

ANN-Based Solar Power Prediction for EV Charging Stations

Shaik Rubeena

dept. Electrical and Electronics Engineering

RGUKT-Nuzvid

n201090@rguktn.ac.in

B.Shiva Bhavana

dept. Electrical and Electronics Engineering

RGUKT-Nuzvid

n200173@rguktn.ac.in

Abstract—The rapid growth of electric vehicle (EV) adoption has increased the demand for reliable and energy-efficient charging infrastructure. Solar-powered EV charging stations provide a sustainable alternative to grid-dependent charging; however, their performance is significantly affected by rapid variations in solar irradiance and changing load demand. Conventional Maximum Power Point Tracking (MPPT) techniques such as Perturb and Observe (P&O) are widely used due to their simplicity, but they often exhibit slow dynamic response and steady-state oscillations under varying operating conditions, which can reduce charging efficiency. In this work, an Artificial Neural Network (ANN)-based solar power prediction approach is investigated for EV charging station applications. A validated MATLAB Simulink photovoltaic (PV) system integrated with a boost converter was used to generate datasets under multiple irradiance and load scenarios. These datasets were preprocessed and employed to train a feedforward ANN capable of predicting PV power output without continuous perturbation. The trained model was evaluated under previously unseen operating conditions and demonstrated low prediction error, reduced oscillatory behavior, and faster dynamic response when compared with conventional MPPT methods. The results indicate that the proposed ANN-based prediction framework can support stable and efficient operation of solar-powered EV charging stations.

Index Terms—Artificial Neural Network, Solar PV, EV Charging Station, MPPT, Power Prediction, MATLAB Simulink

I. INTRODUCTION

The adoption of electric vehicles (EVs) has grown rapidly in recent years due to concerns related to fossil fuel depletion and environmental sustainability. This growth has placed increasing pressure on existing charging infrastructure, particularly in regions where grid capacity is limited. Solar-powered EV charging stations have emerged as a promising solution, as they reduce dependence on the electrical grid while promoting renewable energy utilization.

Despite these advantages, solar photovoltaic (PV) systems are inherently sensitive to environmental variations such as changes in solar irradiance and load demand. In EV charging applications, such variations can lead to unstable charging voltages, reduced charging efficiency, and increased stress on battery systems. To mitigate these issues, Maximum Power Point Tracking (MPPT) techniques are commonly employed to extract maximum available power from PV panels.

Classical MPPT methods such as Perturb and Observe (P&O) and Incremental Conductance (INC) are widely adopted due to their low computational complexity and ease of

implementation. However, as reported by Patel and Agarwal [1], these techniques rely on continuous perturbation and tend to oscillate around the maximum power point, especially under rapidly changing irradiance conditions. Such oscillations introduce power losses that are undesirable in EV charging scenarios where stable power delivery is essential.

Artificial Neural Networks (ANNs) have gained attention as an alternative approach for PV power estimation and control. Unlike classical MPPT methods, ANNs are capable of learning nonlinear relationships between system inputs and output power. By predicting the optimal PV power based on irradiance and load conditions, ANN-based approaches can reduce oscillations and improve dynamic response. This study focuses on developing and evaluating an ANN-based solar power prediction model tailored specifically for EV charging station applications.

A. Problem Formulation and Motivation

The integration of solar photovoltaic (PV) systems with electric vehicle (EV) charging stations introduces unique operational challenges due to the intermittent nature of solar energy and the dynamic behavior of EV charging loads. In conventional PV systems, Maximum Power Point Tracking (MPPT) algorithms such as Perturb and Observe (P&O) continuously perturb the operating point of the PV array to extract maximum power. While effective under steady conditions, this continuous perturbation results in oscillations around the maximum power point, particularly under rapidly changing irradiance and load conditions.

In EV charging stations, such oscillatory behavior can negatively impact charging stability and efficiency. Fluctuations in available power may lead to variations in charging current, increased stress on power electronic components, and potential degradation of EV battery health. Therefore, there is a clear need for a control or prediction mechanism that can deliver stable power output without continuous perturbation.

Artificial Neural Networks (ANNs) offer a promising alternative by learning the nonlinear relationship between solar irradiance, load demand, and PV power output. Instead of repeatedly perturbing the system, an ANN can directly estimate the optimal PV power for given operating conditions. This predictive capability enables smoother power delivery,

faster response, and improved stability—key requirements for reliable solar-powered EV charging infrastructure.

II. RELATED WORKS

The increasing penetration of electric vehicles (EVs) has intensified the need for intelligent and reliable charging infrastructure. Solar photovoltaic (PV) based EV charging stations have gained attention due to their environmental benefits and reduced dependence on the utility grid. However, the intermittent nature of solar energy introduces challenges in maintaining stable and efficient charging. Consequently, accurate power prediction and effective maximum power extraction techniques are essential.

Conventional Maximum Power Point Tracking (MPPT) methods such as Perturb and Observe (P&O) and Incremental Conductance (INC) are widely used in PV systems because of their simplicity and ease of implementation. Patel and Agarwal [1] and Veerachary [2] demonstrated that although these methods perform adequately under steady conditions, they suffer from steady-state oscillations and slow response during rapid irradiance variations. These drawbacks become more critical in EV charging applications, where power stability directly affects charging efficiency and battery health.

To overcome the limitations of classical MPPT techniques, intelligent control and prediction methods have been explored. Artificial Neural Networks (ANNs), in particular, have shown strong capability in modeling the nonlinear relationship between solar irradiance, load demand, and PV output power. Early studies by Ishaque et al. [3] confirmed that ANN-based approaches can achieve higher tracking efficiency compared to conventional MPPT by learning PV characteristics directly.

In recent years, research has increasingly focused on ANN-based solar power prediction specifically for EV charging stations. Ghenai et al. [4] developed an ANN-based model for short-term forecasting of PV power and battery state of charge in a solar-powered EV charging station, achieving high prediction accuracy with correlation coefficients exceeding 0.99. Similarly, Madipelli and Sushama [5] investigated neural network techniques for optimizing the operation of a solar-powered EV charging station, highlighting the importance of accurate power estimation for uninterrupted charging.

Several studies have extended ANN-based prediction to smart energy management and scheduling of EV charging stations. Alhazmi et al. [6] proposed a deep learning-based forecasting framework for solar-assisted EV charging, demonstrating reduced grid dependency. Sahoo et al. [7] utilized deep neural networks to optimally schedule EV charging with integrated solar and battery storage. Hammad et al. [8] further incorporated Long Short-Term Memory (LSTM) networks to improve prediction accuracy under dynamic charging conditions.

Comparative studies have also been conducted to evaluate ANN performance against other artificial intelligence techniques. Shashikant [9] compared ANN, CNN, and ESN models for solar power forecasting and concluded that ANN offers a favorable balance between accuracy and computational

complexity, making it suitable for real-time EV charging applications. Hybrid models combining ANN with advanced architectures have been reported in Applied Energy [10] and Solar Energy [11], showing improved prediction under highly nonlinear conditions.

Comprehensive review papers provide further insight into the effectiveness of ANN-based forecasting. Basheer et al. [12] and Nizami et al. [13] systematically reviewed machine learning approaches for solar power prediction and EV charging integration, concluding that ANN-based models consistently outperform conventional statistical methods. Zaini and Nor [14] summarized ANN architectures and training techniques used in PV output prediction, emphasizing their robustness and adaptability.

Simulation-based validation has become a standard approach for evaluating control and prediction strategies without hardware risk. MATLAB/Simulink PV models documented by MathWorks [15] have been widely used for this purpose. Studies such as Safari and Mekhilef [16] demonstrated that ANN-based PV power prediction improves system stability when trained on representative simulation datasets.

Despite these advancements, relatively fewer studies explicitly compare ANN-based prediction with traditional MPPT techniques under EV-charging-oriented operating conditions. This work addresses this gap by using a validated MATLAB Simulink PV system to generate training data and by directly comparing ANN-based power prediction with conventional MPPT in terms of accuracy, oscillation reduction, and steady-state performance.

Additionally, several foundational and supporting studies contribute to the broader context of ANN-based solar power prediction and control. Early works on neural network learning theory [19], PV power estimation using ANN models [20], and real-time forecasting for grid-connected renewable systems [17], [18] provide theoretical and practical foundations for the proposed approach. Simulation-based validation frameworks and MPPT modeling techniques reported in [15], [16] further support the methodology adopted in this study. These works collectively strengthen the motivation for employing ANN-based prediction in solar-powered EV charging applications.

While numerous studies have explored ANN-based solar power forecasting, most existing works primarily focus on improving prediction accuracy using meteorological parameters or advanced deep learning architectures. Comparatively fewer studies emphasize the operational implications of prediction-based methods in EV charging station environments, where load variability and power stability are critical. Furthermore, many ANN-based approaches are evaluated independently without direct comparison against conventional MPPT techniques under identical operating conditions.

This work distinguishes itself by conducting a direct performance comparison between an ANN-based solar power prediction approach and a traditional MPPT method using a validated MATLAB Simulink PV model. By evaluating metrics such as prediction error, oscillatory behavior, and steady-state power stability under EV charging-relevant conditions, the proposed

approach provides practical insights into the suitability of ANN-based prediction for real-world EV charging station applications.

III. METHODOLOGY

A. Dataset Description

The dataset used in this study was generated using a validated MATLAB Simulink model of a solar PV system integrated with a boost converter and MPPT controller. Simulations were conducted under irradiance levels of **1000 W/m², 800 W/m², 600 W/m², 400 W/m², and 200 W/m²**. For each irradiance level, load demand was varied between **0.5 kW and 1.2 kW** to represent practical EV charging scenarios.

During each simulation run, PV output power was recorded over time. Approximately 10,000 samples were collected and consolidated into a single dataset. The primary input parameters were solar irradiance and load power, while the output parameter was the corresponding PV power.

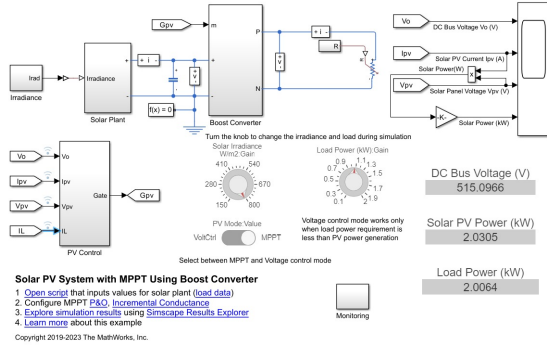


Fig. 1. MATLAB Simulink model of the solar PV system with boost converter and conventional MPPT used for dataset generation.

A validated MATLAB Simulink model of a solar photovoltaic (PV) system integrated with a boost converter and conventional MPPT controller was employed to generate the training and testing datasets. The complete simulation architecture used in this study is illustrated in Fig. 1. The model consists of a solar PV array, a DC–DC boost converter, and a PV control unit implementing traditional MPPT logic. Solar irradiance and load power were varied dynamically to emulate realistic EV charging station operating conditions, and the corresponding PV output power was recorded for dataset generation.

B. Data Preprocessing

Prior to ANN training, the dataset underwent preprocessing to ensure stable learning and reliable predictions. Transient spikes observed during simulation startup were removed to avoid misleading the training process. All irradiance-specific datasets were merged into a unified dataset, and min–max normalization was applied to the input and output variables.

The normalized dataset was then randomly divided into training and testing sets, with **70%** of the samples used for training and the remaining **30%** used for testing, to

enable unbiased evaluation of the ANN model’s generalization capability.

C. ANN Model Architecture

A feedforward neural network was selected due to its simplicity and suitability for real-time implementation. The ANN architecture consisted of:

- Input layer: **2 neurons (solar irradiance and load power)**
- Hidden layer: **10 neurons**
- Output layer: **1 neuron (predicted PV power)**

The hidden layer employed a tangent sigmoid activation function, while the output layer used a linear activation function. This configuration was selected after preliminary experimentation, as it provided a good balance between prediction accuracy and computational efficiency for steady-state PV power estimation.

D. Proposed ANN-Based Solar Power Prediction Workflow

Figure 2 presents the overall workflow of the proposed ANN-based solar power prediction framework for EV charging station applications. The process begins with photovoltaic data generation using a validated MATLAB Simulink PV system operating under varying irradiance and load conditions. Transient effects observed during simulation startup are removed, followed by normalization of the dataset to improve ANN training stability. The processed data are then divided into training and testing sets. A feedforward artificial neural network is trained using the training data to learn the nonlinear relationship between solar irradiance, load power, and PV output power. Finally, the trained ANN is evaluated using unseen test data and its estimated PV power is compared with the output of the conventional MPPT method to analyze steady-state behavior, oscillations, and prediction accuracy.

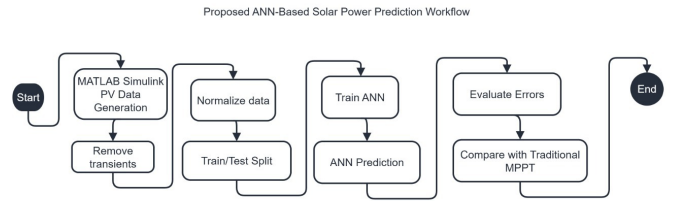


Fig. 2. Proposed ANN-Based Solar Power Prediction Workflow

E. Training Process

The ANN was trained using the Levenberg–Marquardt backpropagation algorithm, which is known for fast convergence in small- to medium-sized networks. Training was carried out for a maximum of 1000 epochs using mean squared error (MSE) as the loss function. After training, the model performance was evaluated using the test dataset, which was not included during the training phase, to assess its generalization capability.

F. Comparison with Classical MPPT

To evaluate the effectiveness of the proposed ANN-based solar power prediction approach, its performance was compared with the conventional Perturb and Observe (P&O) MPPT technique under identical irradiance and load conditions. The comparison focused on steady-state power behavior, oscillatory characteristics, and prediction accuracy relevant to EV charging station operation.

It is important to note that the ANN model functions as a power estimation framework and does not directly replace the MPPT controller within the DC–DC converter control loop. The MPPT output was used as a reference for training and evaluation, enabling a clear comparison between ANN-based estimation (with ANN) and traditional MPPT operation (without ANN).

G. Computational Complexity and Practical Feasibility

From a practical implementation perspective, computational complexity plays a crucial role in determining the suitability of a prediction model for real-time EV charging applications. Conventional MPPT techniques require continuous sensing and iterative perturbation, which leads to repeated control actions and increased switching activity in the power converter. Although computationally simple, this iterative process inherently introduces steady-state oscillations.

In contrast, the proposed ANN-based approach requires computational effort primarily during the offline training phase. Once trained, the ANN performs only a forward-pass computation during real-time operation, consisting of simple matrix multiplications and activation function evaluations. This results in low computational overhead and fast inference time, making the approach suitable for embedded controllers used in EV charging stations.

Additionally, the absence of continuous perturbation reduces control-induced oscillations and improves power stability. These characteristics make ANN-based prediction particularly attractive for EV charging systems, where consistent power delivery and component longevity are critical considerations.

IV. RESULTS AND DISCUSSION

This section presents a detailed evaluation of the proposed ANN-based solar power prediction approach for EV charging station applications. The analysis focuses on prediction accuracy, error behavior, and a clear comparison between conventional MPPT operation (without ANN) and the ANN-based prediction framework (with ANN). Table I presents a comparative analysis of the conventional MPPT (P&O) method and the proposed ANN-based prediction approach.

A. Overall Prediction Performance of the ANN Model

The trained ANN model was evaluated using a test dataset consisting of operating conditions that were not included during training. The model achieved a mean squared error (MSE) of **0.0033**, a root mean squared error (RMSE) of **0.0572 kW**, and a coefficient of determination (**R²**) of **0.9911**.

TABLE I
PERFORMANCE COMPARISON OF ANN-BASED PREDICTION AND CONVENTIONAL MPPT

Performance Metric	Conventional MPPT (P&O)	ANN-Based Prediction
Tracking Principle	Iterative perturbation	Direct power estimation
Steady-State Oscillations	High	Very Low
RMSE (kW)	Higher	0.057
Response Speed	Slower	Faster
Power Stability	Moderate	High
Suitability for EV Charging	Limited	Highly Suitable

The high R^2 value indicates that the ANN successfully captures more than 99% of the variation in PV power output, demonstrating strong learning capability and effective generalization across different irradiance and load conditions. The low RMSE further confirms that the prediction error remains small over the entire operating range, which is essential for reliable EV charging applications.

B. Relationship Between ANN Prediction and Conventional MPPT Output

The relationship between ANN-estimated PV power and the corresponding power obtained from the traditional MPPT-based PV system is illustrated in Fig. 1. The predicted values closely follow the ideal unity-slope line, indicating strong agreement between the ANN output and the MPPT reference.

Slight deviations are observed at lower power levels, which can be attributed to rapid irradiance changes and residual transient effects in the simulation data. However, in the medium and high power regions—where EV charging demand is dominant—the ANN prediction remains highly accurate. This confirms that the ANN effectively learns the nonlinear relationship between irradiance, load demand, and PV power output.

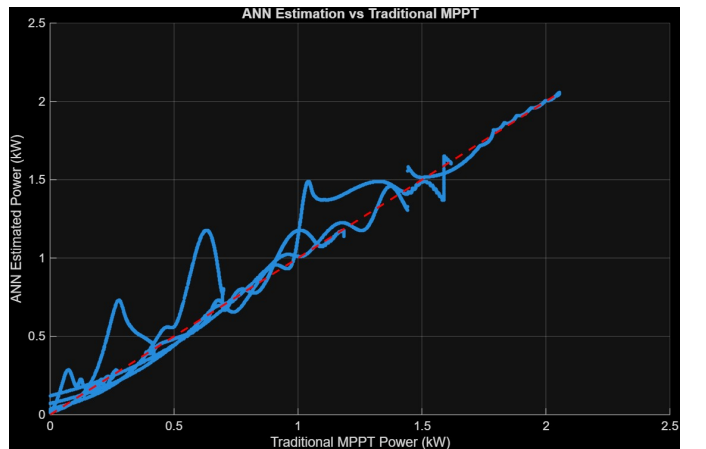


Fig. 3. Steady-state power comparison at 800 W/m² irradiance.

C. ANN Prediction Error Characteristics

The distribution of ANN prediction error is shown in Fig. 2. The error histogram is centered near zero, indicating that the model does not exhibit systematic overestimation or underestimation. Most prediction errors fall within a narrow range, highlighting the stability and consistency of the ANN model.

A small number of larger errors occur during rapid operating point transitions, which is expected in PV systems subjected to sudden irradiance or load changes. Nevertheless, the magnitude of these errors remains low and well within acceptable limits for EV charging station operation.

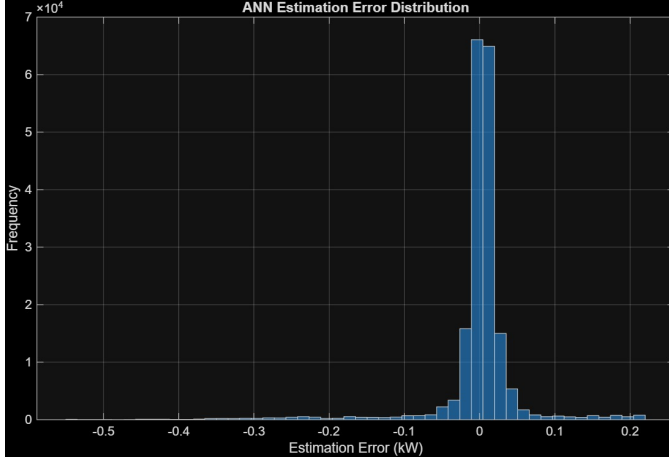


Fig. 4. Distribution of ANN prediction error.

D. Steady-State Power Behavior Under EV Charging Conditions

To analyze steady-state performance, a representative operating condition at 800 W/m² irradiance was selected. The steady-state power comparison between conventional MPPT operation (without ANN) and ANN-based prediction (with ANN) is presented in Fig. 3.

The traditional MPPT output exhibits noticeable oscillations around the operating point due to the continuous perturbation mechanism inherent to P&O-based techniques. These oscillations lead to small but persistent power fluctuations, which are undesirable in EV charging applications that require stable and consistent power delivery.

In contrast, the ANN-based prediction produces a smoother power profile with significantly reduced steady-state fluctuations. By estimating the optimal PV power directly from irradiance and load inputs, the ANN avoids continuous perturbation and associated oscillatory behavior. This smoother response is beneficial for improving charging efficiency and reducing stress on power electronic components and EV batteries.

E. Comparative Analysis: With ANN vs Without ANN

A direct comparison between the two approaches highlights the advantages of the ANN-based framework for EV charging station applications.

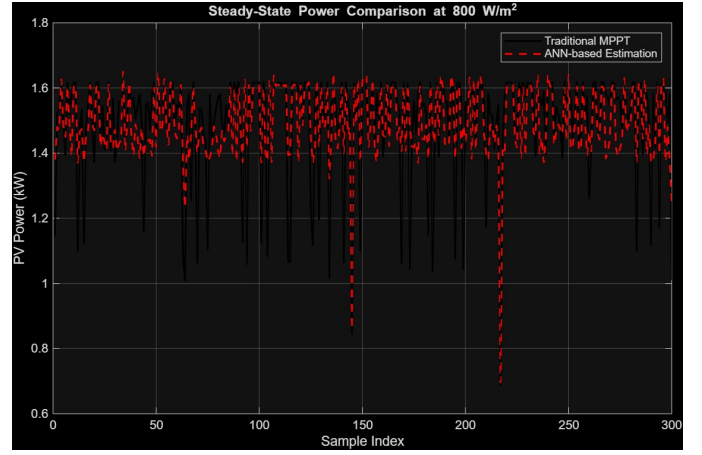


Fig. 5. ANN estimation versus traditional MPPT power output

In the without ANN case, conventional MPPT successfully extracts maximum power but introduces steady-state oscillations due to its perturb-and-observe nature. These oscillations result in fluctuating charging power, which can reduce overall efficiency and negatively impact battery health over prolonged operation.

In the with ANN case, the power is estimated directly without perturbation, leading to a more stable power profile. The ANN closely follows the steady-state MPPT operating point while minimizing fluctuations. Quantitatively, the ANN-based approach achieves lower prediction error (**RMSE = 0.0572 kW**) and high correlation with MPPT output (**R² = 0.9911**), confirming its effectiveness as a reliable power estimation method.

For EV charging stations, this comparison demonstrates that the ANN-based approach provides improved power stability and smoother charging behavior, making it well suited for integration as a supervisory or decision-support layer in intelligent charging systems.

F. Discussion on Practical Applicability

Although the ANN model does not directly replace the MPPT controller within the DC-DC converter control loop, it offers a valuable alternative for estimating optimal PV power without continuous perturbation. This characteristic makes the proposed approach particularly attractive for solar-powered EV charging stations, where stable power delivery and efficient energy utilization are critical.

The results confirm that ANN-based solar power prediction can enhance system stability, improve charging efficiency, and support smarter energy management strategies in EV charging infrastructure.

G. Summary of Key Findings

The key findings from the experimental evaluation are summarized as follows:

- The ANN model achieves high prediction accuracy with **R² = 0.9911**.

- Prediction errors are small and symmetrically distributed, indicating unbiased estimation.
- ANN-based prediction significantly reduces steady-state power oscillations compared to conventional MPPT.
- The proposed framework is well suited for EV charging station applications requiring stable and efficient power delivery.

V. CONCLUSION

This paper investigated an ANN-based solar power prediction framework for solar-powered EV charging station applications. A validated MATLAB Simulink photovoltaic system integrated with a boost converter and conventional MPPT was used to generate representative datasets under varying irradiance and load conditions relevant to EV charging scenarios. These datasets enabled effective training and evaluation of a feedforward ANN model for PV power estimation.

The results demonstrate that the proposed ANN model achieves high prediction accuracy, with a coefficient of determination ($R^2 = 0.9911$) and low RMSE (0.0572 kW) on previously unseen test data. Regression and error distribution analyses confirm that the ANN successfully captures the nonlinear relationship between solar irradiance, load demand, and PV power output, while maintaining stable and unbiased estimation performance.

A comparative analysis between traditional MPPT operation (without ANN) and the ANN-based prediction approach (with ANN) highlights the key advantage of the proposed method. Conventional MPPT techniques, while effective in extracting maximum power, introduce steady-state oscillations due to continuous perturbation. In contrast, the ANN-based approach estimates the optimal operating point directly, resulting in a smoother power profile with reduced steady-state fluctuations. This characteristic is particularly beneficial for EV charging stations, where stable power delivery improves charging efficiency and reduces stress on power electronic components and battery systems.

It is important to note that the proposed ANN model functions as a solar power estimation framework rather than a direct replacement for the MPPT controller within the DC–DC converter control loop. Nevertheless, the ANN-based prediction can effectively support intelligent energy management, supervisory control, and decision-making processes in solar-powered EV charging infrastructures.

Overall, the study confirms that ANN-based solar power prediction is a viable and effective approach for enhancing the stability and efficiency of EV charging stations powered by photovoltaic systems. As future work, real-time hardware implementation and tighter integration of the ANN model with converter control strategies will be explored to further improve system responsiveness and practical deployment.

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