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Enhanced Integration of Solar and Wind Renewable Energy for Electric Vehicle Charging Using Multi-Port Integrated Topology with ANN Control

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ABSTRACT

This paper presents a novel approach to integrating solar and wind renewable energy sources with the electrical power grid for electric vehicle (EV) charging, employing an off-board multi-port integrated topology (MPIT) with artificial neural network (ANN) control for enhanced performance. The MPIT consists of four power converters sharing a single common dc-link, facilitating efficient power transfer between EVs, renewable energy sources (wind and solar photovoltaic panels), and the grid. The MPIT operates in four distinct modes: Grid-to-vehicle (G2V), Vehicle-to-grid (V2G), Renewable-to-grid (R2G), and Renewable-to-vehicle (R2V), enabling bidirectional energy flow and flexibility in grid integration. An ANN controller is implemented for maximum power point tracking (MPPT) to optimize the utilization of solar and wind energy resources. The paper details the operation principles of the MPIT, the design and implementation of the ANN controller, and the simulation results demonstrating the system's effectiveness in enhancing renewable energy utilization and EV charging efficiency. The proposed approach holds promise for advancing the integration of renewable energy sources into smart grid systems while meeting the growing demand for sustainable transportation solutions.

Index Terms— ***Smart grid, Electric vehicle (EV) charging, Solar and wind energy, Multi-port integrated topology (MPIT), Artificial neural network (ANN) control, Maximum power point tracking (MPPT)***

1. INTRODUCTION

Electric mobility is a crucial driver for enhancing sustainability and efficiency in the transport sector, encompassing various vehicles like electric vehicles (EVs), hybrid EVs, fuel cell vehicles, and electric bicycles [1-2]. To avoid power quality issues, maximise interaction with other electrical appliances, and take advantage of possibilities in microgrids, smart grids, and smart homes, meticulous supervision is required when EVs are integrated into the electrical grid. Considering the customer's viewpoint, power demand, and aggregator income is vital for optimising the EV charging procedure in this setting. Energy efficiency is also driving the rise of two-way energy exchange modes, such as grid-to-vehicle (G2V) and vehicle-to-grid (V2G) operations [3-5]. Proposed solutions include a single-phase on-board bidirectional charger capable of G2V and V2G modes, hierarchical energy management strategies, and economic dispatch models for EVs with renewable [5-8]. Furthermore, strategies such as smart charging techniques and cost minimization of charging stations with EVs and photovoltaic's (PVs) are being explored [9]. To address the challenges of integrating EVs and renewables (both solar and wind) into the grid, a Multi-Port Integrated Topology (MPIT) is proposed [10-13]. This topology facilitates seamless integration of EVs and renewables (both solar and wind) with the electrical grid through streamlined power converters [14]. Unlike traditional topologies that require multiple converters and grid intermediaries, the MPIT offers a more efficient and cost-effective solution [15]. It enables bidirectional energy flow, allowing EVs to charge directly from renewables without relying on the grid as an intermediary. Moreover, the MPIT ensures sinusoidal grid current and unitary power factor in all operating modes, mitigating power quality issues [16]. Experimental validation at the residential level demonstrates the effectiveness of the MPIT across various operation modes, including G2V, V2G, renewable-to-grid (R2G), and renewable-to-vehicle (R2V) modes [17]. The proposed MPIT presents a promising solution for integrating EVs and renewables (both solar and wind) into the electrical grid, contributing to sustainability and energy efficiency goals. Its streamlined architecture, bidirectional energy flow capabilities, and focus on power quality make it valuable asset in future smart grid environments [18]. While this paper primarily focuses on PVs and wind energy, other renewable energy sources could be integrated using alternative power converters and control algorithms, further expanding the applicability of the MPIT in diverse residential settings [19]. The transition to sustainable energy sources and the electrification of transportation are critical components of global efforts to mitigate climate change and reduce reliance on fossil fuels. Electric vehicles (EVs) represent a key pathway towards achieving these goals, offering lower emissions and reduced environmental impact compared to conventional internal combustion engine vehicles [20]. However, the widespread adoption of EVs poses significant challenges to the existing energy infrastructure, particularly in terms of charging infrastructure and energy supply. To address these challenges, there is a growing need to develop innovative solutions that integrate renewable energy sources with the electrical power grid to power EVs efficiently and sustainably [21]. Solar and wind energy are two abundant and renewable resources that have gained considerable attention for their potential to power EVs [22]. However, the intermittent nature of solar and wind energy generation presents challenges for reliable and consistent EV charging. Traditional charging methods often rely on grid-connected charging stations, which may draw power from non-renewable sources and contribute to grid instability [23]. To overcome these limitations, there is a need for advanced charging infrastructure that leverages renewable energy sources in a smart and efficient manner. In this context, this paper presents a novel approach to integrating solar and wind renewable energy sources with the electrical power grid for EV charging. Our approach employs an off-board multi-port integrated topology (MPIT) with artificial neural network (ANN) control to enhance the performance and efficiency of renewable energy utilization for EV charging [24]. The MPIT is a sophisticated power electronics system comprising four power converters interconnected through a common dc-link. This architecture facilitates seamless energy transfer between EVs, solar and wind photovoltaic panels, and the grid, enabling bidirectional energy flow and grid integration [25]. Central to our approach is the implementation of ANN control for maximum power point tracking (MPPT), which optimizes the utilization of solar and wind energy resources for EV charging. The ANN controller continuously monitors and adjusts the operation of the MPIT to ensure that the EVs are charged with the maximum available renewable energy while maintaining grid stability [26]. By dynamically adjusting the operation of the power converters based on real-time environmental and grid conditions, the ANN control system maximizes the efficiency of renewable energy utilization and minimizes the reliance on non-renewable energy sources [27]. In addition to presenting the theoretical framework and design principles of the MPIT and ANN control system, this paper also provides detailed simulation results to demonstrate the efficacy of the proposed approach [28]. The simulations show how the MPIT effectively manages energy flow between EVs, renewable energy sources, and the grid, resulting in efficient EV charging and grid integration [29]. Furthermore, the paper discusses the potential implications of the proposed approach for advancing the integration of renewable energy sources into smart grid systems and accelerating the transition towards sustainable transportation solutions. Overall, this paper contributes to the growing body of research on renewable energy integration and EV charging infrastructure by presenting a novel and innovative approach that leverages advanced power electronics and control techniques [30]. By harnessing the power of solar and wind energy for EV charging, our approach offers a sustainable and environmentally friendly solution that aligns with the goals of reducing greenhouse gas emissions and promoting energy sustainability.

2. SYSTEM CONFIGURATION AND DESIGN

The system configuration for enhanced integration of solar and wind renewable energy for electric vehicle (EV) charging revolves around a Multi-Port Integrated Topology (MPIT) with Artificial Neural Network (ANN) control. Solar photovoltaic (PV) panels and wind turbines serve as the primary renewable energy sources, harnessing solar and wind energy, respectively, and converting them into electrical energy as shown in figure .1. The MPIT acts as the central hub, comprising power converters interconnected via a common DC-link, facilitating bidirectional energy flow between the renewable energy sources, the electrical grid, and EVs equipped with bidirectional charging capabilities. This setup enables optimized energy management, allowing EVs to charge from renewable sources when available and discharge excess energy back to the grid as needed. The ANN control system orchestrates this process, continuously monitoring real-time data from solar panels, wind turbines, grid conditions, and EV charging, ensuring efficient utilization of renewable energy and grid stability. Through this integrated approach, the system aims to minimize reliance on non-renewable energy sources, reduce carbon emissions, and promote sustainable transportation solutions.

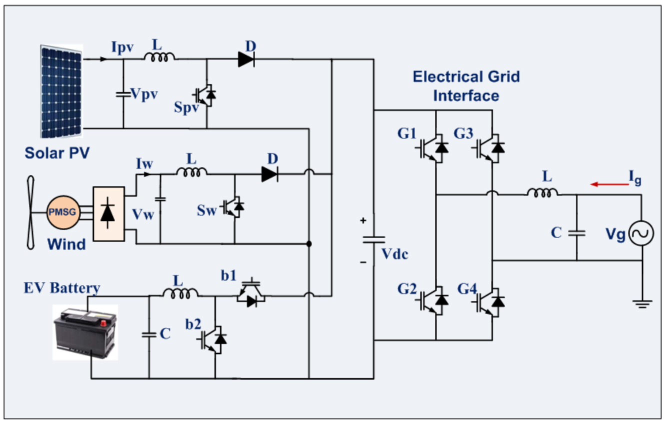


Fig. 1. The proposed MPIT circuit for connecting EVs and renewables to the grid.

3. PHOTOVOLTAIC SYSTEM

The photovoltaic cell can be considered as an ideal source of current supplying a current proportional to the incident light power, in parallel with a diode which is represented by the P-N junction. Consequently, the PV cell can be modelled by Fig.2. The single-diode PV panel is designed by considering open circuit voltage Voc, short circuit current Isc, maximum peak voltage Vmpp, and current Impp, at the MPP of the I-V curve.

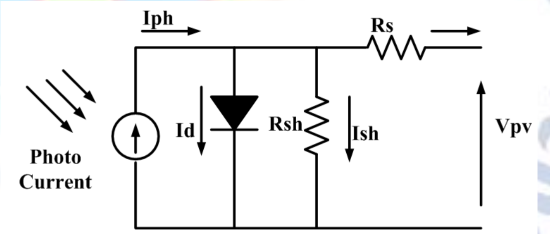


Fig. 2 Electrical circuit of a photovoltaic cell

Based on the circuit, the current generated by the panel can be presented by the following equation:

$$I_{PV} = I_{Ph} - I_d - I_{sh} \qquad (1)$$

The expression of the current at the junction is as follows:

$$I_d = \frac{I_{sc}+k_1 * \Delta T}{\exp\left(\frac{q(v_{OC})+k_V(\Delta T)}{akTN_s}\right)-1} \qquad (2)$$

The current in the resistor Rsh is equal to:

$$I_{sh} = \left(\frac{V_{PV}+R_s * I_{PV}}{R_{sh}}\right) \qquad (3)$$

Iph : the photo- current

Id : the reverse saturation current of the diode

Ns : the number of cells in series

Ipv : the current supplied by cell when it operates as a generator

T : the effective cell temperature in Kelvin (K)

V_{PV} : the voltage across this cell

a : the ideality factor

K : Boltzmann constant (k = 1.38.10−23)

q : the charge of the electron, (q = 1,602.10−19 C)

G : solar irradiation in w / m²,

R_{sh} : the shunt resistance characterizing the leakage currents of the junction

Rs : the series resistance representing the various connection resistances.

4. SOLAR PV BOOST CONVERTER WITH MPPT ALGORITHM.

The solar PV boost converter with Artificial Neural Network (ANN) controlled Perturb and Observe (P&O) Maximum Power Point Tracking (MPPT) algorithm is an advanced approach to optimizing the performance of photovoltaic (PV) systems as shown in figure .3. This system combines the best parts of traditional P&O MPPT with the adaptive learning power of artificial neural networks, making tracking the PV array's maximum power point (MPP) more efficient and accurate. The PV array captures sunlight and converts it into electrical energy, generating a direct current (DC) output that is fed into the boost converter. The P&O MPPT algorithm operates in conjunction with the boost converter to continuously monitor the output power of the PV array and adjust the operating voltage to maximize power extraction. In ANN-controlled P&O MPPT, a computer program is taught to guess the best direction for the perturbation based on past data and inputs in real time. The ANN uses input parameters such as solar irradiance, temperature, and voltage-current characteristics to generate predictions about the optimal perturbation direction. These predictions are used to dynamically adjust the operating voltage of the PV array, guiding it towards the MPP more effectively than traditional P&O MPPT methods. The integration of ANN control with P&O MPPT offers several advantages over traditional MPPT techniques. By leveraging machine learning capabilities, the system can adapt to dynamic and nonlinear behavior in the PV array, resulting in improved accuracy and efficiency in tracking the MPP. Additionally, the ANN can learn from past experiences and adjust its predictions accordingly, leading to enhanced performance and reliability of the PV system over time. The Perturb and Observe (P&O) Maximum Power Point Tracking (MPPT) algorithm is a crucial tool in optimizing power output from solar photovoltaic (PV) systems. It uses a boost converter to raise the voltage the panels produce to a level suitable for load or battery storage. The P&O algorithm determines the maximum power point (MPP), which the boost converter which consists of an inductor, a switch, a diode, and a capacitor plays a crucial role in maintaining. The P&O MPPT algorithm operates by periodically perturbing the voltage or current of the PV system and observing the resulting change in power. If power increases, the algorithm adjusts the voltage in that direction, while if power decreases, it reverses the direction. This iterative process continues until the maximum power point is reached and maintained, adapting to changes in sunlight and temperature. The controller implementing the P&O algorithm adjusts the duty cycle of the boost converter's switch, ensuring the PV system operates at or near its maximum power point, maximizing the efficiency of solar energy conversion. When the boost converter and the P&O MPPT algorithm are combined in a solar PV system, they make it easier to get power and control the voltage. They can also adapt to changes in the environment so that they always get the best power output, which improves the overall performance and dependability of solar renewable energy systems.

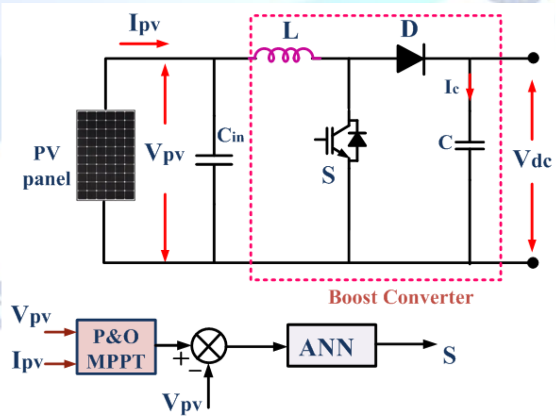


Figure. 3 solar PV boost converter configuration with ANN controlled MPPT algorithm

5. MPPT ALGORITHM FOR SOLAR PV SYSTEM

The Perturb and Observe (P&O) algorithm is a common method used for Maximum Power Point Tracking (MPPT) in solar photovoltaic (PV) systems. This algorithm works by perturbing (i.e., slightly adjusting) the voltage or current of the PV system and observing the resulting change in power as shown in figure .4. The goal is to find the maximum power point (MPP), where the product of current and voltage is maximized. Here is a detailed explanation of the P&O algorithm, including its working operation and the relevant formulas.

a. Working Operation of P&O MPPT Algorithm

1. **Initial Measurement**:
   a) Measure the current voltage (V_k) and current (I_k) from the PV panel.
   b) Calculate the power (P_k) using:
   $P_k = V_k \times I_k$
2. **Perturbation**:
   a) Introduce a small perturbation in the voltage. This can be done by adjusting the duty cycle (D) of the boost converter connected to the PV panels.
   b) The perturbation can be an increase (ΔV) or decrease (−ΔV) in the voltage.
3. **Observation**:
   a) Measure the new voltage (V_{k+1})and current (I_{k+1}).
   b) Calculate the new power (P_{k+1}) using:
      a. $P_{k+1} = V_{k+1} \times I_{k+1}$
4. **Comparison and Decision Making**:
   (i) Compare the new power (P_{k+1}) with the previous power (P_k):
      a) If $P_{k+1} > P_k$, the perturbation has moved the operating point closer to the MPP. Continue perturbing in the same direction (if the previous perturbation was +ΔV, keep +ΔV; if it was −ΔV keep −ΔV).
      b) If $P_{k+1} < P_k$, the perturbation has moved the operating point away from the MPP. Reverse the direction of perturbation (if the previous perturbation was +ΔV, change to −ΔV; if it was −ΔV, change to +ΔV).
5. **Update**:
   a) Update the duty cycle of the boost converter to adjust the voltage accordingly.
6. **Repeat**:
   a) Repeat the process continuously to track the maximum power point.

b. Formulas Used in P&O MPPT Algorithm

1. **Power Calculation**:
   $P_k = V_k \times I_k$
   $P_{k+1} = V_{k+1} \times I_{k+1}$
2. **Change in Power and Voltage**:
   $\Delta P = P_{k+1} - P_k$
   $\Delta V = V_{k+1} - V_k$
3. **Decision Logic**:
   a) If $\Delta P > 0$:
      i. If $\Delta V > 0$, increase voltage perturbation.
      ii. If $\Delta V < 0$, decrease voltage perturbation.
   b) If $\Delta P < 0$:
      i. If $\Delta V > 0$, decrease voltage perturbation.
      ii. If $\Delta V < 0$, increase voltage perturbation.

6. WIND POWER GENERATION SYSTEM

In a wind power generation system utilizing a Permanent Magnet Synchronous Generator (PMSG), the conversion of wind energy to electrical energy involves multiple stages, starting with the capture of kinetic energy by wind turbine blades. These blades are aerodynamically designed to rotate when exposed to wind flow, converting the wind's kinetic energy into mechanical energy. This mechanical energy drives the rotor of the PMSG, generating a three-phase alternating current (AC) in the stator windings due to the rotating magnetic field. The generated AC power is then converted to direct current (DC) using a rectifier. This DC power is subsequently fed into a DC-DC boost converter, which increases the voltage to a desired level, ensuring efficient power transfer and utilization.

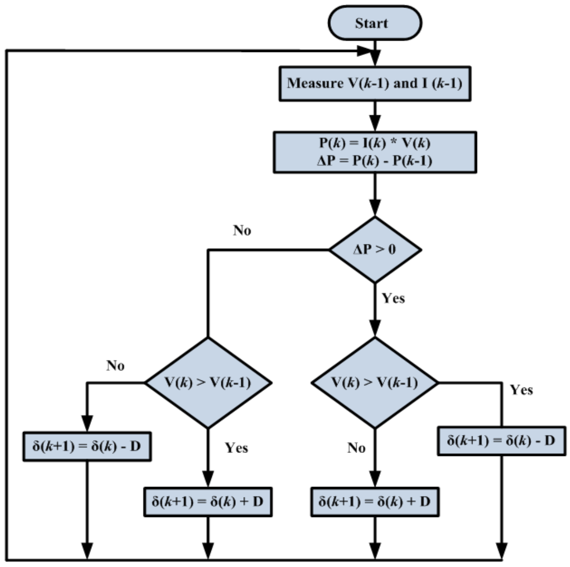


Figure 4 Flow Chart for Perturb and Observation Algorithm for solar PV system

To optimize the power output from the wind turbine, a Maximum Power Point Tracking (MPPT) algorithm is employed specifically the Perturb and Observe (P&O) algorithm. The P&O algorithm operates by periodically perturbing (adjusting) the operating point of the system and observing the resulting changes in power output. If a perturbation leads to an increase in power, the algorithm continues to adjust in that direction; if it leads to a decrease, the direction is reversed. This process iteratively converges on the maximum power point, ensuring that the system consistently operates at its highest efficiency. To further enhance the performance of the MPPT, an Artificial Neural Network (ANN) can be integrated with the P&O algorithm. The ANN, trained on various operating conditions and parameters, provides more accurate predictions and adjustments, improving the responsiveness and accuracy of the MPPT process. The ANN-controlled P&O algorithm dynamically adjusts the duty cycle of the boost converter, optimizing the voltage and current to maintain maximum power output from the wind turbine under varying wind conditions as shown in figure.5. This integrated approach ensures that the wind power generation system operates efficiently and effectively, maximizing energy capture and conversion.

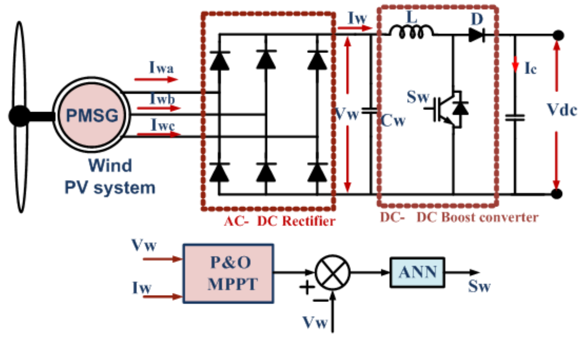


Figure 5. Typical diagram of wind-turbine system with MPPT.

7. P&O MPPT ALGORITHM FOR WIND POWER GENERATION SYSTEM

A Maximum Power Point Tracking (MPPT) boost converter is a critical component in wind power generation systems that use a Permanent Magnet Synchronous Generator (PMSG). The PMSG generates AC power as it converts mechanical energy from wind turbines into electrical energy. To integrate this AC power into a DC system, a rectifier is used to convert the AC output of the PMSG to DC. However, this rectified DC voltage is typically not at its optimal value for maximum power extraction as shown ion figure .6. This is where the boost converter comes into play. The boost converter steps up the rectified DC voltage to a higher, more efficient level for power transfer. The efficiency of this process hinges on the MPPT algorithm, which continuously adjusts the duty cycle of the boost converter to ensure that the wind power system operates at its maximum power point. The Perturb and Observe (P&O) algorithm is one of the most commonly used methods for MPPT. It works by periodically perturbing (adjusting) the duty cycle of the boost converter and observing the change in power output. If the power increases, the algorithm continues in the same direction; if it decreases, the direction is reversed. This iterative process helps in finding and maintaining the maximum power point despite changes in wind speed and other environmental conditions. The integration of an Artificial Neural Network (ANN) with the P&O algorithm further enhances the MPPT process. ANNs can predict the optimal operating point based on historical data and real-time inputs, improving the responsiveness and accuracy of the MPPT system. By combining the predictive capabilities of ANN with the traditional P&O algorithm, the boost converter can adapt more swiftly to changing wind conditions, thereby maximizing the efficiency of the wind power generation system. This combination of advanced control techniques ensures that the wind energy is harnessed effectively, providing a stable and high-voltage DC output suitable for further processing or storage.

1. Wind Power Calculation

The power available in the wind is given by:

$$P_{wind} = \frac{1}{2}\rho A v^3$$

Where: ρ is the air density, A is the swept area of the wind turbine blades ($A = \pi R^2$, with R being the radius of the blades), V is the wind speed.

2. PMSG Output Voltage

The AC voltage generated by the PMSG is proportional to the rotational speed of the wind turbine:

$$V_{PMSG} = k_e \omega$$

Where: k_e is the back EMF constant, ω is the angular speed of the generator (rad/s).

3. Rectified DC Voltage

The rectifier converts the AC voltage from the PMSG to DC voltage:

$$V_{DC} = \sqrt{2} V_{PMSG}$$

4. Boost Converter Voltage Gain

The relationship between the input and output voltage of the boost converter is given by:

$$V_0 = \frac{V_{in}}{1-D}$$

Where: V_{out} is the output voltage of the boost converter, V_{in} is the input voltage to the boost converter, D is the duty cycle of the boost converter (the fraction of the switching period that the switch is on).

5. Perturb and Observe (P&O) Algorithm

The P&O algorithm adjusts the duty cycle to track the maximum power point. The power extracted from the wind turbine is:

$$P = V_0 \cdot I$$

Where: V_0t is the output voltage of the boost converter, I is the current flowing through the load.

In the P&O algorithm, the following steps are taken:

1. Measure the current power $p_{(n)}$ at the $n-th$ step.

2. Perturb the duty cycle D.

3. Measure the new power $P_{(n+1)}$.

4. Compare $P_{(n+1)})$ with P_n:

   a. If $P_{(n+1)} > P_n$, continue in the same direction of perturbation.

   b. If $P_{(n+1)} < P_n$, reverse the direction of perturbation.

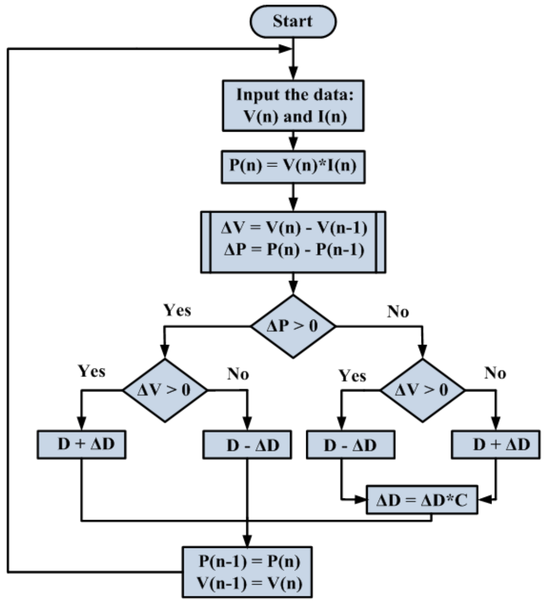


Fig.6 Flow chart of perturb and observe algorithm for wind system

8. ELECTRIC VEHICLE BATTERY ENERGY STORAGE SYSTEM

Optimal utilisation of renewable energy sources and grid supplementation can be achieved through the electric vehicle (EV) battery energy storage system, which employs a bidirectional DC-DC buck-boost converter to dynamically manage power flow (as illustrated in figure.7). Photovoltaic panels, which transform sunlight into electricity, are the first component of the system that is used to capture solar energy. For efficient charging, the converter changes this voltage to the right level. Incorporating wind power is also possible with the help of permanent magnet synchronous generators (PMSGs), which convert alternating current (AC) into direct current (DC) via rectifiers. The converter receives this rectified DC electricity and adjusts its voltage in a manner similar to that of solar power. When renewable energy sources like wind and solar aren't producing enough power, the system switches to using grid electricity. The converter takes electricity from the grid and changes it to a voltage that the electric vehicle's battery can handle. With this automated switching, charging may continue even when renewable energy sources aren't available. When circumstances allow it, this system may reverse power flow, which is a novel function. The bidirectional DC-DC buck-boost converter enables power transmission back to the grid during moments of strong renewable energy output or peak demand. Through energy credits or financial incentives provided by utility providers, EV owners may be able to reap economic advantages thanks to this vehicle-to-grid (V2G) capacity, which also helps maintain system stability. Simply put, this integrated system guarantees dependable electric vehicle charging while optimising the usage of renewable energy sources. To keep the battery performing at its best, it adapts to new circumstances by automatically balancing the flow of electricity from solar, wind, and the grid.

Mode 1: Battery Charging (Buck Mode)

a) **Switch S1 and Diode D2 Operation:** A closed switch S1 and a forward-biased diode D2 constitute this state. When the switch is closed, current may go from the charging station to the electric vehicle's battery, and diode D2 makes sure it can only go in one direction.

b) **Buck Mode Operation:** The converter works in buck mode, reducing the voltage from the external power source to match the lower voltage of the electric vehicle battery. Ensuring the battery obtains the optimum voltage is crucial for efficient charging.

c) **Charging the Battery:** The electric vehicle's battery is charged effectively when electricity is transferred from an external source to it. To accomplish the target voltage conversion ratio while operating in buck mode, one must regulate the switch's duty cycle. Here are the main formulae for buck mode:

- Voltage Conversion Ratio (Duty Cycle, D): D = $\frac{V_{out}}{V_{in}}$
- Inductor Current (I_L): $V_{out} = \frac{V_{in}\times(1-D)}{D\times(1-D)\times I_L}$
- Output Power (Pout): Pout = $V_{out} \times I_L$
- Efficiency (η): η = $\frac{P_{out}}{P_{in}} \times 100\%$

Mode 2: Battery Discharging for Power Delivery (Boost Mode)

a) **Switch S2 and Diode D1 Operation:** Switch S2 is closed and diode D1 is biassed forward in this mode. Diode D1 guarantees one-way current flow, and the closed switch permits current to flow from the EV battery to the load, such as electric motors.

b) **Boost Mode Operation:** To match the voltage needed by the load, the converter functions in boost mode, which means it raises the voltage from the EV battery. Even if the load voltage is greater than the battery voltage, this is critical to ensure that the vehicle's systems get enough power.

c) **Power Delivery:** The ability to move and perform as needed is made possible by the energy flowing from the electric vehicle's battery to the load. In order to obtain the necessary voltage conversion ratio when operating in boost mode, the duty cycle of the switch is controlled. Boost mode's essential formulae are as follows:

- Voltage Conversion Ratio (Duty Cycle, D): D = $\frac{1}{1-\left(\frac{V_{out}}{V_{in}}\right)}$
- Inductor Current (I_L): Vout = $\frac{V_{in}}{(1-D)\times I_L}$
- Output Power (Pout): $P_{out} = V_{out} \times I_L$
- Efficiency (η): η = $\frac{P_{out}}{P_{in}} \times 100\%$

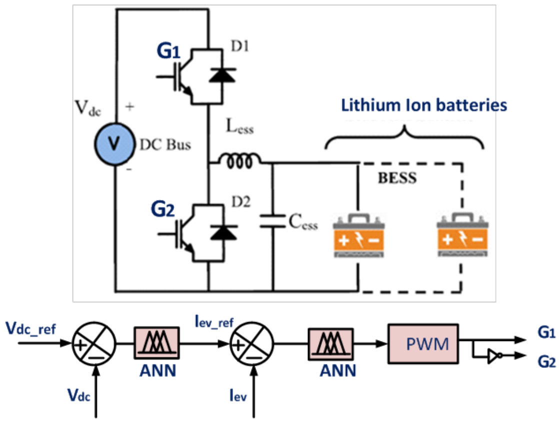


FIGURE 7. Bidirectional DC-DC converter configuration for Electric Vehicle Battery charging.

9. DC-DC UNIDIRECTIONAL CONVERTER

Power converters like the DC-DC unidirectional boost converter (fig.8) increase the input voltage above the output voltage. Power transmission lines are designed to carry electrical current in a single direction, often from a lower-voltage source to a higher-voltage demand. The basic layout of a boost converter mostly consists of an inductor, a switch (often a MOSFET), a diode, and an output capacitor. It is possible to store energy in the magnetic field by keeping the switch closed, which allows current to flow through the inductor. When the switch is opened, the inductor experiences a voltage induction across itself on the other side, allowing it to resist fluctuations in current flow. The voltage across the output capacitor is raised when this voltage is added to the input voltage. The forward-biased diode allows current to flow from the inductor to the output capacitor and load. You can precisely regulate the output voltage of the boost converter by controlling the duty cycle of the switch. It is common practice to use the unidirectional boost converter in power supply, LED driver, and renewable energy system contexts. When the load demands a higher input voltage than what is normally available, this kind of converter is used.

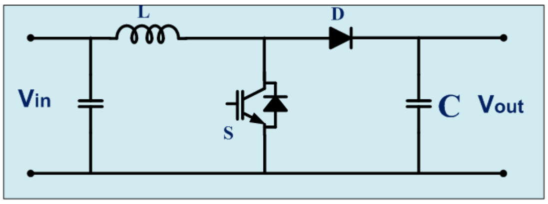


Fig.8 DC-DC unidirectional boost converter

- **Output Voltage (V_{out})**: The output voltage of a boost converter can be calculated using the following formula:

$$V_{out} = \frac{V_{in}}{1-D}$$

Where Vin is the input voltage and D is the duty cycle of the converter.

- **Input Current (I_{in})**: The input current of the boost converter can be calculated as:

$$I_{in} = \frac{I_{out}}{1-D}$$

Where I_{out} is the output current of the converter.

- **Output Current (I_{out})**: The output current of the boost converter can be approximated as: $I_{out} = \frac{P_{out}}{V_{out}}$

Where P_{out} is the output power.

- **Efficiency (η)**: The efficiency of the boost converter can be calculated as the ratio of output power to input power:

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

Where Pin is the input power.

- **Inductor Current Ripple (ΔI_L)**: The peak-to-peak ripple current flowing through the inductor can be approximated as:

$$\Delta I_L = \frac{V_{in} \times D \times T_{on}}{L}$$

where Ton is the on-time of the switching device and L is the inductance.

- **Output Voltage Ripple (ΔV_{out})**: The peak-to-peak ripple voltage at the output can be approximated as:

$$\Delta V_{out} = \frac{V_{in} \times D \times T_{on}}{C}$$

Where C is the output capacitance.

10. AC - DC BIDIRECTIONAL CONVERTER

An intricate component of modern power networks, the AC-DC bidirectional converter is seen in figure 9. Essential because it allows for efficient and versatile control of power flow between alternating current (AC) and direct current (DC) grids. When functioning in the AC to DC mode, the converter also rectifies voltage. Powering it down to DC is a breeze, whether you're plugging it into the wall or using another AC source. Intricate control algorithms and semiconductors like diodes, thyristors, or IGBTs are required to change the voltage. These devices smooth down the AC current's waveform and convert it to DC. Beyond their rectification capabilities, bidirectional converters may also work in reverse mode, transforming DC power into AC. Applications like grid-tied renewable energy systems need this inversion, or conversion, from direct current to alternating current. In these setups, converting DC power from sources like solar panels or batteries to AC power is necessary for feeding it into the grid or powering AC loads. Bidirectional converters maximise system efficiency by allowing efficient conversion with minimum losses via clever regulation of semiconductor device switching. Furthermore, bidirectional converters have the advantage of bidirectional power flow, allowing energy to be transferred between AC and DC networks to suit the needs of the circumstance. Energy storage systems and similar applications benefit greatly from this bidirectional capacity since it enables the storage of energy in batteries during periods of low demand and its subsequent discharge into the grid or conversion to alternating current power during periods of high demand. By allowing power to flow in both ways, these converters help stabilise the grid, integrate renewable energy sources, and make the system more resilient overall. Typically, modern power systems cannot function without AC-DC bidirectional converters. With their help, AC and DC sources may be seamlessly integrated, resulting in maximum efficiency, flexibility, and reliability. Electric vehicles, grid-connected power systems, renewable energy systems, and industrial power sources are just a few of the many uses for their versatility. Because of this, they play a significant role in building long-term, environmentally friendly energy infrastructure.

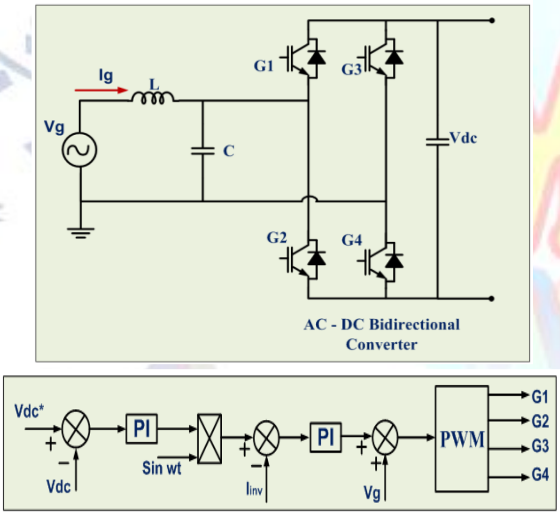


Fig.9 configuration of a AC-DC Bidirectional Converter control

Rectification operation

Rectification Efficiency: A diode-based rectifier's rectification efficiency may be determined by comparing the DC output power to the AC input power, taking into account the forward voltage drop of the diode and any additional losses:

$$\frac{P_{DC}\ output}{P_{AC}\ input} \times 100\%$$

Peak Voltage (V_{Peak}): The rectified output waveform's peak voltage may be determined by:

$$V_{Peak} = V_{rms} \times \sqrt{2}$$

Where V_{rms} is the root mean square (RMS) voltage of the AC input waveform.

Peak-to-Peak Voltage (V_{PP}): In the rectified output waveform, the voltage between the two highest points is double the original peak:

$$V_{PP} = 2 \times V_{Peak}$$

Average DC Voltage (V_{avg}): The rectified output waveform's average DC voltage may be roughly calculated as follows:

$$V_{avg} = \frac{V_{Peak}}{\pi}$$

Ripple Voltage (V_{ripple}): The DC output voltage variation, or ripple voltage, may be expressed as:

$$V_{ripple} = V_{Peak} - V_{avg}$$

Ripple Factor: The correlation coefficient, which measures the voltage ripple relative to the average DC voltage, may be determined by:

$$Ripple\ factor = \frac{V_{ripple}}{V_{avg}} \times 100\%$$

Peak Current (I_{Peak}): The formula for determining the maximum current passing through the load resistance is:

$$I_{Peak} = \frac{V_{Peak}}{R}$$

Where R is the load resistance.

- **Inversion operation**

A measure of an inverter's effectiveness in transforming DC input power into AC output power is the inversion efficiency (η). In order to determine it, one must take into account losses and compare the AC output power to the DC input power.

$$\text{Inversion Efficiency } (\eta) = \frac{P_{AC\ output}}{P_{DC}\ \text{input}} \times 100\%$$

Where P_{AC} output is the power delivered to the load by the inverter in the form of AC voltage and current, and P_{DC} input is the power supplied to the inverter from the DC source.

AC Power Output (P_{AC}): The inverter's AC power output is determined by multiplying the output AC waveform's root-mean-square (RMS) voltage and current:

$$P_{AC} = V_{rms} \times I_{rms}$$

DC Power Input (P_{AC}): The inverter receives its DC power from the voltage and current multiplied by the DC input:

$$P_{DC} = V_{DC} \times I_{DC}$$

Power Losses (P_{loss}): Various inverter power losses, including as switching losses and conduction losses, may be determined by subtracting the DC input power from the AC output power:

$$P_{loss} = P_{DC} - P_{AC}$$

Efficiency Losses:

The inverter's efficiency losses, which are the discrepancy between the ideal and real inversion efficiencies, may be expressed as:
Efficiency Losses=100%−η

11. NEURAL NETWORK MODEL:

For a single-input, single-output (SISO) control system, let:

- $x(t)$ be the input at time t,
- $u(t)$ be the control output at time t,
- $y(t)$ be the actual output of the system at time t.

The neural network consists of an input layer, a hidden layer, and an output layer. Let:

- *wij* be the weight connecting the *i*-th node in the input layer to the *j*-th node in the hidden layer,
- *vj* be the bias of the *j*-th node in the hidden layer,
- *zj*(t) be the output of the *j*-th node in the hidden layer.

Similarly, let:

- *bk* be the bias of the *k*-th node in the output layer,
- *wjk* be the weight connecting the *j*-th node in the hidden layer to the *k*-th node in the output layer,
- *yk*(t) be the output of the *k*-th node in the output layer.

Forward Pass Equations:

The forward pass of the neural network can be expressed as follows:

Hidden Layer Output (*zj*(t)):

$$z_j(t) = \sigma\left(\Sigma_i w_{ij} \cdot x(t) + v_j\right)$$

Where σ is the activation function (e.g., sigmoid, tanh, ReLU).

Output Layer Output (*yk*(t)):

$$y_k(t) = \Sigma_j w_{jk} \cdot z_j(t) + b_k$$

Training and Backpropagation:

During training, the weights and biases are adjusted to minimize a chosen loss function L. One common loss function for regression problems is the mean squared error:

$$L = \frac{1}{2N}\sum_{t=1}^{N}\left(y(t) - u(t)\right)^2$$

To find the loss function's gradients with regard to the biases and weights, the backpropagation technique is used. Next, optimisation methods like gradient descent are used to update the biases and weights. The function that determines how the weights of the hidden layer wij are updated is:

$$\Delta w_{ij} = -\eta \frac{\partial L}{\partial w_{ij}}$$

Where η is the learning rate.

In the backpropagation process, the partial derivatives are computed using the chain rule. This is only a simplified version; in practice, other factors like optimisation tactics, activation functions, and regularisation methods may be more important. The qualities of the control algorithm and the control issue dictate which of these components are chosen in particular.

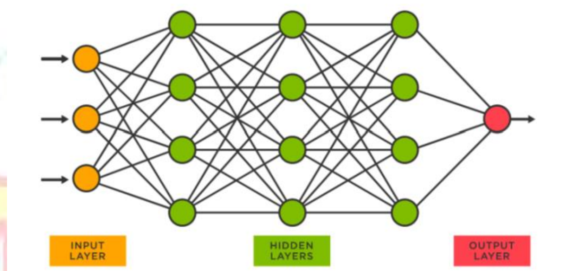


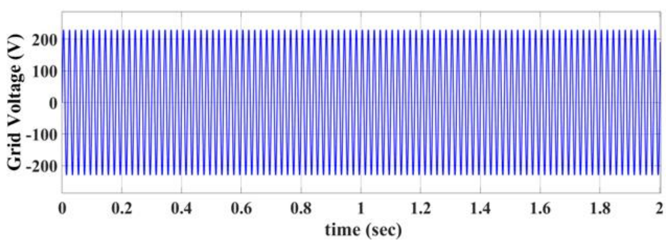
Fig. 10 Design of a backpropagation network to provide a standard reference signal.

12. RESULTS AND DISCUSSION

A. Integration of Grid and Renewable Energy for Electric Vehicle Charging Using MPIT with ANN Control

The simulation results for the enhanced integration of solar and wind renewable energy for electric vehicle (EV) charging using a multi-port integrated topology with ANN control demonstrate a dynamic and highly efficient system capable of adapting to various energy source conditions as shown in figure .11. The simulation is divided into specific time intervals, each representing different combinations of energy sources contributing to EV charging and grid interaction. From 0 to 0.3 seconds, the system relies entirely on grid power to charge the EV. During this period, grid-to-vehicle (G2V) operation ensures that the EV receives a stable and reliable power supply despite the absence of renewable energy contributions. The ANN controller effectively manages the power flow to maintain optimal charging rates and power quality. Between 0.3 and 0.7 seconds, both grid and wind power are utilized to charge the EV. In this

Grid and Wind to vehicle scenario, the system dynamically adjusts to incorporate wind energy as it becomes available, thereby reducing the dependency on grid power and enhancing the overall efficiency of the charging process. The ANN controller continuously monitors and balances the power inputs to ensure a seamless integration and consistent charging performance. From 0.7 to 1.2 seconds, the system transitions to using both wind and photovoltaic (PV) solar power for EV charging. In the Wind and PV to vehicle condition, the ANN controller maximizes the utilization of renewable energy sources, minimizing grid power usage. This period highlights the system's capability to leverage multiple renewable inputs to maintain effective and eco-friendly charging operations. Between 1.2 and 1.5 seconds, the system operates in the Wind and PV to grid mode. During this interval, excess energy generated from wind and solar sources is fed back into the grid. This not only contributes to grid stability but also optimizes the use of renewable energy, preventing waste and potentially generating economic benefits through energy credits. From 1.5 to 2 seconds, the system operates in the Vehicle-to-Grid (V2G) mode. In this condition, the energy stored in the EV batteries is transferred back to the grid. This operation supports grid stability during peak demand periods or when renewable energy generation is insufficient. The ANN controller manages the discharge process to ensure that it does not adversely affect the EV's operational readiness while providing valuable support to the grid. The simulation results illustrate the versatility and efficiency of the multi-port integrated topology with ANN control. The system effectively manages transitions between different energy sources and operational modes, ensuring reliable EV charging and optimal utilization of renewable energy. By dynamically adjusting to varying conditions, the system not only enhances the sustainability of EV charging but also contributes to grid stability and resilience.



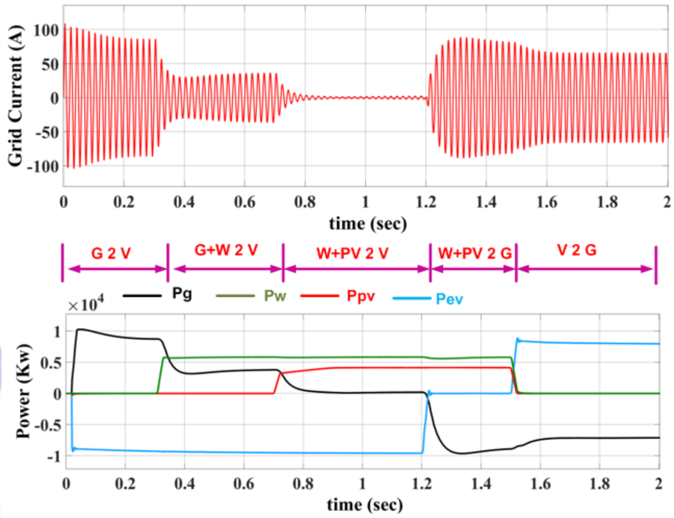


Figure.11Simulation Results for Grid Integration of Renewable Energy for Electric Vehicle Charging Using Multi-Port Integrated Topology with ANN Control.

B. G2V and V2G Operation Modes

a. Grid-to-Vehicle (G2V) Condition.

During the Grid-to-Vehicle condition, the voltage and current waveforms of the grid exhibit an in-phase relationship. This alignment signifies the efficient transfer of power from the grid to the electric vehicle's charging system. As the vehicle draws power from the grid for charging, the voltage and current supplied by the grid remain synchronized, ensuring optimal utilization of grid resources. The simulation captures this behavior accurately, illustrating the smooth and synchronous flow of energy from the grid to the electric vehicle.

b. Vehicle-to-Grid (V2G) Condition.

In contrast, during the Vehicle-to-Grid condition, the voltage and current waveforms of the grid demonstrate an out-of-phase relationship. This asynchronous behavior occurs when the electric vehicle's battery transfers power back to the grid. As the vehicle supplies excess energy to the grid, the voltage and current waveforms exhibit a phase shift, indicating the reverse flow of energy. Despite the bidirectional nature of the power transfer, the simulation ensures that the grid operates efficiently even when receiving power from the electric vehicle. By accurately modeling the phase relationship between voltage and current, the simulation provides valuable insights into the dynamic interaction between the grid and electric vehicle during V2G operation. Through detailed simulation analysis, the behavior of the grid and electric vehicle under different operating conditions, including G2V and V2G scenarios, has been thoroughly examined. The simulation results demonstrate the effectiveness of the integrated system in facilitating bidirectional power flow between the grid and electric vehicle, ensuring efficient charging and discharging operations. By accurately capturing the voltage and current waveforms and their phase relationships, the simulation provides valuable insights for optimizing the performance of renewable energy-integrated electric vehicle charging systems.

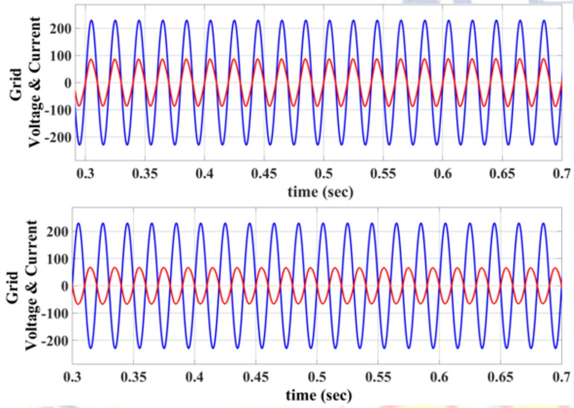


Figure.12. Simulation Results for Grid-to-Vehicle (G2V) and Vehicle-to-Grid (V2G) Conditions.

13. CONCLUSIONS

The integration of solar and wind renewable energy for electric vehicle (EV) charging using a multi-port integrated topology with artificial neural network (ANN) control is a significant advancement in sustainable transportation and renewable energy utilization. This system reduces dependence on traditional fossil fuels, contributing to environmental sustainability and mitigating greenhouse gas emissions. The multi-port integrated topology allows for simultaneous connection and management of solar panels, wind turbines, EV charging stations, and the electrical grid, ensuring efficient power flow management while maintaining grid stability and reliability. The integration of multiple ports provides flexibility and resilience, allowing for seamless adaptation to varying environmental conditions and energy demand patterns. ANN control algorithms enhance the system's performance and efficiency by optimizing power flow, managing energy storage, and coordinating charging operations. Artificial neural networks can learn and adapt to changing conditions, allowing intelligent decision-making and real-time adjustments to maximize energy utilization and minimize wastage. This system offers a cost-effective, environmentally friendly, and technologically advanced approach to electric mobility, with immense potential for shaping a cleaner, greener, and more sustainable future.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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