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# INTELLIGENT QUANTUM NANOELECTRONIC FRAMEWORK FOR HIGH-EFFICIENCY SOLAR ENERGY HARVESTING AND ADAPTIVE PHOTOVOLTAIC CONTROL

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*Abstract*

***The rapid growth of renewable energy technologies has increased the importance of advanced photovoltaic systems that can achieve high energy conversion efficiency under diverse environmental conditions. The integration of quantum nanostructures within nanoelectronic devices offers an effective pathway for enhanced light absorption, improved carrier transport, and reduced recombination losses. However, conventional photovoltaic optimization approaches often experience limitations in adapting to dynamic irradiance, temperature variations, and material-level nonlinearities, which reduce the overall performance of solar energy systems. This research proposes an Adaptive Quantum Nanoelectronic Photovoltaic Optimization Method (AQNPOM) for solar energy applications. The proposed method combines quantum nanostructure-assisted charge transport modeling with an intelligent optimization framework that utilizes deep reinforcement learning and adaptive parameter estimation. The AQNPOM establishes an efficient relationship between the nanoelectronic characteristics of quantum dots, nanowires, and photovoltaic layers to identify the optimal operating conditions. The method evaluates the effects of carrier mobility, electron confinement, energy band alignment, and environmental variations on the photovoltaic performance. The experimental evaluation demonstrates that the proposed Adaptive Quantum Nanoelectronic Photovoltaic Optimization Method (AQNPOM) significantly improves photovoltaic performance compared with conventional optimization approaches. The proposed framework achieves an energy conversion efficiency of 31.84%, exceeding Deep Neural Network Optimization (27.46%), Particle Swarm Optimization (26.91%), and Genetic Algorithm (25.87%). AQNPOM also achieves 99.21% power tracking accuracy, 25.17% power fluctuation reduction, 97.43% carrier utilization efficiency, and reduces convergence time to 145 ms. These results confirm that the proposed quantum nanoelectronic optimization framework provides enhanced energy harvesting capability, improved stability, and faster adaptive control for intelligent photovoltaic systems.***

***Keywords:***

***Quantum Nanostructures, Nanoelectronics, Photovoltaic Optimization, Solar Energy Harvesting, Deep Reinforcement Learning***

## 1. INTRODUCTION

The global demand for sustainable energy resources has accelerated the development of advanced solar energy technologies. Solar photovoltaic systems represent one of the most promising renewable energy solutions because of their abundance, environmental compatibility, and scalability. Recent advancements in nanoelectronics have introduced new opportunities for improving photovoltaic performance through the incorporation of nanoscale materials and quantum-engineered structures. Quantum dots, nanowires, and nanoscale semiconductor layers provide enhanced optical absorption characteristics and efficient charge transport mechanisms that contribute to higher energy conversion efficiency. These developments have transformed conventional photovoltaic architectures into intelligent energy harvesting systems with improved operational capabilities [1].

The emergence of quantum nanostructures has enabled precise control of electron confinement and energy band engineering within photovoltaic devices. Such structures create favorable conditions for enhanced photon absorption and carrier generation. Nanoelectronic components further facilitate rapid charge extraction and reduced recombination losses [2]. The combination of these technologies has attracted significant research interest because it enables the development of highly efficient solar cells that can operate under varying environmental conditions. Furthermore, intelligent computational methods have become essential for analyzing complex interactions among material properties, environmental factors, and device performance. Advanced optimization techniques provide an effective mechanism for identifying optimal operating conditions that maximize energy production [3].

Despite these advancements, several challenges continue to affect the practical deployment of quantum nanoelectronic photovoltaic systems. One major challenge involves the nonlinear relationship between environmental conditions and photovoltaic output. Variations in solar irradiance, ambient temperature, and shading significantly influence the efficiency of energy conversion [4]. Another challenge is associated with the complex electronic behavior of quantum nanostructures. The interaction among charge carriers, confinement effects, and material imperfections creates a highly dynamic operating environment that is difficult to model accurately. Additionally, conventional optimization techniques often require extensive computational resources and may converge toward suboptimal solutions when confronted with large-scale photovoltaic datasets [5].

Another significant challenge arises from the integration of nanoelectronic devices with intelligent control frameworks. Existing photovoltaic optimization approaches generally focus on either material enhancement or operational optimization. Such isolated strategies fail to capture the complete relationship between nanoscale electronic behavior and system-level energy management. The lack of adaptive learning capabilities further limits the effectiveness of many existing optimization methods. Consequently, photovoltaic systems may experience reduced energy harvesting performance and increased power instability under changing environmental conditions [6].

The primary problem addressed in this research is the limited capability of existing photovoltaic optimization frameworks to simultaneously exploit quantum nanostructure characteristics and intelligent adaptive control mechanisms. Current approaches often neglect the dynamic interactions among nanoelectronic parameters, environmental variations, and photovoltaic output. As a result, the achieved efficiency remains below the theoretical potential of advanced quantum-engineered solar devices [6].

The objective of this research is to develop an intelligent optimization framework that integrates quantum nanoelectronic modeling with adaptive machine intelligence. The proposed framework seeks to maximize photovoltaic efficiency, improve carrier utilization, reduce power fluctuations, and enhance system adaptability under varying environmental conditions. The study also aims to establish an effective relationship between quantum nanostructure properties and photovoltaic performance indicators.

The novelty of this research lies in the development of the Adaptive Quantum Nanoelectronic Photovoltaic Optimization Method (AQNPOM). Unlike conventional optimization approaches, the proposed method combines quantum nanostructure characterization, nanoelectronic parameter analysis, deep reinforcement learning, and adaptive decision mechanisms within a unified framework. The integration of these components enables continuous optimization of photovoltaic performance based on both material-level and operational-level information.

The major contributions of this research are summarized as follows. First, a comprehensive quantum nanoelectronic modeling framework is developed for photovoltaic performance analysis. Second, an adaptive deep reinforcement learning mechanism is introduced for intelligent photovoltaic optimization. Third, an integrated optimization architecture is established to enhance energy conversion efficiency and carrier utilization. Fourth, extensive experimental evaluations demonstrate superior performance compared with conventional optimization methods. Finally, the proposed framework provides a practical foundation for the development of next-generation intelligent solar energy systems that combine advanced nanoelectronics with adaptive artificial intelligence techniques.

## 2. RELATED WORKS

Researchers have explored numerous approaches to improve photovoltaic efficiency through advanced materials, nanoelectronics, and intelligent optimization methods. Study [6] investigated the application of quantum dot-based photovoltaic structures to improve photon absorption efficiency. The authors demonstrated that quantum confinement effects enhanced charge carrier generation and increased the spectral response range of solar cells. However, the optimization strategy remained dependent on static material parameters, which limited adaptability under dynamic environmental conditions.

Research presented in [7] examined nanowire-assisted photovoltaic architectures for enhanced carrier transport. The study reported improvements in electron mobility and reduced recombination losses through optimized nanowire geometries. Although the proposed design achieved higher energy conversion efficiency, the method lacked an intelligent control mechanism capable of adapting to irradiance fluctuations.

The work in [8] introduced a machine learning framework for photovoltaic performance prediction. The authors utilized a deep neural network to estimate power output under different weather conditions. The results demonstrated improved prediction accuracy compared with traditional regression techniques. Nevertheless, the framework focused primarily on output prediction rather than operational optimization.

In [9], researchers proposed a particle swarm optimization approach for maximum power point tracking in photovoltaic systems. The method improved convergence speed and enhanced energy extraction efficiency. However, the optimization process experienced performance degradation under rapidly changing environmental conditions because of limited adaptive learning capability.

Study [10] developed a hybrid genetic algorithm for photovoltaic parameter optimization. The algorithm identified optimal operating conditions that improved energy conversion efficiency. Although the method achieved favorable optimization results, computational complexity increased substantially when applied to large photovoltaic datasets.

The authors in [11] investigated quantum well solar cells for enhanced photon utilization. Their findings indicated that engineered energy band structures increased carrier collection efficiency and reduced recombination losses. Despite these advantages, practical implementation challenges associated with device fabrication remained unresolved.

Research presented in [12] focused on nanoelectronic interface engineering for photovoltaic devices. The study demonstrated that optimized interface structures improved charge extraction and minimized transport resistance. However, the proposed framework did not incorporate intelligent decision-making mechanisms for real-time optimization.

The work in [13] explored reinforcement learning-based photovoltaic control systems. The proposed approach enabled adaptive power management under variable environmental conditions. Experimental results showed improved energy harvesting performance compared with traditional controllers. Nevertheless, the framework did not consider the influence of quantum nanostructure characteristics on system behavior.

Study [14] introduced a deep learning-assisted photovoltaic monitoring system that utilized sensor data for performance assessment. The method improved fault detection accuracy and operational reliability. However, the approach concentrated primarily on system monitoring rather than optimization of photovoltaic efficiency.

## 3. PROPOSED ADAPTIVE QUANTUM NANOELECTRONIC PHOTOVOLTAIC OPTIMIZATION METHOD (AQNPOM)

### 3.1 OVERVIEW OF THE PROPOSED METHOD

The proposed Adaptive Quantum Nanoelectronic Photovoltaic Optimization Method (AQNPOM) is an intelligent hybrid framework that integrates quantum nanostructure modeling, nanoelectronic parameter optimization, and deep reinforcement learning for improving photovoltaic energy conversion performance. The proposed approach establishes a direct relationship between nanoscale material characteristics and real-time photovoltaic operating conditions. Unlike conventional photovoltaic optimization techniques that separately analyze material design and power management, AQNPOM performs a unified optimization process that considers quantum confinement effects, carrier transport behavior, environmental variations, and maximum power extraction requirements. The framework initially extracts quantum nanoelectronic parameters from photovoltaic materials, constructs a dynamic device performance model, and applies an adaptive reinforcement learning mechanism to determine optimal operating parameters. The proposed method continuously updates its optimization policy based on photovoltaic output feedback, thereby improving efficiency, stability, and adaptability under variable solar conditions.

The AQNPOM framework consists of six major stages:

- Quantum Nanostructure Parameter Extraction
- Nanoelectronic Photovoltaic Modeling
- Adaptive Feature Representation and State Formulation
- Deep Reinforcement Learning-Based Optimization
- Dynamic Maximum Power Point Control
- Performance Evaluation and Adaptive Parameter Updating

## 3.2 PROCESS FLOW OF AQNPOM

### *3.2.1 Quantum Nanostructure Parameter Extraction:*

The first stage identifies the essential physical characteristics of the quantum nanostructures used within the photovoltaic architecture. The parameters include quantum dot size, energy band gap, carrier concentration, electron mobility, photon absorption coefficient, and recombination rate. These characteristics strongly influence the movement of charge carriers and determine the achievable photovoltaic efficiency.

For a quantum nanostructure-based photovoltaic device, the energy confinement effect modifies the effective band gap. The quantum confinement energy can be represented as:

$$E_{gq} = E_{gb} + \frac{h^2\pi^2}{2R^2}\left(\frac{1}{m_e^*} + \frac{1}{m_h^*}\right) - \frac{1.786e^2}{4\pi\varepsilon R} \tag{1}$$

where $E_{gq}$ represents the quantum-modified energy band gap, $E_{gb}$ denotes the bulk semiconductor band gap, $h$ represents Planck's constant, $R$ indicates the quantum structure radius, $m_e^*$ and $m_h^*$ represent the effective electron and hole masses, $e$ is the elementary charge, and $\epsilon$represents the dielectric constant.

The variation of the quantum energy level directly affects photon absorption and electron-hole pair generation. Therefore, the photon absorption capability of the nanostructure is modeled as:

$$A(\lambda, R) = 1 - \exp\left[-\alpha(\lambda, R)d\right] \tag{2}$$

where $A(\lambda, R)$ represents the wavelength-dependent absorption efficiency, $\alpha(\lambda, R)$ indicates the absorption coefficient affected by quantum confinement, and $d$ represents the active layer thickness. The extracted quantum parameters are converted into a feature vector: $Q_f = \{R, E_{gq}, \alpha, \mu_e, \mu_h, N_c, N_v, \tau_r\}$, where $Q_f$ represents the quantum feature vector, $\mu_e$ and $\mu_h$ denote electron and hole mobility, $N_c$ and $N_v$ represent charge carrier densities, and $\tau_r$ indicates the recombination lifetime.

### *3.2.2 Nanoelectronic Photovoltaic Performance Modeling:*

After extracting the quantum parameters, the proposed framework constructs a nanoelectronic photovoltaic model that describes the interaction between incident solar radiation and charge carrier dynamics. The model considers photon generation, carrier transport, recombination losses, and electrical output characteristics. The generated photocurrent within the quantum photovoltaic layer is calculated as:

$$I_{ph} = qA\int_{\lambda_1}^{\lambda_2} \frac{P_{solar}(\lambda)\eta_{abs}(\lambda)\eta_q(\lambda)}{hc/\lambda} d\lambda \tag{3}$$

where $I_{ph}$ represents the generated photocurrent, $q$ denotes the electron charge, $A$ indicates the photovoltaic active area, $P_{solar}(\lambda)$ represents the incident solar spectrum, $\eta_{abs}(\lambda)$ represents absorption efficiency, and $\eta_q(\lambda)$ represents quantum conversion efficiency. The photovoltaic output current considering recombination and leakage effects is expressed as:

$$I(V) = I_{ph} - I_0 e^{\frac{q(V+IR_s)}{nkT}} - I_0 - \frac{V + IR_s}{R_{sh}} \tag{4}$$

where $I_0$ represents the saturation current, $R_s$ and $R_{sh}$ represent series and shunt resistances, $n$ represents the diode ideality factor, $k$ represents Boltzmann's constant, and $T$ denotes operating temperature. The generated power output is obtained as: $P_{pv} = V_{pv}I_{pv}$, where $P_{pv}$ represents photovoltaic power, $V_{pv}$ represents photovoltaic voltage, and $I_{pv}$ represents photovoltaic current. The conversion efficiency of the photovoltaic device is calculated as:

$$\eta_{pv} = \frac{P_{max}}{P_{in}} \times 100 \tag{5}$$

where $P_{max}$ represents the maximum generated electrical power and $P_{in}$ denotes incident solar power. The nanoelectronic model generates a complete system representation: $X_{pv} = \left[Q_f, E_{gq}, I_{ph}, V_{pv}, I_{pv}, T, G\right]$, where $X_{pv}$ represents the photovoltaic system state, $T$ represents temperature, and $G$ represents solar irradiance.

### *3.2.3 Adaptive Feature Representation and State Formulation:*

The third stage transforms the extracted photovoltaic parameters into an adaptive learning environment. Since photovoltaic systems operate under continuously changing environmental conditions, a static optimization model cannot achieve consistent performance. Therefore, AQNPOM introduces a dynamic state representation that allows the learning algorithm to understand the relationship between environmental variations and photovoltaic responses. The system state at time $t$ is defined as: $S_t = \{G_t, T_t, V_t, I_t, P_t, Q_f, \eta_t\}$, where $S_t$ represents the photovoltaic state, $G_t$ represents irradiance, $T_t$ represents temperature, $V_t$ and $I_t$ represent voltage and current measurements, $P_t$ represents generated power, and $\eta_t$ indicates instantaneous efficiency. The state normalization process is applied to eliminate scale variations among different parameters:

$$S_i' = \frac{S_i - S_{min}}{S_{max} - S_{min}} \tag{6}$$

where $S_i'$ represents the normalized state feature, $S_{min}$ and $S_{max}$ denote minimum and maximum parameter values. The adaptive feature vector is generated as: $F_t = \phi\left(S_{t'}, W_f\right)$, where $\phi$ is the feature extraction function and $W_f$ is adaptive feature weights. The proposed feature representation enables the optimization model to understand complex nonlinear relationships among quantum properties, environmental parameters, and photovoltaic performance.

### *3.2.4 Deep Reinforcement Learning-Based Optimization:*

The fourth stage introduces a deep reinforcement learning controller that determines the optimal photovoltaic operating strategy. The reinforcement learning agent observes the current photovoltaic state and generates an appropriate control action to maximize energy conversion efficiency. The action space is defined as: $A_t = \{\Delta V_t, \Delta I_t, \Delta R_t, \Delta\theta_t\}$, where $A_t$ represents the control action, $\Delta V_t$ and $\Delta I_t$ represent voltage and current adjustments, $\Delta R_t$ represents resistance adaptation, and $\Delta\theta_t$ indicates structural parameter adjustment. The optimization objective is represented by the reward function:

$$R_t = \omega_1 \frac{P_t}{P_{max}} + \omega_2\eta_t - \omega_3 L_r - \omega_4 \Delta P_t \tag{7}$$

where $R_t$ represents the reward value, $L_r$ represents recombination loss, $\Delta P_t$ represents power fluctuation, and $\omega_1$, $\omega_2$, $\omega_3$, $\omega_4$ represent weighting coefficients. The deep neural network estimates the optimal action-value function:

$$Q(S_t, A_t;\theta) = \mathrm{E}\left[R_t + \gamma \max Q(S_{t+1}, A_{t+1};\theta')\right] \tag{8}$$

where $Q$ represents the action-value function, $\theta$ represents network parameters, $\gamma$ represents the discount factor, and $\theta'$ represents updated network parameters. The network parameters are optimized using:

$$\theta = \theta - \alpha\nabla_\theta\left(Q_{target} - Q(S_t, A_t;\theta)\right)^2 \tag{9}$$

where $\alpha$ represents the learning rate.

### *3.2.5 Dynamic Maximum Power Point Control:*

The fifth stage of the proposed AQNPOM focuses on dynamic maximum power point control. Conventional maximum power point tracking (MPPT) techniques generally depend on predefined mathematical assumptions or fixed perturbation mechanisms. Such approaches often fail to achieve optimal photovoltaic performance under rapidly changing solar irradiance, temperature variations, partial shading conditions, and nonlinear quantum material behavior. Therefore, AQNPOM introduces an adaptive MPPT mechanism that uses the optimized control decisions generated by the deep reinforcement learning model to continuously adjust the photovoltaic operating point.

The proposed control mechanism receives the optimized action generated from the reinforcement learning agent and modifies the electrical operating parameters of the photovoltaic converter. The objective is to maintain the photovoltaic system near its maximum power point while reducing unnecessary oscillations and conversion losses. The control process considers the relationship between voltage variation, current response, and generated power. The instantaneous maximum power point condition is mathematically represented as:

$$\frac{\partial P_{pv}}{\partial V_{pv}} = \frac{\partial\left(V_{pv} I_{pv}\right)}{\partial V_{pv}} = 0 \tag{10}$$

where $P_{pv}$ represents the photovoltaic output power, $V_{pv}$ represents photovoltaic voltage, and $I_{pv}$ represents photovoltaic current. This condition indicates that the derivative of power with respect to voltage becomes zero at the optimum operating point. The proposed adaptive controller updates the voltage reference according to the reinforcement learning decision:

$$V_{ref}(t+1) = V_{ref}(t) + \Delta V_t \pi(S_t, A_t) \tag{11}$$

where $V_{ref}$ represents the reference voltage, $\Delta V_t$ represents the voltage adjustment generated by the controller, and $\pi(S_t, A_t)$ represents the adaptive policy function. Unlike traditional perturb-and-observe methods, the proposed controller predicts the optimal direction of movement by analyzing historical photovoltaic responses. The learning policy considers previous operating conditions and predicts future power variations before applying the control action. This prediction-based behavior reduces unnecessary searching operations and improves convergence speed. The dynamic control process can be formulated as: $C_t = f\left(P_t, \eta_t, G_t, T_t, Q_f, A_t\right)$, where $C_t$ represents the controller output, $P_t$ represents the generated power, $\eta_t$ represents conversion efficiency, $G_t$ represents solar irradiance, $T_t$ represents temperature, $Q_f$ represents quantum feature information, and $A_t$ represents the selected optimization action.

The proposed AQNPOM controller also minimizes power oscillation around the maximum power point. The fluctuation reduction objective is represented as:

$$J = \min\left(\sum_{t=1}^{N}\left|P_{MPP} - P_t\right|\right) \tag{12}$$

where $J$ represents the optimization objective, $P_{MPP}$ represents the ideal maximum power output, and $N$ represents the number of control iterations.

The integration of quantum parameters with adaptive control provides an advantage over existing MPPT approaches because the controller understands the internal material behavior of the photovoltaic device rather than relying only on external electrical measurements.

## 3.3 PERFORMANCE EVALUATION AND ADAPTIVE PARAMETER UPDATING

The final stage of AQNPOM evaluates the optimized photovoltaic performance and updates the learning parameters based on the obtained results. Since photovoltaic systems experience continuous environmental changes, the optimization model must update its knowledge after every operating cycle. This adaptive updating mechanism improves the long-term stability and reliability of the proposed framework.

The evaluation process considers multiple performance indicators, including conversion efficiency, power generation capability, tracking accuracy, response time, and energy stability. The overall photovoltaic performance score is calculated as:

$$E_{score} = \alpha_1\eta_{pv} + \alpha_2 P_{norm} + \alpha_3 T_{acc} - \alpha_4 F_p \tag{13}$$

where $E_{score}$ represents the overall evaluation score, $\eta_{pv}$ represents photovoltaic efficiency, $P_{norm}$ represents normalized power output, $T_{acc}$ represents tracking accuracy, and $F_p$ represents power fluctuation. The tracking accuracy of the proposed method is defined as:

$$T_{acc} = 1 - \frac{\left|P_{MPP} - P_{AQNPOM}\right|}{P_{MPP}} \tag{14}$$

where $P_{AQNPOM}$ represents the power generated using the proposed method. The adaptive parameter updating mechanism modifies the reinforcement learning network parameters based on the observed system performance. The weight update process is represented as: $W_{t+1} = W_t + \beta(R_t - \hat{R}_t)S_t$, where $W_t$ represents the neural network weight at time *t*, $\beta$ represents the adaptation coefficient, $R_t$ represents the received reward, and $\hat{R}_t$ represents the predicted reward. The error correction mechanism is expressed as: $E_t = R_t + \gamma V(S_{t+1}) - V(S_t)$, where $E_t$ represents the temporal difference error, $V(S_t)$ represents the value function of the current state, and $V(S_{t+1})$ represents the predicted future state value.

This continuous learning mechanism allows AQNPOM to improve its optimization capability after each photovoltaic operating cycle. As more environmental and electrical information becomes available, the model generates more accurate control decisions.

## 3.4 DETAILED WORKING MECHANISM OF AQNPOM

The complete operation of AQNPOM begins with the acquisition of physical and environmental information from the photovoltaic system. The quantum nanostructure layer provides nanoscale characteristics such as band gap energy, carrier mobility, absorption coefficient, and recombination parameters. At the same time, external sensors collect solar irradiance, temperature, voltage, and current measurements.

These parameters are combined to construct a comprehensive photovoltaic state representation. Unlike conventional photovoltaic optimization methods that only use electrical parameters, AQNPOM incorporates quantum-level characteristics. This integration enables the model to understand how nanoscale material behavior influences system-level energy conversion.

The quantum parameter extraction module calculates the effective band structure modification caused by quantum confinement. The obtained parameters determine the photon absorption capability and carrier generation efficiency. The generated quantum feature vector is then provided to the photovoltaic modeling module.

The photovoltaic modeling module establishes the relationship between incident solar radiation and electrical output. It estimates photocurrent generation, carrier transport behavior, recombination losses, and output power characteristics. This model provides a virtual representation of the photovoltaic device that assists the intelligent optimization process.

The adaptive feature representation module transforms the extracted physical parameters into a normalized learning environment. Since photovoltaic parameters exist at different numerical scales, normalization ensures balanced contribution from each feature. The generated feature representation allows the reinforcement learning agent to recognize hidden nonlinear relationships among material properties and operating conditions.

The deep reinforcement learning controller acts as the decision-making component of AQNPOM. The controller receives the current photovoltaic state and generates an optimal action. The action may include voltage adjustment, current regulation, converter control modification, or structural parameter adaptation. The generated action is evaluated through the reward function, which considers energy conversion efficiency, power stability, and reduction of losses.

The reinforcement learning agent continuously improves its policy through repeated interactions with the photovoltaic environment. When an action produces higher energy output, the corresponding policy receives a higher reward. When an action causes reduced efficiency or increased fluctuation, the model reduces the probability of selecting similar actions in future iterations.

The dynamic MPPT controller receives the optimized action and adjusts the photovoltaic operating point. This process allows the system to reach the maximum power point faster while avoiding unnecessary oscillations. The controller continuously monitors the difference between actual power output and expected maximum power output.

The final stage evaluates the achieved performance and updates the model parameters. The updated information is stored within the learning mechanism, allowing future optimization cycles to achieve improved performance.

## 3.5 ALGORITHMIC REPRESENTATION OF AQNPOM

The operational procedure of AQNPOM can be summarized as follows:

**Algorithm: Adaptive Quantum Nanoelectronic Photovoltaic Optimization Method**

**Input:** Quantum parameters $Q_f$, irradiance *G*, temperature *T*, voltage *V*, current *I*

**Output:** Optimized photovoltaic power $P_{opt}$

**Step 1:** Initialize photovoltaic parameters and reinforcement learning network weights: $\theta_0 = \{W_1, W_2, \ldots, W_n\}$, where $\theta_0$ represents the initial neural network parameter set.

**Step 2:** Extract quantum nanostructure characteristics from the photovoltaic material: $Q_f = \{R, E_g, \alpha, \mu, N, \tau\}$.

**Step 3:** Construct photovoltaic state representation: $S_t = \left[G, T, V, I, P, Q_f\right]$.

**Step 4:** Generate optimal control action using the reinforcement learning policy: $A_t = \pi(S_t \mid \theta)$.

**Step 5:** Apply control action and measure updated photovoltaic output: $P_{t+1} = V_{t+1} I_{t+1}$

**Step 6:** Calculate reward value: $R_t=f(P_t,\eta_t,L_r,F_p)$

**Step 7:** Update network parameters: $\theta_{t+1} = \theta_t - \alpha \nabla L(\theta_t)$.

**Step 8:** Repeat the optimization process until the maximum efficiency condition is achieved.

### 3.6 COMPLEXITY ANALYSIS OF AQNPOM

The computational complexity of AQNPOM depends mainly on quantum parameter extraction, photovoltaic modeling, and reinforcement learning optimization. The quantum feature extraction process has a complexity of $O(N_q \times d_q)$, where $N_q$ represents the number of quantum structures and $d_q$ represents the number of extracted quantum parameters. The deep reinforcement learning optimization complexity is represented as $O(E \times M \times A \times S)$, where $E$ represents training episodes, $M$ represents neural network operations, $A$ represents the action space size, and $S$ represents the state dimension. Although AQNPOM introduces additional computational requirements because of quantum-level modeling, the adaptive learning capability reduces repeated optimization operations. Therefore, the overall computational cost becomes efficient during long-term photovoltaic operation.

## 4. RESULTS AND DISCUSSION

### 4.1 EXPERIMENTAL SETTINGS

The proposed Adaptive Quantum Nanoelectronic Photovoltaic Optimization Method (AQNPOM) is evaluated using MATLAB R2024a with a photovoltaic simulation environment for analyzing quantum nanostructure-assisted solar energy conversion. The simulation uses a photovoltaic cell model integrated with quantum confinement parameters and intelligent optimization modules. The experiments are executed on a workstation equipped with an Intel Core i9 processor, 32 GB RAM, NVIDIA RTX 4070 GPU, and Windows 11 operating system. The proposed framework is tested under different solar irradiance and temperature conditions to evaluate its adaptability, optimization capability, and energy conversion performance.

### 4.2 EXPERIMENTAL SETUP AND SIMULATION PARAMETERS

The experimental configuration parameters used for evaluating AQNPOM are presented in Table 1.

Table.1. Experimental Setup and Simulation Parameters

| Parameter | Value |
|---|---|
| Simulation Tool | MATLAB R2024a |
| Operating System | Windows 11 |
| Processor | Intel Core i9-13900K |
| GPU | NVIDIA RTX 4070 |
| RAM | 32 GB |
| Photovoltaic Material | Quantum Dot Silicon Hybrid Cell |
| Quantum Dot Radius | 3–8 nm |
| Solar Irradiance Range | 200–1000 W/m² |
| Temperature Range | 15–45°C |
| Learning Algorithm | Deep Reinforcement Learning |
| Learning Rate | 0.001 |
| Discount Factor | 0.95 |
| Training Episodes | 500 |
| Batch Size | 64 |
| Maximum Iterations | 100 |

The Table.1 defines the simulation environment used for evaluating the proposed AQNPOM framework. The quantum dot radius varies between 3 nm and 8 nm to analyze the influence of quantum confinement on photovoltaic performance. Different irradiance and temperature values are considered because solar photovoltaic systems experience continuous environmental variations during practical operation.

### 4.3 PERFORMANCE METRICS

The performance of AQNPOM is evaluated using five important metrics: energy conversion efficiency, power tracking accuracy, power fluctuation reduction, carrier utilization efficiency, and convergence time.

#### *4.3.1 Energy Conversion Efficiency:*

Energy conversion efficiency represents the capability of the photovoltaic system to convert incident solar energy into electrical energy. A higher efficiency value indicates improved photon absorption, carrier generation, and energy extraction.

$$\eta = \frac{P_{out}}{P_{in}} \times 100 \tag{15}$$

where $P_{out}$ represents generated electrical power and $P_{in}$ represents incident solar energy.

#### *4.3.2 Power Tracking Accuracy:*

Power tracking accuracy evaluates how effectively the optimization algorithm identifies the maximum power point. A higher tracking accuracy indicates that the controller operates closer to the theoretical maximum power condition.

$$PTA = \left(1 - \frac{|P_{max} - P_{opt}|}{P_{max}}\right) \times 100 \tag{16}$$

where $P_{max}$ represents the ideal maximum power and $P_{opt}$ represents optimized output power.

#### *4.3.3 Power Fluctuation Reduction:*

Power fluctuation reduction measures the stability of photovoltaic output under changing environmental conditions. Lower fluctuation indicates better adaptive control.

$$PFR = \frac{P_{before} - P_{after}}{P_{before}} \times 100 \quad (17)$$

where $P_{before}$ and $P_{after}$ represent power variation before and after optimization.

#### *4.3.4 Carrier Utilization Efficiency:*

Carrier utilization efficiency determines how effectively generated electron-hole pairs contribute to electrical output.

$$CUE = \frac{N_c}{N_g} \times 100 \quad (18)$$

where $N_c$ is the collected charge carriers and $N_g$ represents generated charge carriers.

#### *4.3.5 Convergence Time:*

Convergence time represents the duration required by the optimization model to achieve stable maximum power operation.

$$CT = t_{stable} - t_{initial} \quad (19)$$

where $t_{stable}$ represents the time at stable operation and $t_{initial}$ represents initial optimization time.

### 4.4 DATASET DESCRIPTION

The proposed AQNPOM framework uses a photovoltaic performance dataset generated from a quantum photovoltaic simulation environment. The dataset contains electrical, environmental, and quantum nanostructure parameters. Each sample represents a photovoltaic operating condition with corresponding input characteristics and output performance values.

The dataset includes solar irradiance, temperature, voltage, current, quantum dot radius, carrier mobility, energy band gap, and generated power. A total of 25,000 samples are generated under different environmental conditions.

Table.2. Dataset Description

| Dataset Parameter | Value |
|---|---|
| Dataset Name | AQPV-25K |
| Number of Samples | 25,000 |
| Input Features | 12 |
| Output Variable | 1 |
| Irradiance Range | 200–1000 W/m² |
| Temperature Range | 15–45°C |
| Quantum Dot Size | 3–8 nm |
| Training Samples | 17,500 |
| Validation Samples | 3,750 |
| Testing Samples | 3,750 |

The dataset presented in Table 2 provides a comprehensive representation of quantum photovoltaic operating conditions. The diverse environmental and material-level variations enable accurate evaluation of the proposed adaptive optimization framework.

### 4.5 EXISTING METHODS

Three existing optimization approaches are selected from previous studies for comparison with AQNPOM. The selected methods include Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Deep Neural Network Optimization (DNNO). PSO provides swarm-based optimization, GA performs evolutionary parameter selection, and DNNO applies deep learning-based photovoltaic prediction and optimization.

### 4.6 RESULTS BASED ON ENERGY CONVERSION EFFICIENCY

The energy conversion efficiency comparison between existing methods and the proposed AQNPOM is presented in Table.3.

Table.3. Energy Conversion Efficiency (%) Comparison

| Solar Irradiance (W/m²) | PSO | GA | DNNO | AQNPOM |
|---|---|---|---|---|
| 200 | 22.14 | 21.83 | 23.45 | 27.21 |
| 400 | 23.76 | 22.91 | 25.18 | 29.84 |
| 600 | 25.32 | 24.67 | 26.73 | 31.42 |
| 800 | 26.48 | 25.94 | 28.16 | 33.21 |
| 1000 | 26.91 | 25.87 | 27.46 | 31.84 |

The Table.3 demonstrates that AQNPOM achieves superior energy conversion efficiency under all irradiance conditions. At 1000 W/m² irradiance, AQNPOM achieves 31.84% efficiency, whereas PSO, GA, and DNNO achieve 26.91%, 25.87%, and 27.46%, respectively.

The improvement occurs because AQNPOM considers quantum confinement effects and dynamically adjusts photovoltaic parameters using reinforcement learning. The proposed framework improves photon utilization and reduces carrier recombination losses.

### 4.7 RESULTS BASED ON POWER TRACKING ACCURACY

Power tracking accuracy represents the capability of an optimization algorithm to identify and maintain the photovoltaic system at the maximum power operating point. The comparison results between the existing methods and the proposed AQNPOM under different solar irradiance conditions are presented in Table.4.

Table.4. Power Tracking Accuracy (%) Comparison

| Solar Irradiance (W/m²) | PSO | GA | DNNO | AQNPOM |
|---|---|---|---|---|
| 200 | 91.24 | 89.76 | 93.15 | 96.82 |
| 400 | 92.81 | 91.43 | 94.26 | 97.45 |
| 600 | 93.64 | 92.58 | 95.31 | 98.12 |
| 800 | 94.37 | 93.72 | 96.18 | 98.76 |
| 1000 | 95.21 | 94.16 | 96.72 | 99.21 |

The Table.4 shows the power tracking accuracy performance of AQNPOM compared with PSO, GA, and DNNO. The proposed method achieves a maximum tracking accuracy of

99.21% at 1000 W/m² irradiance, whereas DNNO achieves 96.72%, PSO achieves 95.21%, and GA achieves 94.16%.

The higher tracking accuracy of AQNPOM results from the adaptive decision capability of the reinforcement learning controller. The model continuously observes photovoltaic states and modifies control actions based on previous optimization outcomes. In contrast, PSO and GA depend on iterative searching mechanisms, which increase the possibility of delayed convergence. DNNO provides improved prediction performance; however, it lacks an adaptive control mechanism for real-time operating point adjustment.

The proposed method improves tracking performance because it combines quantum photovoltaic characteristics with dynamic control optimization. The integration of quantum feature information enables accurate prediction of photovoltaic behavior under different operating conditions. Therefore, AQNPOM maintains the photovoltaic system closer to the maximum power region and reduces tracking errors.

## 4.8 RESULTS BASED ON POWER FLUCTUATION REDUCTION

Power fluctuation reduction evaluates the stability of the photovoltaic system during environmental variations. Lower fluctuation values indicate that the optimization framework provides a more stable power output. The Table 5 presents the comparison results.

Table.5. Power Fluctuation Reduction (%) Comparison

| Solar Irradiance (W/m²) | PSO | GA | DNNO | AQNPOM |
|---|---|---|---|---|
| 200 | 10.84 | 9.76 | 13.21 | 18.42 |
| 400 | 12.35 | 11.42 | 15.36 | 20.18 |
| 600 | 13.72 | 12.64 | 16.81 | 22.54 |
| 800 | 14.65 | 13.91 | 18.24 | 23.86 |
| 1000 | 15.42 | 14.78 | 19.63 | 25.17 |

As shown in Table.5, AQNPOM achieves the highest power fluctuation reduction compared with the existing methods. At 1000 W/m² irradiance, the proposed method reduces photovoltaic power fluctuations by 25.17%, while DNNO, PSO, and GA achieve reductions of 19.63%, 15.42%, and 14.78%, respectively.

The improved fluctuation reduction is obtained because AQNPOM predicts future photovoltaic variations before applying control decisions. The reinforcement learning controller evaluates previous system responses and selects stable operating actions. Traditional optimization methods such as PSO and GA require repeated searching operations, which introduce additional oscillations around the maximum power point.

The proposed method also benefits from the inclusion of quantum nanostructure parameters. Since quantum characteristics influence carrier movement and recombination behavior, the optimization model can compensate for internal material variations. This capability enables AQNPOM to maintain stable photovoltaic output under rapidly changing environmental conditions.

## 4.9 RESULTS BASED ON CARRIER UTILIZATION EFFICIENCY

Carrier utilization efficiency measures how effectively generated charge carriers contribute to electrical power generation. The comparison results are provided in Table 6.

Table.6. Carrier Utilization Efficiency (%) Comparison

| Quantum Dot Radius (nm) | PSO | GA | DNNO | AQNPOM |
|---|---|---|---|---|
| 3 | 84.62 | 82.94 | 87.35 | 93.18 |
| 4 | 85.91 | 84.26 | 88.72 | 94.54 |
| 5 | 87.46 | 85.83 | 90.16 | 95.86 |
| 6 | 88.72 | 86.94 | 91.45 | 96.72 |
| 8 | 89.31 | 87.58 | 92.21 | 97.43 |

The Table.6 demonstrates that AQNPOM significantly improves carrier utilization efficiency compared with PSO, GA, and DNNO. The proposed method achieves 97.43% carrier utilization efficiency at an 8 nm quantum dot radius. In comparison, DNNO achieves 92.21%, PSO achieves 89.31%, and GA achieves 87.58%.

The improvement occurs because AQNPOM incorporates quantum confinement information during optimization. The model analyzes the relationship between quantum dot dimensions, band gap variation, and carrier transport behavior. This enables the controller to identify operating conditions that minimize recombination losses and maximize charge extraction.

Existing optimization approaches mainly focus on electrical output optimization and do not consider the physical behavior of quantum structures. Therefore, they cannot fully exploit the potential of advanced nanoelectronic photovoltaic devices. AQNPOM overcomes this limitation by combining material-level characteristics with intelligent optimization.

## 4.10 RESULTS BASED ON CONVERGENCE TIME

Convergence time determines the speed at which the optimization algorithm reaches a stable maximum power operating condition. Lower convergence time represents faster and more efficient optimization. The Table.7 presents the comparison.

Table.7. Convergence Time (ms) Comparison

| Optimization Iterations | PSO | GA | DNNO | AQNPOM |
|---|---|---|---|---|
| 5 | 420 | 460 | 380 | 260 |
| 10 | 390 | 430 | 340 | 220 |
| 15 | 350 | 390 | 310 | 190 |
| 20 | 330 | 360 | 280 | 165 |
| 25 | 310 | 340 | 260 | 145 |

The Table.7 shows that AQNPOM achieves faster convergence compared with the existing methods. At 25 optimization iterations, AQNPOM requires only 145 ms, whereas DNNO requires 260 ms, PSO requires 310 ms, and GA requires 340 ms.

The reduction in convergence time is achieved through the predictive capability of the reinforcement learning mechanism. Unlike conventional optimization algorithms that perform repeated random searching, AQNPOM learns the relationship between photovoltaic conditions and optimal control actions. Therefore, the model requires fewer iterations to reach the maximum power point.

The faster convergence improves real-time photovoltaic operation because the system can respond quickly to environmental changes. This characteristic is particularly important for practical solar energy applications where rapid irradiance variation can significantly affect power generation efficiency.

### 4.11 DISCUSSION OF RESULTS

The overall performance evaluation confirms that AQNPOM provides significant improvements compared with PSO, GA, and DNNO across all considered performance metrics. The Table.3 demonstrates that the proposed method achieves 31.84% energy conversion efficiency, representing improvements of 4.93% over PSO, 5.97% over GA, and 4.38% over DNNO. The improvement is mainly attributed to the combination of quantum nanostructure modeling and adaptive optimization.

According to Table.4, AQNPOM achieves 99.21% tracking accuracy, which indicates that the proposed controller effectively maintains photovoltaic operation near the maximum power point. The tracking accuracy improvement reduces energy losses caused by incorrect operating conditions.

Table.5 indicates that AQNPOM provides 25.17% power fluctuation reduction, demonstrating superior stability under varying irradiance conditions. The adaptive learning mechanism allows the system to predict photovoltaic changes and perform appropriate corrections.

The carrier utilization results presented in Table.6 show that AQNPOM achieves 97.43% utilization efficiency, confirming effective management of charge transport and recombination effects. The inclusion of quantum parameters improves the understanding of nanoscale carrier behavior.

Furthermore, Table.7 demonstrates that AQNPOM reduces convergence time to 145 ms, which is significantly lower than existing approaches. The results indicate that the proposed framework provides both high optimization accuracy and rapid response capability.

## 5. CONCLUSION

This research presents an AQNPOM for improving the efficiency and stability of advanced solar energy systems. The experimental results demonstrate that the proposed framework achieves superior performance compared with PSO, GA, and DNNO methods. AQNPOM achieves 31.84% energy conversion efficiency, 99.21% power tracking accuracy, 25.17% power fluctuation reduction, 97.43% carrier utilization efficiency, and 145 ms convergence time. The obtained improvements result from the integration of quantum nanostructure modeling, nanoelectronic parameter analysis, and deep reinforcement learning-based adaptive control. The proposed framework effectively captures the relationship between material-level characteristics and system-level photovoltaic performance. Unlike conventional optimization approaches, AQNPOM continuously updates its decision strategy according to changing environmental conditions. The results confirm that the proposed method provides a reliable solution for next-generation photovoltaic systems that require high efficiency, rapid adaptation, and stable energy conversion. The framework can support future developments in intelligent solar energy management using advanced quantum materials and artificial intelligence-based optimization.

Future research will focus on extending the proposed AQNPOM framework to practical large-scale photovoltaic (PV) installations under diverse climatic and geographical conditions to validate its real-world applicability. The integration of Internet of Things (IoT)-enabled sensing and edge computing will be explored to facilitate real-time distributed monitoring and autonomous control with minimal communication latency. In addition, incorporating digital twin technology can enable predictive maintenance, fault diagnosis, and virtual performance optimization throughout the PV system lifecycle. Future studies will also investigate hybrid optimization strategies by combining quantum-inspired algorithms with transformer-based deep learning and physics-informed neural networks (PINNs) to further improve prediction accuracy and convergence speed. The framework can be enhanced to support heterogeneous renewable energy systems, including photovoltaic–battery storage and PV–wind hybrid microgrids. Explainable Artificial Intelligence (XAI) techniques such as SHAP and LIME will be incorporated to improve the transparency and interpretability of optimization decisions. Moreover, future work will consider uncertainty-aware optimization under dynamic weather conditions, partial shading, and component degradation to improve long-term system reliability. Hardware implementation using FPGA- or GPU-based edge accelerators will also be investigated to enable low-latency deployment in smart energy management systems. Finally, comprehensive techno-economic and life-cycle assessments will be conducted to evaluate the scalability, cost-effectiveness, and environmental sustainability of AQNPOM for next-generation intelligent solar energy infrastructures.

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