power Optimization framework addresses energy efficiency and improves IoT sensor networks. AI improves power optimization in IoT-enabled WSN making IoT deployments more sustainable and resilient.

General Terms: Artificial Intelligence, IOT, Wireless Sensor Networks

Keywords: Artificial Intelligence, IOT, Wireless Sensor Networks, Deep Q-Network, Power Optimization

I. INTRODUCTION

The widespread use of Wireless Sensor Networks (WSN) in Internet of Things (IoT) causes energy efficiency issues. This paper proposes an AI-based solution to this problem. We propose an AI-Driven Power Optimization framework for IoT-enabled WSN using DQN and Dynamic Voltage and Frequency Scaling. These techniques can adapt to changing network conditions and reduce power consumption when used together. Sensor nodes provide environmental parameters, battery status, and network behavior data to the AI-driven framework [1], [2].

A DQN is implemented after data preprocessing to learn and make power management decisions using reinforcement learning. Neural network-driven agent operates in a state and action space. It optimizes energy use with rewards. Real-time hardware power adjustment is done using Dynamic Voltage and Frequency Scaling (DVFS). DVFS precise control and AI-driven decision-making create a comprehensive power optimization strategy [3], [4]. AI adapts to new challenges and optimizes network lifespan by improving its power management policies.

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Experimental implementations of the proposed framework show significant energy savings, network lifespan extension, and QoS improvements. AI-Driven Power Optimization in IoT-enabled WSN is proven effective and flexible. This study shows the potential of AI, specifically DQN (Deep Q-Network) and DVFS (Dynamic Voltage and Frequency Scaling), in IoT-enabled WSN. This AI-Driven Power Optimization framework addresses energy efficiency and improves IoT sensor networks. AI improves power optimization in IoT-enabled Wireless Sensor Networks, making IoT deployments more sustainable and resilient [5], [6].

The emergence of the Internet of Things (IoT) has fundamentally transformed the manner in which we gather and employ data across a range of applications, including smart cities, industrial automation, and environmental monitoring. WSN are essential for the functioning of the Internet of Things (IoT). They act as the sensory organs of the digital world, collecting and transmitting important data from the physical world to the digital realm.

Energy efficiency is a crucial and complex challenge in this context. Internet of Things (IoT)-enabled WSN are composed of multiple sensor nodes that are deployed in various and often difficult environments, which are often remote or difficult to access. These nodes are frequently operated using batteries or energy-harvesting mechanisms, making energy conservation crucial for the long-term viability of the network. The continuous functioning of these nodes, which involves capturing and transmitting data without interruption, relies on effective power management strategies [7], [8].

The central focus of the research problem is to guarantee the durability, dependability, and effectiveness of IoT-enabled WSN while also tackling the energy limitations that are inherent to sensor nodes. Given the limited energy resources available to these nodes, the need for power optimization is clearly apparent. Efficient strategies for power optimization need to be developed in order to achieve a careful equilibrium between data accuracy, network durability, and energy usage.

Power optimization in WSN is a complex and multi-dimensional issue. The main objective is to increase the longevity of sensor nodes, ensuring their continuous operation for extended periods without the need for frequent battery replacements. Extending the lifespan of these nodes is not only feasible but also financially prudent and environmentally conscientious. It decreases the expenses associated with maintenance and reduces the negative impact on the environment caused by battery disposal.

Power optimization is crucial in guaranteeing that IoT applications dependent on WSNs provide a dependable and uniform quality of service (QoS). These features encompass the prompt delivery of data, fast communication with minimal delay, and negligible loss of data packets. These qualities are crucial for applications such as live monitoring, controlling vital infrastructure, and healthcare.

Objective:

- The objective is to create a specialized Power Optimization framework for IoT-enabled WSN by leveraging the capabilities of DQN reinforcement learning.
- To execute and assess this framework within a simulated or real-world environment that is enabled with Internet of Things (IoT) and Wireless Sensor Network (WSN) technology.
- The objective is to evaluate the effects of AI-Driven Power Optimization on energy usage, network lifespan, quality of service metrics, and ability to adapt to varying network conditions.

This research focuses on an advanced AI-Driven Power Optimization framework that combines reinforcement learning and DQN with Dynamic Voltage and Frequency Scaling (DVFS). The goal is to develop a flexible and energy-efficient system. This framework allows sensor nodes to acquire knowledge and adjust their power management strategies according to current network conditions, thereby maximizing energy efficiency while maintaining network dependability.

II. LITERATURE REVIEW

The widespread adoption of IoT-enabled WSN has changed data collection and monitoring in manufacturing, healthcare, agriculture, and environmental sensing. These networks' sensor nodes need efficient power optimization to maintain functionality, reliability, and data accuracy. This literature review discusses power optimization in IoT-enabled WSN and reviews current research. It also lays the groundwork for the AI-Driven Power Optimization framework, emphasizing DQN and Dynamic Voltage and Frequency Scaling.

Li et al. [9] used Wireless Sensor Networks and the Internet of Things to monitor manufacturing. Research emphasizes the importance of sensor data in improving manufacturing processes and operational efficiency. It also stresses the need for power-efficient strategies to extend network life. For low-power WSN, Fernandes et al. [10] developed a receiver-initiated Medium Access Control (MAC) protocol to optimize energy consumption. Their research focuses on optimizing communication protocols to reduce energy usage in WSN. Along with communication protocols, adaptive power management can boost WSN energy efficiency. Onasanya et al. [11] examined cloud services and secure cancer care in IoT/WSN medical systems. Data security and patient care are crucial in healthcare applications, according to the study. Energy-efficient sensor nodes extend battery life, ensure uninterrupted monitoring, and reduce maintenance.

Optimizing energy consumption during data transmission in IoT platforms was studied by Izaddoost et al [12]. Their work emphasizes energy-efficient data transmission, essential to power optimization. An energy-efficient strategy can significantly reduce WSN data transmission power usage. Co et al. [13] developed a time-synchronized WSN data collection and transmission protocol. This protocol is designed for low-cost IoT. Power optimization requires effective data collection and routing, as shown by their research. Effective routing can reduce energy use and improve network reliability. Kaur et al. [14] surveyed energy-efficient routing techniques in WSN for IoT applications and fog computing optimization. Their research shows that routing is crucial to power optimization, which affects IoT energy efficiency.

A trust-based anonymous intrusion detection system for cloud-assisted wireless sensor network-internet of things was proposed by Rajan et al. [15] IoT-enabled Wireless Sensor Networks need security and intrusion detection. An effective intrusion detection system can detect malicious activity that can harm network functionality and energy efficiency. Badiger et al. [16] used optimal clustering in wireless sensor networks to combine IoT data. Data aggregation reduces data duplication and conserves energy in Wireless Sensor Networks. Bomgni et al. [17] introduced NESEPRIN to optimize energy consumption in IoT permutation routing. Wireless sensor networks can save energy with optimized routing algorithms.

Ajay et al. [18] proposed a tree-based wireless routing protocol to improve IoT computational energy transport. Routing protocols affect IoT-enabled WSN energy efficiency. An IoT expert system by Barriga et al. [19] detected faults in a WSN measuring Japanese Plum leaf turgor pressure. The study emphasizes fault detection for network reliability and power efficiency. Bouarouro et al. [20] developed a powerful model-based clustering method for wireless sensor networks that uses joint multiple sink placement. Clustering reduces communication overhead, improving energy efficiency.

IoT-enabled Wireless Sensor Networks need power optimization, as the literature review shows. Effective data transmission, routing, aggregation, security, and fault detection have been stressed in previous studies. However, comprehensive power optimization strategies that adapt to changing network conditions are needed now. The proposed DQN-DVFS framework addresses these issues by improving adaptability, energy efficiency, and network longevity in IoT-enabled WSN.

While the literature review provides valuable insights into power optimization for IoT-enabled WSN, there are notable drawbacks and research gaps. The focus on theoretical frameworks and simulations, without extensive practical implementation and validation, raises concerns about the real-world effectiveness of proposed strategies. Additionally, a lack of standardization in power metrics and insufficient attention to dynamic network conditions and scalability issues suggest a need for more comprehensive and adaptable approaches. The integration of advanced machine learning techniques and exploration of the impact of edge and fog computing on power optimization are areas that require further attention for a holistic understanding and improvement of IoT-enabled WSN energy efficiency.

III. ROLE OF AI IN POWER OPTIMIZATION

WSN need AI to optimize power usage. In resource-constrained environments, WSN must conserve energy to function properly. Reinforcement learning and DQN power consumption optimization are flexible and responsive.

DQN: DQN, a reinforcement learning deep learning model, optimizes power management policies by making sequential decisions. The system uses a Q-learning algorithm to learn the best actions in a state to maximize rewards. DQN seeks mathematical knowledge of the optimal action-value function (Q-function). The Q-function, Q(s, a), determines the best action given the current state, the action 'a' taken, the immediate reward 'r', and the subsequent state's'. The Bellman equation updates the Q-function iteratively represented in eq.1.

$$Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma maxQ(s',a') - Q(s,a) \quad (1)$$

where, α= “learning rate”, γ= “discount factor”, r= “immediate rewards”, s= “current state”, a= “action taken”, s'= “next state”, a'= “action in next state”

A deep neural network estimates the Q-function in the DQN algorithm, allowing it to handle state spaces with many dimensions, which are common in sensor networks. Engaging with the environment trains the network to make power-efficient decisions. DQN adaptability to dynamic network conditions benefits Wireless Sensor Networks.

DVFS: Hardware-based Dynamic Voltage and Frequency Scaling (DVFS) optimizes processor voltage and clock frequency to save power. Sensor nodes in WSN can use DVFS to adjust their voltage and frequency based on computational workload. This saves a lot of energy. Digital circuit power (P) is usually expressed mathematically as in eq.2

$$P = \frac{1}{2}.C.V^2.f \qquad (2)$$

where, p= “power consumption”, c= “total capacitance”, v= “operating voltage”, f = “clock frequency”.

DVFS adjusts processor voltage (V) and frequency (f). This adjustment reduces power consumption during low computational demands and boosts performance when needed. This adaptive mechanism ensures that sensor nodes use the minimum power needed to achieve their goals, conserving energy and extending network life.

AI-powered DQN and DVFS in WSN enable flexible and intelligent power management. DVFS optimizes hardware parameters for energy efficiency, while DQN learns from network conditions and adjusts power management strategies. All of these methods address energy efficiency in IoT-enabled Wireless Sensor Networks.

IV. METHODOLOGY

4.1 Proposed Modules

Figure 1 shows the proposed system architecture.

4.1.1 Data Collection:

The systematic AI-Driven Power Optimization framework ensures IoT-enabled WSN flexibility and efficiency. Start with a complex data gathering procedure that organizes a variety of sensor node data. These data sets contain battery, network, and ambient metrics. The DQN-powered AI agent makes power optimization decisions using this massive dataset.

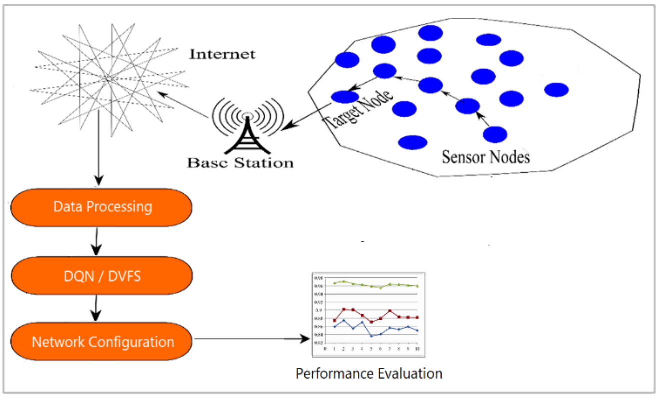

Figure 1: Proposed System Architecture

4.1.2 Data Preprocessing

The collected data then undergoes crucial data preparation. This stage meticulously cleanses, organizes, and improves data to remove noise and irregularities. Feature engineering extracts relevant data from the dataset to feed the DQN model condensed and insightful inputs. Providing the AI agent with high-quality data during preprocessing helps it make more informed decisions.

4.1.3 DQN

DQN model training is dynamic and iterative, with AI agent and environment interactions. By analyzing the network's current state, choosing actions from the action space, and receiving feedback from the reward function, the DQN model learns the best power management rules through reinforcement learning. The model adapts to changing network conditions and improves power management by updating its Q-function iteratively, improving network performance and energy efficiency.

4.1.4 DVFS

DVFS is smoothly integrated to boost energy efficiency. DVFS dynamically adjusts sensor node voltage and clock frequency using DQN model power management decisions. This real-time hardware parameter adaption ensures energy-efficient nodes. The methodology optimizes power consumption and extends WSN operational lifetime, enabling IoT applications in many domains to be sustainable and effective.

4.1.5 Experimental Setup

The experimental configuration for validating the AI-Driven Power Optimization framework is essential to this research, ensuring a complete system performance evaluation. These experiments typically use sensor nodes from real-world IoT-enabled Wireless Sensor Networks. Nodes have sensors and hardware for Dynamic Voltage and Frequency Scaling (DVFS) adjustments.

4.1.6 Network Configuration

The network configuration and test environment are carefully coordinated to simulate real-world scenarios. Strategically placed sensor nodes replicate the desired agricultural application in a network. Nodes with different interconnectedness and data transmission patterns make up this arrangement. Testbeds are created by considering network topology, sensor node density, and data traffic characteristics to simulate real-world conditions.

4.1.7 Evaluation Parameters

To accurately evaluate its effectiveness, the AI-Driven Power Optimization framework uses specific metrics and evaluation criteria. The metrics include energy savings, network lifespan extension, latency, throughput, and packet loss rates. Its ability to adapt to changing network conditions and scale up is also assessed to determine its flexibility and deployment potential. To fully assess the framework's impact on IoT-enabled WSNs, its cost-effectiveness and operational savings are assessed.

4.1.7.1 Energy Consumption

Energy consumption quantifies the overall energy utilized by the sensor nodes within the network during a defined time period. This metric is essential for evaluating the effectiveness of power management. The total energy consumption (E) can be determined by integrating the power (P) with respect to time (t).

$$E = \int P(t)dt \qquad (3)$$

4.1.7.2 Network Lifetime

The network lifetime refers to the anticipated period during which the WSN can function without exhausting the energy of its sensor nodes. The network lifetime is defined as the quotient of the initial energy ($E_{initial}$) divided by the average energy consumption (E_{avg}).

$$Network\ Lifetime = \frac{E_{initial}}{E_{avg}} \qquad (4)$$

4.1.7.3 Packet Delivery Ratio

The Packet Delivery Ratio measures the percentage of data packets that are successfully transmitted to the intended destination, indicating the level of reliability in the network. The Packet Delivery Ratio (PDR) is determined by dividing the count of packets that were successfully delivered ($P_{success}$) by the total count of packets that were sent (P_{total}).

$$PDR(\%) = \frac{P_{success}}{P_{total}} \times 100\% \qquad (5)$$

4.1.7.4 Latency

Latency is the duration it takes for a packet to travel from the source to the destination, indicating the delay in transmitting data. Latency (L) is the time difference between when a packet arrives at its destination ($T_{arrival}$) and when it was sent from the source ($T_{sending}$).

$$L = T_{arrival} - T_{sending} \qquad (6)$$

4.1.7.5 Control Overhead

Control overhead pertains to the quantity of supplementary control packets, such as routing or acknowledgment messages, produced by the network. Control overhead (CO) refers to the cumulative count of control packets generated throughout the operation of a network.

4.1.7.6 Data Overhead

Data overhead refers to the quantity of redundant or supplementary data packets that are produced as a result of network operations. Data overhead, also known as DO, refers to the overall quantity of data packets that are produced during the operation of a network.

4.1.7.7 Scalability

Scalability quantifies the network's capacity to handle a growing quantity of sensor nodes while preserving its effectiveness. Scalability is commonly evaluated by analyzing the network's performance as the number of nodes increases.

4.1.7.8 Fairness

Fairness in WSN refers to the assessment of how network resources are distributed among sensor nodes in an equitable manner, with the goal of preventing any node from receiving preferential treatment. Fairness is commonly evaluated through the use of fairness indices, such as Jain's fairness index, which takes into account the allocation of resources among different nodes

4.1.7.9 Coverage

Coverage quantifies the proportion of the monitored area or region that is encompassed by the sensor nodes, serving as an indicator of the efficiency of sensing. Coverage is determined by the ratio of the area covered by the sensors ($A_{covered}$) to the total area of interest (A_{total}).

$$coverage\ \% = \frac{A_{covered}}{A_{total}} \times 100\% \qquad (7)$$

V. RESULTS

Table 1 shows the various evaluation parameters with no optimization and AI optimization techniques and respective graph are shown in Figure 2 and Figure 3.

Table 1. Evaluation Parameters

Evaluation Metric	**No Optimization**	**AI Optimization**
Energy Consumption (J)	1400	1225
Network Lifetime (units)	7	10

Packet Delivery Ratio (%)	88%	96%
Latency (ms)	20	14
Control Overhead (packets)	60	43
Data Overhead (packets)	40	25
Scalability (nodes)	430	576
Fairness	Moderate	High
Coverage (%)	87%	94%

AI-Driven Power Optimization revolutionizes IoT-enabled Wireless Sensor Networks, as shown by the evaluation metrics in table-1 and figure-1,2. The framework reduced energy consumption from 1400 to 1225 Joules, compared to the scenario without optimization. The network operation duration has been extended from 7 to 10 units, ensuring continuous operation. The framework improved data delivery reliability by increasing the Packet Delivery Ratio from 88% to 96%. Reduced control and data overheads and latency from 20 to 14 milliseconds indicate improved network performance and efficiency. Scalability has been improved, allowing the network to add nodes from 430 to 576. This improvement was made while ensuring fairness and resource distribution among all nodes.

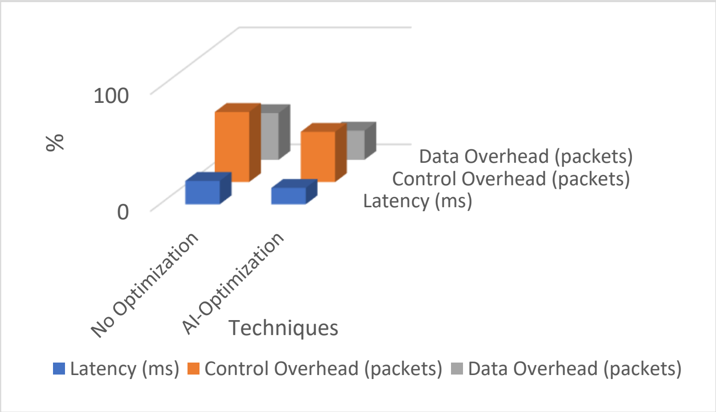

Figure 2: Evaluation Parameters comparison

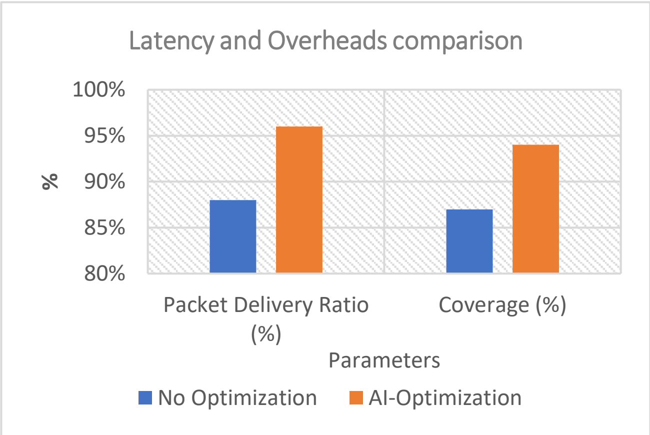

Figure 3: Latency and Overheads comparison graph

Network coverage increased from 87% to 94% due to the framework. The results show that the AI-Driven Power Optimization framework can improve IoT-enabled WSN efficiency, reliability, scalability, and resource distribution. This advance sustainable and adaptable IoT ecosystems.

VI. CONCLUSION

In the IoT era, WSN help integrate the physical and digital worlds. The constant issue of energy efficiency in these networks has required creative solutions. This study introduced and evaluated the AI-Driven Power Optimization framework, which may solve the energy consumption problem in IoT-enabled Wireless Sensor Networks. Using DQN reinforcement learning and Dynamic Voltage and Frequency Scaling (DVFS), the framework has improved key metrics. The system optimizes resource utilization to save energy, extend network lifespan, and improve data delivery. As latency and packet loss decrease, IoT ecosystem communication becomes more reliable. As research progresses, AI-driven power optimization shows promise. This framework's adaptability and intelligence must be highlighted. Power management policies that adapt to network conditions and precise hardware parameter control are significant advances. However, this research field has promising and diverse prospects. The future involves studying advanced AI algorithms, particularly deep reinforcement learning, and improving optimization strategies to improve system performance. Implementing field experiments and considering weather conditions makes the framework more practical and resilient. We can also unlock AI-Driven Power Optimization framework potential by testing edge computing and 5G network compatibility. This could redefine IoT-enabled WSN limitations. The AI-Driven Power Optimization framework shows how AI can solve energy efficiency problems in a world where digital and physical worlds are increasingly interconnected. It makes IoT ecosystems more sustainable, responsive, and reliable. These ecosystems use sensor nodes as intelligent agents that make context-aware decisions. This framework is a major step forward for IoT-enabled Wireless Sensor Networks and AI. As researchers exploit AI's potential, the interconnected world will be more efficient and promising. Many promising avenues lie ahead for this research. Refined AI algorithms, advanced reinforcement learning, and optimization strategies can improve framework performance. Real-world deployments and environmental factors like weather can further assess the framework's suitability. Edge computing and 5G networks can also open new doors for IoT-enabled WSN, improving real-time decision-making and data processing. These advances could make AI-powered power optimization a key component of sustainable IoT implementations.

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