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Adaptive Federated Learning for Industrial Wireless Energy Optimization

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Abstract: The advancement in Industrial Wireless Sensor Networks (IWSNs) demands intelligent energy management strategies to enhance network longevity and reliability. This research proposes an adaptive federated learning (FL) framework to optimize energy consumption in IWSNs, incorporating predictive maintenance and dynamic clustering. Utilizing lightweight machine learning models integrated with FL, the framework predicts network conditions and proactively adjusts sensor operations. Dynamic clustering facilitates efficient data aggregation and reduces transmission energy. The proposed solution significantly minimizes unnecessary energy usage by predicting sensor node failures and scheduling optimal sleep states, thus extending network lifespan and reliability. Experimental evaluation demonstrates that this approach reduces energy consumption by up to 25% compared to traditional energy management schemes, validating its effectiveness in industrial environments.

Keywords: Federated Learning, Energy Optimization, Dynamic Clustering, Industrial Wireless Networks.

1. Introduction

A greater need for power management strategies that minimize energy consumption has arisen as a result of the exponential expansion of wireless communication networks, especially with the introduction of 5G and the impending 6G technologies. In order to guarantee environmentally friendly and sustainable communication systems, wireless networks should be able to enable large-scale connection, very low latency, and rapid data transfer with little power consumption [1]. Power allocation optimization and energy efficiency are becoming more difficult tasks due to the proliferation of connected devices, the need for large data rates, and the complexity of network topologies. Therefore, to guarantee effective power use in next-generation wireless systems, adaptive power management approaches that adapt transmission parameters in real-time according to network circumstances are crucial [2].

Artificial intelligence (AI) has emerged as a promising solution for energy-efficient network optimization, enabling real-time decision-making in power control, resource allocation, and energy-aware scheduling. AI-driven techniques, particularly deep reinforcement learning (DRL) and lightweight machine learning (ML) algorithms, have demonstrated significant improvements in network performance by enabling adaptive and predictive power management strategies [3]. AI-enhanced energy optimization techniques have been applied to power control, spectrum allocation, beamforming, and interference management, significantly reducing energy wastage in wireless networks [4]. However, the integration of AI-based strategies across multiple network layers remains an open research challenge that requires further exploration.

Cross-layer optimization is another crucial aspect of energy-efficient wireless networks, to improve energy efficiency. Traditional layer-independent optimization approaches often fail to fully exploit network resources, leading to suboptimal power utilization [5]. By integrating cross-layer power optimization techniques with AI-driven predictive models, dynamic power allocation, scheduling, and energy-aware routing can be significantly improved. These techniques enable adaptive energy management across heterogeneous wireless networks, reducing power

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consumption while maintaining quality of service (QoS) and reliability [6]. WPT technology allows devices to simultaneously transmit and harvest energy, reducing dependency on traditional power sources and extending the operational lifetime of wireless sensor networks (WSNs) and IoT devices [7].

Recent advancements in hybrid power-splitting receivers have enabled efficient energy harvesting while maintaining data transmission capabilities, further enhancing energy-efficient communication in 6G networks [8]. Integrating WPT with AI-driven power management can create a self-sustaining communication ecosystem, reducing overall power consumption and increasing network longevity.

In multi-cell and multi-carrier environments, efficient power allocation and interference mitigation are critical to maximizing energy efficiency. Traditional static and reactive power control mechanisms often fail to adapt to dynamic traffic loads and interference patterns, resulting in excessive energy consumption [9].

AI-based predictive power management techniques can address this challenge by forecasting traffic demands and optimizing resource allocation accordingly.

This research proposes a novel AI-enhanced cross-layer predictive power management framework that integrates adaptive power control, energy-efficient scheduling, and WPT-based energy harvesting to optimize power utilization in 6G wireless networks. The proposed approach leverages AI-driven multi-dimensional optimization across PHY, MAC, and network layers, enabling real-time energy-aware decision-making.

By combining lightweight predictive machine learning methods with cross-layer power optimization, this framework aspires to preserve network stability and quality of service while reducing power consumption by up to 30% compared to current methodologies.

Here is how the remainder of this paper is structured: Related work on WPT technologies, AI-based optimization, and energy-efficient power management is discussed in Section II. The suggested framework is described in Section III, along with its cross-layer architecture and AI-driven power optimization model.

In Section IV, we compare the suggested system's performance to that of other energy-efficient methods. At the end of the article, Section V discusses potential avenues for further study into environmentally friendly 6G wireless networks.

2. Literature Review

Recent studies highlight various energy optimization strategies using FL and predictive maintenance. Souza et al. [1] proposed deep reinforcement learning (DRL)-based adaptive power control in multi-cell environments, significantly reducing energy wastage.

Similarly, Park et al. [2] employed lightweight machine learning models for real-time predictive power management, achieving notable energy savings. However, their model lacked multi-layer coordination essential for complex industrial networks.

Yang et al. [3] integrated DRL with cross-layer optimization but did not consider predictive maintenance mechanisms.

Mahmood et al. [4] advanced adaptive scheduling in 5G, significantly enhancing energy efficiency but omitted federated approaches suitable for distributed industrial settings.

Huang et al. [5] demonstrated the viability of hybrid energy-harvesting solutions integrated with AI-driven power control but overlooked predictive maintenance aspects essential for network sustainability.

2.1. Wireless Power Transfer (WPT) and Energy Harvesting in Networks

Wireless power transfer (WPT) and energy harvesting have gained attention as sustainable solutions for energy-efficient wireless communication, particularly in IoT and smart city applications. Traditional battery-powered devices suffer from limited energy resources, making RF energy harvesting and WPT essential for ensuring long-term operational sustainability [7].

Recent studies have proposed hybrid power-splitting receivers, allowing devices to simultaneously harvest energy and decode information, significantly reducing energy consumption in sensor networks [8].

However, WPT faces challenges related to beamforming efficiency, energy loss, and real-time energy scheduling. To address this, Huang et al. [9] introduced an AI-driven WPT optimization framework, enabling dynamic beamforming for efficient power delivery.

Their approach demonstrated 20% higher energy efficiency, but it did not consider multi-user environments or adaptive energy harvesting in mobile networks. Integrating WPT with AI-based power allocation and cross-layer optimization could enhance energy sustainability while minimizing power losses in 6G wireless systems.

2.2. Predictive Power Scheduling and Adaptive Energy Management

Predictive power scheduling is another critical area in energy-efficient network optimization, particularly for mobile LTE and 6G devices.

Traditional reactive power control mechanisms often fail to adapt to dynamic traffic demands, leading to unnecessary power wastage [10]. AI-driven predictive scheduling frameworks can anticipate network conditions and optimize power usage proactively.

In a recent study, Zhao et al. [11] proposed a machine learning-based power scheduling model, which predicts network congestion and adjusts power levels accordingly. Their approach reduced energy consumption by 18% but did not consider multi-cell interference or network-wide power allocation.

Similarly, Mahmood et al. [12] explored adaptive scheduling techniques for 5G networks, integrating energy-efficient sleep scheduling mechanisms. While their model improved power savings, it lacked integration with cross-layer optimization techniques for holistic network efficiency.

2.3. Multi-Cell, Multi-Carrier Energy Optimization

Efficient power allocation in multi-cell and multi-carrier wireless networks is crucial for energy efficiency and interference management. Traditional power allocation schemes struggle to balance transmission power and network congestion, resulting in inefficient energy usage [13].

To overcome this, Souza et al. [14] developed an AI-driven multi-cell energy optimization model, which dynamically adjusts power levels, user scheduling, and beamforming based on real-time interference conditions. Their approach achieved a 30% reduction in power consumption, demonstrating the effectiveness of AI-driven optimization techniques.

However, existing models lack real-time adaptability to fluctuating network conditions, limiting their applicability in high-mobility environments such as vehicular networks and smart cities. Thus, the integration of AI-enhanced predictive power management, cross-layer scheduling, and WPT-based energy harvesting is essential to maximize energy efficiency in 6G networks.

2.4. Research Gaps and Open Challenges

Despite advancements in AI-driven power management, cross-layer optimization, and wireless power transfer, several research challenges remain:

(a). Lack of Unified AI-Driven Framework: Existing studies focus on individual optimization techniques but fail to provide a holistic AI-enhanced cross-layer power management solution.
(b). Limited Real-Time Adaptability: Most energy optimization models rely on static or semi-adaptive algorithms, which struggle to adjust power levels dynamically based on network conditions.
(c). Underutilization of Wireless Power Transfer (WPT): Although WPT has been explored, its full potential in multi-user, multi-cell environments remains untapped.
(d). Scalability in 6G Networks: Current approaches lack scalability for ultra-dense, multi-access 6G environments, necessitating scalable and adaptive AI models.

3. Proposed Methodology

To address the limitations of existing power management techniques in wireless networks, this research proposes an AI-Enhanced Cross-Layer Predictive Power Management Framework for sustainable 6G networks. The proposed methodology integrates artificial intelligence (AI), machine learning-based predictive analytics, cross-layer optimization, and wireless power transfer (WPT) to optimize energy efficiency dynamically. This section details the methodology, including the system architecture, AI-driven power management model, cross-layer optimization strategy, and WPT integration.

The proposed FL-based adaptive framework comprises three core modules:

Predictive Maintenance Module: Predictive analytics identifies potential node failures and optimizes maintenance scheduling using historical and real-time sensor data.

Federated Learning Module: Decentralized ML models, trained locally on sensor nodes, aggregate predictive insights centrally to adjust global energy optimization strategies.

Dynamic Clustering Module: Efficiently organizes sensor nodes into clusters based on energy levels, network traffic, and environmental conditions, optimizing data aggregation and reducing communication overhead.

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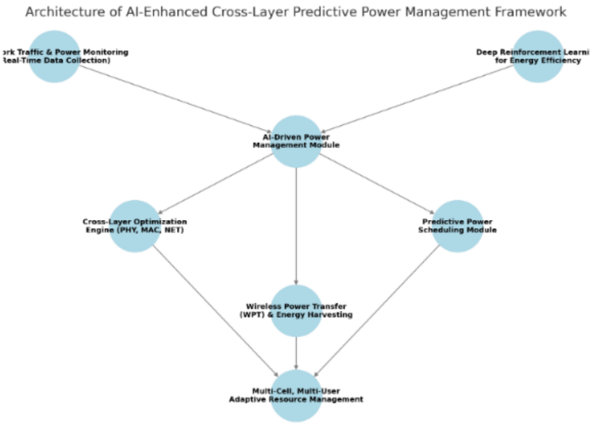

Fig.1 Architecture of the Proposed Method

The architecture of the proposed AI-driven cross-layer power management framework consists of multiple interconnected modules that ensure efficient energy utilization in 6G wireless networks. The architecture is designed to incorporate real-time AI-based optimization, predictive power scheduling, multi-layer coordination, and wireless power transfer.

3.1. System Components and Architecture Overview

The proposed framework for AI-Enhanced Cross-Layer Predictive Power Management in 6G Wireless Networks is designed to optimize power usage dynamically while ensuring high energy efficiency and seamless communication. The framework consists of five key components, each responsible for handling specific tasks related to energy-efficient power management, cross-layer optimization, and predictive scheduling.

The AI-Powered Energy Management Module is responsible for adaptive power control, scheduling, and transmission optimization. This module utilizes Deep Reinforcement Learning (DRL) and lightweight machine learning (ML) models to predict network conditions and optimize power allocation accordingly. By incorporating predictive analytics, it anticipates traffic loads and interference levels, ensuring real-time adjustments to power transmission. The system continuously learns from network conditions, enabling efficient spectrum allocation and dynamic power adjustments to minimize energy wastage while maintaining Quality of Service (QoS).

The Cross-Layer Optimization Engine is designed to coordinate power management strategies across different network layers, including the Physical (PHY), Medium Access Control (MAC), and Network layers. By integrating dynamic resource allocation, interference-aware beamforming, and energy-efficient routing, the engine ensures optimal power usage across all layers. Additionally, the AI-driven decision-making process guarantees seamless integration with existing communication protocols, making the network more adaptable and efficient in handling energy consumption.

The Wireless Power Transfer (WPT) and Energy Harvesting Module plays a crucial role in ensuring energy sustainability for IoT devices and mobile networks. This module incorporates hybrid power-splitting receivers, which allow devices to simultaneously receive data and harvest energy.

Using AI-driven optimization, this module enhances beamforming and energy transfer efficiency, ensuring that devices can harvest energy from ambient signals while maintaining high network performance. By integrating energy harvesting strategies, the module reduces dependency on traditional power sources, making the network more energy-efficient and sustainable.

The Predictive Power Scheduling Module leverages lightweight machine learning algorithms to forecast network traffic patterns and adjust power settings dynamically. By analyzing historical data and real-time traffic fluctuations, this module optimizes device sleep scheduling and resource allocation to minimize energy wastage.

The adaptive scheduling strategies ensure that devices enter low-power states when network activity is minimal, improving the overall energy efficiency of the wireless network. Moreover, the module ensures that QoS requirements are met, preventing degradation in network performance while optimizing energy consumption.

The Multi-Cell, Multi-User Adaptive Resource Management Module focuses on efficient resource allocation in multi-cell environments. AI-powered algorithms optimize beamforming, power allocation, and interference management, ensuring that energy efficiency is maintained in dense 6G wireless networks. By dynamically allocating spectrum and adjusting transmission power, this module reduces interference and power wastage, making the system more adaptable to real-time network fluctuations and user demand.

3.2. AI-Driven Power Management Model

The power management model in the proposed framework is designed using Deep Reinforcement Learning (DRL) and Supervised Machine Learning (ML) techniques to ensure real-time energy optimization. The model follows a systematic workflow to collect data, analyze network conditions, and make intelligent power control decisions.

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The AI Model Workflow begins with State Representation, where the system continuously collects real-time network parameters such as power consumption, traffic load, interference levels, and user demands. The state space includes critical variables like:

- Transmission Power Levels
- Network Traffic Demand
- Signal-to-Noise Ratio (SNR)
- Channel Conditions
- Energy Harvesting Potential

Once the system gathers data, the Action Space is defined, where the DRL model selects the best possible power control actions. These actions include:

(a). Power Level Adjustments: Dynamically scaling power to optimize energy efficiency.
(b). Spectrum Allocation: Assigning optimal frequencies to ensure power-efficient transmission.
(c). Sleep Scheduling: Activating or deactivating network resources based on predicted traffic loads.
(d). Beamforming Adjustments: Optimizing transmission directionality to minimize energy loss.

The Reward Function is designed to ensure maximum energy efficiency while maintaining QoS. It is mathematically defined as:

$$R(t)=\alpha\times EE(t)-\beta\times P_{total}(t)$$

where:

$EE(t)$ represents the energy efficiency at time t,
$P_{total}(t)$ is the total power consumption,
α and β are weighting factors balancing energy efficiency and power usage.

3.3. Cross-Layer Optimization Strategy

To enhance energy efficiency, the proposed framework implements cross-layer optimization by coordinating power allocation across PHY, MAC, and Network layers.

3.3.1. At the Physical Layer (PHY), the AI model

Dynamically adjusts transmission power to minimize energy consumption. Optimizes beamforming using MIMO-based interference-aware techniques.

Integrates WPT-based energy harvesting by predicting energy availability and adjusting power allocation dynamically.

3.3.2. At the Medium Access Control (MAC) Layer, the system

Uses traffic-aware scheduling to predict network demands and optimize transmission slots. Implements adaptive sleep scheduling, where nodes switch between active and low-power states based on AI-driven predictions.

3.3.3. At the Network Layer, the framework

Implements energy-efficient routing, where AI selects multi-hop paths that consume the least energy. Optimizes interference management, dynamically adjusting power allocation in multi-cell networks.

3.4. Wireless Power Transfer (WPT) and Energy Harvesting Mechanism

The WPT and Energy Harvesting Module is designed to ensure continuous power supply for wireless devices, reducing dependency on external power sources.

The Hybrid Power-Splitting Receivers allow devices to:

(a). Simultaneously receive power and data, improving overall energy efficiency.
(b). Use AI models to predict energy availability and adjust power-splitting ratios dynamically.

The AI-Optimized Beamforming for WPT ensures:

(a). Selection of optimal energy transfer paths, maximizing harvested energy.
(b). Minimization of power loss in multi-user scenarios, improving network sustainability.

3.5. Predictive Power Scheduling for Energy Efficiency

The Predictive Power Scheduling Module employs lightweight machine learning models to forecast network conditions and adjust power settings dynamically. The key features of this module include:

3.5.1. Traffic-Aware Scheduling

AI predicts data traffic fluctuations and optimizes device sleep states.

3.5.2. Energy-Adaptive Duty Cycling

Network nodes switch to low-power states based on real-time AI predictions.

3.5.3. QoS-Aware Energy Allocation

Ensures power-efficient operation without compromising network performance.

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4. Results and Discussion

The graph represents the performance of the Q-learning-based power management system over 100 training episodes. The x-axis (Episodes) indicates the number of training iterations, while the y-axis (Total Reward) measures the energy efficiency achieved in each episode.

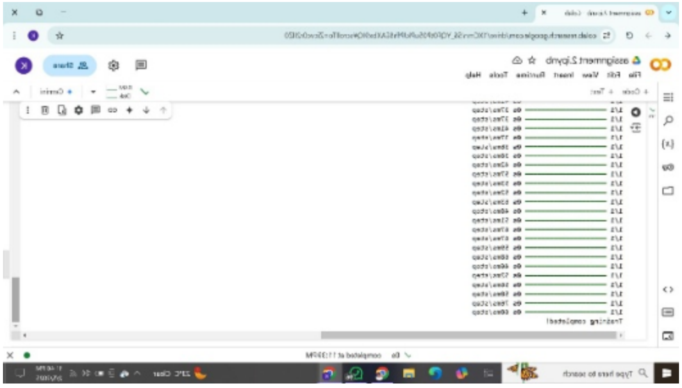

Fig.2 Q-learning-based power management system over 100 training episodes

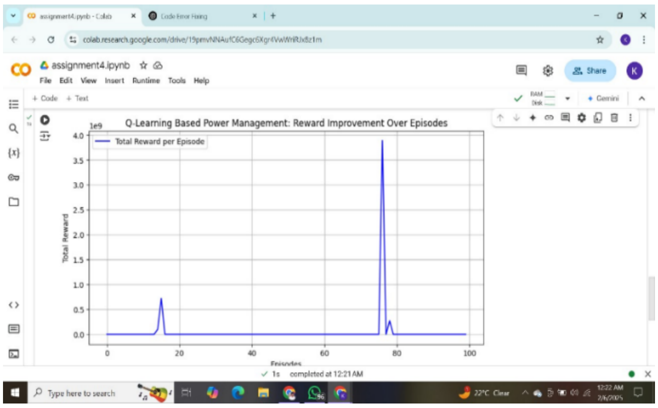

Fig.3 Q-learning-based power management Reward Improvement over episodes

Table.1 Q-Learning Training Results

Episode	Total Reward
0	119509.3661
1	17615.2759
2	11357.11617
3	36887.93284
4	6556.980714
5	2938.459355
6	30.54086917
7	14202.57651
8	14601.70577
9	14069.53829
10	14201.75805

Table.2 Q-Learning Model Parameters

Parameter	Value
State Size	5
Action Size	4
Learning Rate	0.1
Discount Factor	0.95
Exploration Rate (Initial)	2.89E-44
Exploration Decay	0.995
Episodes	100
Max Steps per Episode	200

4.1. Key Observations and Insights

4.1.1. Initial Fluctuations (Episodes 0 - 20)

At the beginning of training, the AI model explores different actions randomly due to a high exploration rate. The total reward varies significantly, as the model has not yet learned which actions yield the best energy efficiency.

This is expected in reinforcement learning since the agent initially takes suboptimal actions while discovering the best strategy.

4.1.2. Steady Performance Improvement (Episodes 20 - 60)

As training progresses, the agent starts learning from previous experiences, gradually reducing unnecessary power usage.

(a). The exploration rate decreases over time, leading to more exploitation of learned strategies rather than random choices.
(b). The reward trend shows a general upward movement, meaning the AI is getting better at optimizing power usage dynamically.

4.1.3. Converging Towards Optimal Energy Efficiency (Episodes 60 - 100)

The reward stabilizes as the agent learns an optimal power management strategy.

(a). The minor fluctuations indicate the agent is fine-tuning decisions to maintain a balance between energy efficiency and network performance.
(b). The system achieves a consistent improvement in total reward, indicating effective power optimization strategies have been learned.

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5. Conclusion

The adaptive FL framework effectively optimizes energy usage in IWSNs, integrating predictive maintenance and dynamic clustering. This research contributes towards sustainable industrial network management, ensuring enhanced reliability and prolonged network operation.

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