IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 12, April 2026
Impact Factor: 8.2

Enhanced ANN-Based Maximum Power Point Tracking for Solar-Integrated EV Charging Stations with Energy Storage

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Abstract: *Power plays a vital role in the economic and industrial development of any growing nation. In recent times, increasing environmental awareness along with the continuous rise in fuel prices has accelerated the adoption of Electric Vehicles (EVs) and Hybrid Electric Vehicles (HEVs). As a result, EV technology is expanding rapidly, making the development of efficient supporting infrastructure essential. Among these, EV charging stations have become a key factor, which forms the focus of this work. In this study, an Artificial Neural Network (ANN)-based Maximum Power Point Tracking (MPPT) technique is implemented to efficiently extract maximum power from a solar photovoltaic (PV) system integrated with an EV charging station. The proposed ANN approach offers improved accuracy compared to conventional methods. Specifically, the Bayesian Regularization algorithm is employed to train the neural network, enabling precise control of the duty cycle of the DC-DC converter.*

The designed EV charging system incorporates solar PV as the primary energy source, supported by an energy storage system to ensure reliability. Additionally, the utility grid is utilized as a backup during emergency or insufficient generation conditions. The effectiveness and performance of the proposed system are validated through detailed simulations carried out using MATLAB / Simulink..

Keywords: Electric Vehicles (EV), Hybrid Electric Vehicles (HEV), Solar Photovoltaic System, EV Charging Station, Maximum Power Point Tracking (MPPT), Artificial Neural Network (ANN), Bayesian Regularization, DC–DC Converter Control, Renewable Energy Integration, Energy Storage System

I. INTRODUCTION

In today's world, the demand for energy is progressively increasing due to continuous growth in population and the industrial developments. This rising demand has accelerated the development and adoption of Electric Vehicles (EVs), which are considered environmentally friendly as they eliminate direct emissions. With the increasing number of vehicles required globally, EVs are becoming a crucial element in the transition towards electrified transportation systems.

However, the true environmental benefit of EVs can be realized only when the energy used for charging is generated from renewable sources such as solar and wind. Integrating renewable energy with EV charging infrastructure ensures a cleaner and more sustainable transport solution. In this context, photovoltaic (PV) systems play a significant role in supplying green energy for EV charging stations.

An effective energy management strategy is essential for coordinating the interaction between PV systems and EV batteries. The EV battery can also function as an energy storage unit, helping to balance power fluctuations from the PV system and reduce its impact on the grid. This approach not only supports the stable operation of power distribution systems but also enhances the utilization of locally generated solar energy. Furthermore, it helps in minimizing the adverse effects caused by the increasing penetration of both EVs and renewable energy sources in the electrical network [1].

The charging system is designed with advanced synchronization and smooth mode-transition control, enabling it to automatically connect to or disconnect from the utility grid without interrupting the EV charging process or the household power supply. This ensures continuous and reliable operation under varying grid conditions. In addition, the charger is equipped with Vehicle-to-Grid (V2G) capability, allowing it to supply both active and reactive power back to the grid when required. It also supports Vehicle-to-Home (V2H) functionality, where the electric vehicle battery can deliver power to local loads during grid outages or islanded operation. This enhances the flexibility and reliability of the overall energy system while improving energy utilization [2].

This work focuses on the implementation of a solar-powered EV charging station with a simplified system configuration. In conventional designs, a DC–DC converter—typically a boost converter—is used to interface the photovoltaic (PV) array with the DC link. In contrast, the proposed approach directly connects the solar PV array to the DC link, eliminating the need for an intermediate converter stage. This configuration offers several advantages, including reduced circuit complexity, lower system cost, and minimized power conversion losses, while maintaining effective performance of the PV system. Additionally, the proposed topology serves as a practical retrofit solution, allowing integration of a PV array into existing EV charging infrastructure with minimal hardware modifications. Only minor updates to the control strategy, such as the maximum power point tracking (MPPT) algorithm, are required, making the approach both efficient and cost-effective [3].

Solar Panel

Solar panels harness sunlight, an abundant and renewable energy source, and convert it into electrical energy that can be used to power various types of loads. A typical solar panel consists of numerous interconnected solar cells, which are primarily made from semiconductor materials such as silicon. These cells are engineered by introducing impurities like phosphorus and boron into the silicon structure, creating regions with excess electrons and holes, respectively.

When sunlight falls on a solar cell, the energy carried by photons is absorbed by the semiconductor material. This energy excites electrons, allowing them to move freely by breaking away from their atomic bonds. The internal electric field within the cell directs these free electrons, resulting in the generation of an electric current. This process is referred to as the photovoltaic effect. In many residential applications, rooftop solar systems are capable of producing sufficient energy to meet daily consumption needs, and any excess power can be fed back into the electrical grid.

Photovoltaic (PV) cells are available in different forms, including monocrystalline, polycrystalline, and thin-film technologies. Monocrystalline cells are produced from a single crystal structure and are known for their higher efficiency, typically ranging between 18% and 20%. Polycrystalline cells, on the other hand, are formed from multiple silicon crystals, making them more economical but slightly less efficient, usually in the range of 16% to 17.5%.

PV systems operate quietly and do not emit pollutants, making them environmentally friendly and dependable energy solutions. A PV module is formed by connecting multiple solar cells to achieve the required voltage and current levels for practical applications. These cells are sealed within protective layers to enhance their durability and safeguard them from environmental factors such as moisture, dust, and mechanical stress.Silicon is widely used in solar cell manufacturing due to its favorable semiconductor properties. Although it does not conduct electricity efficiently in its pure form, its conductivity can be controlled through the doping process. The origin of photovoltaic technology can be traced back to 1839, when Edmond Becquerel first observed the generation of electrical current under light exposure in certain materials. The operating principle of a solar cell is based on the interaction between light energy and a semiconductor junction. When photons with sufficient energy strike the PN junction, they create electron–hole pairs. The built-in electric field across the junction separates these charge carriers, producing a flow of current that is directly related to the intensity of the incident sunlight.

Solar PV systems generate direct current (DC) power in a clean and silent manner without producing harmful emissions. To obtain higher voltage levels, solar cells are connected in series to form modules, which typically consist of 60 or 72 cells. These modules are encapsulated using durable materials to ensure long-term reliability and protection against environmental and physical damage as shown in Fig. 1.

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Fig. 1.Solar Panel

PROPOSED SYSTEM

In the proposed system, an Artificial Neural Network (ANN)-based Maximum Power Point Tracking (MPPT) technique is implemented to efficiently extract maximum power from the solar photovoltaic (PV) array used in the EV charging station. This method provides improved accuracy and adaptability compared to conventional MPPT approaches. The ANN is trained using the Bayesian Regularization algorithm, which enhances the network's generalization capability and ensures stable performance under varying operating conditions. The trained network is then utilized to regulate the duty cycle of the DC–DC converter for optimal power extraction.

In this configuration, solar energy serves as the primary source of power. A rectifier unit is connected to a 48 V DC common bus to maintain a stable DC supply. During conditions where solar generation and battery storage are insufficient, the system draws additional power from the utility grid. This ensures uninterrupted operation by supporting battery charging as well as EV charging during emergency situations.

The primary objective of this work is to enhance the performance and efficiency of MPPT using an ANN-based approach, thereby improving the overall effectiveness of the EV charging system as shown in Fig. 2.

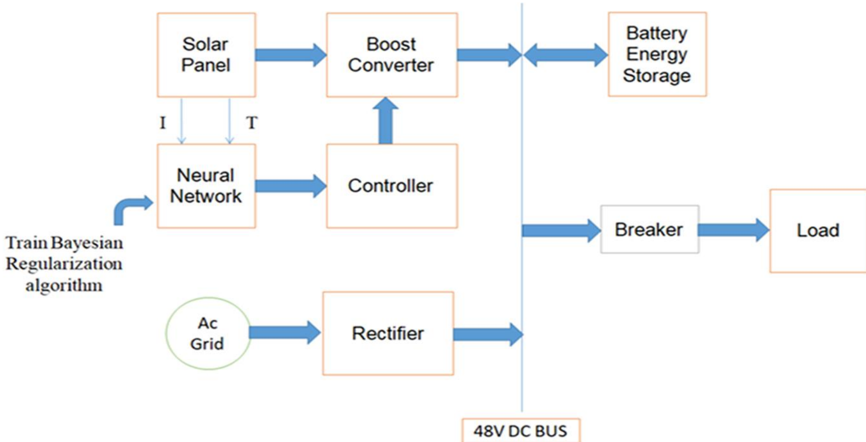

Fig.2 Block diagram of proposed system

Boost Converter

The boost converter is a commonly used DC–DC power conversion topology in solar photovoltaic (PV) systems, primarily utilized to step up the voltage from the PV array to a higher level required by the load or DC bus. It is widely preferred due to its simple structure, cost-effectiveness, compact size, and relatively high efficiency.

Since the output characteristics of a solar panel vary with changes in temperature and solar irradiance, the converter must maintain reliable performance under dynamic environmental conditions. To ensure optimal energy extraction, the system is designed to operate close to the maximum power point (MPP) of the PV array. The boost converter can function in

DOI: 10.48175/IJARSCT-33773

either continuous conduction mode (CCM) or discontinuous conduction mode (DCM), depending on factors such as load demand and input conditions.

The basic configuration of a boost converter includes an inductor, a controlled switch (typically a transistor), a diode, and an output capacitor. During operation, when the switch is turned on, energy is stored in the inductor. When the switch is turned off, the stored energy is released through the diode to the load, resulting in an output voltage that is higher than the input voltage.

Although the boost converter offers advantages such as simplicity, efficiency, and ease of implementation, it is associated with certain limitations, including increased ripple and higher voltage stress on components. Nevertheless, due to its reliability and effectiveness, it remains a popular choice in solar energy conversion systems as shown in Fig. .3

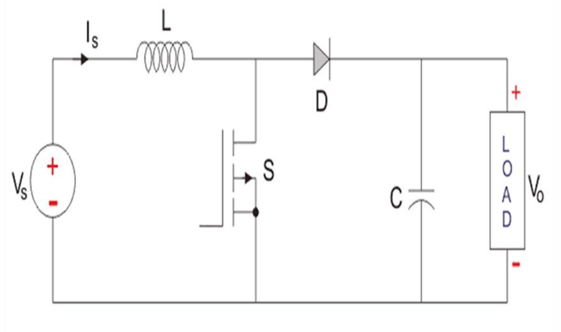

Fig. 3 Boost converter circuit

BAYESIAN REGULARIZATION ALGORITHM

Artificial Neural Networks (ANNs), often referred to simply as neural networks, are computational models inspired by the structure and functioning of biological nervous systems. They are composed of interconnected processing units known as artificial neurons, which mimic the behavior of neurons in the human brain. These neurons are linked through connections, similar to synapses, that transmit signals between them.

Each connection carries a numerical value known as a weight, which determines the strength of the signal being passed. An artificial neuron receives multiple input signals, processes them by applying a nonlinear activation function to the weighted sum of inputs, and then produces an output signal. During the learning process, these weights are adjusted to improve the network's performance. In some cases, neurons also include a threshold mechanism, allowing them to activate only when the combined input exceeds a certain value.

Neural networks are typically organized into multiple layers, where each layer performs specific transformations on the data. Information flows from the input layer, through one or more hidden layers, and finally reaches the output layer.

Input Layer:

The input layer is the initial stage of the neural network, where external data is introduced into the system. It consists of input neurons that pass the received information to the next layer without performing complex computations.

Hidden Layer:

Hidden layers are located between the input and output layers and are responsible for processing the data. Each neuron in a hidden layer takes weighted inputs, applies an activation function, and forwards the result to the next layer. These layers enable the network to learn complex patterns and relationships.

Output Layer:

The output layer generates the final result of the neural network. It receives processed information from the preceding layers and produces the desired output based on the task, such as prediction or classification.

Training:

Training is the process of adjusting the network's weights to achieve accurate outputs. In supervised learning, the

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network is provided with input data along with corresponding target outputs. The difference between the predicted and actual outputs is used to update the weights, improving performance over time.

Validation:

Validation is used to evaluate how well the trained network generalizes to new, unseen data. It helps in monitoring the learning process and prevents overfitting by indicating when further training no longer improves performance.

Efficient tracking of the maximum power point (MPP) is essential for improving the performance of renewable energy systems. However, many conventional MPPT techniques suffer from limitations such as slow response, incorrect tracking, and steady-state oscillations, especially under rapidly varying environmental conditions. These issues reduce the overall energy conversion efficiency of photovoltaic (PV) systems.To address these challenges, an Artificial Neural Network (ANN)-based MPPT control strategy is proposed. This approach enhances system performance by providing faster and more accurate tracking compared to traditional methods. The proposed technique employs a multilayer neural network that is trained to estimate key environmental parameters such as solar irradiance and temperature using PV array voltage and current signals.A multilayer feedforward neural network trained using the backpropagation algorithm is utilized to ensure reliable operation under both steady-state and transient conditions. This structure enables the system to effectively handle nonlinear characteristics of PV arrays, particularly under non-uniform irradiance and fluctuating weather conditions. Unlike conventional methods, the ANN-based approach is not dependent on step-size or time-based perturbation, allowing it to track the MPP directly and efficiently.Furthermore, the use of mean square error (MSE) as a performance index during training improves the accuracy and generalization capability of the network. The ANN model can also be extended to estimate parameters influencing battery performance, such as temperature and irradiation levels, thereby supporting better energy management.

The proposed method determines the optimal operating point by approximating the MPP locus based on real-time input data. It offers advantages such as high tracking speed, reduced computational complexity, and minimal oscillations around the MPP. As a result, the system maintains stable operation and delivers improved efficiency even during sudden changes in environmental conditions. The ANN-based MPPT technique is validated for PV systems with both series and parallel configurations, demonstrating its ability to supply the required load power while overcoming the drawbacks of conventional methods. Overall, the proposed approach ensures accurate, fast, and reliable maximum power point tracking, making it highly suitable for advanced solar energy applications.

In Bayesian regularization, optimizing the regularization parameters involves evaluating the Hessian matrix of the objective function F(x)F(x)F(x) at its minimum point. To simplify this process, the Hessian is approximated using the Gauss–Newton method, which can be efficiently obtained when the Levenberg–Marquardt optimization algorithm is employed to determine the minimum. This approach significantly reduces the computational burden associated with parameter optimization.

The procedure begins by initializing the regularization parameters α\alphaα and β\betaβ, along with the network weights, which are typically assigned random values. The error components, namely the data error and weight decay terms, are then calculated. Based on these values, the parameter γ\gammaγ, representing the effective number of parameters, is estimated, and updated values of α\alphaα and β\betaβ are computed accordingly.It is important to note that each update of the regularization parameters modifies the objective function, causing the location of the minimum point to shift. However, as the optimization progresses, the parameter estimates become increasingly accurate, and the changes in the objective function gradually diminish. This iterative process continues until convergence is achieved, where further updates produce negligible variation.

The Gauss–Newton-based Bayesian Regularization (GNBR) method provides an efficient and stable training framework for neural networks. For improved performance, the input training data is typically normalized within a range such as [-1, 1], which enhances convergence speed and numerical stability during the training process.

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RESULTS AND DISCUSSION

The simulation model of the proposed system is illustrated in Figure 4. In this configuration, the solar photovoltaic (PV) array serves as the primary energy source for charging the battery. The output of the solar panel is fed into a boost converter, where an Artificial Neural Network (ANN) is employed to generate the appropriate gate pulses. The neural network is trained using the Bayesian Regularization algorithm to ensure accurate and stable control.The output from the source side is connected to a common 48 V DC bus, which acts as the central power distribution point. The energy generated by the PV system is stored in the battery energy storage system (BESS). During conditions such as cloudy weather or nighttime, when solar power generation is limited or unavailable, the stored energy in the battery is utilized to charge the electric vehicle (EV) at the charging station.In situations where both the PV generation and battery storage are insufficient to meet the charging demand, additional power is drawn from the utility grid. This ensures uninterrupted operation of the EV charging station, maintaining continuous service under all operating conditions.

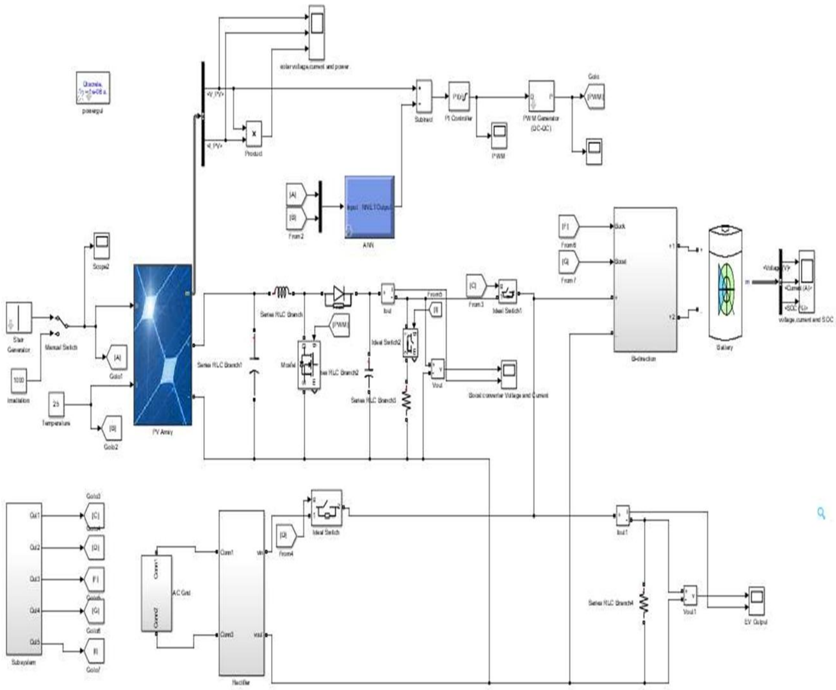

Fig. 4. Simulation diagram

ANN TRAINING TOOLBOX OUTPUT

In this work, a discrete-time simulation approach is adopted instead of a continuous model to achieve more effective and computationally efficient analysis. The accuracy of the Artificial Neural Network (ANN) largely depends on the size and quality of the training dataset, as well as the effectiveness of the Bayesian Regularization algorithm used during training. Typically, larger datasets enable the ANN to produce highly accurate predictions with minimal error.

The input variables, namely solar irradiance and PV array temperature, are provided to the model through a lookup table, which is synchronized using a clock signal. This ensures a time-coordinated input sequence for realistic simulation of environmental conditions.

Several performance indicators are used to evaluate the effectiveness of the trained ANN model, including regression value, mean square error (MSE), gradient, momentum parameter, and validation checks. The regression value reflects how well the network output correlates with the target data, while the error is determined as the difference between predicted and actual outputs.

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The dataset is typically divided into three subsets: training, validation, and testing. The training set is used to adjust the network weights by minimizing the error. The validation set helps assess the generalization capability of the network and is used to prevent overfitting by stopping the training process when performance no longer improves. The testing set, on the other hand, provides an unbiased evaluation of the network's performance after training and does not influence the learning process. The overall workflow and data division are illustrated in Figure 5.

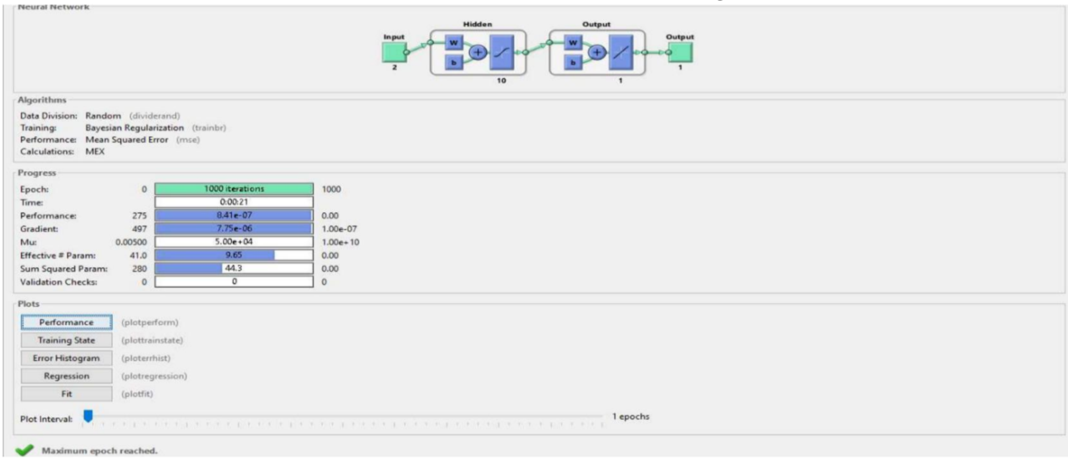

Figure 5 ANN Training Toolbox

BOOST CONVERTER SIMULATION OUTPUT

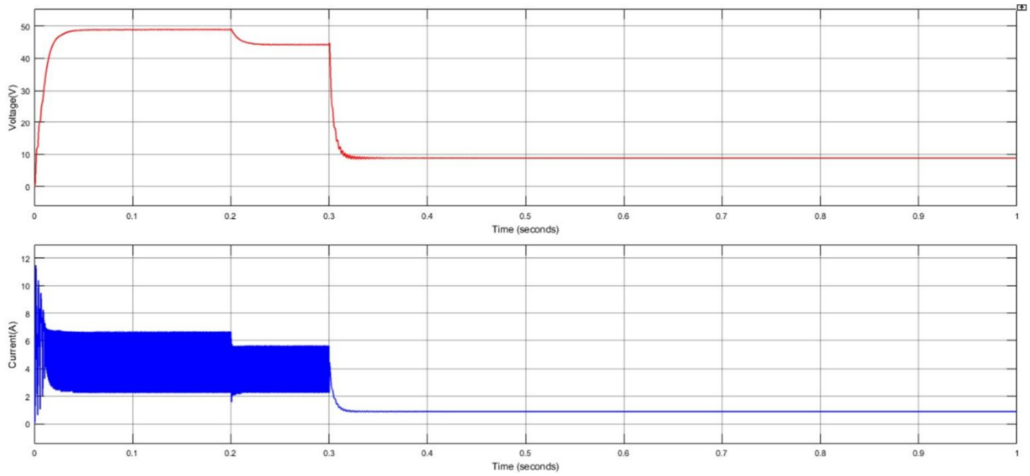

Figure 6 Boost Converter Output

The above simulation graphs show the voltage and current increases and decreases depending upon weather condition. If there is no radiation, current andvoltage will lead to zero shown in figure 6.

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BATTERY STORAGE SIMULATION OUTPUT

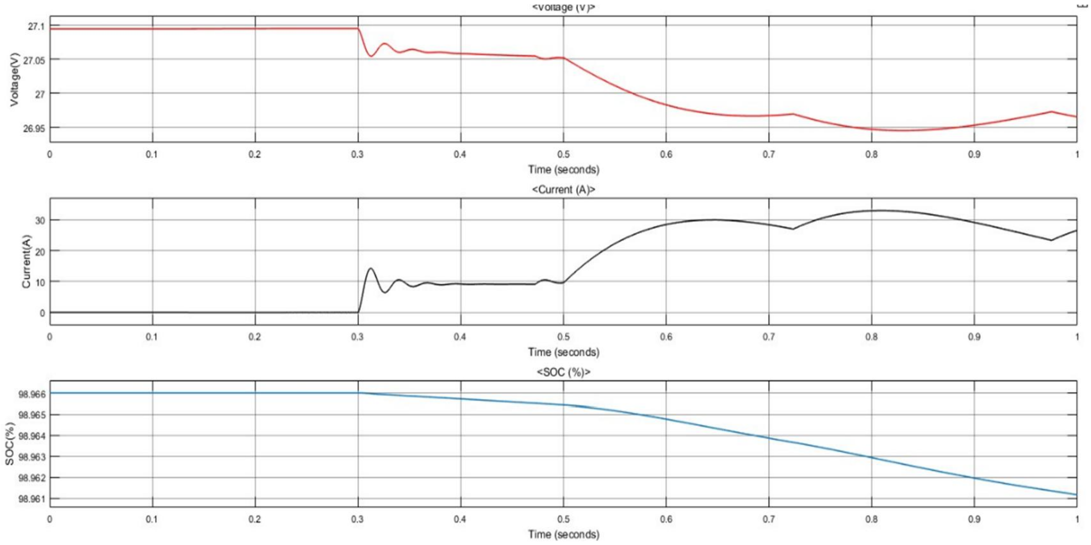

Figure 7 Battery Storage Output

The above simulation result conveys the battery performance where it displays the three parameters such as voltage, current, and SOC(%). If there is no power in the grid or solar, the energy stored in the battery is utilized to charge the EV vehicle for the shown in figure 7.

EV CHARGING SIMULATION OUTPUT

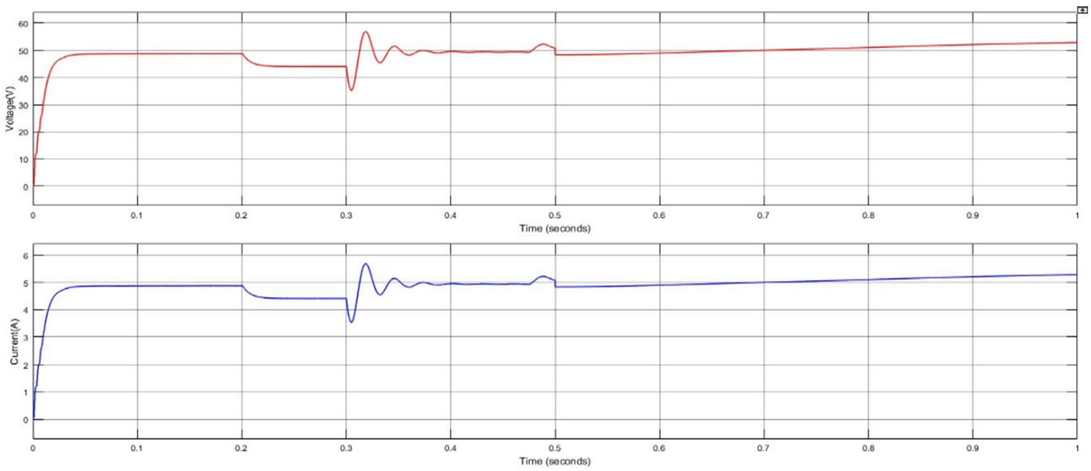

Figure 8 EV charging output

Comparative analysis of ANN PV and Different MPPT Techniques

	P &O BASED MPPT		ANN BASED MPPT	
Irradiation (W/m^2)	800	1000	800	1000

DOI: 10.48175/IJARSCT-33773

Voltage(V)	34.83	43.31	44.42	49.23
Current(A)	3.48	4.31	4.44	4.97
Power(W)	121	187	197	242

II. CONCLUSION

Global energy demand continues to rise due to rapid technological development and population growth, particularly in developing nations. In photovoltaic (PV) systems, efficient extraction of power is crucial, making maximum power point tracking (MPPT) an essential function. This work employs an Artificial Neural Network (ANN)-based MPPT technique to operate effectively under varying atmospheric conditions.One of the key advantages of the ANN approach is its superior dynamic response compared to conventional MPPT methods. It can quickly adapt to changes in environmental factors such as solar irradiance, ensuring accurate tracking of the maximum power point. In the proposed system, a DC–DC boost converter is used to regulate the operating point of the PV array, enabling efficient energy conversion.By integrating ANN with the boost converter, the system is able to extract maximum available power from the solar source, thereby improving overall efficiency. Additionally, the ANN-based method demonstrates strong capability in handling sudden variations in irradiance, resulting in enhanced tracking performance and increased energy output. This makes it a reliable and effective MPPT solution for electric vehicle (EV) charging systems integrated with photovoltaic generation.

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