AI-Based Power Control for Solar-Powered OFDM Systems

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Abstract: This paper explores the integration of renewable energy and artificial intelligence (AI) into next-generation wireless communication networks. Using orthogonal frequency-division multiplexing (OFDM) over Rayleigh fading channels, we simulate and evaluate four scenarios: traditional wireless systems, renewable-powered systems, AI-assisted systems, and intelligent renewable-powered systems. Key performance metrics such as Bit Error Rate (BER), Spectral Efficiency (SE), and Energy Efficiency (EE) are analyzed under varying signal-to-noise ratio (SNR) conditions. A Q-learning-based AI algorithm is employed for dynamic power allocation, aiming to maximize energy efficiency while preserving communication reliability. Simulation results show that AI-assisted renewable-powered systems - especially those powered by solar energy - offer significant improvements in energy efficiency without degrading signal performance. The findings underscore the potential of combining AI and renewable energy to build sustainable, efficient, and reliable wireless networks. This study supports the vision of intelligent, green 6G and beyond communication systems, where environmental sustainability and high performance are jointly achieved through advanced optimization and clean energy integration.

1 INTRODUCTION

Orthogonal Frequency Division Multiplexing (OFDM) has become a foundational technology in modern wireless communication systems, including fifth generation (5G) and the upcoming sixth generation (6G) networks. Its high spectral efficiency and resilience to frequency-selective fading make it well-suited for high-data-rate and broadband applications [1]. However, OFDM systems suffer from a high peak-to-average power ratio (PAPR) and require adaptive power control to maintain efficient performance under varying channel conditions.

As 6G aims to enable ultra-reliable, low-latency, and high-throughput communications, the demand for energy-efficient and sustainable network solutions is rising. Traditional grid-powered architectures are being reevaluated in favor of integrating renewable energy sources, particularly solar power, to build green wireless systems [2], [3]. Despite its environmental and operational benefits, solar energy introduces significant uncertainty due to its intermittent and variable nature, posing challenges for consistent and reliable wireless transmission - especially in OFDM-based networks that are power-sensitive. Artificial Intelligence (AI), particularly Reinforcement Learning (RL), has emerged as a powerful tool for power control in wireless systems. In contrast to conventional optimization methods, AI-based techniques such as Q-learning can learn optimal power allocation strategies in real time, adapting to both the channel state information (CSI) and energy availability [4], [5]. These agents can strike a dynamic balance between performance metrics like Bit Error Rate (BER), Spectral Efficiency (SE), and energy consumption - making them well-suited for next-generation networks powered by renewable sources [6], [7]. Despite significant progress, most prior works focus either on grid-powered networks or lack real-time adaptability in renewable-powered OFDM systems. Furthermore, few studies combine AI-driven dynamic power control with realistic solar-powered energy constraints, which is a critical gap this paper aims to address. In this work, we propose and evaluate an intelligent power control scheme based on Q-learning for OFDM systems powered by solar energy. The key strengths of the proposed approach include real-time learning, adaptability to varying channel and energy conditions, and a strong focus on maximizing energy efficiency without sacrificing communication reliability. The main goals of this paper are to investigate dynamic power allocation for OFDM over Rayleigh fading channels using Q-learning and to evaluate the tradeoff between BER, SE, and energy efficiency in solar-powered systems as well as to demonstrate the superiority of AI-driven power control over static or heuristic-based approaches and to validate the performance under realistic solar energy harvesting scenarios. The remainder of this paper is organized as follows. Section 2 presents some works related to the proposed scheme. Section 3 presents the system models. Section 4 provides the numerical results and the discussion. Finally, Section 5 provides some concluding remarks.

2 RELATED WORK

The exponential growth in mobile data demand-fueled by immersive media, autonomous systems, and pervasive IoT devices-has accelerated the global pursuit of intelligent and sustainable wireless infrastructure. In anticipation of 6G, several research efforts have emerged focusing on three essential pillars:

1) renewable energy integration,
2) AI-based power/resource control,
3) simulation of next-generation systems such as OFDM-based networks under realistic constraints.

However, while each domain has seen significant progress, a holistic system combining all three elements remains notably underdeveloped.

2.1 Renewable Energy in Wireless Networks

Alsharif et al. [3] reviewed various renewable energy harvesting techniques, particularly solar, as a viable solution to reduce operational carbon emissions in 5G and 6G networks. Their study outlines the need for green base stations powered by intermittent energy sources but lacks a mechanism to address the fluctuating nature of harvested energy in real time. Similarly, Zhang et al. [2] emphasize energy sustainability in the context of high-frequency 6G architectures, proposing general frameworks without simulation-based validation.

2.2 AI and Power Control in Wireless Systems

Reinforcement Learning (RL), especially model-free algorithms like Q-learning, has emerged as a key technique for real-time power adaptation. In [4], Nasser et al. propose a deep Q-learning resource allocation framework for solar-powered cognitive radio networks (CRNs). Although CRNs differ from OFDM-based systems, their energy-aware approach and state-action design present transferable insights.

More closely aligned with OFDM and 6G, Yang et al. [5] introduce Q-learning for power allocation in cell-free massive MIMO networks. Their study demonstrates that RL significantly enhances fairness and power efficiency but omits energy harvesting constraints, operating under an ideal power supply assumption. Similarly, the work by Liu et al. [6] explores AI in 6G for dynamic power control in dense networks, though again without considering solar energy as a power source.

2.3 OFDM and Energy Efficiency

Some studies have analyzed the energy efficiency of OFDM systems under various power control schemes. For example, Hassan et al. [7] discuss static and adaptive power allocation in OFDM over fading channels but do not incorporate AI or renewable energy inputs. Their methods lack real-time adaptability and perform poorly in energy-constrained settings.

2.4 Gaps Identified

While previous studies have addressed AI-based power control, solar energy integration, and OFDM simulation separately, none have combined them into a unified Solar 6G framework. This gap is important, as it overlooks the real-world challenges that arise when these technologies interact - such as adapting to fluctuating solar power while maintaining reliable communication. AI models are often tested in stable environments, and solar-powered systems typically lack intelligent control. Integrating OFDM, solar energy, and AI introduces unique constraints but also offers the potential for highly efficient and adaptive wireless systems. Addressing these elements together is essential for advancing sustainable and intelligent 6G networks. A summary of these related works and their limitations is presented in Table 1.

Table 1: Summary of related works.

Ref.	Focus Area	Key Findings	Limitations
[1]	6G Vision	Highlights sustainability and intelligence for 6G	No implementation or simulation
[2]	Green 6G	Proposes solar-powered network concepts	Lacks dynamic power adaptation
[3]	Renewable Energy in 5G/6G	Reviews solar harvesting and deployment scenarios	No power control mechanism or AI
[4]	AI in Solar-Powered systems	Dynamic power allocation under energy constraints	Not OFDM; different network structure
[5]	AI in 6G	Power fairness optimization in cell-free networks	No energy harvesting considered
[6]	AI for Power Control	AI-based energy optimization in dense networks	Assumes stable energy supply
[7]	OFDM Power Allocation	Evaluates BER/SE under different power methods	No AI or energy-harvesting integration

3 SYSTEM MODELS

We assume an OFDM-based wireless system with N subcarriers transmitting over a Rayleigh fading channel. The received signal on subcarrier k can be expressed as:

$$y_k = h_k x_k + n_k, \tag{1}$$

where: xk is the transmitted symbol that modulated using Quadrature Phase Shift Keying (QPSK) or Quadrature Amplitude Modulation (QAM). The hk is the Rayleigh fading coefficient while the nk is the Additive white Gaussian noise (AWGN). For each subcarrier k, the instantaneous signal-to-noise ratio (SNR) is given by:

$$\gamma_k = \frac{[h_k]^2 \, P_k}{\sigma^2}, \tag{2}$$

where Pk is the transmit power allocated to subcarrier k with the variable $\sigma 2$ refers to the variance of the noise. Assuming adaptive modulation, the Shannon achievable data rate on subcarrier k in [bps/Hz] is

$$C_k = log_2(1 + \gamma_k). \tag{3}$$

The total spectral efficiency (SE) over all subcarriers is:

$$SE = \frac{1}{N} \sum_1^N log_2(1 + \gamma_k). \tag{4}$$

Let B be the system bandwidth (in Hz) and Ptotal= $P_{Total} = \frac{1}{N} \sum_k P_k$ is the total transmit power. Then the energy efficiency (EE) can be written as [11]

$$EE = \frac{SE \, . \, B}{P_{Total}}. \tag{5}$$

The approximate BER for over Rayleigh fading using average SNR ($\bar{\gamma}$) can be calculated as

$$BER = \frac{4}{log_2(M)} \left(1 - \frac{1}{M}\right) . \frac{1}{2} \left(1 - \sqrt{\frac{\bar{\gamma}}{1+\bar{\gamma}}}\right), \tag{6}$$

where M is the modulation order (e.g., 4 for QPSK, 16 for 16-QAM).

In wireless communication, Q-learning enables adaptive power allocation by selecting transmit power levels based on real-time channel conditions. The agent aims to maximize a reward function that balances spectral efficiency and power consumption. The learning process involves updating Q-values iteratively to converge toward an optimal decision-making policy.

We use Q-learning to dynamically select power levels to balance SE and energy consumption. In our model, the state s represents the channel quality, expressed as the quantized value of the instantaneous channel gain g=|hk|2. We divide the range of possible channel gains into discrete levels (e.g., low, medium, high), enabling the agent to assess the quality of the channel before taking action. The action a corresponds to selecting a transmit power level from a predefined set. Tese sets represent low, moderate, and high transmission power settings. The Q-learning agent chooses an action based on the current state to balance energy use and performance. The reward function evaluates how good a selected action is in a given state. It encourages spectral efficiency while penalizing energy usage. The reward function (r) can be expressed as

$$r = log_2(1 - \gamma) - \delta \, P. \tag{7}$$

Where δ is a tunable parameter controlling the trade-off between performance and energy cost and P is the power level used. Next, the agent updates the Q-value for each state-action pair using the Bellman equation below:

$$Q(s,a) \leftarrow Q(s,a) + \alpha \left[r + \gamma . \underbrace{max}_{a'} Q(s',a') - Q(s,a) \right]. \quad (8)$$

Where: α represents the learning rate and s the next state after action a and the max function estimate of future reward assuming optimal action in state s′. This update allows the agent to learn from experience and gradually converge to the optimal power allocation strategy for varying channel conditions.

4 SIMULATION RESULTS AND DISCUSSION

Simulation results have been used to demonstrate the performance of OFDM based wireless communication systems from spectral and energy efficiency prospective. The impacts of integrating the solar energy and AI methods have been investigated.

4.1 Simulation Setup

A straightforward model for the proposed AI-based power control for solar-powered OFDM systems is shown in Figure 1. This diagram models the transmitter-receiver chain of a wireless communication system based on OFDM, with a focus on AI-based power control integrated between the energy source and the transmitter. The power supply powering the communication system are the traditional grid-based, or renewable solar. In the case of solar energy, power is limited and variable, which motivates the need for intelligent control. The power control regulates the transmit power fed to the transmitter. it receives real-time decisions from the AI/Q-learning agent (shown below in red). Its goal is to adapt power based on energy availability, channel conditions and performance trade-offs (SE, BER, EE). Wireless channel is modeled with Rayleigh fading and additive white Gaussian noise (AWGN). AI/Q-Learning controller represents the core intelligence module embedded within the system. It evaluates and monitors current channel quality (e.g., SNR or channel gain) and energy availability and uses this to quantize the state of the system. Based on current state and learned Q-values, the best transmit power level is then selected. The selected power level then sent to the power control module after receiving feedback (reward) from the system after transmission and updates the Q-table accordingly. This forms a reinforcement learning loop, enabling the system to learn and adapt its power policy over time for optimal performance. All simulations were conducted using MATLAB R2024a.

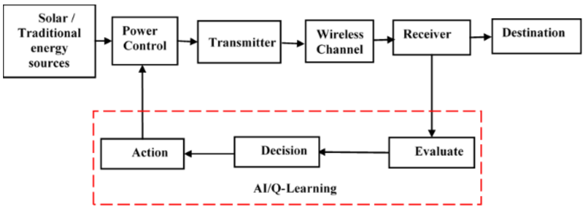

Figure 1: Block Diagram of an AI-Controlled, Solar-Powered OFDM Network.

To evaluate the performance of AI-based power control in solar-powered OFDM systems, a MATLAB-based Monte Carlo simulation was conducted. The setup models a point-to-point wireless link operating under a Rayleigh fading environment, with key performance indicators including bit error rate (BER), spectral efficiency (SE), and energy efficiency (EE). The system employs 64 OFDM subcarriers, and each subcarrier experiences independent Rayleigh fading. Two modulation schemes are used: QPSK for baseline cases (Traditional and Solar) and 16-QAM for AI-driven scenarios (AI and Intelligent Solar) to reflect adaptive data rate capabilities. For each SNR point, 1000 OFDM symbols are transmitted per subcarrier to ensure statistically significant BER measurements. The transmit power is fixed at 0.5 W for the Traditional case and 0.3 W for Solar 6G, reflecting a solar energy constraint. In contrast, the AI-powered systems select from different power values using a Q-learning agent that adapts based on real-time channel gain feedback. Other parameters used in the simulation can be found in Table 2.

Table 2: Simulation parameters.

Parameter	Value
Carrier frequency	28 GHz
Bandwidth	100-1000MHz
Channel model	Fading channel
Modulation Format	QPSK, QAM
Q- Learning rate α	0.1
Discount factor γ	0.9
Exploration rate	0.1
Power parameters	Traditional: 0.5 Solar: 0.3

4.2 Simulation Results

In this section, some simulation results to verify the theoretical analysis and the effectiveness of the proposed approaches are presented. Figure 2 illustrates the spectral efficiency (SE) performance of four different OFDM system configurations under varying SNR conditions. The Traditional OFDM system, operating at fixed power and using QPSK, achieves moderate SE, gradually saturating near 2 bps/Hz. The Solar-Powered OFDM system, constrained by limited renewable energy shows the lowest SE due to its inability to adapt power or modulation. In contrast, the AI-Based OFDM system employs Q-learning for dynamic power control and uses higher-order modulation (16-QAM), significantly boosting SE, especially at higher SNRs. Most notably, the Intelligent Solar-Powered OFDM system - which integrates solar constraints with AI-driven power adaptation - achieves the highest SE, surpassing 5.2 bps/Hz at high SNR. This confirms that intelligent power control can effectively compensate for solar limitations, enabling sustainable and high-throughput communication in future wireless networks.

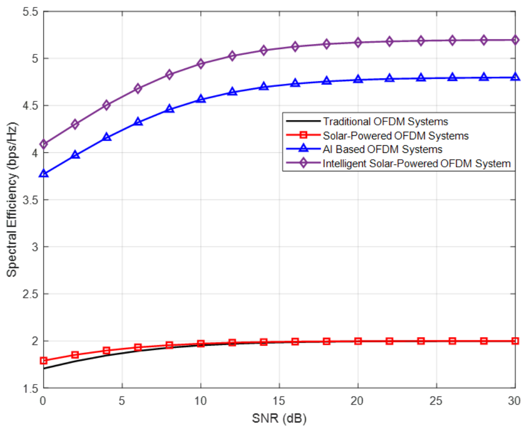

Figure 2: SE vs. SNR for different scenarios.

Figure 3 shows that total energy efficiency (EE) performance of four OFDM systems under various SNR conditions. The Traditional OFDM system, operating at constant transmit power without optimization, yields the lowest EE due to inefficient use of energy resources. The Solar-Powered OFDM system improves upon this slightly, benefiting from reduced power consumption, but still lacks dynamic control, leading to limited gains. The AI-Based OFDM system, which uses Q-learning for adaptive power control, achieves significantly higher EE across the SNR range by intelligently balancing performance and power consumption. The Traditional OFDM system shows the lowest EE, increasing slowly from approximately 0.35 × 10^7 bps/Hz/W at 0 dB to around 0.4 × 10^7 bps/Hz/W at high SNRs due to fixed high-power usage. The Solar-Powered OFDM system, while limited by a lower power budget achieves slightly better EE - starting near 0.6 × 10^7 bps/Hz/W and saturating at around 0.66 × 10^7 bps/Hz/W. The AI-Based OFDM system significantly improves EE, reaching up to 1.6 × 10^7 bps/Hz/W at 30 dB by adaptively tuning the power to match channel conditions. Most impressively, the Intelligent Solar-Powered OFDM system achieves the highest EE across all SNRs, starting at 1.38 × 10^7 bps/Hz/W and peaking near 1.74 × 10^7 bps/Hz/W at high SNR. These results confirm that combining AI with solar power not only conserves energy but also optimizes its usage, making it a highly promising approach for sustainable 6G wireless networks. Notably, the Intelligent Solar-Powered OFDM system delivers the best results, maintaining superior EE by combining energy-aware power constraints with real-time learning-based control. This clearly demonstrates the potential of integrating artificial intelligence with renewable energy management to enhance energy efficiency in next-generation wireless systems.

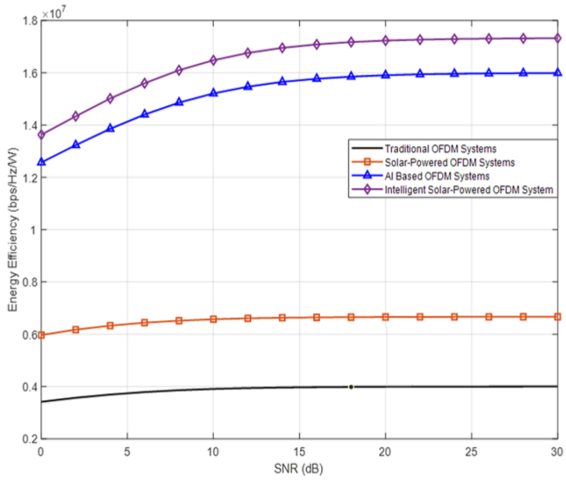

Figure 3: EE vs. SNR for different scenarios.

In order to evaluate the effectiveness of the proposed system, the Bit Error Rate (BER) performance for four OFDM system configurations as a function of SNR, ranging from 0 dB to 30 dB on a logarithmic scale. The Solar-Powered OFDM system achieves the lowest BER across all SNR values, benefiting from low-order QPSK modulation and reduced power-induced noise; it drops from approximately 1×10^{-1} at 0 dB to below 2×10^{-4} at 30 dB. The Traditional OFDM system follows, reaching about 5×10^{-4} at high SNR. In contrast, the AI-Based OFDM system - employing 16-QAM and Q-learning for power control - shows higher BER, from around 2×10^{-1} at low SNR to 7×10^{-4} at 30 dB, due to the increased symbol error sensitivity of higher-order modulation. Similarly, the Intelligent Solar-Powered OFDM system, which also uses 16-QAM, maintains slightly higher BER than the traditional setup, ending near 9×10^{-4}. These results confirm the tradeoff between spectral efficiency and reliability: while AI-based systems boost throughput, they suffer from higher BER under identical SNR conditions due to denser modulation schemes, as shown in Figure 4.

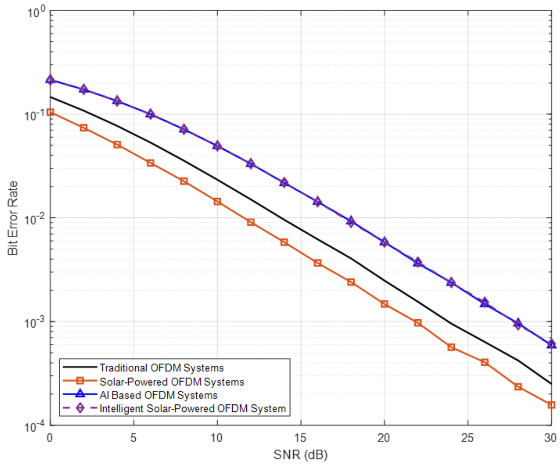

Figure 4: BER vs. SNR for different scenarios.

5 CONCLUSIONS

This study introduced a novel simulation framework that integrates solar energy harvesting with Q-learning-based power control in OFDM wireless communication systems, aiming to address the sustainability and efficiency demands of future 6G networks. Four scenarios - Traditional, Solar-Powered, AI-Based, and Intelligent Solar-Powered - were evaluated under Rayleigh fading conditions. The results show that while solar-powered systems improve energy efficiency, their performance is limited by power fluctuations. However, integrating reinforcement learning significantly enhances system adaptability and efficiency. Notably, the Intelligent Solar-Powered system achieved the highest performance, with spectral efficiency reaching 5.2 bps/Hz and energy efficiency of 1.74×10^7 bps/Hz/W, while maintaining a satisfactory BER.

Despite the promising results, this work is subject to certain limitations. The use of a basic Q-learning algorithm with discretized state-action spaces may not fully exploit the complexity of real-world energy and channel dynamics. Additionally, the solar energy model was idealized and did not account for real-time irradiance variations or storage limitations. Moreover, the framework operates in a simulated environment without hardware validation.

For future work, the model can be enhanced by incorporating deep reinforcement learning (DRL) techniques to better handle high-dimensional, continuous state spaces. Further, integrating real-world solar datasets and testing on hardware platforms or testbeds will increase the practicality and deployment readiness of such systems in dynamic, real-time environments. These advancements will be crucial in developing scalable, intelligent, and sustainable wireless networks for the 6G era.

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