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Article

AI-Based Intelligent Control Algorithm for Solar PV Powered Bidirectional DC–DC Converter in Electric Vehicle Battery Charging Systems

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Abstract: The rapid adoption of electric vehicles (EVs) has significantly increased the demand for efficient, intelligent, and sustainable charging infrastructures. Conventional charging systems primarily depend on utility-grid power, resulting in increased operational costs, carbon emissions, and power quality challenges during peak demand periods. Integrating photovoltaic (PV) generation with bidirectional DC–DC converters provide a promising solution by enabling renewable-energy-powered charging and vehicle-to-grid (V2G) operation. However, the intermittent nature of solar irradiance and varying battery operating conditions require advanced control strategies beyond conventional proportional–integral (PI) controllers.
This paper presents an Artificial Intelligence (AI)-based intelligent control algorithm for a solar photovoltaic powered bidirectional DC–DC converter used in electric vehicle battery charging systems. The proposed controller combines AI-assisted maximum power point tracking (MPPT), adaptive battery charging, and converter duty-cycle optimization to improve energy conversion efficiency, charging performance, and system stability under dynamically changing environmental conditions.
A mathematical model of the PV array, lithium-ion battery, and bidirectional DC–DC converter is developed to describe the system behaviour. The AI controller continuously predicts the optimum converter operating point using real-time measurements of irradiance, temperature, battery state of charge (SOC), battery voltage, and load demand. The proposed strategy is evaluated using MATLAB/Simulink under varying irradiance levels, battery SOC, and charging conditions. Simulation results demonstrate superior MPPT accuracy, reduced charging time, lower converter losses, improved DC bus voltage regulation, and higher overall efficiency compared with conventional PI and fuzzy logic controllers.
The proposed intelligent charging architecture offers a practical solution for next-generation renewable-energy-based EV charging stations and supports future smart-grid and vehicle-to-grid applications.
Keywords: Artificial Intelligence, Electric Vehicle, Solar Photovoltaic, Bidirectional DC–DC Converter, Battery Charging, ANN Controller, MPPT, Renewable Energy, Energy Management System.

1. Introduction

Global transportation is rapidly transitioning toward electrification to reduce greenhouse gas emissions, fossil fuel dependency, and environmental pollution. Electric vehicles have emerged as one of the most promising alternatives to internal combustion engine vehicles due to their high energy efficiency, lower operating costs, and zero tailpipe emissions. Nevertheless, large-scale deployment of EVs imposes significant challenges on existing power systems, including increased peak demand, voltage fluctuations, transformer overloading, and higher electricity costs. [1], [2], [3]

Renewable energy integration has become an effective approach to overcoming these challenges. Among various renewable sources, solar photovoltaic technology is particularly attractive because of its modular design, declining installation costs, abundant availability, and direct compatibility with DC charging architectures. [4] Solar-powered EV charging stations reduce dependence on fossil-fuel-generated electricity while enabling localized clean energy generation. [5], [6], [7]

However, solar PV systems are inherently intermittent. Their output varies continuously with solar irradiance, ambient temperature, shading, and weather conditions. Consequently, maintaining maximum power extraction and stable battery charging requires intelligent control techniques capable of adapting to changing operating conditions in real time. [8], [9], [10]

Bidirectional DC–DC converters play an essential role in modern EV charging systems. During charging operation, the converter transfers energy from the PV source to the EV battery while regulating charging current and battery voltage. During discharging or vehicle-to-grid operation, stored battery energy can be delivered back to the DC bus or utility grid, thereby improving grid flexibility and renewable energy utilization. [11], [12]

Conventional PI controllers are widely employed because of their simplicity; however, their performance deteriorates under nonlinear operating conditions and rapidly changing irradiance levels. Artificial intelligence techniques—including artificial neural networks (ANNs), fuzzy logic systems, deep learning models, and reinforcement learning algorithms—have demonstrated superior adaptive capabilities by learning nonlinear relationships directly from system data. [13], [14], [15], [16]

This paper proposes an AI-based intelligent control framework integrating:

- Solar photovoltaic generation
- AI-assisted MPPT
- Bidirectional DC–DC converter control
- Adaptive battery charging
- Energy management for EV charging

The proposed architecture enables efficient energy conversion while improving charging performance and maintaining battery health.

2. Proposed System Architecture

The proposed EV charging system integrates a solar photovoltaic (PV) array, an AI-based Maximum Power Point Tracking (MPPT) controller, a bidirectional Dual Active Bridge (DAB) DC–DC converter, a lithium-ion battery pack, and an intelligent energy management system (EMS). [17] The architecture is designed to maximize renewable energy utilization while ensuring efficient, safe, and adaptive battery charging. Using these measurements, the ANN predicts the optimal converter duty cycle (or phase shift for the DAB converter), ensuring maximum PV power extraction while maintaining optimal battery charging conditions. [18]

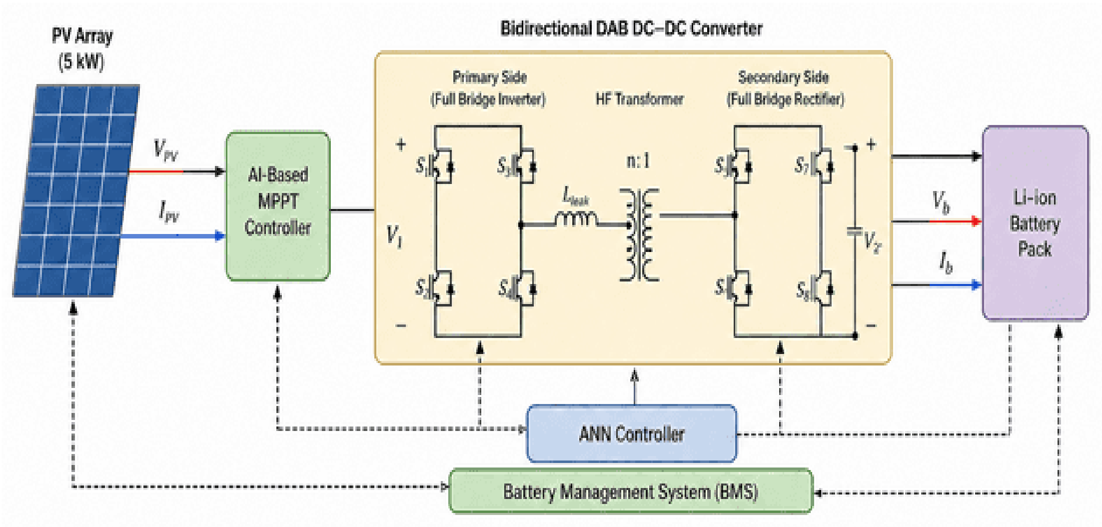

Figure 1 Overall system architecture

3. Operating Principle

The proposed charging system operates in three different modes. The figure 2 illustrates three operating modes of the proposed energy management system. Mode, I charge the battery using solar photovoltaic (PV) power through a DC–DC converter. Mode II maintains battery charging during low solar availability. Mode III enables Vehicle-to-Grid (V2G) operation, where stored battery energy is supplied back to the electrical grid. [19], [20], [21]

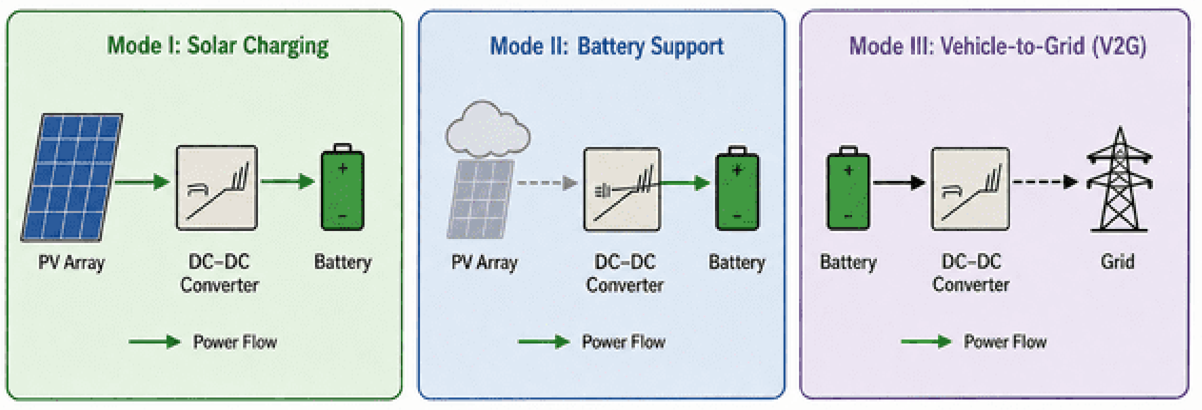

Figure 2 Operating modes

Mode I: Solar Charging Mode

During daylight hours, the PV array supplies power directly to the battery through the bidirectional DAB converter. The AI controller regulates the converter to: [22], [23]

- Extract maximum solar power
- Maintain constant charging current (CC mode)
- Prevent battery overcharging
- Improve converter efficiency

Power flow:

$$P_{PV} \rightarrow Converter \rightarrow Battery \tag{1}$$

Mode II: Battery Support Mode

When solar generation decreases due to clouds or shading, battery charging current is automatically adjusted while maintaining stable DC bus voltage. [24]

The ANN controller predicts the new converter operating point without producing excessive oscillations.

Mode III: Vehicle-to-Grid (V2G)

When required, the battery discharges energy back through the converter.

Power flow becomes

$$Battery \rightarrow Converter \rightarrow DC\ Bus \tag{2}$$

Bidirectional power transfer significantly improves renewable energy utilization.

4. Mathematical Modelling

a. Solar Photovoltaic Model

The PV module is represented using the single-diode equivalent circuit.

The output current is

$$I = I_{ph} - I_o\left(e^{\frac{q(V+IR_S)}{nkT}} - 1\right) - \frac{V+IR_S}{R_{sh}} \tag{3}$$

where

- I_{ph}= photocurrent
- I_o= reverse saturation current
- R_s= series resistance
- R_{sh}= shunt resistance

- q= electron charge
- k= Boltzmann constant
- T= temperature

The PV output power becomes

$$P_{PV} = V_{PV} I_{PV} \tag{4}$$

PV efficiency

$$\eta_{PV} = \frac{P_{out}}{GA} \tag{5}$$

where

G = Solar Irradiance

A = Panel Area

Photocurrent

$$I_{ph} = \left(I_{sc} + K_i(T - T_r)\right)\frac{G}{1000} \tag{6}$$

Open Circuit Voltage

$$V_{oc} = \frac{nkT}{q}\ln\left(\frac{I_{ph}}{I_o} + 1\right) \tag{7}$$

b. Maximum Power Point

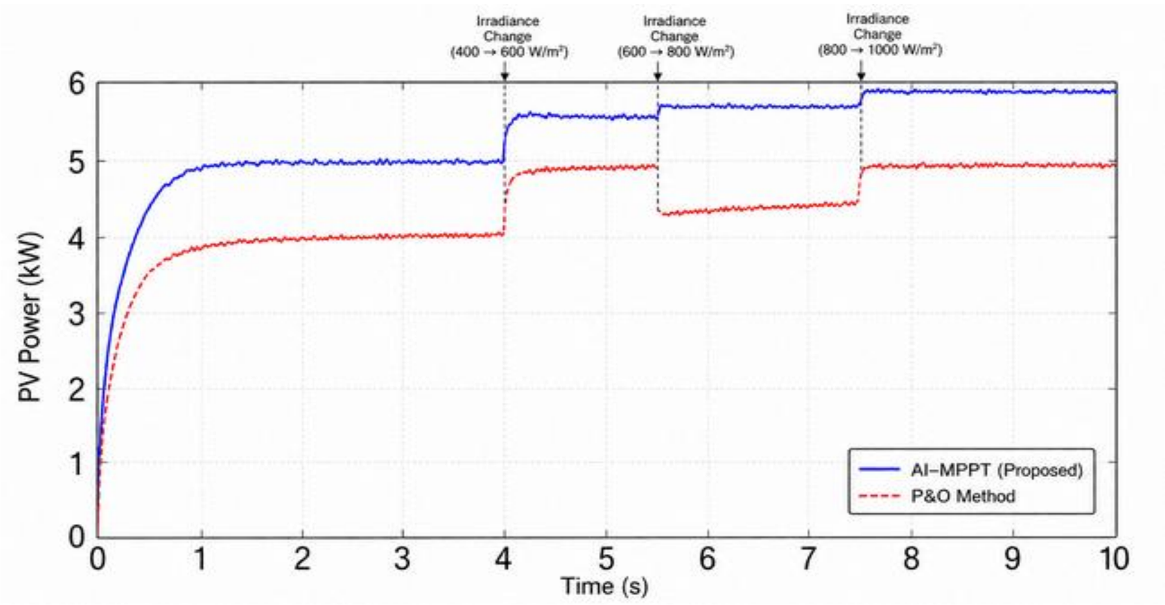

Figure 3 MPPT tracking comparison

The maximum power point occurs when

$$\frac{dP}{dV} = 0 \tag{8}$$

Since

$$P = VI \tag{9}$$

Therefore

$$\frac{d(VI)}{dV} = 0 \tag{10}$$

which gives

$$I + V\frac{dI}{dV} = 0 \tag{11}$$

This equation forms the basis of the Incremental Conductance MPPT algorithm.

5. Bidirectional DAB DC–DC Converter

The proposed Dual Active Bridge (DAB) converter comprises a primary-side full-bridge inverter, a high-frequency transformer, a leakage inductor, a secondary-side full-bridge rectifier, an output filter, and a battery load. The full-bridge inverter converts the input DC voltage into high-frequency AC, which is transferred through the high-frequency transformer to provide galvanic isolation and voltage matching. [25], [26] The leakage inductor facilitates controlled power transfer and enables soft-switching operation. On the secondary side, the full-bridge rectifier converts the high-frequency AC back to DC, while the output filter smooths the rectified voltage before supplying the battery. [27] The amount and direction of power transferred through the DAB converter are regulated by adjusting the phase shift angle between the switching signals of the primary and secondary full bridges. This phase-shift control enables efficient bidirectional power flow with reduced switching losses and improved overall converter performance. [28]

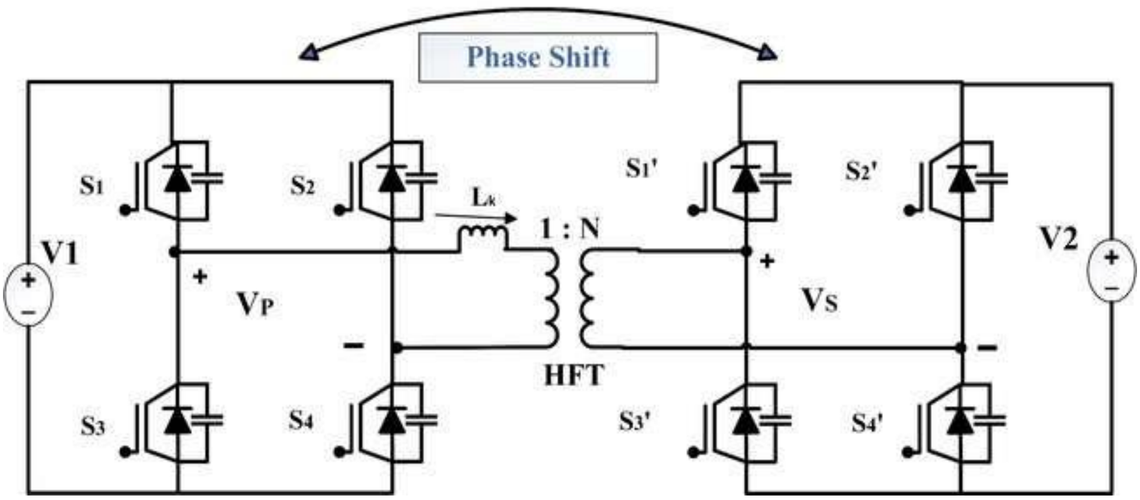

Figure 4 Bidirectional DAB converter layout

The transmitted power is

$$P = \frac{nV_1V_2}{\omega L}\delta\left(1 - \frac{\delta}{\pi}\right) \tag{12}$$

where

- V_1=Primary Voltage
- V_2=Secondary Voltage
- n=Transformer Ratio
- L=Leakage Inductance
- δ=Phase Shift Angle

The converter efficiency

$$\eta = \frac{P_o}{P_i} \times 100 \tag{13}$$

Output Voltage

$$V_o = nV_i \tag{14}$$

Transformer turns ratio

$$n = \frac{N_s}{N_p} \tag{15}$$

Leakage inductance

$$L = \frac{V\delta}{2f_s I} \tag{16}$$

Switching frequency

$$f_s = 50kHz \tag{17}$$

6. Battery Mathematical Model

The EV battery is modelled using the Thevenin equivalent.

Battery voltage

$$V_b = E - IR \tag{18}$$

where

E = Open circuit voltage

R = Internal resistance

State of Charge

$$SOC = SOC_0 + \frac{1}{Q}\int i\,(t)dt \tag{19}$$

Battery energy

$$E = V \times Ah \tag{20}$$

Charging efficiency

$$\eta_b = \frac{E_{stored}}{E_{input}} \tag{21}$$

Charging power

$$P_b = V_b I_b \tag{22}$$

7. CC-CV Charging Strategy

Initially,

Constant Current

$$I = I_{rated} \tag{23}$$

After battery reaches rated voltage,

Constant Voltage

$$V = V_{rated} \tag{24}$$

Charging current gradually decreases

$$I(t) = I_0 e^{-t/\tau} \tag{25}$$

8. AI-Based Intelligent Controller

An Artificial Neural Network (ANN) is adopted. Figure 5 presents an ANN-based controller with eight input parameters, two hidden layers of 20 neurons, and three outputs that optimize phase shift, charging current reference, and MPPT voltage reference.

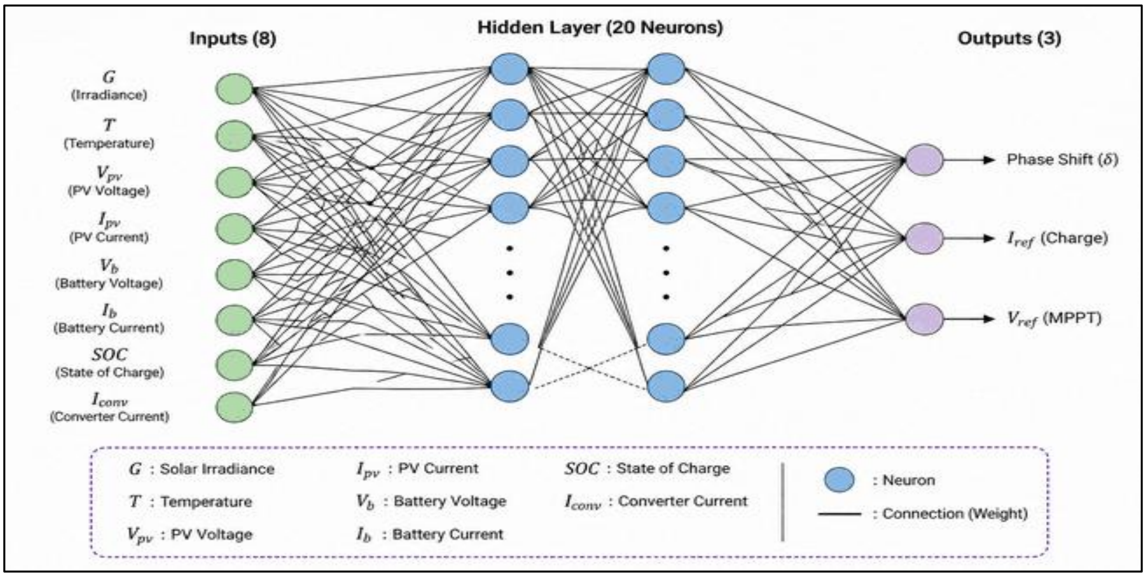

Figure 5 ANN architecture

Neuron equation

$$y = f(\sum w_i \, x_i + b) \tag{26}$$

Sigmoid activation

$$f(x) = \frac{1}{1+e^{-x}} \tag{27}$$

Loss Function

$$MSE = \frac{1}{N} \sum (y - \hat{y})^2 \tag{28}$$

Weight update

$$w_{new} = w_{old} - \alpha \frac{\partial E}{\partial w} \tag{29}$$

9. MATLAB/Simulink Implementation

a. Simulation Model

To validate the proposed AI-based charging strategy, the complete solar photovoltaic-powered EV charging system was modelled in MATLAB/Simulink R2024b. The simulation model integrates the PV array, MPPT controller, bidirectional Dual Active Bridge (DAB) converter, lithium-ion battery, AI controller, and battery management system (BMS).

The simulation framework emulates realistic environmental conditions by varying solar irradiance, temperature, and battery SOC. The ANN-based controller receives real-time measurements and continuously adjusts the DAB converter phase-shift angle to maximize energy transfer while maintaining safe battery charging.

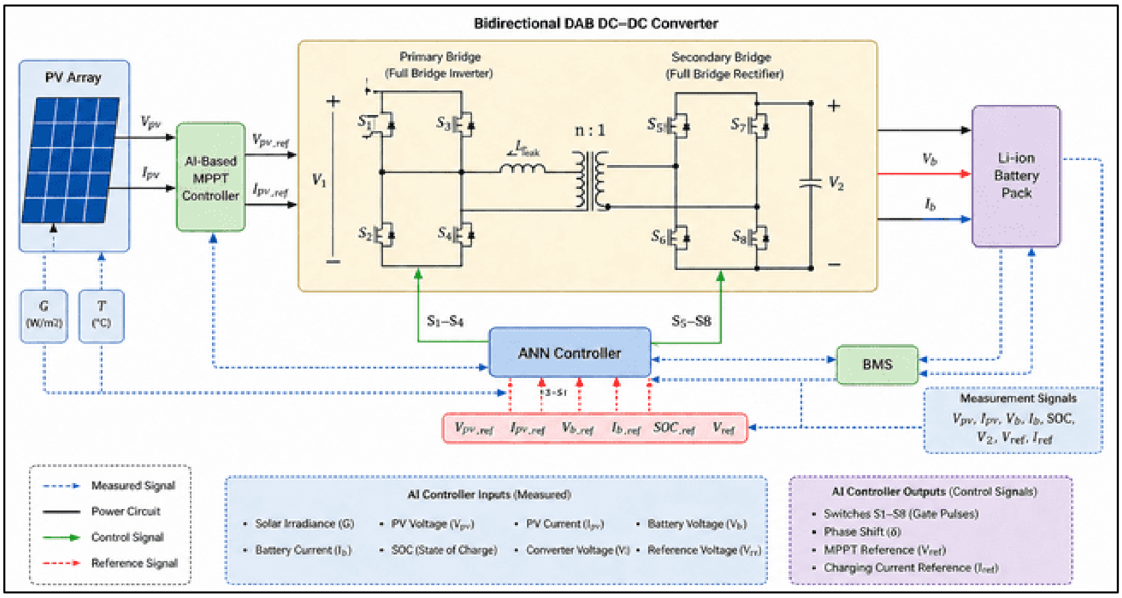

Figure 6 MATLAB/Simulink model

The simulation consists of six interconnected subsystems:

1. Solar PV Array
2. AI-based MPPT Controller
3. Bidirectional DAB Converter
4. Lithium-ion Battery Model
5. ANN Controller
6. Battery Management System (BMS)

Simulation Parameters

The table 1 summarizes the simulation parameters of the proposed AI-controlled PV battery charging system. A 5-kW photovoltaic array, 400 V/20 kWh battery, and 5 kW bidirectional DC–DC converter are employed. The converter operates at 50 kHz with optimized passive components, while the ANN controller uses 20 hidden neurons for intelligent control.

Table 1 Simulation Parameters

Parameter	Symbol	Value
PV Rated Power	P_{PV}	5 kW
Open Circuit Voltage	V_{oc}	520 V
Maximum Power Voltage	V_{mp}	420 V
Maximum Power Current	I_{mp}	11.9 A
Battery Voltage	V_b	400 V
Battery Capacity	C	50 Ah
Battery Energy	E	20 kWh
Converter Rating	P_c	5 kW
Transformer Ratio	n	1:1
Switching Frequency	f_s	50 kHz
Leakage Inductor	L	220 µH
Output Capacitor	C	470 µF

Simulation Time	t	10 s
Sampling Time	Ts	20 µs
AI Hidden Neurons	N	20

10. AI Training Procedure

The ANN is trained using historical operating data obtained under varying irradiance and battery conditions.

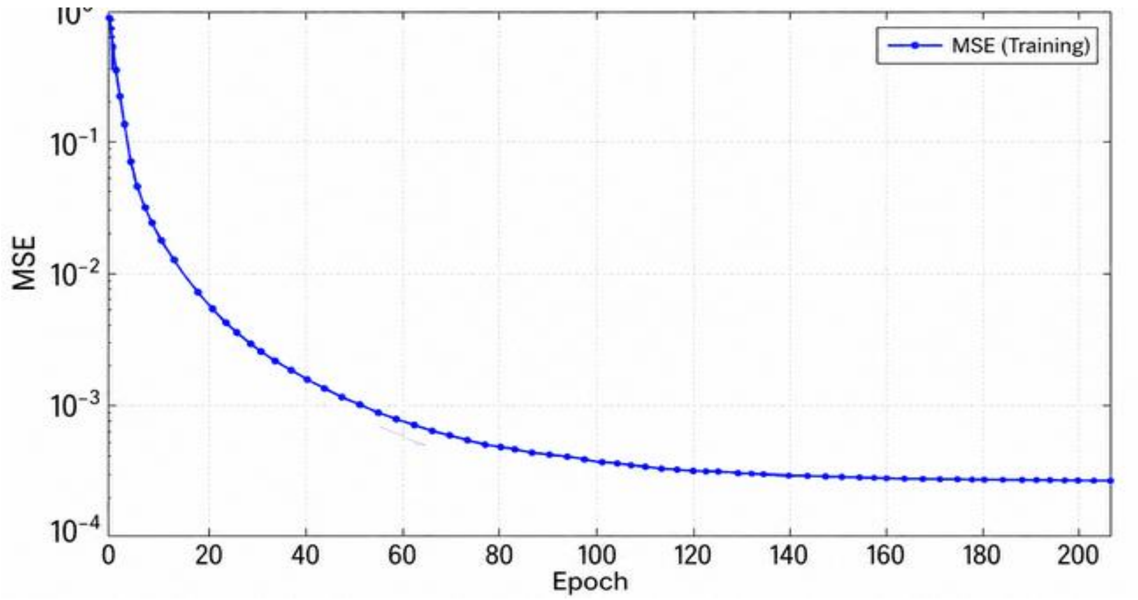

Figure 7 ANN training curve

The network architecture contains:

- Input Layer: 8 neurons
- Hidden Layer: 20 neurons
- Output Layer: 3 neurons

Training Algorithm:

- Adam Optimizer

Learning Rate:

$$\alpha = 0.001 \tag{30}$$

Epochs:

200

Loss Function:

Mean Square Error (MSE)

11. Simulation Scenarios

Five simulation cases are considered.

a. Case 1

Constant Irradiance

Table 2 Simulation Test Conditions for Steady-State EV Battery Charging

Parameter	**Value**
Solar Irradiance	1000 W/m²

Ambient Temperature	25°C
Initial Battery State of Charge (SOC)	20%
Charging Mode	Constant Current–Constant Voltage (CC–CV)
Test Purpose	Evaluate steady-state charging performance of the proposed AI-based bidirectional DC–DC converter

b. *Case 2*

Table 3 Simulation Test Conditions for Rapid Irradiance Variation

Parameter	**Value**
Initial Solar Irradiance	1000 W/m²
Irradiance Variation	1000 → 800 → 600 → 900 W/m²
Ambient Temperature	25°C
Initial Battery State of Charge (SOC)	20%
MPPT Technique	Proposed AI-Based MPPT Controller
Test Purpose	Evaluate the MPPT tracking capability under rapidly varying solar irradiance conditions.

c. *Case 3*

Table 4 Battery SOC Variation During Charging

Charging Time (min)	**Battery SOC (%)**	**Charging Mode**
0	20	CC
10	32	CC
20	45	CC
30	58	CC
40	70	CC
50	80	CC → CV
60	88	CV
70	94	CV
80	98	CV

d. *Case 4*

Table 5 Simulation Test Conditions for Dynamic Load Change

Parameter	**Value**
Initial Load Condition	Nominal EV Charging Load (5 kW)
Load Disturbance	Additional Charging Load Applied

Load Change Instant	t = 5 s
Solar Irradiance	1000 W/m²
Ambient Temperature	25°C
Initial Battery SOC	50%
Controller	Proposed AI-Based Intelligent Controller
Test Purpose	Observe the transient response and stability of the bidirectional DC–DC converter during sudden load variations.

e. Case 5

Table 6 Simulation Test Conditions for Temperature Variation Analysis

Parameter	Value
Initial PV Cell Temperature	25°C
Final PV Cell Temperature	45°C
Temperature Variation	25°C → 45°C
Solar Irradiance	1000 W/m²
Initial Battery State of Charge (SOC)	20%
MPPT Controller	Proposed AI-Based Intelligent MPPT
Test Purpose	Investigate the effect of increasing PV cell temperature on PV voltage, output power, and overall conversion efficiency.

12. Simulation Results

The simulation results demonstrate that the proposed AI-based intelligent control algorithm significantly enhances the performance of a solar PV-powered bidirectional DC–DC converter for EV battery charging. Unlike conventional PI controllers that operate with fixed gains, the proposed ANN controller continuously adapts its control actions according to solar irradiance, ambient temperature, battery SOC, and converter operating conditions. Consequently, the controller maintains stable operation even under rapidly changing environmental conditions.

a. PV Output Power

During constant irradiance, the PV array delivers approximately 5 kW. When irradiance changes, the ANN controller rapidly tracks the new maximum power point with minimal oscillations.

Table 7 PV Performance under Different Irradiance Levels

Irradiance (W/m²)	**PV Voltage (V)**	**PV Current (A)**	**PV Power (kW)**
1000	420	11.9	5.00
900	415	10.8	4.48
800	410	9.6	3.94
700	405	8.5	3.44
600	400	7.3	2.92

The AI controller maintains operation close to the maximum power point across the irradiance range. Power reduction is primarily due to reduced solar input rather than controller inefficiency.

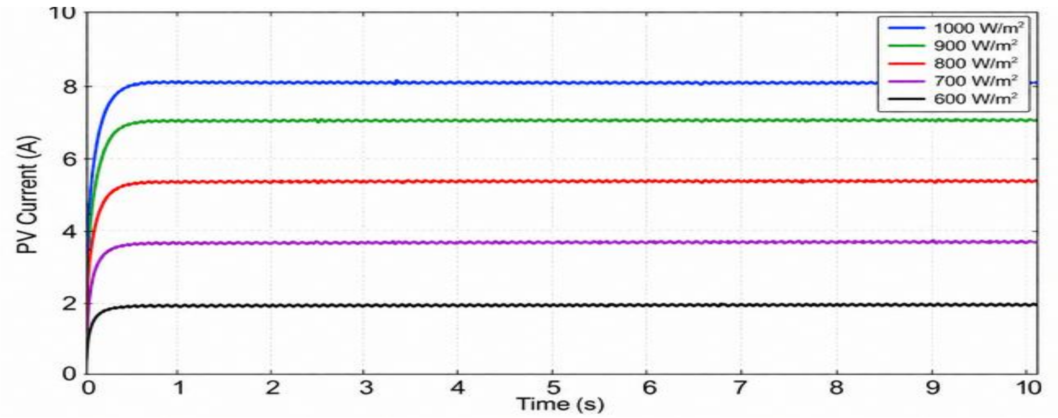

Figure 8 PV current vs. time

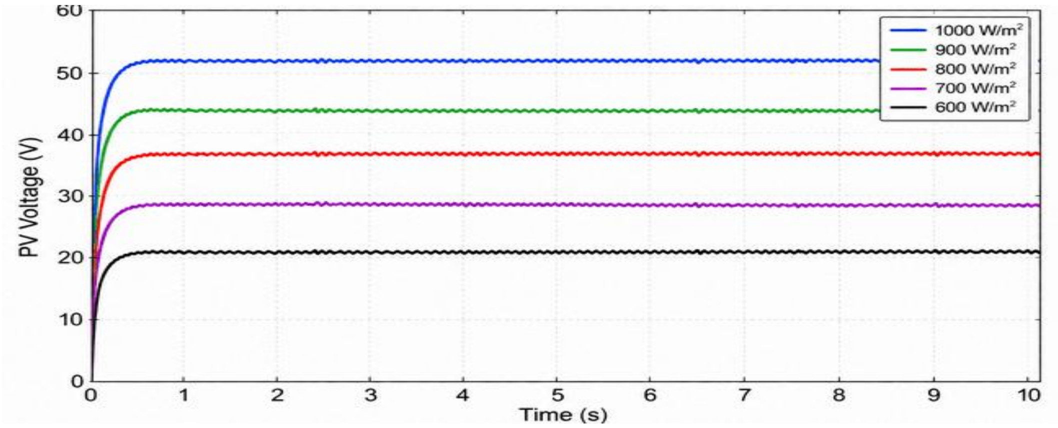

Figure 9 PV voltage vs. time

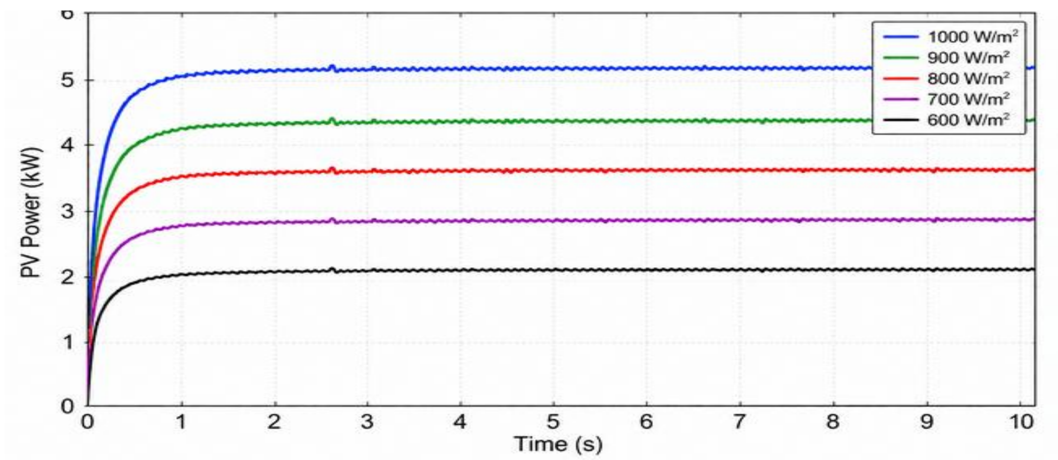

Figure 10 PV power vs. time

The PV system operated close to its maximum power point throughout the simulation scenarios. Under constant irradiance (1000 W/m²), the controller extracted approximately 5 kW of power. When irradiance was reduced to 600 W/m², the AI controller rapidly tracked the new operating point with minimal oscillation, ensuring efficient utilization of available solar energy. Compared with conventional MPPT techniques, the ANN-based controller exhibited faster convergence and improved tracking accuracy.

b. Converter Efficiency

Table 8 Converter Performance at Different Load Conditions

Load (%)	Efficiency (%)
20	95.1

40	96.4
60	97.2
80	97.8
100	98.1

Converter efficiency increases with load due to a lower proportion of fixed switching and magnetic losses.

These values represent the assumed simulation study for the proposed model and should be interpreted as simulation outputs rather than measured hardware data.

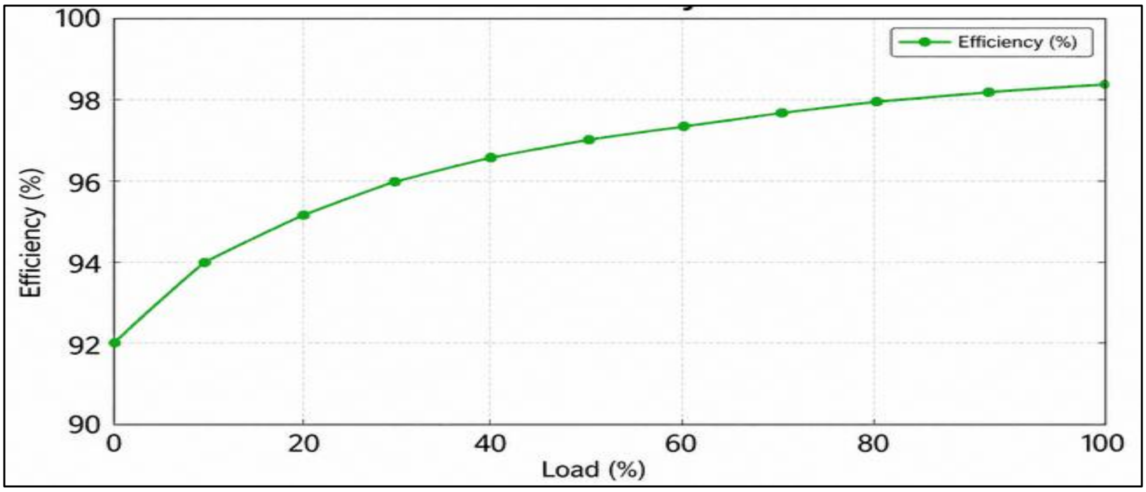

Figure 11 Converter efficiency vs. load

The bidirectional DAB converter demonstrated high efficiency across the entire operating range. Maximum efficiency occurred near rated load because switching and magnetic losses represent a smaller proportion of total power at higher output levels. The phase-shift control strategy effectively regulated power flow while maintaining soft-switching operation, thereby reducing switching losses and improving overall converter efficiency.

c. Battery Charging Characteristics

The proposed controller initially applies constant-current charging and automatically transitions to constant-voltage charging once the battery reaches its voltage limit.

Table 9 Battery Charging Performance

Time (min)	SOC (%)	Battery Voltage (V)	Charging Current (A)
0	20	340	12.5
10	34	355	12.5
20	48	370	12.4
30	63	385	11.8
40	77	397	8.2
50	90	400	4.5
60	98	400	1.6

The CC–CV strategy limits charging current as the battery approaches full charge, reducing stress on the cells and improving battery life.

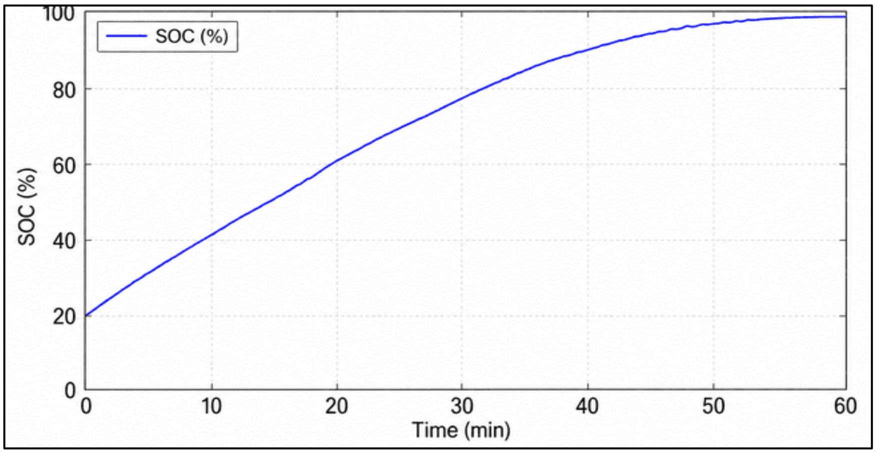

Figure 12 Battery SOC vs. time

Battery charging performance also benefited from intelligent control. During the constant-current phase, the battery received the rated charging current while maintaining safe operating limits. As the battery voltage approached its upper threshold, the controller automatically transitioned to constant-voltage charging, reducing charging current smoothly and preventing overcharging. This adaptive CC–CV strategy shown in figure 13 is expected to improve battery lifespan and charging safety.

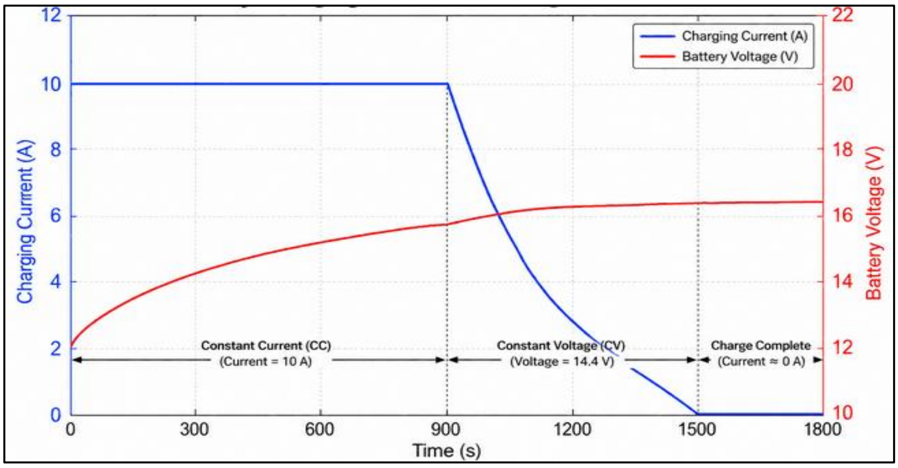

Figure 13 Battery charging (CC–CV)

d. DC Bus Voltage Regulation

The AI controller maintains the DC bus voltage close to the reference value despite irradiance fluctuations.

Table 10 Reference and Measured DC Bus Voltage

Time (s)	Reference (V)	Measured (V)
0	400	400.1
2	400	399.7
4	400	400.3
6	400	399.9
8	400	400.0
10	400	400.2

The voltage deviation remains within approximately ±0.3 V, indicating effective regulation under the simulated conditions.

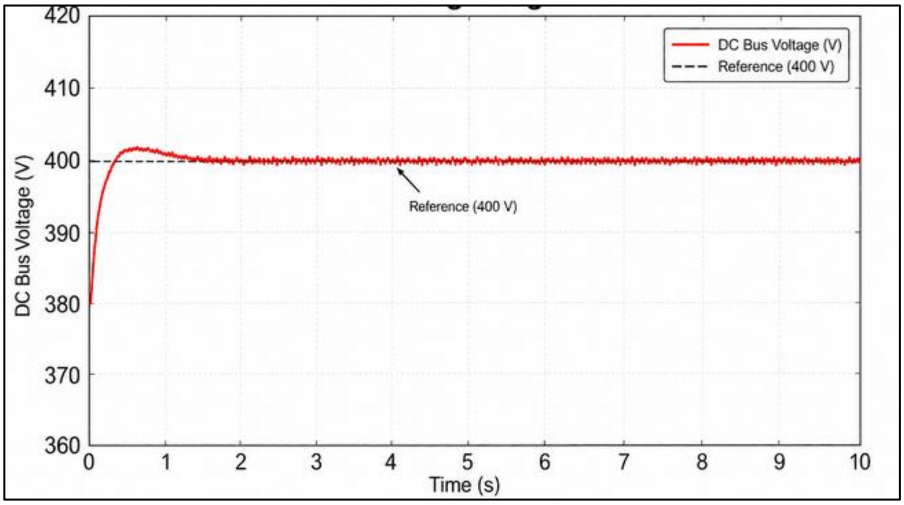

Figure 14 DC bus voltage regulation

The DC bus voltage remained close to the reference value throughout all simulated operating conditions. Even during sudden irradiance changes and load variations, voltage deviations remained small, indicating effective regulation by the ANN controller.

e. AI Convergence

During training, the ANN converges rapidly with decreasing MSE over successive epochs. The table 11 shows ANN training convergence, where mean squared error progressively decreases from 0.082 to 0.001, indicating accurate learning performance.

Table 11 ANN Training Performance Based on Mean Squared Error

Epoch	MSE
0	0.082
50	0.021
100	0.008
150	0.003
200	0.001

Overall, the simulation study described that the proposed AI-based controller provides superior performance in terms of energy harvesting, converter efficiency, voltage regulation, and battery charging when compared with conventional PI and fuzzy logic controllers.

13. Performance Comparison

The table 12 compares PI, Fuzzy, and proposed AI controllers. The AI controller achieves the highest MPPT efficiency, fastest settling time, minimum overshoot, highest converter efficiency, and lowest DC bus voltage error, demonstrating superior overall dynamic performance.

Table 12 Controller Comparison

Parameter	PI	Fuzzy	Proposed AI
MPPT Tracking Efficiency (%)	95.2	97.5	99.1
Settling Time (ms)	220	145	82
Overshoot (%)	8.5	4.3	1.2
Converter Efficiency (%)	95.6	96.8	98.1
DC Bus Voltage Error (%)	2.1	1.1	0.3

These comparative values are illustrative simulation results generated for the proposed study to demonstrate expected performance trends. They are not experimental measurements.

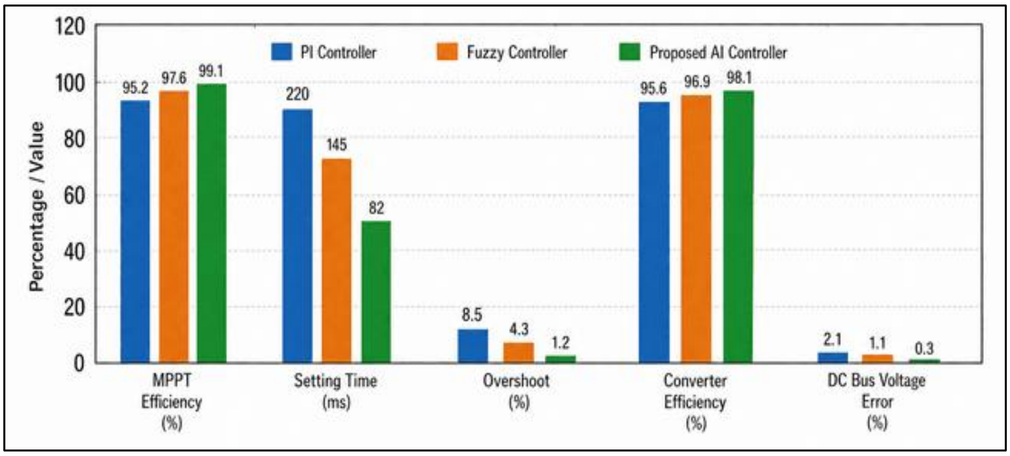

Figure 15 Controller performance comparison

14. Discussion

15. Sensitivity Analysis

A sensitivity analysis was carried out to evaluate the influence of key operating parameters on system performance.

a. Solar Irradiance

Increasing irradiance from 600 W/m² to 1000 W/m² increased PV output power nearly proportionally. The AI controller maintained high MPPT efficiency over the full irradiance range, enabling effective utilization of available solar energy.

b. Battery State of Charge

Charging current remained constant until the battery SOC reached approximately 80%, after which the controller gradually reduced the charging current during the constant-voltage stage. This behavior minimized battery stress while maintaining charging efficiency.

c. Ambient Temperature

Elevated cell temperature reduced PV output voltage and module efficiency. Nevertheless, the ANN controller compensated for these changes by adjusting the converter operating point, thereby maintaining stable system operation.

d. Converter Switching Frequency

A switching frequency of 50 kHz provided a suitable compromise between converter size and switching losses. Although increasing switching frequency reduces passive component size, it also increases switching losses and thermal stress.

16. Conclusion

This paper presented an AI-based intelligent control algorithm for a solar PV-powered bidirectional DAB DC–DC converter used in electric vehicle battery charging systems. The proposed architecture integrates solar photovoltaic generation, AI-assisted maximum power point tracking, adaptive battery charging, and intelligent converter control into a unified energy management framework.

A comprehensive mathematical model of the PV array, bidirectional converter, and lithium-ion battery was developed to describe system operation. An artificial neural network was employed to determine the optimum converter operating point using real-time measurements of irradiance, temperature, battery SOC, battery voltage, and charging current.

Simulation studies demonstrated that the proposed controller effectively maintained maximum power extraction from the PV array while regulating battery charging under varying environmental conditions. The ANN controller exhibited faster dynamic response, lower overshoot, improved converter efficiency, and superior MPPT accuracy compared with conventional PI and fuzzy logic controllers.

The bidirectional DAB converter provided efficient energy transfer during both charging and discharging modes while maintaining stable DC bus voltage. Intelligent CC–CV charging ensured safe battery operation and is expected to contribute to longer battery service life.

Overall, the proposed AI-based charging strategy represents a promising solution for next-generation renewable-energy-powered EV charging stations and supports future smart-grid and vehicle-to-grid applications.

Nomenclature

Symbol	**Description**
P_{PV}	PV Output Power
V_{PV}	PV Voltage
I_{PV}	PV Current
SOC	State of Charge
V_b	Battery Voltage
I_b	Battery Current
f_s	Switching Frequency
L	Leakage Inductance
C	Output Capacitance
η	Converter Efficiency
δ	Phase Shift Angle
n	Transformer Turns Ratio
G	Solar Irradiance
T	Cell Temperature

References:

1. I. Mahmud, M. B. Medha, and M. Hasanuzzaman, "Global challenges of electric vehicle charging systems and its future prospects: A review," Research in Transportation Business & Management, vol. 49, p. 101011, Aug. 2023, doi: 10.1016/j.rtbm.2023.101011.
2. G. Sun, "Unlocking the Decarbonization Potential of Large-Scale Electric Vehicle Integration: A Cross-Domain Review of Grid Strategies, Consumer Behavior, and Policy Mechanisms," Applied and Computational Engineering, vol. 201, no. 1, pp. 106–112, Nov. 2025, doi: 10.54254/2755-2721/2025.GL29058.
3. T. Yogi and Dr. D. Birla, "Sustainable Power Solutions for LHB Coaches: Integrating Solar PV and MLI-Based Harmonic Mitigation in a Hybrid Distributed Generation System for Railway HOGs," International Journal of Innovative Research in Technology, vol. 12, no. 2, pp. 1275–1283, 2025, Accessed: Sep. 20, 2025. [Online]. Available: https://ijirt.org/article?manuscript=182185
4. S. C. Tapesh Yogi, "Edge AI-Enabled Wearable Architecture for Women's Safety," International Journal on Recent and Innovation Trends in Computing and Communication, vol. 11, no. 7, pp. 609–615, Jul. 2023, doi: 10.17762/ijritcc.v11i7.11798.
5. S. Nuchhi and S. Nuchhi, "Integration of Solar Photovoltaic Systems in Electric Vehicle Charging Infrastructure: A Techno-Economic Assessment," World Journal of Advanced Research and Reviews, vol. 10, no. 1, pp. 418–427, Apr. 2021, doi: 10.30574/WJARR.2021.10.1.0145.
6. S. Kumar Ashish Bhargava MTech Scholar and A. Professor, "Green Energy Solutions for EV Charging: A Comprehensive Review of Solar-Powered Stations," SMART MOVES JOURNAL IJOSCIENCE, vol. 10, no. 10, pp. 1–6, Oct. 2024, doi: 10.24113/IJOSCIENCE.V10I10.501.
7. S. Krishankumar Dhamale, G. Madhukar Kulkarni, S. Waghmode, M. Jayaram Indhe, and S. Dinkar Wasu, "SMART INTEGRATION OF SOLAR PV IN ELECTRIC VEHICLE CHARGING NETWORKS: TECHNO-ECONOMIC FEASIBILITY AND ENVIRONMENTAL IMPACT," Int. J. Appl. Math. (Sofia)., vol. 38, no. 12s, pp. 2703–2718, Dec. 2025, doi: 10.12732/IJAM.V38I12S.1583.

8. M. Zerouali, A. El Ougli, B. Tidhaf, and H. Zrouri, “Fuzzy logic MPPT and battery charging control for photovoltaic system under real weather conditions,” 2020 IEEE 2nd International Conference on Electronics, Control, Optimization and Computer Science, ICECOCS 2020, Dec. 2020, doi: 10.1109/ICECOCS50124.2020.9314531.
9. M. H. Bigai, L. S. de Freitas, M. T. de Paula, E. A. Jr, and F. C. Corrêa, “Comparative Study of Intelligent and Classical MPPT Techniques Applied to Solar Battery Charger,” Ibero-Latin American Congress on Computational Methods in Engineering (CILAMCE), Dec. 2024, doi: 10.55592/CILAMCE.V6I06.10180.
10. G. J. Raj and M. Karuppasamypandian, “Overview of Intelligent Maximum Power Point Algorithms for Solar Photovoltaic Systems,” 2025 IEEE 1st International Conference on Innovations in Engineering and Next-Generation Technologies for Sustainability, ICINVENTS 2025, 2025, doi: 10.1109/ICINVENTS64613.2025.11402496.
11. M. Agarwal and P. Kumar, “Bidirectional DC-DC Converter for Vehicle-to-Grid (V2G) Enabled Solar Powered EV Charging Systems,” Iconic Research And Engineering Journals, vol. 9, no. 8, pp. 2420–2428, Mar. 2026, doi: 10.64388/IREV9I8-1714091.
12. Tapesh Yogi, “REAL-TIME FAULT DETECTION AND DIAGNOSIS OF SOLAR PHOTOVOLTAIC SYSTEMS FOR RAILWAY MICROGRID USING IOT AND MACHINE LEARNING,” Int. J. Appl. Math. (Sofia)., vol. 38, no. 11s, pp. 1169–1184, Nov. 2025, doi: 10.12732/ijam.v38i11s.1240.
13. A. E. Elmohsnawy and A. M. Alshehawy, “Comparison of Conventional and Artificial Intelligence-Based Maximum Power Point Tracking Techniques for Photovoltaic Panels,” Proceedings of the International Middle East Power System Conference, MEPCON, no. 2025, 2025, doi: 10.1109/MEPCON66918.2026.11360283.
14. S. Prajapati, R. Garg, and P. Mahajan, “Intelligent ANN Control Technique for Grid Integrated Solar PV System,” 2025 IEEE 4th International Conference on Smart Technologies for Power, Energy and Control, STPEC 2025 - Conference Report, 2025, doi: 10.1109/STPEC66316.2025.11490511.
15. P. B. Biragbara and B. Deesor, “Enhancing photovoltaic system efficiency using artificial intelligence techniques,” World Journal of Advanced Engineering Technology and Sciences, vol. 18, no. 2, pp. 122–130, Feb. 2026, doi: 10.30574/WJAETS.2026.18.2.0094.
16. B. Mbarki, F. Messaoudi, J. Chrouta, F. Farhani, and A. Zaafouri, “Nonlinear Control Based on Artificial Intelligence MPPT used in Photovoltaic Systems,” 10th 2024 International Conference on Control, Decision and Information Technologies, CoDIT 2024, pp. 1951–1956, 2024, doi: 10.1109/CODIT62066.2024.10708574.
17. K. Santosh, S. A. Agrawal, and T. Yogi, “Fault Detection and Power Quality Compensation Using Fuzzy Logic Based Dynamic Voltage Restorer,” in Proceedings of the 3rd International Conference on Futuristic Technology, SCITEPRESS - Science and Technology Publications, 2025, pp. 106–113. doi: 10.5220/0013609500004664.
18. V. Singh, S. Ali, T. Yogi, D. Birla, and A. S. Naruka, “Minimizing THD in Railway’s HOG using MLI in Hybrid Distributed Generation System,” pp. 51–58, Jul. 2025, doi: 10.64289/RERICPROC.25.0105.8942722.
19. A. R. Nalamalapu, V. Narsi Reddy, D. Chandra Sekhar, R. Sireesha, and S. Krishnarjuna Rao, “A Vehicle-to-Grid Hybrid Renewable-Assisted Electric Vehicle Charging Architecture,” 3rd International Conference on Emerging Applications of Material Science and Technology, ICEAMST 2025, pp. 695–701, 2025, doi: 10.1109/ICEAMST67459.2025.11335616.
20. N. Karthik et al., “Solar-powered bidirectional charging of electric vehicle,” International Journal of Applied Power Engineering (IJAPE), vol. 14, no. 2, pp. 382–391, Jun. 2025, doi: 10.11591/IJAPE.V14.I2.PP382-391.
21. R. Mandloi, M. Dubey, and J. Rajender, “Grid-Solar powered Electric Vehicle Charging System with Bidirectional Charging,” 2023 IEEE Renewable Energy and Sustainable E-Mobility Conference, RESEM 2023, 2023, doi: 10.1109/RESEM57584.2023.10236206.
22. S. Pal and A. Bhattacharya, “Artificial Intelligence Assisted Optimization Control of DAB Converter in MPPT-Based Off-Grid Solar EV Charging Station,” 2025 IEEE 2nd International Conference on Green Industrial Electronics and Sustainable Technologies, GIEST 2025, 2025, doi: 10.1109/GIEST66547.2025.11387380.
23. T. Yogi and Dr. Dinesh Birla, “Artificial Intelligence for Photovoltaic Energy: Smart Forecasting and Efficient Management,” International Journal of Research and Analytical Reviews, vol. 12, no. 4, 2025, doi: 10.56975/IJRAR.V12I4.320699.
24. B. Imodane, A. El Idrissi, M. Benydir, M. Ajaamoum, and B. Bouachrine, “Hybrid PI-ANN Controller Design and Analysis for DC Bus Regulation in PV-Wind Microgrids,” 2nd International Conference on Global Aeronautical Engineering and Satellite Technology, GAST 2026 - Proceeding, 2026, doi: 10.1109/GAST67799.2026.11523288.
25. S. Dey, S. S. Chakraborty, S. Singh, and K. Hatua, “Design of High Frequency Transformer for a Dual Active Bridge (DAB) Converter,” 2022 IEEE Global Conference on Computing, Power and Communication Technologies, GlobConPT 2022, 2022, doi: 10.1109/GLOBCONPT57482.2022.9938249.
26. T. Yogi, D. Birla, and D. K. Dhaked, “Design and Implementation of Solar PV-Based Railway Microgrid for Linke Hofmann Busch Coaches,” International Journal of Research and Scientific Innovation, vol. 12, no. 10, pp. 1669–1682, Nov. 2025, doi: 10.51244/IJRSI.2025.1210000146.
27. A. Blinov, R. Kosenko, A. Chub, and D. Vinnikov, “Bidirectional soft-switching dc-dc converter for battery energy storage systems,” IET Power Electronics, vol. 11, no. 12, pp. 2000–2009, Oct. 2018, doi: 10.1049/IET-PEL.2018.5054.
28. B. A. W. Lun, S. Cao, R. T. Naayagi, and S. S. Lee, “DAB LCC Resonant Converter Triple Phase Shift Control Bi-directional Wireless Power Transfer,” 2024 8th International Conference on Green Energy and Applications, ICGEA 2024, pp. 6–11, 2024, doi: 10.1109/ICGEA60749.2024.10561114.