RES MILITARIS
Social Science Journal

NEURAL NETWORK-BASED MPPT AND BUCK CONVERTER INTEGRATION FOR EFFICIENT EV CHARGING: A MATLAB SIMULINK IMPLEMENTATION

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Abstract - This paper presents a novel neural network- based Maximum Power Point Tracking (MPPT) system integrated with a buck converter for efficient electric vehicle (EV) charging using MATLAB Simulink. The system maximizes energy harvested from photovoltaic (PV) panels while ensuring optimal charging conditions for EV batteries. The neural network-based MPPT predicts and tracks the Maximum Power Point (MPP) of the PV panels under varying conditions, improving accuracy and adaptability compared to traditional methods. The buck converter regulates the voltage and current to the EV battery, ensuring safe and efficient charging.Simulation results in MATLAB Simulink demonstrate the system's effectiveness in maintaining the MPP and achieving high energy conversion efficiency. The neural network-based MPPT quickly and accurately tracks the MPP even under changing conditions, while the buck converter ensures safe battery charging, enhancing battery longevity. This research highlights the potential of combining neural networks with power electronics to create advanced, efficient EV charging solutions, promoting the adoption of renewable energy in transportation.
Keywords: Neural Networks, Maximum Power Point Tracking, Buck Converter, Electric Vehicle Charging, Photovoltaic Systems.

1 INTRODUCTION

The Solar-based microgrids are essential for a sustainable energy future, leveraging localized renewable sources to provide decentralized and efficient power, particularly for electric vehicle (EV) charging. The use of photovoltaic (PV) panels addresses the intermittent nature of solar energy, ensuring a more consistent energy supply for EVs. Neural networks (NNs) enhance the performance of these microgrids by predicting equipment failures, optimizing energy management, balancing loads, and maintaining grid stability.NNs analyze historical data and operational metrics to facilitate predictive maintenance, reducing downtime and maintenance costs. They forecast energy demand and supply based on weather, usage patterns, and market prices, managing resource allocation efficiently. For EV charging, NNs optimize the charging schedules and storage of excess energy, ensuring availability during peak demand or low production periods.

NNs also ensure effective load balancing by predicting consumption behaviors and adjusting energy distribution in real-time, improving microgrid performance and infrastructure longevity. This is particularly crucial for EV charging, which can impose significant loads on the grid.

Moreover, NNs contribute to grid stability by responding to fluctuations in energy production and consumption, maintaining a stable supply. They enable advanced energy trading strategies by predicting prices and demand, maximizing economic benefits in deregulated markets. NNs support smart grid technologies by enhancing communication between energy system components, creating an intelligent, responsive grid.

1.1 Proposed model

Integrating NNs into solar-based microgrids for EV charging significantly advances sustainable, efficient, and resilient energy systems. Their predictive, analytical, and optimization capabilities ensure a reliable energy supply for EVs, positioning AI as a crucial element in modern energy management. A block diagram of solar based microgrid for the EV charging is shown in the figure below.

Figure 1 Block diagram of solar based microgrid

As shown in the figure, Solar PV array converts the light energy into electrical energy. The efficiency of the solar energy generation is improved by the MPPT (Maximum Power Point Tracking) controller. The electrical energy is stored in a battery bank. This battery bank parameter are observed and managed by monitoring and control system and further given to the DC loads like electric vehicle. The energy stored in the battery bank may provide power to the AC load, after the inversion opearation.

1.2 MPPT Controller

Solar-based microgrids are essential for a sustainable energy future, leveraging localized renewable sources to provide decentralized and efficient power, particularly for electric vehicle (EV) charging. A critical component in these systems is the Maximum Power Point Tracking (MPPT) controller, which maximizes the efficiency and energy output of photovoltaic (PV) panels. The MPPT controller continuously adjusts the electrical load to ensure operation at the Maximum Power Point (MPP), adapting to varying environmental conditions to optimize power generation.

MPPT controllers are vital because they enhance the overall efficiency of solar power systems, ensuring PV panels produce the maximum possible power output despite environmental changes like cloud cover or shading. This efficiency boost results in increased electricity generation and shorter payback periods for solar installations. Additionally, MPPT controllers extend the lifespan of batteries in off-grid or hybrid solar systems by delivering appropriate voltage and current levels, preventing overcharging and deep discharging, which can damage batteries and reduce their longevity. In our design, we have implemented the perturbation and observation algorithm for the MPPT controller, ensuring consistent maximum power production. In our model, The Duty_Cycle function continuously adjusts the duty cycle based on changes in voltage and power to ensure the solar panels operate at their maximum efficiency. This method helps in maximizing the energy output from the PV panels by finding and maintaining the Maximum Power Point (MPP). The algorithm used here is a perturb and observe method, where small changes in voltage and power are observed to determine the direction in which to adjust the duty cycle. Circuit diagram of MPPT with buck converter and design consideration is shown below

Rated power=213W
Open circuit voltage=36.3V
Input voltagurre =28-36V
Output voltage =12V
Current ripple=10%
Voltage ripple=1%
Switching frequency = 25kHz
Output current = Rated Power / Input voltage =213/12=17.75
Current ripple 10% of 17.75= 1.775
Voltage ripple= 1% of 12=0.12V

$$Inductor = \frac{\mathrm{Vop(Vin - Vop)}}{\mathrm{fsw * Iripple * Vin}} = \frac{12(28-12)}{25000 * 1.775 * 28} = 156e - 6H$$

$$\mathrm{Capacitor} = \frac{I\,ripple}{8 * \mathrm{fsw} * \mathrm{V\,ripple}} = \frac{1.775}{8 * 25000 * 0.12} - 74e - 6F$$

Simulink model with Buck charging and MPPT is shown below

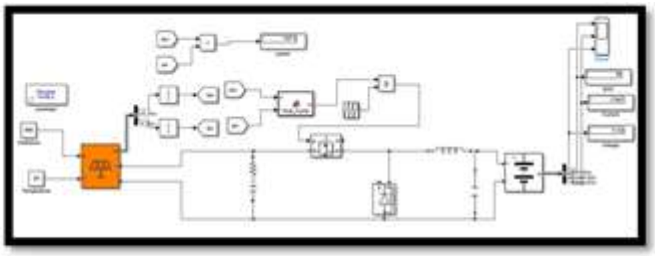

Figure 2 Simulink model with MPPT (P&O)

From the above model, we will be replacing the MPPT with a Neural Network controller. To do this, a dataset has to be created to train the neural network. Here the solar voltage is taken as the input parameter and the duty cycle is taken as the output parameter.

As shown in the figure below, the input and output parameter has 10001 entries.

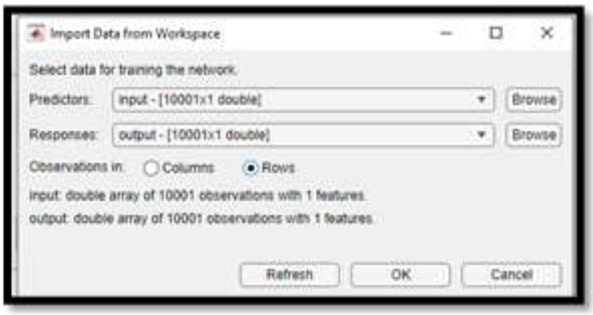

Figure 3 Selecting data for the training purposes

After this Lavenberg Marquardt algorithm has been selected for the training purpose with 10 neurons. The developed neural network replaced the conventional MPPT in the model as shown in the figure below.

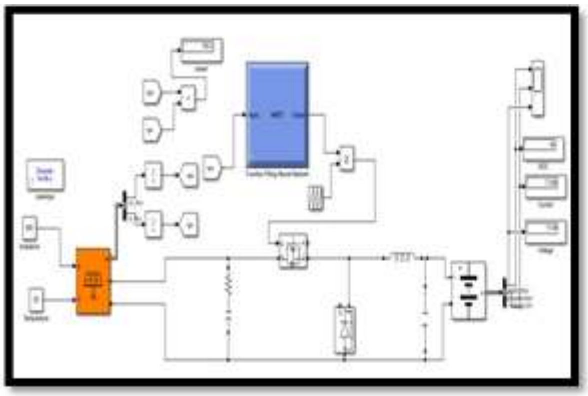

Figure 4 Simulink model with the trained neural network

2 SIMULATION RESULTS

2.1 Trained neural network training analysis

2.1.1 Mu (Learning Rate)

Mu, or the learning rate, controls the step size during the weight update process in the neural network training. A well-tuned Mu ensures that the network converges efficiently without overshooting the minimum error. In the context of the trained neural network, a balanced Mu helped achieve optimal convergence speed, enhancing the MPPT accuracy for the solar-based EV charging system. Mu of 1e-9 is obtained during the training phase.

2.1.2 Gradient

The gradient represents the rate of change of the error with respect to the network weights. It guides the direction in which the weights should be adjusted to minimize the error. In our trained neural network, monitoring the gradient ensured that the weight adjustments were moving towards reducing the prediction error. Low gradient values indicated successful convergence towards the minimum error point, validating the training process's effectiveness. Gradient of 3.13e-6 is obtained during the training phase.

2.1.3 Epoch

An epoch refers to one complete pass through the entire training dataset. The number of epochs indicates how many times the neural network has seen the entire dataset during training. For our neural network, training over multiple epochs allowed the model to iteratively improve its performance. The final trained model showed reduced error rates and improved MPPT predictions, demonstrating the effectiveness of sufficient epochs in achieving accurate and reliable results. 61 epochs has been taken by the model to reach the desired state. These parameters collectively contributed to the successful training of the neural network, ensuring efficient energy harvesting and optimal charging conditions in the solar-based EV charging system.

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	61	1000
Elapsed Time	-	[illegible]	-
Performance	[illegible]	[illegible]	0
Gradient	[illegible]	[illegible]	[illegible]
Mu	[illegible]	[illegible]	[illegible]
Validation Checks	[illegible]	[illegible]	[illegible]
Training Progress			

3 TRAINING, VALIDATION AND TESTING MSE AND REGRESSION

3.1 MSE (Mean Squared Error):

MSE measures the average squared difference between actual and predicted values. A low MSE indicates high accuracy in predicting the Maximum Power Point (MPP) for the solar-based EV charging system, ensuring efficient energy conversion.

3.2 R (Correlation Coefficient):

R measures the linear relationship between actual and predicted values, ranging from -1 to 1. A high R value signifies a strong correlation, demonstrating the neural network's reliability in accurately predicting MPP under varying conditions. Regression of more than 99 % is obtained during training, validation and testing phase.

Low MSE and high R values together confirm the neural network's effectiveness and reliability in optimizing the MPPT system for efficient EV charging

	Observations	MSE	R
Training	7001	2.4827e-04	0.9958
Validation	1500	1.7334e-04	0.9971
Test	1500	1.5233e-04	0.9973

Figure 5 MSE and R of the trained neural network

3.3 Error histogram of the trained neural network

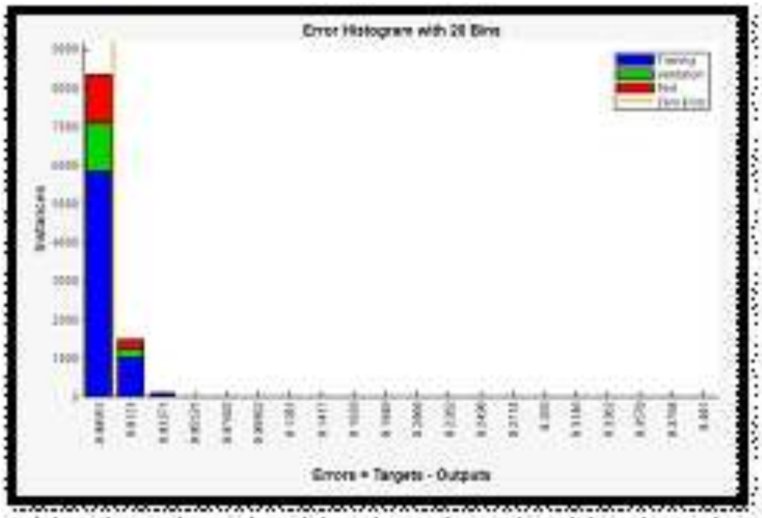

Figure 6 Error histogram

3.4 Regression plot of the trained neural network

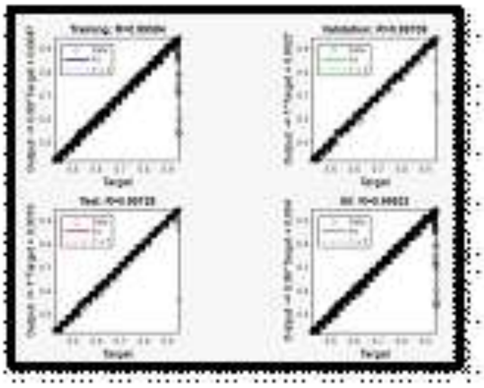

Figure 7 Regression coefficient of the trained neural netwrk

4 MAXIMUM POWER POINT TRACKING USING ANN

The MPPT waveform obtained from the neural network reflects real-time adjustments of the solar panel's operating point to maximize power output. It shows dynamic changes in voltage and current to track the Maximum Power Point (MPP) under varying sunlight conditions. This waveform demonstrates the neural network's ability to optimize energy harvesting efficiency by adapting swiftly to environmental changes, ensuring consistent and reliable performance in solar-based EV charging applications. It can be seen in the below figure that the waveform is reaching the maximum power point of 213W.

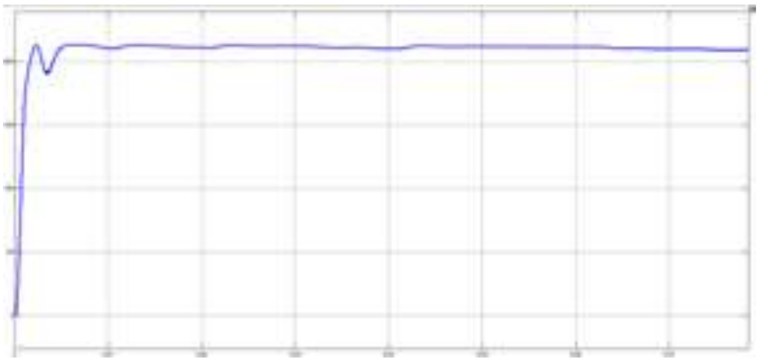

Figure 8 Power vs time during MPPT operation

5 BATTERY CHARGING STATUS USING NEURAL NETWORK

The voltage waveform shows variations as the battery charges, reflecting the applied charging voltage and the battery's response to charging current. It typically increases steadily during constant current charging phases and levels off during the constant voltage phase as the battery approaches full charge. SOC, representing the amount of energy stored in the battery as a percentage of its total capacity, increases gradually during charging. The SOC waveform rises as energy is transferred into the battery and decreases when energy is drawn from it. The current waveform fluctuates based on the charging stage and the battery's charging characteristics. It is typically high during the initial constant current phase and decreases as the battery reaches higher SOC levels during the constant voltage phase.

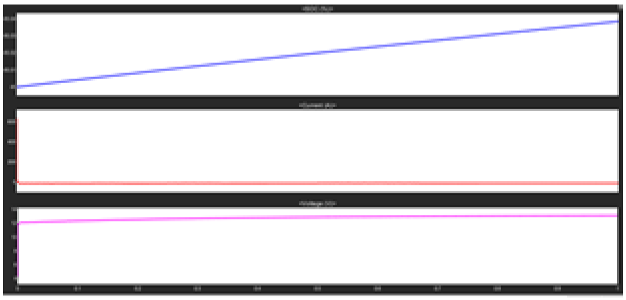

Figure 9 SOC, current and voltage waveform of battery

6 CONCLUSION AND FUTURE SCOPE

This paper introduces a novel approach integrating a neural network-based Maximum Power Point Tracking (MPPT) system with a buck converter in MATLAB Simulink for efficient electric vehicle (EV) charging. By optimizing energy from photovoltaic (PV) panels and ensuring optimal EV battery charging conditions, the system surpasses traditional methods. The neural network-based MPPT accurately predicts and tracks the PV panels' Maximum Power Point under various conditions, enhancing efficiency. Simulation results validate its effectiveness in maintaining high energy conversion efficiency, even under dynamic conditions. The buck converter ensures safe charging, extending battery life and reliability. This study underscores the potential of neural networks and power electronics in advancing sustainable transportation with renewable energy. Future research can focus on real-world deployment validation, advanced optimization algorithms for MPPT, integration with smart grids, enhanced battery management strategies, and scalability for broader EV charging networks. These efforts will further enhance system efficiency, reliability, and adoption of renewable energy solutions in transportation.

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