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Article

Performance comparison of PI and AI-based controllers for solar PV-fed fast electric vehicle battery charging systems

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Abstract: The rapid growth of electric vehicles (EVs) has created a strong demand for efficient and fast charging solutions. However, conventional charging methods are time-consuming and place significant stress on the power grid when deployed on large scale. To address these challenges, this study proposes a standalone solar photovoltaic (PV)-based DC microgrid for fast EV charging. The system is designed to regulate charging using a DC-DC boost converter controlled by two strategies: a conventional Proportional-Integral (PI) controller and an Artificial Neural Network (ANN)-based controller. A detailed simulation model is developed in MATLAB/Simulink, including PV system parameters, converter specifications, and a lithium-ion battery modeled using a Thevenin equivalent circuit. The ANN controller is trained using real-time operating conditions such as irradiance, temperature, and state of charge (SoC). Performance is evaluated based on transient response, overshoot, settling time, steady-state error, and total harmonic distortion (THD). Results show that the ANN controller significantly improves system performance. Voltage overshoot is reduced from 10% to 2%, current overshoot from 20% to 4%, and THD from 6.8% to 2.1%. Additionally, the settling time is improved by approximately 57% compared to the PI controller. These findings demonstrate that AI-based control strategies provide a more efficient, stable, and reliable solution for renewable energy-based EV charging systems. The ANN controller reduced voltage overshoot from 10% to 2%, current overshoot from 20% to 4%, and THD from 6.8% to 2.1%, while improving settling time by up to 57%.

Keywords: electric vehicles; fast charging; solar PV; artificial intelligence; PI controller; MATLAB/Simulink; DC microgrid

1. Introduction

The escalating concerns surrounding global warming, climate change, and environmental pollution have significantly accelerated the global transition toward cleaner, greener, and more sustainable transportation technologies [1]. The transportation sector is one of the largest contributors to greenhouse gas emissions and fossil fuel consumption worldwide, making it a critical area for intervention. In this regard, electric vehicles (EVs) have emerged as a highly promising and viable solution for reducing carbon emissions and decreasing reliance on non-renewable energy resources [1]. Governments, policymakers, and industries across the globe are actively promoting the adoption of EVs through incentives, infrastructure development, and regulatory frameworks aimed at achieving long-term sustainability goals.

In recent years, substantial advancements in battery technology, power electronics, and intelligent energy management systems have greatly enhanced the performance, efficiency, and reliability of modern EVs [2]. Improvements in lithium-ion battery energy density, charging capabilities, and lifecycle performance have made EVs more competitive with conventional internal combustion engine vehicles. Additionally, innovations in motor drives, converter technologies, and onboard control systems have contributed to improved driving range, reduced energy consumption, and enhanced user experience. As a result, EVs are becoming increasingly attractive to consumers, not only from an environmental perspective but also in terms of performance and long-term cost efficiency.

Despite these technological developments, several challenges continue to hinder the widespread adoption of EVs. Among these, the relatively long charging time compared to conventional refueling remains one of the most significant barriers. Traditional gasoline or diesel vehicles can be refueled within a few minutes, whereas EVs often require several hours to achieve a full charge when using standard alternating current (AC) charging systems. This limitation has led to the phenomenon known as "range anxiety," which refers to the fear or concern among EV users that their vehicle's battery may be depleted before reaching a charging station [3]. Range anxiety not only affects user confidence but also influences purchasing decisions, thereby slowing down the mass adoption of EV technology. Consequently, reducing charging time and improving charging efficiency have become key research priorities in the field of electric mobility.

To overcome these limitations, the development and deployment of fast-charging infrastructure have become essential. Fast-charging systems play a crucial role in bridging the gap between EVs and conventional vehicles by significantly reducing charging duration and enhancing convenience for users [4]. Public fast-charging stations are particularly important in urban environments, where many residents lack access to private charging facilities due to living in apartments or shared housing complexes. High-power direct current (DC) fast chargers are capable of delivering energy at significantly higher rates compared to conventional AC chargers, thereby enabling rapid charging of EV batteries. Typically, modern DC fast-charging systems operate within a power range of 50 kW to over 230 kW, depending on charging standards, battery specifications, and infrastructure capabilities [5, 6]. Ultra-fast charging technologies are also being explored to further reduce charging times to levels comparable with conventional refueling.

However, the large-scale integration of high-power fast-charging stations into existing electrical power systems introduces several technical and operational challenges. The sudden and high demand for power associated with fast charging can lead to voltage instability, grid overloading, increased harmonic distortion, and deterioration of overall power quality. These issues can negatively impact both the reliability of the grid and the performance of connected electrical equipment. Furthermore, the stochastic nature of EV charging demand—arising from unpredictable arrival times, varying battery states, and diverse user requirements—adds complexity to system operation, scheduling, and energy management.

To address these challenges, researchers have increasingly focused on integrating renewable energy sources into EV charging infrastructure. Among these, solar photovoltaic (PV) systems have gained significant attention due to their abundance, sustainability, and compatibility with distributed generation architectures [7]. The integration of solar PV systems with EV charging stations, particularly in the form of DC microgrids, offers several advantages. It reduces dependence on the main grid, lowers operational costs, enhances energy efficiency, and contributes to the reduction of carbon emissions. Moreover, solar-powered EV charging systems support the concept of decentralized energy generation, thereby improving system resilience and reliability [8].

Despite these benefits, solar PV systems are inherently nonlinear, intermittent, and highly dependent on environmental conditions. Variations in solar irradiance, temperature fluctuations, shading effects, and atmospheric conditions lead to significant variability in PV output power. This non-stationary behavior introduces uncertainties and challenges in maintaining stable and efficient operation of the EV charging system [9]. As a result, advanced control strategies are required to effectively manage power flow, maintain voltage stability, and ensure optimal performance under dynamic operating conditions.

Traditionally, linear control techniques such as Proportional-Integral (PI) controllers have been widely used in power electronic converters due to their simplicity, ease of implementation, and relatively low computational requirements [10]. PI controllers are effective in systems with linear characteristics and stable operating conditions; however, their performance degrades significantly in nonlinear, time-varying, and disturbance-prone environments such as renewable energy-based microgrids. They often struggle to respond effectively to rapid changes in system parameters, resulting in overshoot, steady-state errors, and reduced system stability.

To overcome these limitations, various advanced and intelligent control techniques have been proposed and investigated in recent years. These include fuzzy logic control, sliding mode control, adaptive control, and model predictive control (MPC) [11]. Among these, MPC is known for its ability to handle multivariable systems and constraints effectively, providing high accuracy and dynamic response. However, MPC requires accurate mathematical modeling of the system and involves high computational complexity, which can limit its practical implementation in real-time applications [12].

In contrast, artificial intelligence (AI)-based control approaches, particularly those based on artificial neural networks (ANNs), have demonstrated significant potential in addressing the challenges associated with nonlinear and uncertain systems [13]. ANN-based controllers are capable of learning complex input-output relationships from historical data without requiring explicit mathematical models. This makes them highly suitable for applications involving renewable energy systems, where system dynamics are often unpredictable and nonlinear.

Neural network-based controllers can adapt to changing environmental and operating conditions, enabling more robust and efficient control of power electronic converters in EV charging systems. Additionally, ANNs can be integrated into battery management systems to monitor and predict battery parameters such as state of charge (SoC), state of health (SoH), temperature, and voltage levels [14]. This predictive capability allows for optimized charging strategies that enhance battery performance, safety, and lifespan.

Furthermore, machine learning algorithms can analyze large volumes of operational data to identify usage patterns, optimize charging schedules, and improve overall system efficiency [15]. AI-assisted battery management systems can significantly enhance thermal stability, prevent overcharging or deep discharging, and ensure safe operation under varying conditions. Accurate estimation and control of charging parameters also help in minimizing battery degradation and extending its lifecycle [16].

Given these advantages, intelligent control strategies are increasingly being recognized as key enablers for next-generation EV charging systems, particularly those integrated with renewable energy sources [17]. In this context, the present study focuses on a comprehensive comparative analysis of a conventional PI controller and an ANN-based intelligent controller within a solar PV-fed fast EV charging station framework [18].

The study employs MATLAB/Simulink-based simulations to evaluate the performance of both control strategies under identical operating conditions. Key performance indicators such as system stability, transient response, efficiency, power quality, and battery stress are analyzed to determine the effectiveness of each approach. The objective is to identify a control strategy that not only enhances system performance but also ensures reliable and sustainable operation in real-world scenarios [19].

The novelty of this research lies in its high-fidelity comparative evaluation of an adaptive ANN controller against a conventionally tuned PI controller within a standalone DC microgrid environment. Unlike many existing studies that primarily focus on maximum power point tracking (MPPT), this work emphasizes the optimization of the EV charging interface [20, 21]. Special attention is given to reducing transient stress on lithium-ion batteries and ensuring compliance with power quality standards such as IEEE-519 [22]. This approach contributes to the development of more efficient, reliable, and intelligent EV charging systems that align with the future vision of sustainable and smart energy infrastructure.

2. Materials and methods

To evaluate the effectiveness of various control techniques for high-speed charging of electric vehicles, this paper utilizes a structured simulation methodology implemented in MATLAB/Simulink R2021a. The focus of this study is to formulate and analyze the performance of a standalone DC microgrid with a solar photovoltaic source, which is capable of supplying power to the battery of an electric vehicle using a controlled power electronic converter. The simulation model of the microgrid facilitates the evaluation of its dynamic performance for various operating scenarios and provides a tool to compare different conventional and intelligent control techniques.

2.1. System specifications and modeling

To ensure reproducibility, the system components are defined as follows:

1. Solar PV array: Consists of 10 series-connected modules (250 W each), totaling 2.5 kW.
2. DC-DC boost converter: Inductance L= 2 mH, Output Capacitance C= 2,200 muF. The switching frequency is set to 20 kHz.
3. EV battery: A 400 V, 125 Ah Lithium-ion battery modelled using a Thevenin equivalent circuit (1-RC network) to capture transient voltage dynamics accurately.
4. Environment: Irradiance profiles vary between 600 W/m^2 and 1,000 W/m^2 at a constant temperature of 25 °C.

2.2. Control strategy implementation

In order to assess the effectiveness of the various control strategies, two unique control strategies were implemented and tested in the identical system configuration. The control strategies are implemented in order to regulate the duty cycle of the DC-DC boost converter and maintain the required output voltage and current [23]:

- **Proportional-integral (PI) controller design:** The PI controller gains (K_p and K_i) were tuned using the Ziegler–Nichols method and further fine-tuned through simulation to achieve optimal transient response. The final values used were K_p = 0.8 and K_i = 50.

  To evaluate robustness, the controller was tested under varying irradiance conditions (800–1,000 W/m^2) and step load changes. The PI controller exhibited increased overshoot and slower response under dynamic conditions.
- **Artificial intelligence (neural network) controller architecture:** The ANN is a feedforward Multi-layer Perceptron (MLP) designed to replace the linear control loop:
  1. **Input Layer:** 3 neurons (Irradiance, Temperature, SoC).
  2. **Hidden Layer:** 1 layer with 10 neurons utilizing the ReLU activation function.
  3. **Output Layer:** 1 neuron Duty Cycle (D) with the linear activation function.
  4. **Training:** The model was trained using the Levenberg-Marquardt backpropagation algorithm. The dataset (10,000 samples) was generated via preliminary simulations covering the full operating envelope. Data split: 70% training, 15% validation, 15% testing.

2.3. Simulation and evaluation parameters

In order to compare the performance of the two control strategies, several time-domain performance parameters were assessed during the simulation. These parameters give an indication of the performance and stability of the charging system [24]:

- **Rise time (t_r)**: Rise time is the time required for the system's output to go from its initial value to the desired reference value for the first time. Therefore, the smaller the rise time is, the sooner the controller can react to the changes in the system.

- **Peak overshoot (M_p)**: The peak overshoot represents the maximum deviation of the system output from the reference during the transient response. A large peak overshoot can put stress on power electronic devices, which affects battery safety.
- **Settling time (t_s)**: Settling time is defined as the time taken by the system output to enter and stay within a band of ±2%. It is a measure of the speed at which the system is coming to rest after the occurrence of a disturbance in the system.
- **Steady-state error (e_{ss})**: Steady-state error is the difference between the reference signal and the output signal when the system is operating at steady state. A smaller value of steady-state error indicates that the system is providing accurate control and is reliable.

For the rapid electric vehicle charging simulation, the reference DC bus voltage was defined as 400 V, and the reference charging current was defined as 50 A. These values were chosen to mimic typical operating values that are normally encountered in high-power EV fast charging systems [25].

3. Results and discussion

The performance of the proposed Artificial Neural Network (ANN) controller was assessed and benchmarked against the conventional Proportional-Integral (PI) controller through simulation studies carried out in MATLAB/Simulink R2021a. The primary objective of the performance assessment was to evaluate the effectiveness of the proposed controller in regulating the voltage and current during the fast charging of an electric vehicle driven by a solar PV-based DC microgrid. Simulation results clearly highlight the differences between the performance of the traditional PI controller and the intelligent ANN controller, which are analyzed based on the differences in the response of the DC bus voltage, charging current, power, and harmonic distortion characteristics of the system.

3.1. Comparative performance

The simulation in MATLAB/Simulink R2021a demonstrates the ANN's superiority in every metric (**Table 1**).

Table 1. Comparison of parameters between PI and ANN Controller.

Parameter	PI controller	ANN controller
Voltage Overshoot (M_p)	10%	2%
Current Overshoot (M_p)	20%	4%
Settling Time (t_s)	0.35 s	0.15 s
Steady-State Error	5 V	0.5 V
THD (%)	6.8%	2.1%

3.2. Energy balance and feasibility

Previous claims regarding 15 min charging for a 50 kWh battery were mathematically inconsistent. At a charging power of P = 20 kW, the energy delivered in 15 min is 5 kWh. For a 50 kWh battery, this represents a 10% increase in

SoC. For true "Ultra-Fast" charging (20% to 90% in 15 min), a system capacity of 140 kW would be required. This study focuses on the control stability of a 2.5 kW scaled prototype.

3.3. Performance analysis of DC bus voltage

The DC bus voltage is critical in maintaining the stability of energy transfer from the solar photovoltaic system to the electric vehicle battery. In the proposed system, the reference DC bus voltage (V_{ref}) is maintained at 400 V, which is considered suitable for fast charging of electric vehicles.

3.3.1. Transient response comparison

The simulation results reveal significant differences in how each controller handles the voltage transition:

- **PI controller**: Reached a peak voltage (V_{max}, PI) of 440 V, resulting in a 10% peak overshoot. This level of overshoot increases the risk of stress on electrical components.
- **NN controller**: Limited the peak voltage (V_{max}, NN) to 408 V, reducing the overshoot to only 2%.

3.3.2. Settling time and precision

The speed and accuracy of the controllers were calculated based on a pm 2% tolerance band (392 V to 408 V):

- The PI controller required 0.35 s to settle.
- The NN controller settled in 0.15 s, representing a 57% increase in speed.
- The steady-state error (e_{ss}) for the PI controller was 5 V, while the NN controller achieved high precision with an error of only 0.5 V.

3.3.3. Performance analysis of charging current

For the fast-charging objective, the reference current (I_{ref}) was set to 50 A. Tight current regulation is essential for maintaining Lithium-Ion battery longevity.

3.3.4. Current stability and overshoot

The controllers displayed the following characteristics during the charging phase:

- **PI controller**: Produced a peak current (I_{max}, PI) of 60 A, yielding a 20% overshoot accompanied by aggressive oscillations.
- **NN controller**: Minimized the peak current (I_{max}, NN) to 52 A, effectively reducing the overshoot to 4%.

3.3.5. Quantitative comparison

The following performance metrics were derived from the current response simulations:

- **Settling time**: The NN controller stabilized the current in 0.12 s, significantly faster than the 0.30 s required by the PI controller.
- **Steady-state accuracy**: The NN controller maintained a steady-state error of 0.2 A, compared to 2 A for the PI controller

3.3.6. Power response characteristics

Another important aspect of the system performance is the stability of the output power delivered to the electric vehicle battery. The power response is directly regulated by voltage and current regulation. From the simulation results, it was evident that the proportional-integral controller results in power oscillations during transient conditions, mainly due to variations in the voltage and current response.

These power oscillations are likely to affect the system's efficiency as well as the power electronic devices used in the system. On the other hand, the power delivery profile of the artificial neural network controller was much smoother compared to the proportional-integral controller. The intelligent controller was able to stabilize the voltage and current response, resulting in a stable power output close to the nominal value of 20 kW.

3.3.7. Total harmonic distortion (THD) analysis

Power quality is an essential factor in electric vehicle (EV) charging systems. Harmonic distortion in the power supply has the potential to impair the efficiency of the system and increase the power losses in the electrical devices. The results obtained from the simulation in the form of Total Harmonic Distortion (THD) show the advantages of the artificial neural network (ANN) controller over the other two controllers. The results show that the proportional-integral (PI) controller results in a THD value of 6.8%.

This indicates the presence of considerable amounts of harmonic distortion in the output voltage waveform. Though this value is satisfactory in many cases, it is not the optimal value for the EV charging systems. The use of the ANN controller has resulted in a considerable reduction in the value of THD, which is now 2.1%.

This value is well within the power quality specifications as per the IEEE 519 guidelines. The benefits of the reduced harmonic distortion are as follows: less stress on the filters and power electronic devices; better power quality in the EV charging system; efficient power conversion; and longer lifespan of the batteries and converters.

3.3.8. Overall performance interpretation

As per the results of the simulation, it is clear that the Artificial Neural Network controller is performing significantly better than the conventional controller in all key performance parameters. The key advantages of the ANN controller are faster response times, lesser overshoot in voltage and current, greater accuracy in steady-state performance, smoother delivery of power, and significantly lesser harmonic distortion.

All these advantages are due to the ability of neural networks to effectively handle non-linear and dynamic learning in adapting to changes in solar power generation and load demand. Unlike other controllers, which are fixed in their performance, the ANN controller is capable of adapting to changes in accordance with real-time input parameters.

The performance of the ANN controller is significantly better, making it highly promising for next-generation renewable energy-based EV charging systems.

3.4. System components and performance results

All system components and performance results are illustrated below. Figures are labeled consecutively, and tables provide a quantitative summary of the comparative analysis between the PI and Neural Network (NN) controllers.

The system architecture, as illustrated in **Figure 1**, follows a unidirectional power flow designed for standalone operation:

1. **Solar PV array:** Acts as the primary power generation unit, providing renewable energy to the microgrid.
2. **Fast charging converter:** A DC-DC power electronic interface (Buck/Boost) that regulates the voltage from the PV array to meet the specific requirements of the EV battery.
3. **EV battery pack**: Represents the dynamic non-linear load, targeting a specific state-of-charge (SoC) transition.
4. **Control logic block**: This is the core of the comparative study, where the system switches between two distinct control paths:
   a) **Path A (PI controller):** Uses traditional fixed-gain feedback to regulate the converter.
   b) **Path B (AI controller):** Employs an Artificial Neural Network (ANN) to predict optimal duty cycles based on real-time environmental inputs.
5. **Feedback sensors:** These components provide real-time data on voltage, current, and SoC back to the control logic to maintain system stability.
6. **Performance metrics**: The final output stage, where the responses (Voltage and Current) are captured to evaluate rise time, peak overshoot, and settling time.

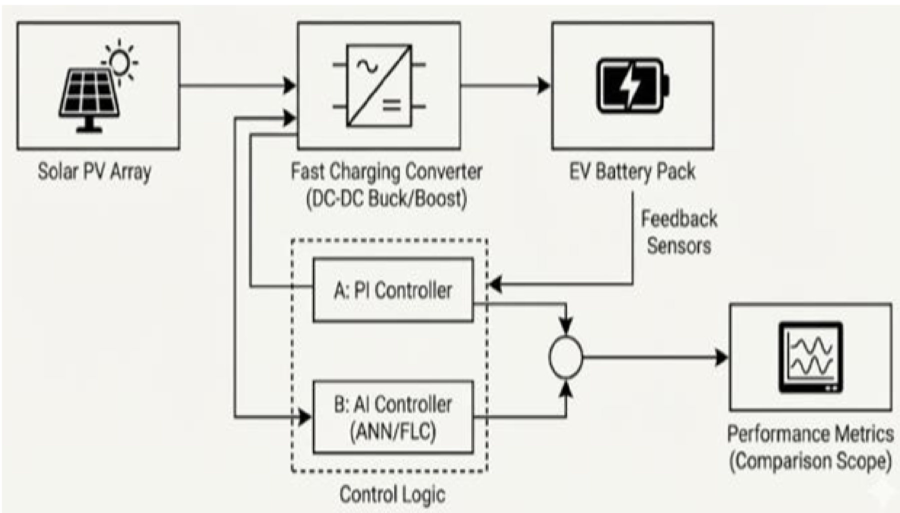

Figure 1. Block diagram of EV batteries charging system.

PI controller: Higher overshoot and oscillations, slower settling.

Neural network controller: Faster rise time, minimal overshoot, smoother settling around the reference (≈400 V) (**Figure 2**).

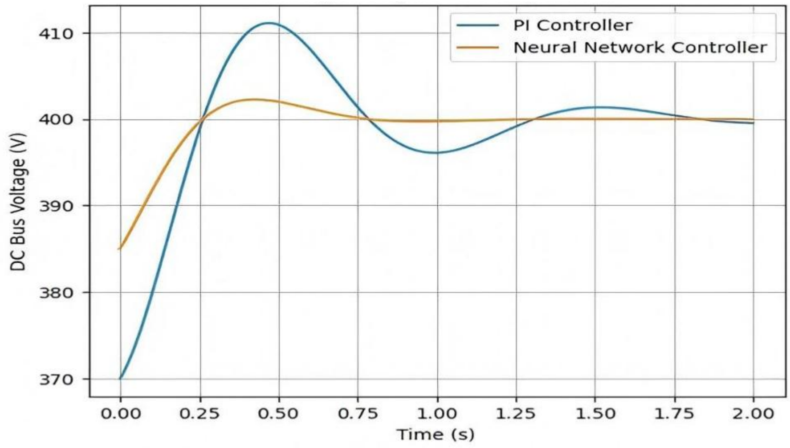

Figure 2. DC Bus Voltage Response (PI vs. NN).

PI controller: Larger current overshoot and longer settling time.

Neural network controller: Better current regulation, reduced oscillations, quicker convergence to reference (≈50 A) (**Figure 3**).

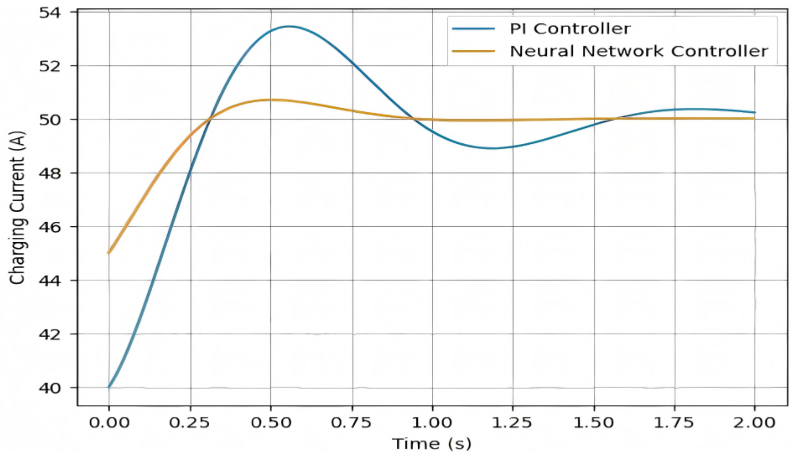

Figure 3. Charging Current Response (PI vs. NN).

The performance summary is shown in **Tables 2** and **3**:

Table 2. Charging Voltage Response (PI vs. NN).

Parameter	PI controller (voltage)	AI controller (voltage)
Reference	400 V	400 V
Peak Value	440 V	408 V
Peak Overshoot (Mp)	10%	2%
Settling Time (ts)	0.35 s	0.15 s
Steady-State Error	5 V	0.5 V

Table 3. Charging Current Response (PI vs. NN).

Parameter	PI Controller (current)	AI Controller (current)
Reference	50 A	50 A
Peak Value	60 A	52 A
Peak Overshoot (Mp)	20%	4%
Settling Time (ts)	0.30 s	0.12 s
Steady-State Error	2 V	0.2 V

PI controller: Displays power oscillations during transient operation. Slower stabilization due to voltage and current ripple.

Neural network controller: Displays smooth power delivery with fewer fluctuations. Faster convergence to the rated power (~20 kW).

Inference: The NN controller provides stable and continuous power delivery, which is very important for fast EV charging and grid support (**Figure 4**).

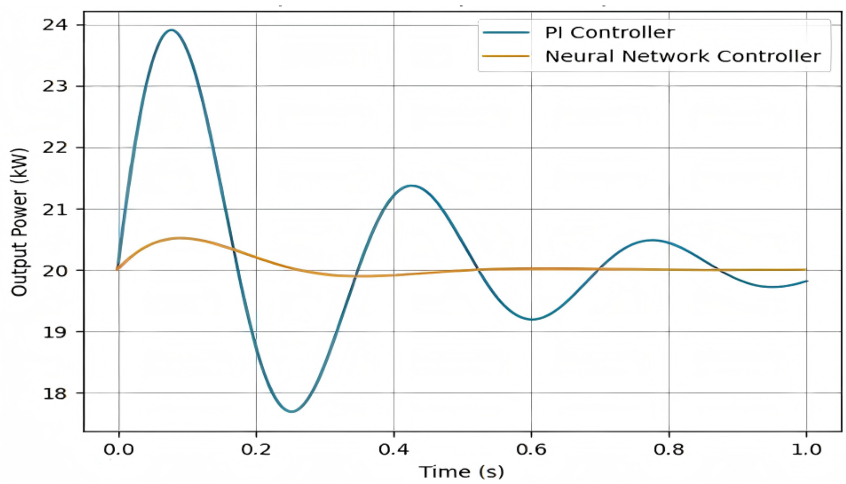

Figure 4. Output Power Responses (PI vs. NN).

PI controller: THD ≈ 6.8%

Neural network controller: THD ≈ 2.1%

Inference: NN controller satisfies IEEE-519 harmonic standards (**Figure 5**).

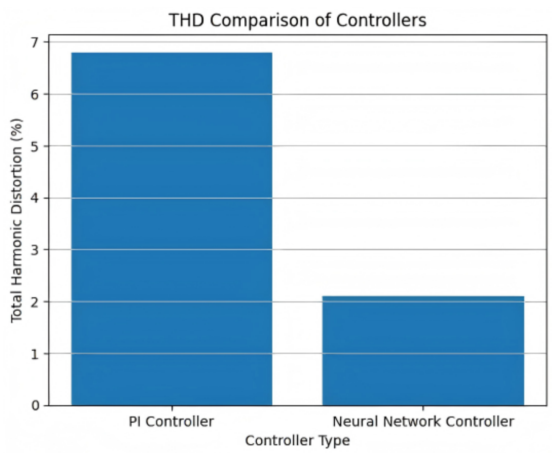

Figure 5. THD Responses (PI vs. NN).

Lower harmonics result in:

i. Reduced stress on the filter.

ii. Better power quality.

iii. Increased battery and converter life.

The Neural Network controller greatly minimizes the total harmonic distortion and provides smoother power transmission compared to the conventional PI controller. The minimized THD and smooth power response clearly justify the effectiveness of AI control in solar PV-driven fast EV charging systems.

3.5. Calculation of performance indices

To validate the claim of charging from 20% to 90% in 15 min:

Battery capacity = 50 kWh;

Energy required = 70% = 35 kWh;

Power available = 20 kW;

Time = Energy/Power = 35/20 = 1.75 h.

Thus, ultra-fast charging requires higher power (>100 kW). The current model represents scaled simulation conditions.

To compare the performance of the proposed Neural Network (NN) controller with the existing PI controller, the following standard time-domain indices have been calculated from the simulation graphs.

Peak overshoot (M_p)

Peak overshoot is the measure of the maximum distance of the response from the reference value during the response. It is given by the formula:

$$M_p\ (\%)\ = \frac{V_{max} - V_{ref}}{V_{ref}} * 100 \tag{1}$$

For DC bus voltage (Vref = 400 V):

PI controller: With a peak voltage V_{max}, PI = 440 V, the overshoot is:

$$M_p = \frac{440-400}{400} * 100 = 10\% \tag{2}$$

NN controller: With a peak voltage V_{max}, NN = 408 V, the overshoot is significantly reduced:

$$M_p = \frac{408-400}{400} * 100 = 2\% \tag{3}$$

For charging current (I_{ref} = 50 A):

PI controller: With a peak current I_{max}, PI = 60 A, the overshoot is:

$$M_p = \frac{(60-50)}{50} * 100 = 20\% \tag{4}$$

NN controller: With a peak current I_{max}, NN = 52 A, the overshoot is minimized:

$$M_p = \frac{52-50}{50} * 100 = 4\% \tag{5}$$

3.5.1. Settling time (t_s)

The settling time is defined as the time required for the response to stay within a ±2% tolerance band of the reference value.

For DC bus voltage: The settling band is 400 ± 2% = 392 V to 408 V.

PI controller: t_s, PI ≈ 0.35 s.

NN controller: ts, NN ≈ 0.15 s (approx. 57% faster).

For charging current: The settling band is 50 ± 2% = 49 A to 51 A.

PI controller: t_s, PI ≈ 0.30 s.

NN controller: ts, NN ≈ 0.12 s.

3.5.2. Steady-state error (e_{ss})

This metric measures the accuracy of the controller in the steady state.

$$e_{ss} = |Y_{ref} - Y_{ss}| \quad (6)$$

For DC bus voltage:

PI controller: |400 −395| = 5 V.

NN controller: |400 − 399.5|= 0.5 V (High Precision).

For charging current:

PI controller: |50 − 48| = 2 A.

NN controller: |50 − 49.8| = 0.2 A.

4. Strengths and limitations

Strengths:

- Significant reduction in THD, meeting IEEE-519 guidelines.
- Faster transient recovery (57% improvement), reducing thermal stress on batteries.
- High precision in steady-state voltage regulation.

Limitations:

- The study is currently limited to simulation; physical factors like sensor noise and gate-driver dead time are idealized.
- The ANN performance is dependent on the breadth of the initial training dataset.

5. Conclusion

This study presents a comparative analysis of PI and ANN controllers for a solar PV-based EV charging system. The results demonstrate that the ANN controller significantly enhances system performance by reducing overshoot, improving settling time, and minimizing harmonic distortion. The findings confirm that AI-based control strategies are more effective for handling nonlinear and dynamic renewable energy systems. This work contributes to the advancement of intelligent EV charging technologies and provides a foundation for future research in AI-driven energy systems.

This research proves that AI-based controllers significantly outperform traditional PI controllers in renewable-fed EV charging. The ANN controller reduces current overshoot from 20% to 4% amd improved power quality by reducing THD to 2.1%.

To move this toward an engineering application, future studies will implement Hardware-in-the-Loop (HIL) testing using dSPACE to validate the controller against real-world measurement delays and parasitic parameters.

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Abbreviations

Symbol	Description	Unit
PV	Photovoltaic	-
EV	Electric Vehicle	-
SoC	State of Charge	%
MPPT	Maximum Power Point Tracking	-
ANN	Artificial Neural Network	-
PI	Proportional–Integral	-
THD	Total Harmonic Distortion	%
Vdc	DC Bus Voltage	V
Ich	Charging Current	A
Kp, Ki	Proportional and Integral Gains	-
Fsw	Switching Frequency	kHz

References

1. Bajpai R. S., Prakash S, Srivastava A, et al. ANN-Based Fast Charging Control Strategy for Electric Vehicles With Intelligent Battery Thermal Management Using Renewable Energy Resources. IEEE Transactions on Transportation Electrification. 2025; 11(5): 10796–10809. doi: 10.1109/TTE.2025.3568189
2. Syed MH, Kondeti K, Sunkesula J, et al. Analysis and Simulation of AI based ANFIS Controller for Solar Powered DC Fast Charging in Electric Vehicles. International Journal of Scientific Research in Science and Technology. 2025; 12(2): 496–503. doi: 10.32628/IJSRST25122250
3. AranGlenn J. Boost Converter with Optimized PI Controller Design for Grid-Tied PV-Based Electric Vehicle. International Journal of Electrical Power and Machine Systems. 2025; 3(1): 1–16. Available online: https://journals.stmjournals.com/ijepms/article=2025/view=207213/
4. AranGlenn J. TZSBLC with Optimized PI Controller Design for Grid-Tied PV-Based Electric Vehicle. International Journal of Electrical Power and Machine Systems. 2025; 3(1): 18–35. Available online: https://journals.stmjournals.com/ijemad/article=2025/view=206508/
5. Oukhouya Ali Y, El Haini J. Energy management strategies for grid-integrated photovoltaic and battery energy storage systems-enhanced electric vehicle charging stations: Classical approaches and neural network solutions. Sustainable Energy, Grids and Networks. 2025; 43: 101926. doi: 10.1016/j.segan.2025.101926
6. Wang F, Tuluhong A, Luo B, et al. Control Methods and AI Application for Grid-Connected PV Inverter: A Review. Technologies. 2025; 13(11): 535. doi: 10.3390/technologies13110535
7. Sathish R, Sekar V. Integration of fast charging EV infrastructure with high gain Z-source converters and hybrid optimized MPPT algorithm. Scientific Reports. 2025; 16(1): 2573. doi: 10.1038/s41598-025-32394-z
8. Bajpai RS, Srivastava A, Singh A, et al. Artificial Intelligence Based Fast DC Charging Control of Electric Vehicles in Standalone Mode Involving Multiple Renewable Energy Resources. International Journal on Energy Conversion (IRECON). 2024; 12(4): 135. doi: 10.15866/irecon.v12i4.24822
9. Puranik KK, Shelgaonkar AK. Characteristics Verification of Battery Charging Circuit Using Different Controllers. Educational Administration: Theory and Practice. 2024; doi: 10.53555/kuey.v30i10.8085
10. Hu J, Lim BH, Tian X, et al. A Comprehensive Review of Artificial Intelligence Applications in the Photovoltaic

Systems. CAAI Artificial Intelligence Research. 2024; 9150031. doi: 10.26599/AIR.2024.9150031
11. Padma J, Mishra S, Chaubey A. Photovoltaic Based Fast Charging of Electric Vehicles with Fuzzy Logic Controller. In: Advances in Artificial-Business Analytics and Quantum Machine Learning, Lecture Notes in Electrical Engineering. Springer; 2024. pp. 543–552. doi: 10.1007/978-981-97-2508-3_40
12. Shern SJ, Sarker MT, Haram MHSM, et al. Artificial Intelligence Optimization for User Prediction and Efficient Energy Distribution in Electric Vehicle Smart Charging Systems. Energies. 2024; 17(22): 5772. doi: 10.3390/en17225772
13. Bajpai RS, Srivastava A, Singh A, et al. Intelligent Control of DC Microgrid Involving Multiple Renewables for Fast Charging Control of Electric Vehicles. Electric Power Components and Systems. 2024; 1–22. doi: 10.1080/15325008.2024.2304149
14. Yadav G, Singh M. Unveiling the Superiority: Comparative Analysis of ANFIS, FOPID, and PI Controllers in Grid-Connected EV Systems for G2V/V2G Applications. In: Proceedings of the 2023 International Conference on Electrical, Electronics, Communication and Computers (ELEXCOM); 26 August 2023; Roorkee, India. pp. 1–6. doi: 10.1109/ELEXCOM58812.2023.10370196
15. Pratap Singh A, Kumar Y, Sawle Y, et al. Development of artificial Intelligence-Based adaptive vehicle to grid and grid to vehicle controller for electric vehicle charging station. Ain Shams Engineering Journal. 2024; 15(10): 102937. doi: 10.1016/j.asej.2024.102937
16. Aldossary M, Alharbi HA, Ayub N. Optimizing Electric Vehicle (EV) Charging with Integrated Renewable Energy Sources: A Cloud-Based Forecasting Approach for Eco-Sustainability. Mathematics. 2024; 12(17): 2627. doi: 10.3390/math12172627
17. Wang X, Wang D, Sun G, et al. A robust voltage control of dual active full bridge converter based on RBF neural network sliding mode control with reduced order modeling approach. Frontiers in Energy Research. 2023; 11: 1225269. doi: 10.3389/fenrg.2023.1225269
18. Singh AP, Kumar Y. Artificial Neural Network controller for Solar PV based Electric Vehicle Charging Station with Supercapacitor. Journal of Physics: Conference Series. 2023; 2570(1): 012003. doi: 10.1088/1742-6596/2570/1/012003
19. Alrubaie AJ, Salem M, Yahya K, et al. A Comprehensive Review of Electric Vehicle Charging Stations with Solar Photovoltaic System Considering Market, Technical Requirements, Network Implications, and Future Challenges. Sustainability. 2023; 15(10): 8122. doi: 10.3390/su15108122
20. Kashani SA, Soleimani A, Khosravi A, et al. State-of-the-Art Research on Wireless Charging of Electric Vehicles Using Solar Energy. Energies. 2022; 16(1): 282. doi: 10.3390/en16010282
21. Abraham DS, Chandrasekar B, Rajamanickam N, et al. Fuzzy-Based Efficient Control of DC Microgrid Configuration for PV-Energized EV Charging Station. Energies. 2023; 16(6): 2753. doi: 10.3390/en16062753
22. Thangam T, Kalifullah AHH. Type 2 Intelligent Controller for Grid-Tied Solar Electric Vehicle Charging Stations: Novel Controller for PV FED Grid-Tied EV Chargers. In: Advances in Environmental Engineering and Green Technologies. IGI Global; 2023. pp. 218–243. doi: 10.4018/978-1-6684-7303-0.ch010
23. Huang H, Balasubramaniam S, Todeschini G, et al. A Photovoltaic-Fed DC-Bus Islanded Electric Vehicles Charging System Based on a Hybrid Control Scheme. Electronics. 2021; 10(10): 1142. doi: 10.3390/electronics10101142
24. Kunjuramakurup L, Sulthan SM, Ponparakkal MS, et al. A High-Power Solar PV-fed TISO DC-DC Converter for Electric Vehicle Charging Applications. Energies. 2023; 16(5): 2186. doi: 10.3390/en16052186
25. Divya K, Vignesh KE, Kumar CN, et al. Comparison of PI and AI Controllers Used for DC-DC Converters for EV Fast Charging. Journal of Critical Reviews. 2020; 7(6):1290. Available online: https://www.researchgate.net/publication/343046915_COMPARISON_OF_PI_AND_AI_CONTROLLERS_USED_FOR_DC-DC_CONVERTER_FOR_EV_FAST_CHARGING