Smart Adaptive Vehicle-to-Grid and Grid-to-Vehicle Control for EV Charging Stations Using Artificial Intelligence and Neuro-Fuzzy Systems.

POTNURU ESWARA RAO [1], PILLA JAYA [2], BATTA LOKESH [3], KEERTHI PAVANI [4], KUPIREDDI BHUVAN [5], UPPULURI LAKSHMI [6]

[1]*EEE STUDENT & SANKETIKA INSTITUTE OF TECHNOLOGY AND MANAGEMENT*
[2]*EEE STUDENT & SANKETIKA INSTITUTE OF TECHNOLOGY AND MANAGEMENT*
[3]*EEE STUDENT & SANKETIKA INSTITUTE OF TECHNOLOGY AND MANAGEMENT*
[4]*EEE STUDENT & SANKETIKA INSTITUTE OF TECHNOLOGY AND MANAGEMENT*
[5]*EEE STUDENT & SANKETIKA INSTITUTE OF TECHNOLOGY AND MANAGEMENT*
[6] *Assistant Professor & SANKETIKA INSTITUTE OF TECHNOLOGY AND MANAGEMENT*

ABSTRACT

The rapid growth of electric vehicles (EVs) has increased the demand for efficient and intelligent electric vehicle charging stations (EVCS). This research presents the development of an Artificial Intelligence (AI)-based adaptive Vehicle-to-Grid (V2G) and Grid-to-Vehicle (G2V) controller for a DC microgrid-based EV charging station integrated with a solar photovoltaic system (SPVS), storage battery (SB), electric vehicle (EV), and utility grid. The proposed system is designed for residential buildings and office environments where EVs remain parked for extended periods and can be utilized for intelligent energy management. An Adaptive Neuro-Fuzzy Inference System (ANFIS) combined with Artificial Neural Networks (ANN) is proposed as the power management controller (PMC) to enhance system performance and decision-making capability. The controller dynamically manages the power flow between the SPVS, storage battery, EV, and grid depending on power availability and load demand. The system operates in two distinct modes: Vehicle-to-Grid (V2G) mode, where the EV supplies power to the building or microgrid during power shortages, and Grid-to-Vehicle (G2V) mode, where the EV is charged using power from renewable sources, battery storage, or the grid. When the power generated from the SPVS and storage battery is insufficient to meet the load demand, the controller intelligently extracts power from the EV through V2G operation. If the available renewable and EV power are still inadequate, the deficit power is supplied by the grid using G2V operation. The proposed Neuro-Fuzzy based power management controller maintains a stable DC bus voltage and improves system dynamic performance The results confirm that the proposed intelligent control strategy enhances power management, improves system stability, and increases the efficiency of EV charging stations integrated with renewable energy sources.

1. Introduction

The rapid growth of electric vehicles (EVs) has attracted significant attention due to their advantages such as reduced environmental pollution, high energy efficiency, and low noise levels. As the adoption of EVs continues to increase, the demand for reliable and efficient electric vehicle charging stations (EVCS) has also grown. In the near future, a large number of EVs are expected to be connected to the public grid for charging, which will significantly influence the operation and stability of power systems. Among various renewable energy sources, solar photovoltaic systems (SPVS) are considered one of the most practical and promising solutions for EV charging stations. However, the output power of SPVS is highly dependent on solar irradiance and weather conditions, which introduces uncertainty and fluctuations in power generation. These fluctuations can affect the reliability and stability of renewable-energy-based charging stations. Therefore, integrating SPVS with other energy sources such as battery storage systems and the utility grid is necessary to ensure reliable operation of EV charging infrastructure. A hybrid EV charging station that combines solar photovoltaic systems, battery storage, and the utility grid provides a more dependable and cost-effective solution. The battery storage system acts as an energy buffer, storing excess energy generated by the photovoltaic system and supplying it when renewable power is insufficient. However, the storage capacity of batteries may sometimes be limited, especially during prolonged periods of low solar irradiance or during nighttime operation. In such cases, the utility grid serves as a backup power source to meet the charging station's load demand and maintain continuous operation.

Another promising concept in modern power systems is Vehicle-to-Grid (V2G) technology. In this approach, electric vehicles are not only consumers of electricity but can also act as distributed energy sources. When connected to the grid, EVs can supply power back to the grid or local loads during peak demand periods. This capability improves power system flexibility, reduces peak loads, and enhances the utilization of renewable energy resources. Conversely, in Grid-to-Vehicle (G2V) mode, EV batteries are charged using power from renewable sources, storage systems, or the utility grid. Despite these advantages, integrating EV charging stations with renewable energy sources and microgrid systems introduces several challenges. These include maintaining stable DC bus voltage, managing bidirectional power flow, ensuring efficient energy utilization, and maintaining system reliability under varying load and generation conditions. Disturbances in power flow within a DC microgrid may lead to voltage fluctuations at the DC bus, which can affect system stability and performance. To address these challenges, intelligent power management strategies are required. Artificial intelligence (AI)-based control techniques such as Artificial Neural Networks (ANN) and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) have demonstrated strong capabilities in handling nonlinear systems and dynamic operating conditions. These intelligent controllers can improve decision-making, optimize power flow, and maintain system stability. In this research, an AI-based adaptive power management controller is proposed for a DC microgrid-based EV charging station integrated with a solar photovoltaic system, storage battery, electric vehicle, and utility grid. The proposed controller utilizes ANN and ANFIS techniques to dynamically manage power flow and maintain a stable DC bus voltage during both Vehicle-to-Grid (V2G) and Grid-to-Vehicle (G2V) operations. The system aims to enhance energy management, improve system reliability, and increase the efficiency of EV charging stations integrated with renewable energy sources.

2. System Configuration

The electric vehicle charging station (EVCS) considered in this study consists of a solar photovoltaic system (SPVS), storage battery (SB), utility grid, and electric vehicle (EV) load, as shown in Fig. 1(a). The SPVS acts as the primary renewable energy source for the charging station, converting solar energy into electrical power. However, due to the intermittent nature of solar irradiance, the generated power may vary throughout the day. To ensure continuous power availability, a storage battery is incorporated into the system to store excess energy generated by the SPVS and supply it when solar generation is insufficient.

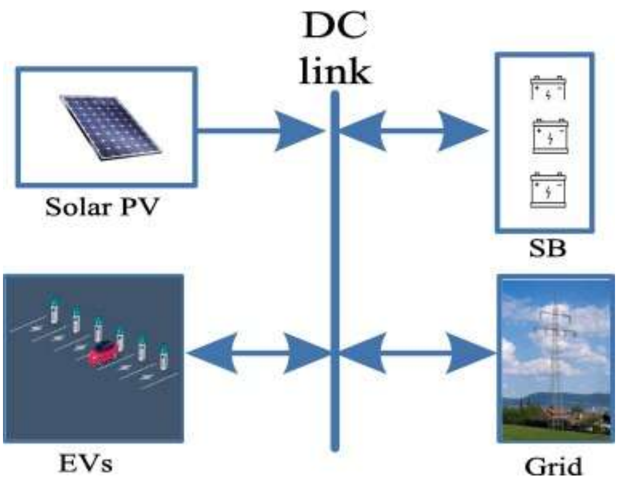

Fig. 1a. Proposed configuration for DC microgrid based EVCS.

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 10 Issue: 04 | April - 2026 SJIF Rating: 8.659 ISSN: 2582-3930

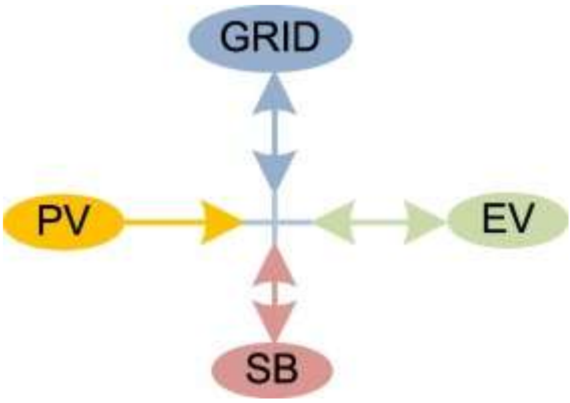

Fig. 1b. Power equilibrium at the DC bus.

The EV battery acts both as a load and as a distributed energy resource within the microgrid. During the charging process, the EV receives energy from the SPVS, storage battery, or the utility grid in Grid-to-Vehicle (G2V) mode. Conversely, during periods of high demand or insufficient renewable energy generation, the EV can supply energy back to the microgrid through Vehicle-to-Grid (V2G) operation. This bidirectional power flow capability enhances the flexibility and efficiency of the EV charging station.

The utility grid serves as a backup power source to maintain system reliability when renewable energy and battery storage are insufficient to meet the load demand. Integrating the grid with renewable sources and storage systems improves the overall stability and operational reliability of the EV charging infrastructure.

In the proposed system, a DC microgrid architecture is adopted in which all energy sources and loads are connected to a common DC bus. Maintaining a stable DC bus voltage is critical for proper operation of the system. Variations in load demand or renewable power generation may lead to fluctuations in the DC bus voltage, which can affect system performance.

To address this issue, an Artificial Neural Network (ANN)-based Power Management Controller (PMC) is implemented, as illustrated in Fig. 1(b). The proposed controller is responsible for regulating the DC bus voltage and managing the power flow between the SPVS, storage battery, EV, and grid. Based on system conditions such as power availability, battery state, and load demand, the controller determines the appropriate operating mode (V2G or G2V) and ensures efficient power distribution within the DC microgrid.

The intelligent control strategy improves system stability, maintains DC bus voltage regulation, and enhances the overall performance of the EV charging station.

2.1 Solar Photovoltaic System (SPVS)

In a solar photovoltaic system (SPVS), photovoltaic (PV) cells are connected in series and parallel combinations to form a PV array. Connecting PV cells in series increases the output voltage of the system, while connecting them in parallel increases the current capacity. This configuration enables the PV array to generate sufficient power for practical applications such as electric vehicle charging stations.

A general equivalent circuit representation of a photovoltaic cell is shown in Fig. 2. An ideal photovoltaic cell can be modeled using a current source connected in parallel with a diode. However, a practical PV cell includes additional components such as series resistance and shunt resistance to represent internal losses. Therefore, a practical PV model consists of a current source, an anti-parallel diode, a series resistance R_s, and a shunt resistance R_{sh}.

The output current of the photovoltaic system can be determined using the following equation:

$$I_S = \left(\frac{\gamma}{\gamma_{ref}}\right) I_{Sref} + \alpha_{ISC}(T_a - T_{ref})$$

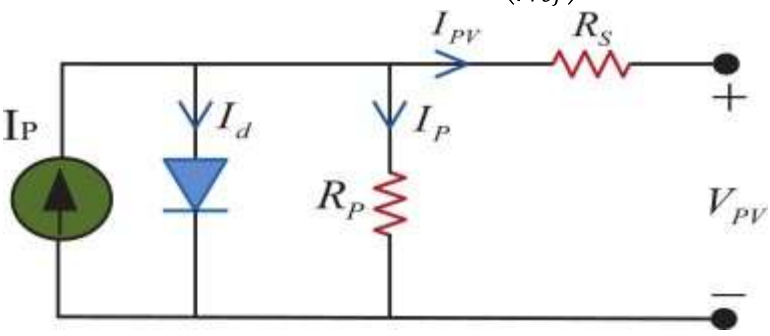

Fig. 2. Solar photovoltaic cell equivalent circuit.

where $I_S$represents the output current of the PV source, $I_{Sref}$is the reference short-circuit current, γdenotes the solar irradiance (W/m²), γ_{ref}represents the reference irradiance, $T_a$is the ambient temperature, and $T_{ref}$is the reference temperature. The parameter α_{ISC}denotes the temperature coefficient of the short-circuit current.

In the equivalent circuit model, $I_D$represents the current flowing through the diode, while $V_P$represents the voltage across the PV cell. The resistances $R_s$and R_{sh}represent the series and shunt resistances respectively, accounting for internal losses within the photovoltaic cell.

To extract maximum power from the photovoltaic system, a Maximum Power Point Tracking (MPPT) technique is implemented. In this work, an Adaptive Neuro-Fuzzy Inference System (ANFIS) based MPPT controller is used. The ANFIS model is trained using two input parameters: solar irradiance and ambient temperature. Based on these inputs, the controller generates an optimal reference voltage corresponding to the maximum power point of the PV system.

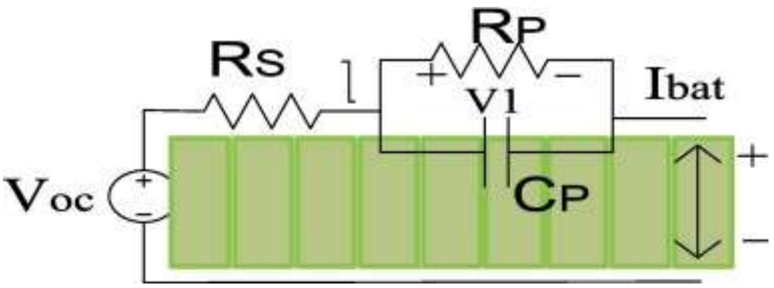

Fig. 3. Storage battery Thevenin model

The output voltage generated by the ANFIS controller is compared with the actual PV voltage through an error generator. The resulting error signal is minimized using a Proportional–Integral (PI) controller. The output of the PI controller is then used to generate Pulse Width Modulation (PWM) signals for controlling a DC–DC converter. This process ensures that the photovoltaic system operates at its maximum power point under varying environmental conditions.

2.2 Storage Battery Model

In an Electric Vehicle Charging Station (EVCS), a storage battery is used as a backup energy source to ensure continuous power supply when renewable generation is insufficient. The battery stores excess energy generated by the solar photovoltaic system and supplies power during periods of low solar irradiance or high load demand. This improves the reliability and stability of the EV charging infrastructure.

The storage battery in the proposed system is modeled using a Thevenin equivalent circuit. This model represents the battery as an open-circuit voltage source combined with internal resistive and capacitive components that reflect the dynamic behavior of the battery. The equivalent circuit consists of an open-circuit voltage source V_{oc}, a series resistance R_s, and a parallel combination of resistance $R_p$and capacitance C_p, as illustrated in Fig. 3. This model accurately represents the battery's voltage response and transient characteristics during charging and discharging operations.

The terminal voltage of the battery can be expressed as:

$$V_{bat}(t) = V_{oc}(soc(t)) - V_1(t) - R_s I_{bat}$$

where V_{bat}represents the battery terminal voltage and I_{bat}denotes the battery current. The open-circuit voltage V_{oc}depends on the battery's state of charge (SOC). The parameter $R_s$represents the internal series resistance of the battery, which accounts for the ohmic voltage drop during operation. The term V_1represents the voltage drop across the parallel resistance R_p, which models the polarization effects within the battery.

The combination of resistance $R_p$and capacitance $C_p$captures the transient behavior and dynamic response of the battery during charging and discharging cycles. This equivalent circuit model is widely used for lithium-ion batteries due to its simplicity and ability to represent real battery characteristics.

In the proposed EV charging station, the storage battery plays a crucial role in maintaining power balance within the DC microgrid. When the power generated from the solar photovoltaic system exceeds the load demand, the excess energy is stored in the battery. Conversely, when solar power is insufficient, the stored energy in the battery is used to support the load and maintain stable DC bus voltage.

2.3 Electric Vehicle Battery Modelling

Lithium-ion (Li-ion) batteries are widely used in electric vehicles due to their high energy density, long life cycle, and low self-discharge rate. The charging and discharging characteristics of EV batteries differ from conventional batteries because of factors such as charging duration and the battery's state of charge (SOC) at arrival and departure.

The state of charge of the EV battery indicates the available energy level in the battery and is an important parameter for energy management in EV charging stations. The SOC of the EV battery can be expressed as:

$$SOC = soc(t_0) + \frac{1}{E_c}\int_{t_0}^{t_0+t} I_{bat}\,(\tau)\,d\tau \times 100\%$$

where $soc(t_0)$represents the initial state of charge of the EV battery, $E_c$denotes the battery capacity, $I_{bat}$is the battery charging or discharging current, and $t$represents the total charging duration. This model helps monitor battery energy during both Vehicle-to-Grid (V2G) and Grid-to-Vehicle (G2V) operations.

2.4 Grid Interface Converter

In the proposed system, the utility grid is connected to the DC microgrid through a single-phase inverter and an LCL filter. The inverter controls the bidirectional power flow between the grid and the DC microgrid.

The grid current is regulated using an Artificial Neural Network (ANN)-based Power Management Controller (PMC), which takes the solar photovoltaic system (SPVS) power and battery state of charge (SOC) as input parameters. Based on these inputs, the controller determines the required grid power to maintain power balance in the microgrid.

The grid current magnitude can be calculated using:

$$I_{grid} = \frac{P_{grid}}{V_{ph}}$$

where P_{grid} represents the grid power, V_{ph} denotes the single-phase grid voltage, and I_{grid} is the grid current magnitude.

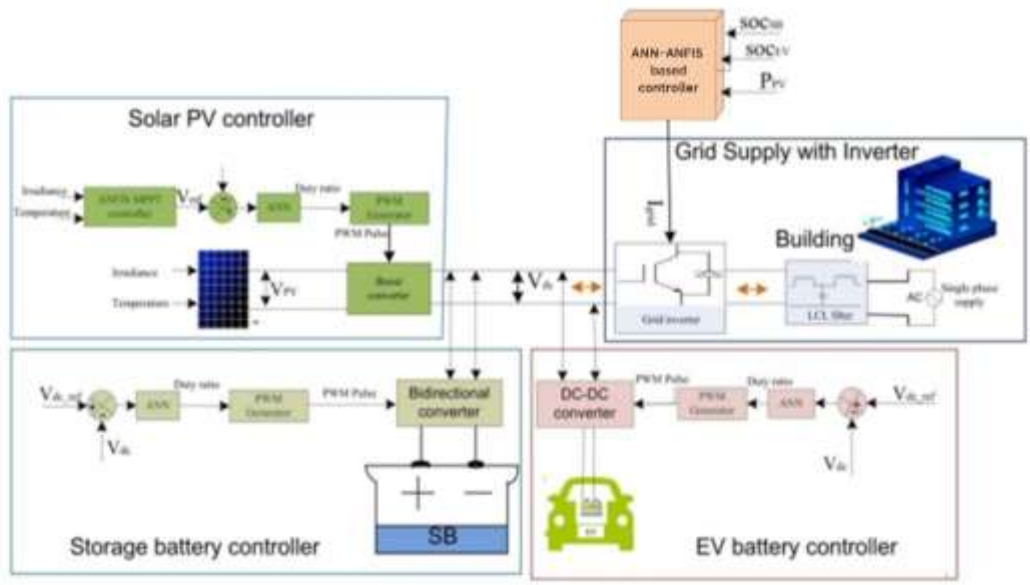

Fig. 4. Schematic illustration of the proposed ANN–ANFIS Based power management controller

3. ANN–ANFIS Based Power Management Controller

An intelligent power management controller (PMC) is proposed to regulate power flow and maintain a stable DC bus voltage in the DC microgrid-based EV charging station. The controller integrates an Artificial Neural Network (ANN) with an Adaptive Neuro-Fuzzy Inference System (ANFIS) to improve system decision-making and dynamic performance. The overall control structure of the proposed system is shown in Fig. 4.

The main function of the PMC is to maintain power balance between the solar photovoltaic system (SPVS), storage battery (SB), electric vehicle (EV), and the utility grid. The controller continuously monitors system parameters such as DC bus voltage, photovoltaic power generation, and battery state of charge (SOC). Based on these inputs, the controller determines the operating mode and controls the power flow within the microgrid.

The DC bus voltage regulation is expressed as

$$V_{dc}^{error} = V_{dc}^{ref} - V_{dc}$$

where V_{dc}^{ref} represents the reference DC bus voltage and V_{dc} is the measured DC bus voltage. The error signal is processed by the ANN controller to generate an appropriate control signal.

The power balance in the DC microgrid can be represented as

$$P_{PV} + P_{bat} + P_{grid} = P_{EV} + P_{load}$$

where P_{PV} represents photovoltaic power, P_{bat} denotes battery power, P_{grid} represents grid power, P_{EV} is the EV charging or discharging power, and P_{load} represents the total load demand.

The ANFIS controller is used in the Maximum Power Point Tracking (MPPT) of the photovoltaic system to extract maximum available power under varying environmental conditions. The ANN controller determines the required grid current and battery power to maintain DC bus voltage stability. The EV charging station operates in two modes. In Vehicle-to-Grid (V2G) mode, the EV battery supplies power to the microgrid when renewable energy and battery storage are insufficient. In Grid-to-Vehicle (G2V) mode, the EV battery is charged using energy from the SPVS, storage battery, or the utility grid. The proposed ANN–ANFIS based PMC improves voltage regulation, reduces DC bus voltage fluctuations, and ensures efficient power management in the EV charging station.

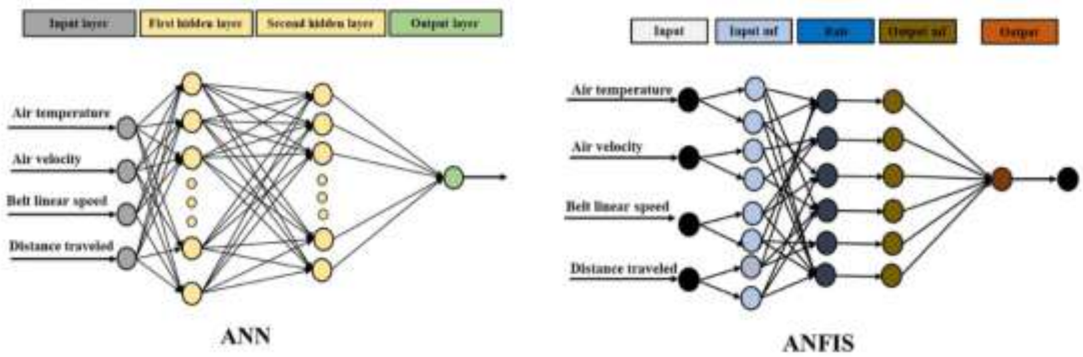

Fig. 5. Artificial neural network (ANN) and adaptive neuro-fuzzy interference system (ANFIS) modelling.

4. Results and Discussion

The performance of the proposed ANN–ANFIS based power management controller is evaluated using MATLAB/Simulink 2020a. The developed model represents a DC microgrid-based electric vehicle charging station (EVCS) integrated with a solar photovoltaic system (SPVS), storage battery, electric vehicle battery, and the utility grid. The intelligent controller manages the power flow between these components while maintaining a stable DC bus voltage. The model consists of a photovoltaic array with an ANFIS-based MPPT controller, a storage battery model, an EV battery model, a grid-connected inverter, and an ANN-based power management controller.

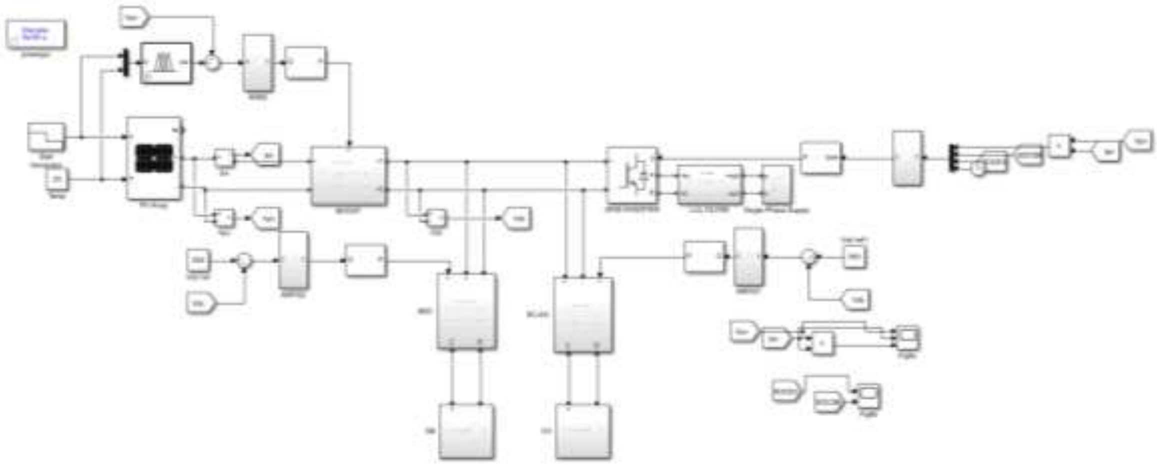

Fig. 6. Simulation circuit diagram using Artificial neural network (ANN) and adaptive neuro-fuzzy interference system (ANFIS) modelling.

The photovoltaic system generates electrical energy from solar irradiance and supplies power to the DC bus. The storage battery and EV battery are connected through bidirectional converters to support both charging and discharging operations. The grid inverter connects the DC microgrid with the utility grid to ensure reliable power supply when renewable generation is insufficient. To improve system intelligence and control performance, a combination of Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) is implemented. The ANFIS controller is primarily used in the Maximum Power Point Tracking (MPPT) of the photovoltaic system, while the ANN controller performs power management and DC bus voltage regulation. The ANFIS controller utilizes fuzzy inference rules combined with neural network learning capability to determine the optimal reference voltage for the PV system under varying irradiance and temperature conditions. This allows the photovoltaic system to operate near the maximum power point and improves energy extraction efficiency. The ANN controller receives key system parameters such as solar PV power, storage battery state of charge (SOC), EV battery SOC, and DC bus voltage as input signals. Based on these inputs, the controller determines the required grid current and controls the power exchange between the grid and the microgrid. By continuously adjusting the grid current, the controller maintains power balance and stabilizes the DC bus voltage. In conventional PV-based systems, fluctuations in solar irradiance may cause voltage instability and power imbalance within the microgrid. However, in the proposed system, the ANN–ANFIS based control strategy effectively compensates for these variations. The grid acts as a support source and supplies the required power when renewable generation and battery storage are insufficient.

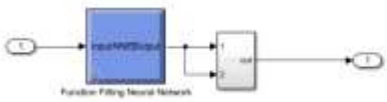

Fig. 7. Adaptive neuro-fuzzy interference system (ANFIS) modelling.

The simulation results are analyzed under two operating conditions. Case I represents the Vehicle-to-Grid (V2G) mode, where the EV battery supplies power to the microgrid during power shortages. Case II represents the Grid-to-Vehicle (G2V) mode, where the EV battery is charged using power from the photovoltaic system, storage battery, or utility grid.

The technical specifications of the DC microgrid-based EV charging station are summarized in Table 1, while the parameters used for the controller are listed in Table 2. The results demonstrate that the proposed intelligent control strategy effectively improves power management, maintains DC bus voltage stability, and enhances the efficiency of the EV charging station integrated with renewable energy sources.

4.1 Case I: Solar Photovoltaic Power Variation, $SOC_{SB}^{min} \geq SOC_{SB}$ and $SOC_{EV}^{max} \leq SOC_{EV}$

In this case, the solar photovoltaic (PV) output power varies due to changes in solar irradiance and temperature conditions, as illustrated in Fig. 8(a): Solar PV Power Variation. This operational condition represents the Vehicle-to-Grid (V2G) mode, where the storage battery state of charge (SOC) is below the minimum threshold while the electric vehicle (EV) battery SOC is above the maximum threshold. Under such circumstances, the EV battery can support the microgrid by supplying power when required. During the time interval from 0 s to 4 s, two main power sources are available in the system: the solar photovoltaic system and the EV battery. These sources provide energy to charge the storage battery (SB) and also supply excess energy to the grid when available. During the initial period from 0 s to 1 s, the solar PV system generates its maximum output power, reaching approximately 2000 W, as shown in Fig. 8(a). At this moment, the storage battery SOC is relatively low, around 9%, which is below the minimum SOC threshold. Therefore, the system prioritizes charging the storage battery. As illustrated in Fig. 8(b): Storage Battery SOC Variation, the SOC of the storage battery gradually increases from 9% to 9.6% over the period of 0 s to 4 s. At the same time, the EV battery operates in V2G mode and contributes additional power to the system. As depicted in Fig. 8(c): Grid Power Exchange, the excess power generated by the PV system and EV battery is delivered to the utility grid. However, due to fluctuations in solar output, the power supplied to the grid changes with time. Between 1 s and 2 s, the solar PV power decreases from 2000 W to approximately 1750 W because of irradiance variation. Since the EV battery SOC is above the maximum threshold, it continues to support the system, and approximately 1750 W of power is exported to the grid, as shown in Fig. 8(c).

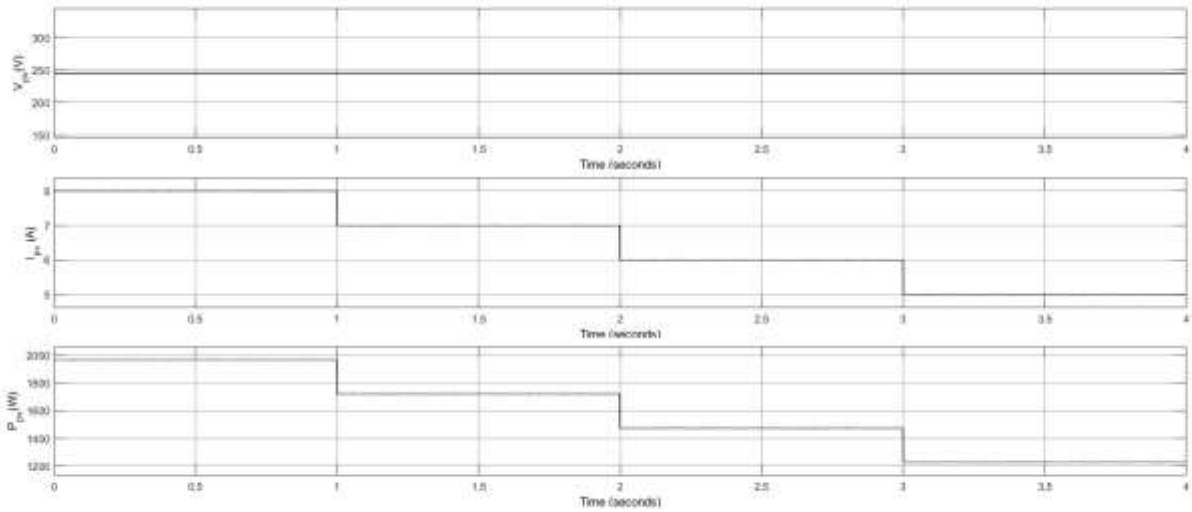

Fig. 8a. Solar photovoltaic voltage, current, and power.

During the time interval from 2 s to 3 s, the PV output power further decreases to around 1500 W. Consequently, the power delivered to the grid reduces to approximately 1300 W in this period. The variation in grid voltage and current throughout the operation is illustrated in Fig. 8(d): Grid Voltage and Current Waveforms. The combined power contribution from the solar PV system and the EV battery not only satisfies the load demand but also delivers surplus power to the public grid. This power balance condition is clearly illustrated in Fig. 8(e): Power Balance of the DC Microgrid. The results indicate that the microgrid maintains a proper equilibrium between power generation and consumption. Furthermore, the dynamic response of the DC bus voltage is shown in Fig. 8(f): DC Bus Voltage Response. Overall, the results demonstrate that the proposed ANN–ANFIS based power management strategy efficiently manages power flow under fluctuating solar conditions and ensures stable operation of the DC microgrid-based EV charging station.

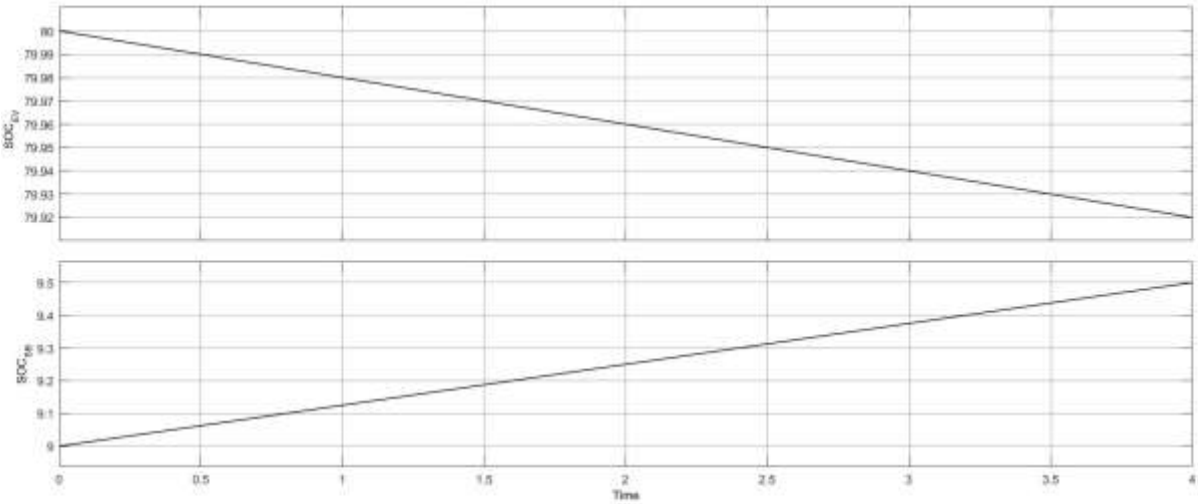

Fig. 8b. Charge status of storage and EV battery.

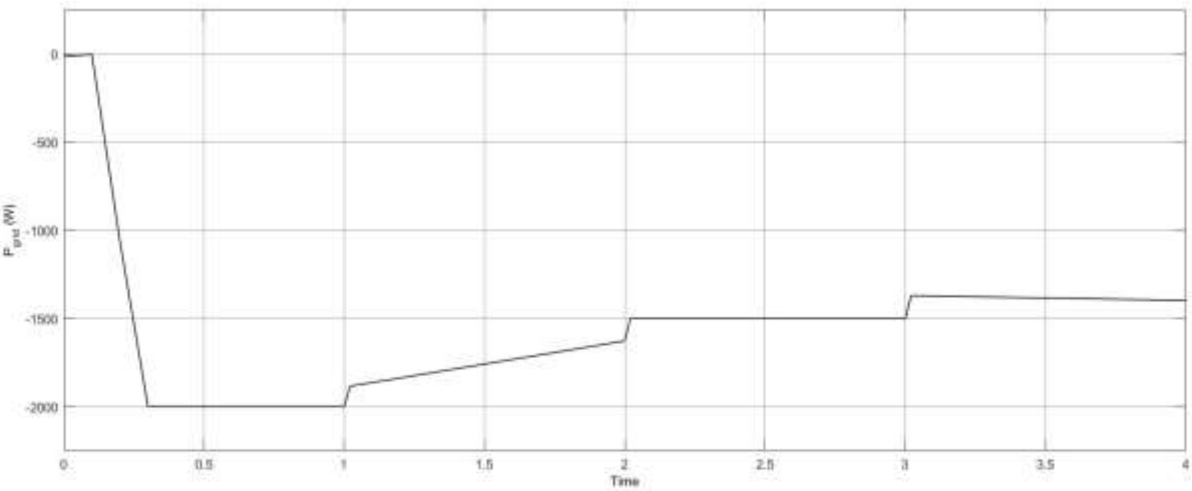

Fig. 8c. Grid power variation during V2G mode of operation.

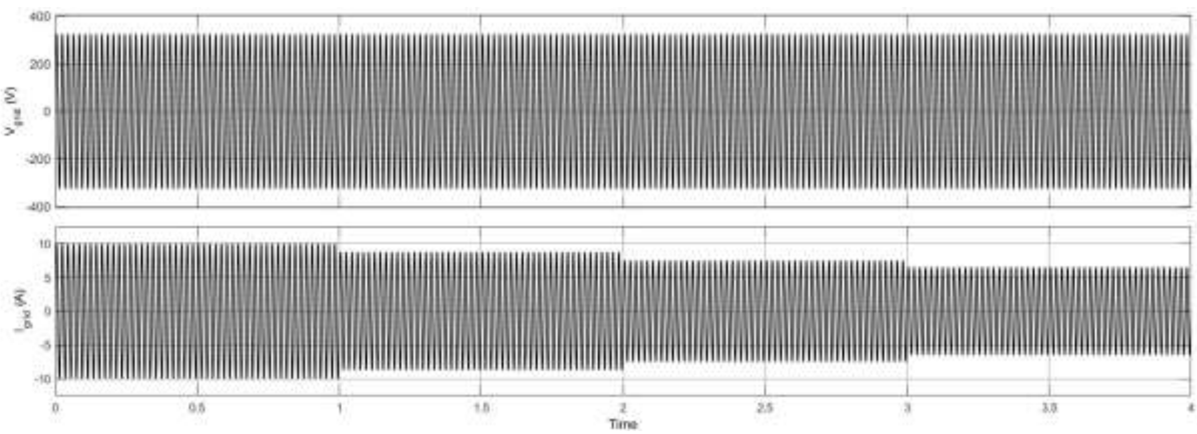

Fig. 8d. Grid voltage and grid current variation in V2G mode of operation.

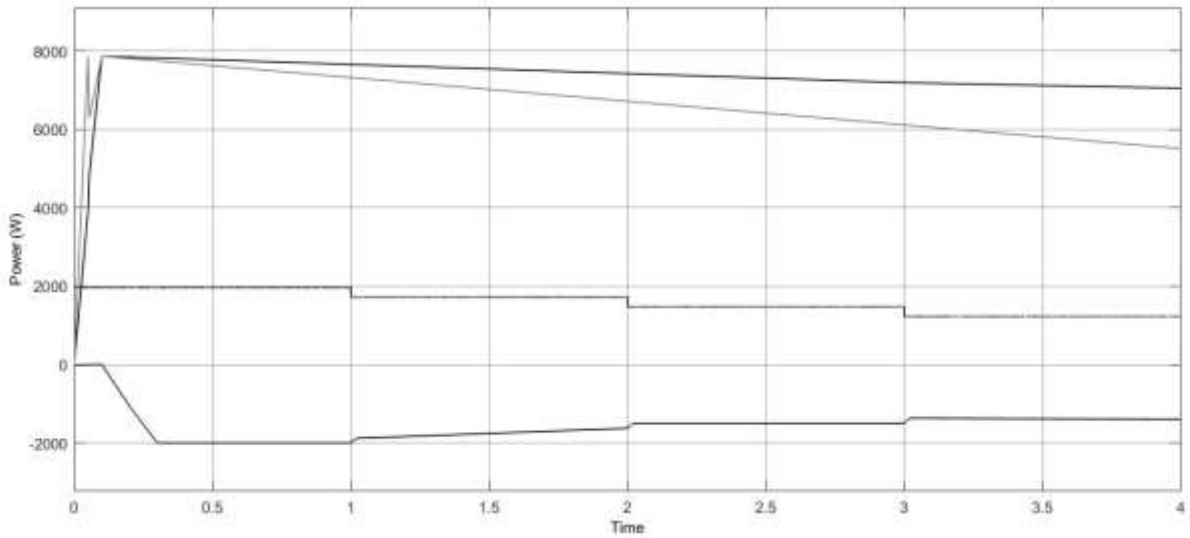

Fig. 8e. Power flow diagram during V2G mode of operation.

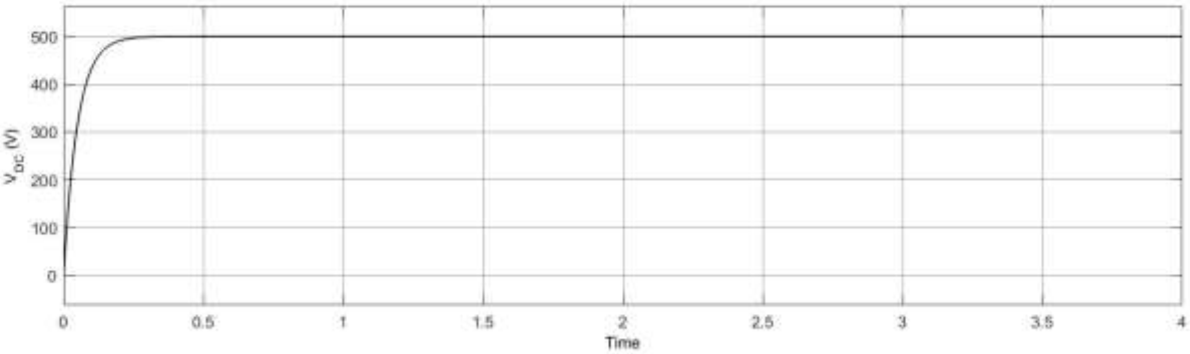

Fig. 8f. DC bus voltage proposed ANN–ANFIS.

4.2 Case II: Solar Photovoltaic Power Variation, $SOC_{SB}^{min} \geq SOC_{SB}$ and $SOC_{EV}^{min} \geq SOC_{EV}$

In this case, the solar photovoltaic (PV) output power fluctuates due to variations in solar irradiance and ambient temperature, as illustrated in Fig. 9(a): Solar PV Power Variation. This operational condition represents the Grid-to-Vehicle (G2V) mode, which occurs when the state of charge (SOC) of both the storage battery (SB) and the electric vehicle (EV) battery fall below their respective minimum SOC limits. Under these conditions, the system prioritizes charging both batteries using the available solar power and additional support from the utility grid. During the time interval from 0 s to 4 s, two energy sources are available in the system: the solar photovoltaic system (SPVS) and the utility grid. These sources provide energy to charge the EV battery as well as the stationary storage battery. During the initial time interval from 0 s to 1 s, the solar photovoltaic system generates its maximum output power of approximately 2000 W, as shown in Fig. 9(a). At this moment, both the EV battery and the storage battery have SOC values below their minimum limits, approximately 9% for the storage battery and 10% for the EV battery. Due to these low SOC values, the system enters charging mode for both batteries. The variation in SOC during the charging process is illustrated in Fig. 9(b): SOC Variation of EV and Storage Battery. As a result of the charging process, the SOC of the EV battery increases from 10% to 10.06%, while the SOC of the storage battery increases from 9% to 9.08% within the 4-second duration. Since the available solar power is insufficient to completely meet the charging demand, additional power is drawn from the utility grid. The power exchange between the grid and the DC microgrid is illustrated in Fig. 9(c): Grid Power Consumption. It can be observed that the grid continuously supplies power to the system throughout the 4-second interval in order to charge both the EV battery and the storage battery. Between 1 s and 2 s, the solar PV output decreases

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 10 Issue: 04 | April - 2026 SJIF Rating: 8.659 ISSN: 2582-3930

from 2000 W to approximately 1750 W due to changes in irradiance conditions. As the solar power decreases, the system compensates by drawing more power from the grid. Consequently, the grid power consumption increases to approximately 900 W, as shown in Fig. 9(d): Grid Voltage and Current Variation. During the time interval from 2 s to 3 s, the solar photovoltaic output power decreases further to around 1500 W. Because of this reduction in solar power generation, the power drawn from the grid increases to approximately 1200 W in order to maintain the charging process of both batteries. This demonstrates the ability of the proposed system to dynamically balance power flow under fluctuating renewable energy conditions. The overall power balance within the DC microgrid is illustrated in Fig. 9(e): Power Balance of the System. The combined power supplied by the solar PV system and the utility grid effectively meets the charging demand of both the EV battery and the storage battery. Therefore, the supply and demand of electrical power within the microgrid remain balanced. The DC bus voltage response during this operation is shown in Fig. 9(f): DC Bus Voltage Response. Overall, the results demonstrate that the proposed ANN–ANFIS based power management strategy effectively manages the charging operation in G2V mode, maintains DC bus voltage stability, and ensures reliable power flow in the DC microgrid-based EV charging station.

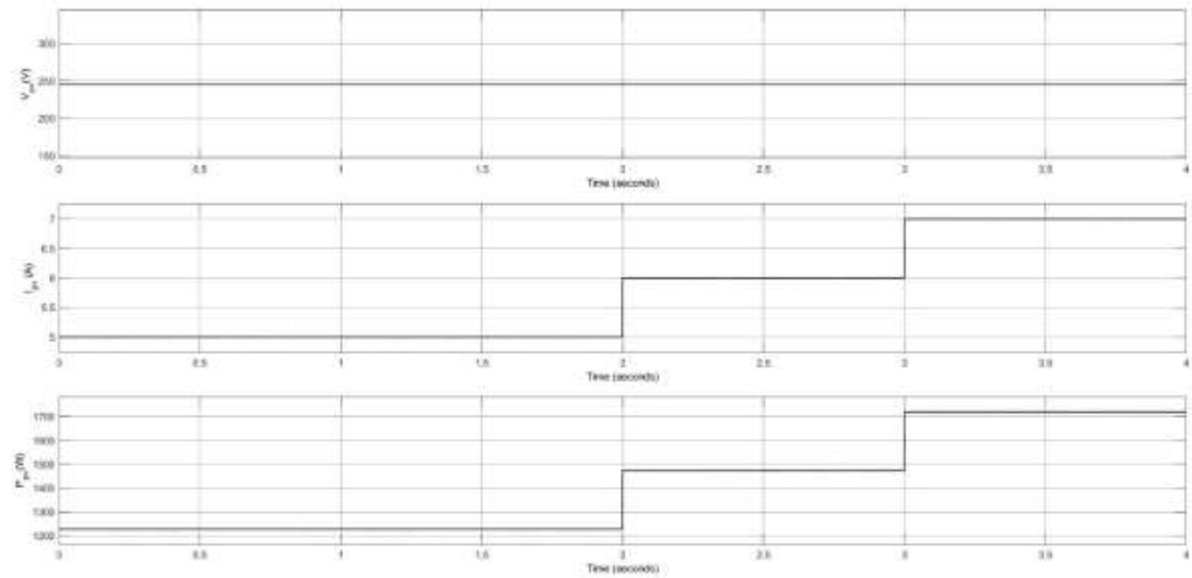

Fig. 9a. Solar photovoltaic voltage, current, and power.

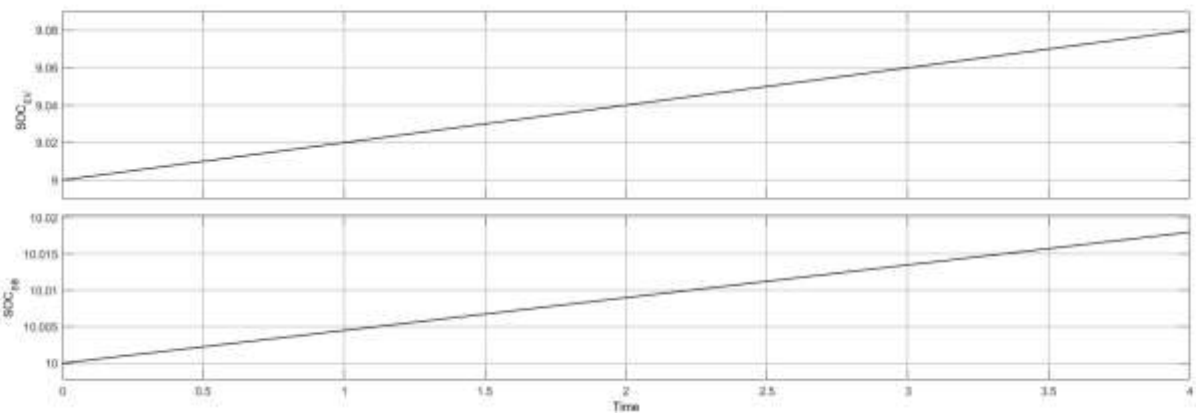

Fig. 9b. Charge status of storage and EV battery.

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 10 Issue: 04 | April - 2026 SJIF Rating: 8.659 ISSN: 2582-3930

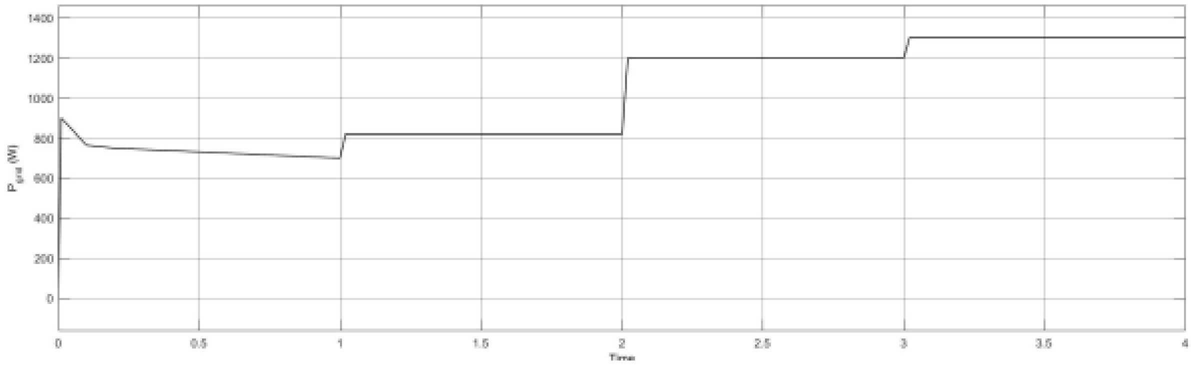

Fig. 9c. Grid power variation during G2V mode of operation.

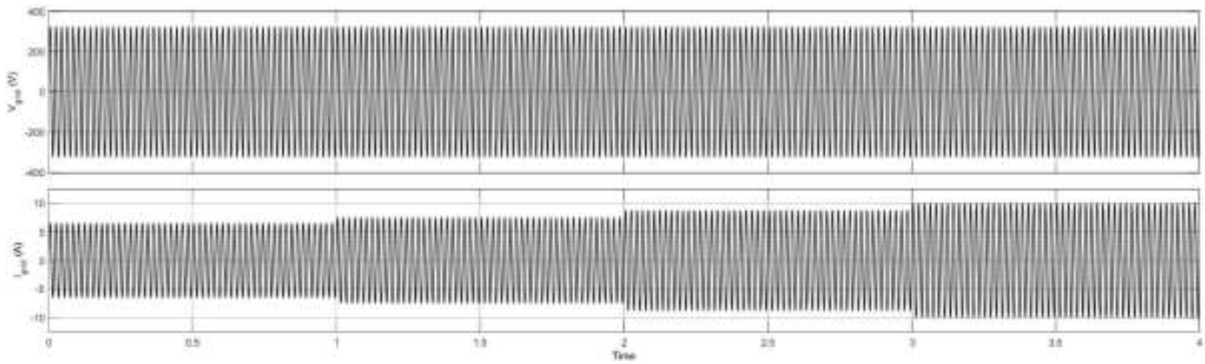

Fig. 9d. Grid voltage and grid current variation during G2V mode of operation.

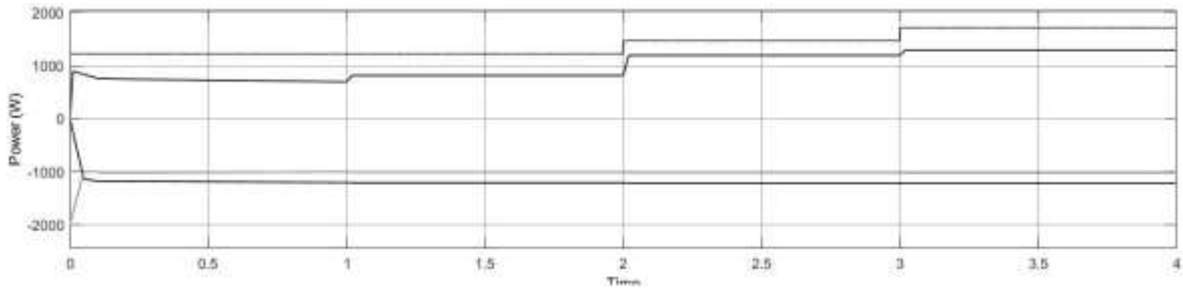

Fig. 9e. Power flow diagram during G2V mode of operation.

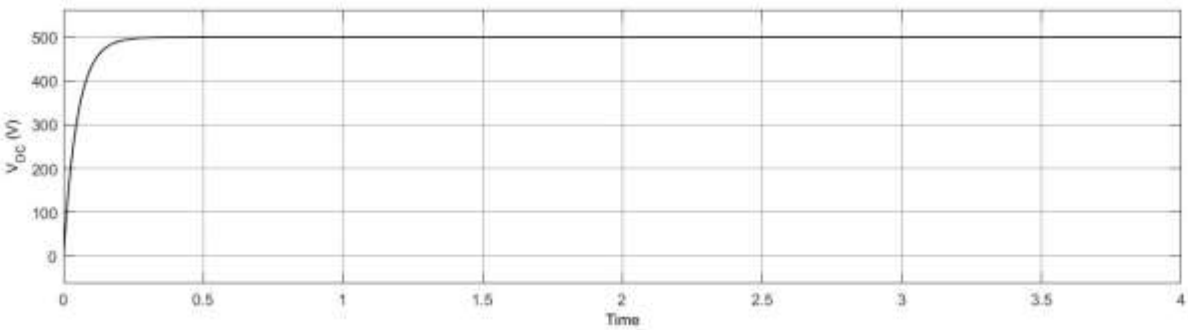

Fig. 9f. DC bus voltage proposed ANN–ANFIS.

Conclusion

This paper presents an Artificial Intelligence-based adaptive Vehicle-to-Grid (V2G) and Grid-to-Vehicle (G2V) controller for a DC microgrid electric vehicle charging station integrated with a solar photovoltaic system, storage battery, electric vehicle battery, and utility grid. An ANFIS-based Maximum Power Point Tracking (MPPT) technique is used to extract maximum power from the solar PV system, while an Artificial Neural Network (ANN) based power management controller regulates the power flow between the PV system, storage battery, EV battery, and grid. The proposed controller maintains a stable DC bus voltage and ensures efficient bidirectional power flow during both V2G and G2V operating modes. Simulation results obtained using MATLAB/Simulink demonstrate that the ANN-based controller significantly improves system performance by reducing voltage overshoot, settling time, and rise time compared to conventional controllers. The results confirm that the proposed intelligent control strategy enhances energy management, improves voltage stability, and increases the efficiency of EV charging stations integrated with renewable energy sources.

References

[1] International Energy Agency, "Global EV Outlook 2021: Accelerating Ambitions Despite the Pandemic," IEA Publications, 2021.

[2] S. M. Shariff, M. S. Alam, F. Ahmad, Y. Rafat, M. S. J. Asghar, and S. Khan, "System design and realization of a solar-powered electric vehicle charging station," *IEEE Systems Journal*, vol. 14, no. 2, pp. 2748–2758, 2020.

[3] A. Verma and S. B. Energy, "Strategy of solar PV-battery and diesel generator based electric vehicle charging station," in *Proc. IEEE Energy Conversion Congress and Exposition (ECCE)*, 2018, pp. 1043–1050.

[4] M. S. Islam, N. Mithulananthan, and K. Y. Lee, "Suitability of PV and battery storage in EV charging at business premises," *IEEE Transactions on Power Systems*, vol. 33, no. 4, pp. 4382–4396, 2018.

[5] N. Saxena, I. Hussain, B. Singh, and A. L. Vyas, "Implementation of a grid-integrated PV-battery system for residential and electric vehicle applications," *IEEE Transactions on Industrial Electronics*, vol. 65, no. 8, pp. 6592–6601, 2018.

[6] H. Mahmood and J. Jiang, "Autonomous coordination of multiple PV/battery hybrid units in islanded microgrids," *IEEE Transactions on Smart Grid*, vol. 9, no. 6, pp. 6359–6368, 2018.

[7] R. R. Deshmukh, M. S. Ballal, H. M. Suryawanshi, and M. K. Mishra, "An adaptive approach for effective power management in DC microgrid based on virtual generation," *IEEE Transactions on Industrial Informatics*, vol. 16, no. 1, pp. 362–372, 2020.

[8] M. O. Badawy and Y. Sozer, "Power flow management of a grid-tied PV-battery system for electric vehicles charging," *IEEE Transactions on Industry Applications*, vol. 53, no. 2, pp. 1347–1357, 2017.

[9] Z. Yi, W. Dong, and A. H. Etemadi, "A unified control and power management scheme for PV-battery-based hybrid microgrids," *IEEE Transactions on Smart Grid*, vol. 9, no. 6, pp. 5975–5985, 2018.

[10] X. Liu, P. Wang, and P. C. Loh, "A hybrid AC/DC microgrid and its coordination control," *IEEE Transactions on Smart Grid*, vol. 2, no. 2, pp. 278–286, 2011.

[11] A. Bharatee, P. K. Ray, and A. Ghosh, "A power management scheme for grid-connected PV integrated with hybrid energy storage system," *Journal of Modern Power Systems and Clean Energy*, vol. 10, no. 4, pp. 954–963, 2021.

[12] S. Sathyan, H. M. Suryawanshi, M. S. Ballal, and A. B. Shitole, "Soft-switching DC–DC converter for distributed energy sources with high step-up voltage capability," *IEEE Transactions on Industrial Electronics*, vol. 62, no. 11, pp. 7039–7050, 2015.

[13] H. M. Mohan, S. K. Dash, and W. Caesarendra, "Performance assessment of three-phase PV tied NPC multilevel inverter based UPQC," in *Proc. IEEE ICICCSP*, 2022, pp. 1–5.

[14] P. Y. Kong and G. K. Karagiannidis, "Charging schemes for plug-in hybrid electric vehicles in smart grid: A survey," *IEEE Access*, vol. 4, pp. 6846–6875, 2016.

[15] D. Wang, M. Sechilariu, and F. Locment, "PV-powered charging station for electric vehicles: Power management with integrated V2G," *Applied Sciences*, vol. 10, no. 18, pp. 1–20, 2020.

[16] A. A. Hepzibah and K. Premkumar, "ANFIS current-voltage controlled MPPT algorithm for solar powered BLDC motor based water pump," *Electrical Engineering*, vol. 102, pp. 421–435, 2020.

[17] J. P. Rivera-Barrera, N. Muñoz-Galeano, and H. O. Sarmiento-Maldonado, "SOC estimation for lithium-ion batteries: Review and future challenges," *Energies*, vol. 10, no. 9, pp. 1–20, 2017.

[18] P. Singh and J. S. Lather, "Artificial neural network-based dynamic power management of a DC microgrid: A hardware-in-loop real-time verification," *International Journal of Ambient Energy*, 2020.

[19] R. D. Brandt and F. Lin, "Can supervised learning be achieved without explicit error back-propagation," in *Proc. IEEE International Conference on Neural Networks*, 1996, pp. 300–305.

[20] S. Shah, A. Jain, and Y. Sawle, "Optimal planning and design of an off-grid solar, wind, biomass hybrid energy system," *Springer Renewable Energy Systems*, 2022.