International Journal of Scientific Research & Engineering Trends
Volume 11, Issue 5, Sep-Oct-2025, ISSN (Online): 2395-566X

Implementation of Neural Network Control Mechanism for Grid Connected Wind-Solar PV Charging Station

Manish Kumar[1], Ishan Sethi[2]

[1] Research Scholar, Department of Electrical Engineering, Swami Devi Dayal Institute of Engineering & Technology, Barwala, Panchkula, Haryana

[2]Professor & Head, Department of Electrical Engineering, Swami Devi Dayal Institute of Engineering & Technology, Barwala, Panchkula, Haryana

Abstract- This work proposes a novel approach to enhance Grid- connected wind-solar PV charging stations face with challenges like fluctuating energy supply, inefficient resource usage, and the necessity for adaptive real-time control. Traditional control methods, like PI controllers, often fall short in optimizing system performance under these dynamic conditions, resulting in inadequate power supply for EV charging. To tackle these hurdles, this study proposes a pioneering approach employing neural network (NN) controllers to enhance grid-connected wind- solar PV charging stations' operation. NN controllers dynamically adjust charging station operations based on real- time data inputs, offering superior adaptability and efficiency. By integrating wind and solar power generation with intelligent NN control mechanisms, the system adeptly responds to varying environmental conditions and grid demands, ensuring more effective utilization of renewable energy sources. The proposed NN controller-based system targets enhancing the reliability, sustainability, and economic feasibility of grid-connected charging stations. Simulations showcase the effectiveness and stability of this approach in integrating renewable energy into transportation infrastructure. Performance evaluation can be conducted using Matlab/Simulink Software.

Keywords – Solar, Wind, Grid, Electric Vehicle, Battery, Inverter, DC to DC converters, PI, Controller, NN controller.

I. INTRODUCTION

The increasing frequency of global climatic disasters highlights the urgent need to address the main issue of global warming. Continued reliance on fossil fuel-based power generation and traditional internal combustion engine vehicles contributes significantly to the emission of harmful gases, exacerbating the rise in global temperatures [1-3].

Renewable sources harness natural drives such as solar irradiation, wind, hydrogen, biogas, and tidal waves without emitting gases left-over during power generation. Similarly, electric vehicles, powered by batteries and devoid of internal combustion engines, produce no emissions or smoke during operation. Integrating these replacements into the energy grid and transportation infrastructure has the potential to significantly mitigate climate change, offering a substantial improvement in global warming reduction [4-6].

Nonetheless, incorporating these components into the grid system presents a challenge, requiring various power electronic devices and circuits to facilitate voltage conversions. RES pose an additional complexity due to their unpredictable nature, as natural energy is variable and unreliable [7-9]. Integrating these energy sources into the grid requires advanced control techniques to ensure synchronization. Our analysis focuses on a test system that includes a solar photovoltaic array, a wind farm, and an EV battery charging station, all connected to a three-phase grid, as depicted in Figure 1.

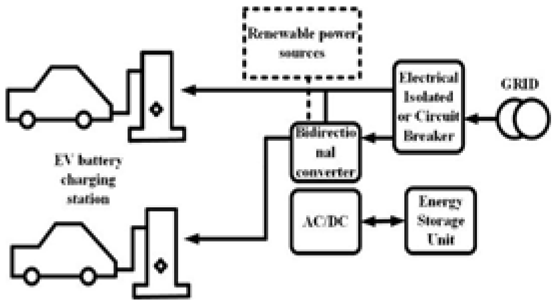


Fig. 1. Suggested configuration for integrating renewable energy sources with an EV battery charging station.

In the suggested experimental configuration, the grid functions concurrently with RES, providing electricity to EV battery charging station. Furthermore, an energy storage unit is connected to setup through an AC-DC converter to collect extra power produced by RES.

The integration of a Grid Connected Electric Vehicle (EV) Charging Station with Multi Renewable Source project using both Proportional-Integral (PI) and Artificial Neural Network (ANN) based systems offers several merits and demerits. On the positive side, utilizing PI and ANN controllers enhances system efficiency by optimizing the utilization of renewable energy sources, leading to reduced energy wastage and environmental benefits. The inclusion of multiple renewable sources ensures a reliable power supply, reducing dependence

International Journal of Scientific Research & Engineering Trends
Volume 11, Issue 5, Sep-Oct-2025, ISSN (Online): 2395-566X

on the grid and promoting sustainability. Additionally, the flexibility of PI and ANN systems allows for adaptable control to varying environmental conditions and grid demands, potentially resulting in long-term cost savings. However, challenges include high initial setup costs, increased system complexity, susceptibility to environmental fluctuations, potential compatibility issues, and a learning curve associated with implementing advanced ANN control systems.

The paper is structured with an introduction in Section I, followed by a system description in Section II, an analysis of the proposed controller's performance in Section III, simulation outcomes in Section IV, and ultimately, a conclusion in Section V.

II. SYSTEM DESCREPTION

As before noted, the proposed test system incorporates two RES: a solar and a wind. These RES inherently generate power in different forms - PVA produces DC power, while the wind farm generates AC power through dynamic rotating generators within its turbines. To enable parallel operation of these sources, one of two approaches must be adopted: synchronizing the PVA's DC power with the wind AC voltage, or converting the wind AC power to DC for parallel connection with the PVA module. However, in line with the requirements of the test system, where DC voltage is needed for battery charging module, no necessity to convert power from RES to AC [10-13].

An MPPT algorithm controls use of a DC-DC booster converter to increase voltage that PVA generates in response

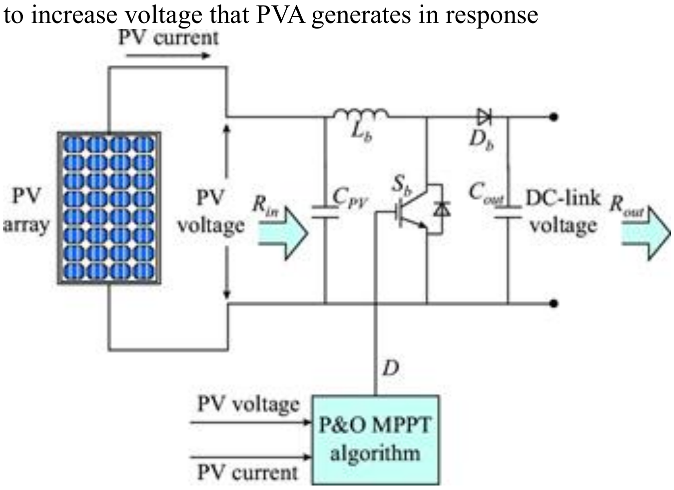


Fig.2 PVA interlinks to boost converter

In Figure 2, the connection of the PVA to boost converter is depicted. The booster converter is controlled by the widely employed and highly responsive MPPT algorithm, typically the P&O method. This MPPT algorithm relies on feedback obtained from both the current and voltage of the PVA, which determines a duty ratio for boosting switch. A flowchart illustrating this process is provided in Fig 3.

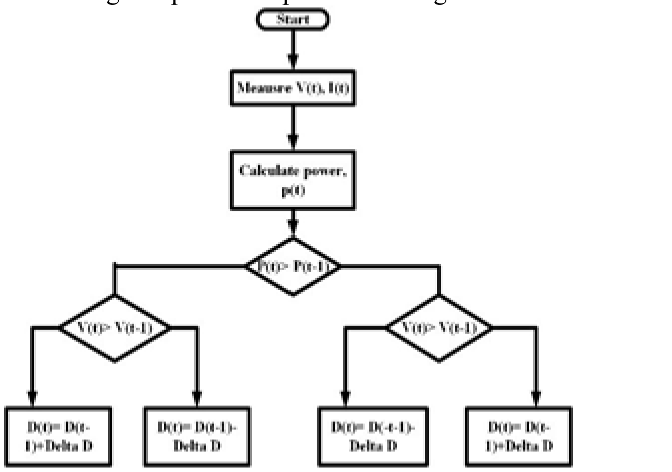


Figure 3. Flowchart of the Perturb and Observe (P&O) Method.

As shown by, the duty cycle of the switch is modified in line with the PVA module's power and voltage levels.

to solar energy. (Maximum Power Point Tracking) is used to extract the maximum power from solar panels, which experience fluctuating energy output due to changing climatic conditions. To ensure sufficient power for the loads, a P&O

$$D(t)=D(t-1)+\Delta D\begin{Bmatrix} If\ P(t)>P(t-1)\wedge V(t)>V(t-1) \\ If\ P(t)\in P(t-1)\wedge V(t)\in V(t-1)\end{Bmatrix} \quad (1)$$

$$D(t)=D(t-1)-\Delta D\begin{Bmatrix} If\ P(t)\in P(t-1)\wedge V(t)\in V(t-1)\end{Bmatrix} \quad (2)$$

(Perturb and Observe) based MPPT technique has been proposed. Figure 2 shows a configuration that represents a modelling of the PVA coupled to the booster converter.

"(t)" shows the current value, while "(t-1)" refers to the earlier value. The duty ratio of switch is adjusted based on historical and current power and voltage data from the PVA. The wind farm utilizes PMSG technology, where mechanical energy from turbines attached to propellers generates electricity [4].Fluctuations in PMSG voltage due to changing wind speeds necessitate a voltage controller converter to stabilize the output. Figure 4 illustrates the circuit topology for power generation at the wind farm.

Variable AC to DC is converted by a diode bridge rectifier, which is connected to terminals of the PMSG machine. An MPPT module, shown in Figure 3, controls the voltage output of the unregulated rectifier, just like the PVA's DC-DC booster converter does. This module stabilizes the DC voltage and optimizes power extraction from the PMSG.

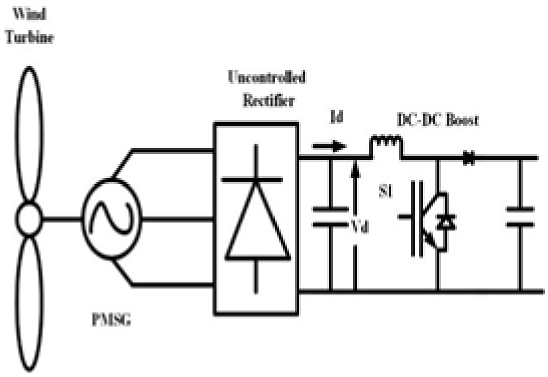


Figure 4. PMSG wind farm configuration

CONVERTERS CONFIGURATION

The system incorporates several converters, including a controlled rectifier for grid integration, a bidirectional DC-DC converter for battery storage, and a booster converter. These components are configured to allow integration of the bidirectional and controlled rectifiers with the booster setup. The bidirectional converter manages the storage and release of excess energy, as depicted in Figure 5.

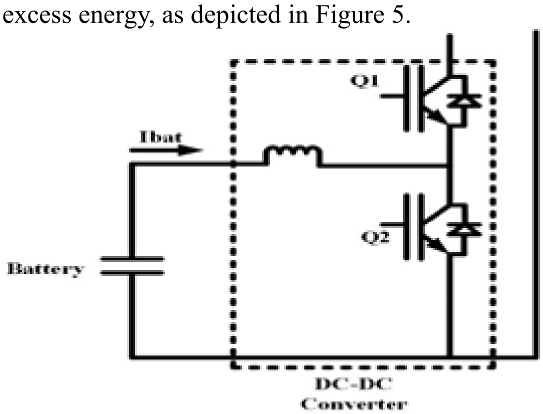


Figure. 5. Bidirectional DC-DC converter for the battery storage unit

The converter integrates two IGBT switches capable of handling high voltages and frequencies. Q1 functions as a buck switch, while Q2 acts as a boost switch, with their ON and OFF states determining battery charging or discharging.

Control of these switches is governed by a voltage feedback controller, dictating their operation mode based on system requirements. During surplus generation, the converter works in buck mode, charging the battery with excess power, while in scenarios of insufficient generation, it switches to boost mode, facilitating battery discharge to EV charging station.

The EV charging station uses the 3-phase grid in addition to power allocation from renewable sources and battery storage when necessary, particularly in situations where stored and renewable power are insufficient. This is made possible by a controlled three-phase rectifier, which uses 6-switches that are controlled by PWM to provide even power distribution. Figure 6 below shows how the controlled rectifier is configured.

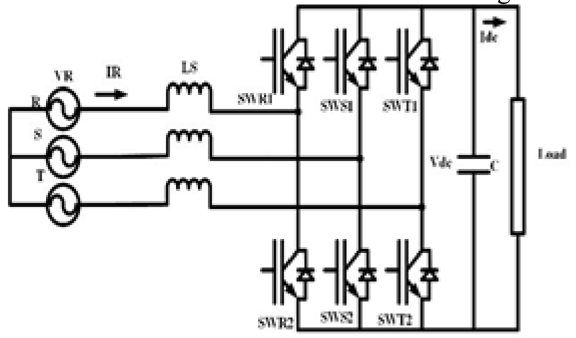


Figure 6. Three phase controlled rectifier

A six-switch rectifier set up in a three-legged configuration, each leg running at a 120-degree phase shift, is used to convert three-phase AC voltage into the required DC voltage. The recti fier's switches are accurately regulated by means of the sinusoi dal PWM technology. In order to generate pulses for the switch es, a feedback loop controller creates the reference signal and c ompares it to a high-frequency triangle waveform. Figure 7 sho ws the controlled rectifier's pulse production procedure.

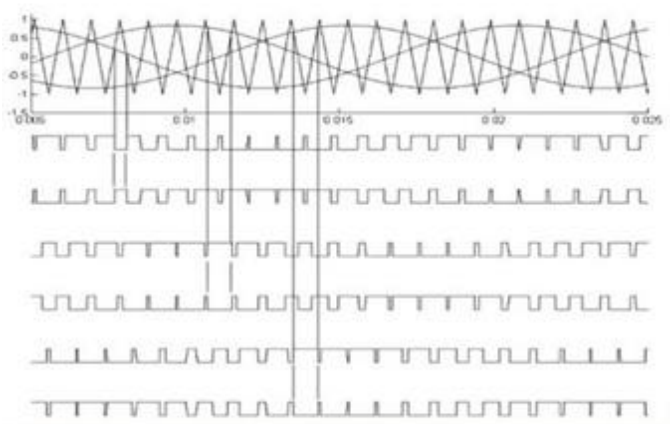


Figure 7. Sinusoidal reference PWM configuration

All of the above mentioned elements are integrated into the simulation under predetermined settings and simulation time. Connected to specific converters, controllers manage the control of renewable energy flow, the battery storage system, and the three-phase grid's regulated rectifier.
The research paper that compares Proportional-Integral (PI) controller and Neural Network (NN) controller, particularly in Section IV.

III. PROPOSED METHOD

In this project we proposed Artificial Neural Network (ANN) controller and the below section provides the ANN structure and operation

A control system inspired by composition and operation of human brain is called an artificial neural network. It uses an ANN as the core computational model to make decisions and control various processes.

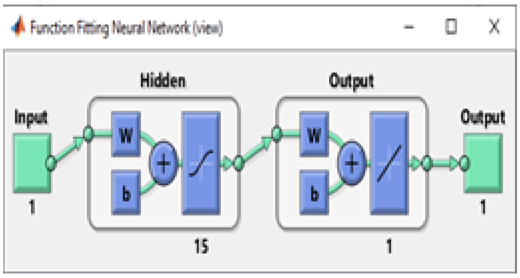
The ANN consists of interconnected nodes, commonly referred to as artificial neurons or units.

Training ANN:

The ANN Network is trained and simulate using forward propagation input data and error is calculated by calculating the error between forecasted output and actual output.

ANN as a Controller:

Once the ANN is trained, it can serve as a controller in various applications.



Structure of ANN:

SIMULATION RESULTS

PI controller based simulation results

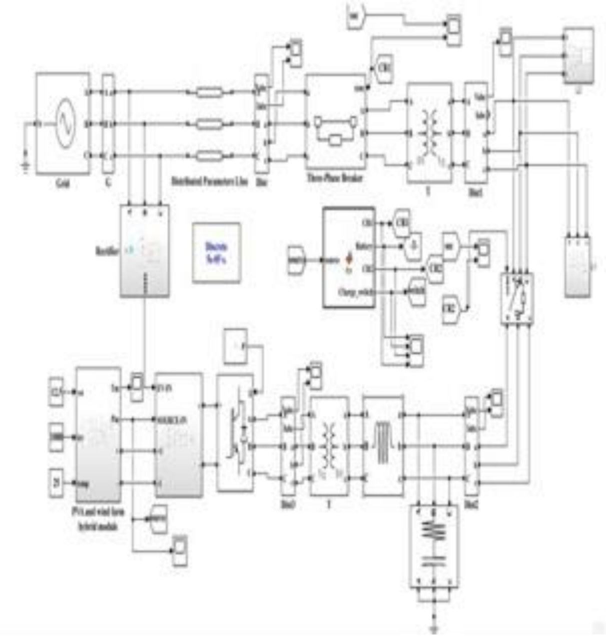


Figure 9. Simulink Model of the Proposed System

The figure visually depicts a proposed test setup, showcasing interconnected modules and their interactions within the Simulink environment. This model faithfully reproduces the behaviour and performance of the grid-connected wind-solar PV charging station. By employing the Sim Power Systems library and MATLAB Simulink, the simulation serves as a comprehensive platform for analyzing and optimizing the charging station's operation.

The simulation results provide valuable insights into the efficiency of the controller, grid stability, power quality, and overall system performance across varying conditions. The utilization of these powerful tools enables efficient testing and validation of the neural network controller's effectiveness, empowering researchers and engineers to make well-informed decisions and enhancements for real-world implementation.

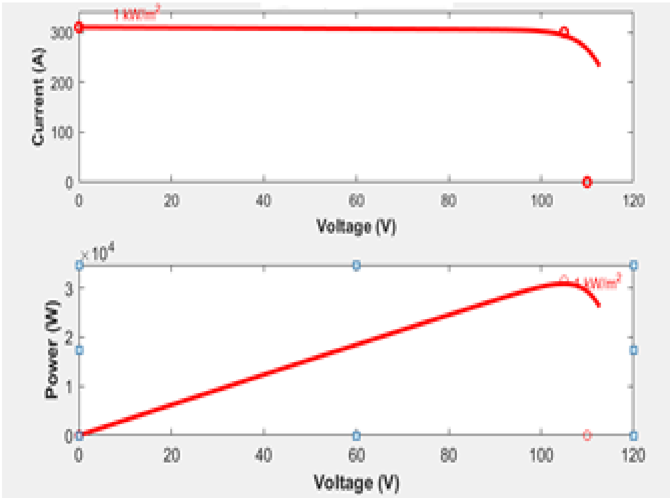


Figure 10: V-I and P-V characteristics of PVA module

The hybrid model's output power is directed to the battery, controlled by user settings. Conditions are maintained with a temperature of 25°C, wind speed of 12.5 m/s, and solar irradiance at 1000 W/m^2. Figure 10 illustrates the solar arrays V-I and P-V characteristics under these settings.

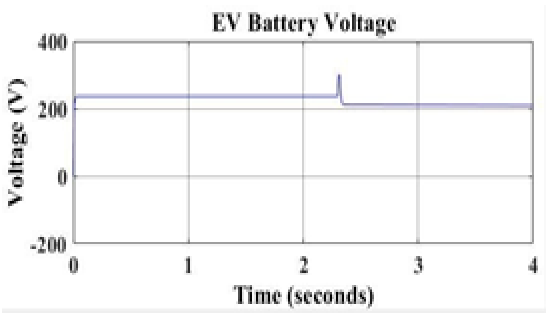


Figure 11: EV battery characteristics with PI Controller

International Journal of Scientific Research & Engineering Trends
Volume 11, Issue 5, Sep-Oct-2025, ISSN (Online): 2395-566X

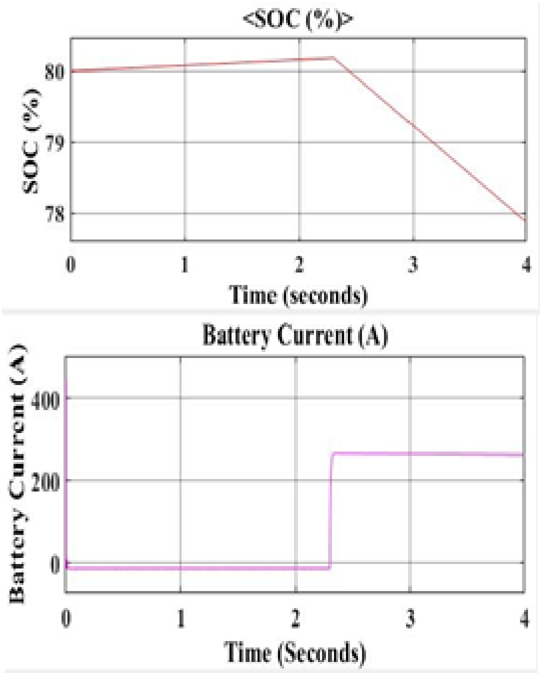
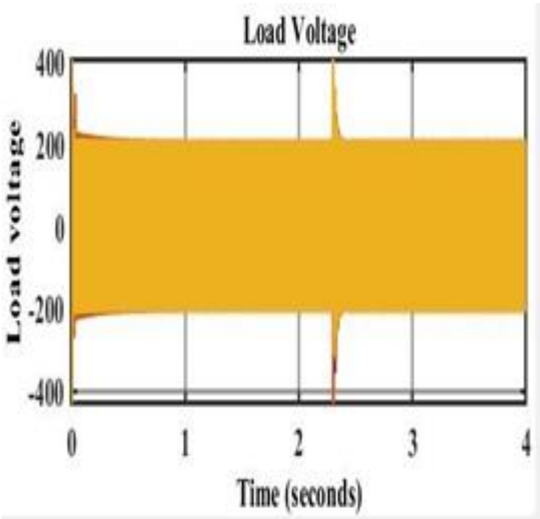


Figure 11: EV battery characteristics



.

Figure 12: Load voltage

The results of the simulation for EV battery systems with distortions are shown in Figure 10. A DC regulator uses feedback from grid parameters to control the voltage reduction of a measured rectifier connected to a step-down transformer. The resulting DC voltage is adjusted to appropriate value. In addition, an LC filter-equipped three-phase inverter is connected to provide electricity to residential loads; Figure 11 displays the output voltage of this inverter.

NN Controller based Simulation Results:

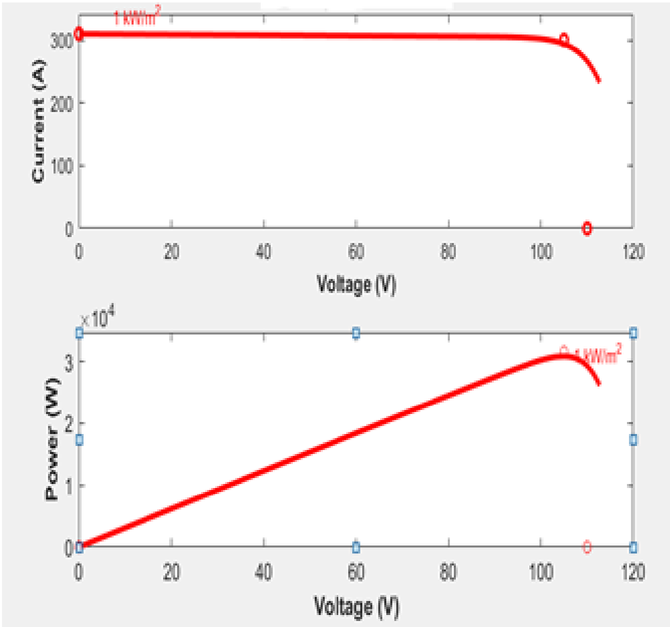


Figure 13: V-I and P-V characteristics of PVA module

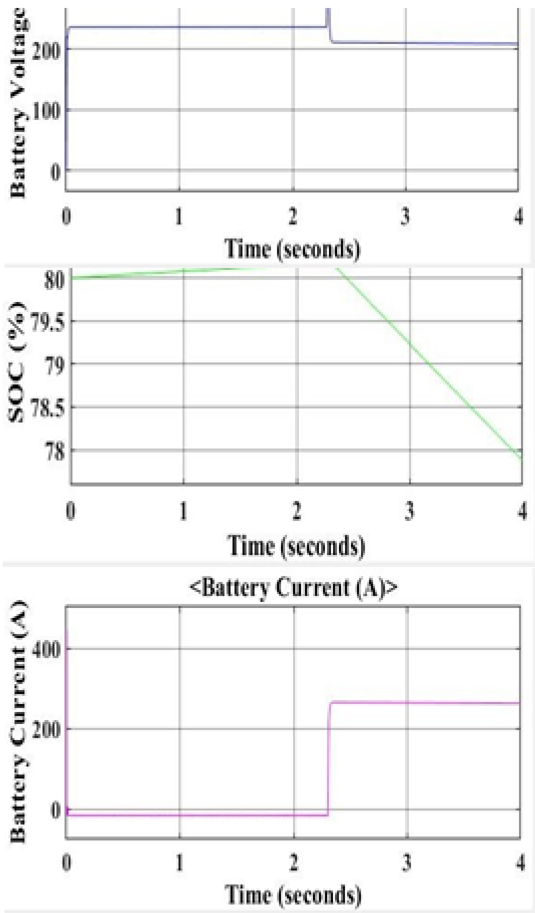


Figure 14: EV battery characteristics with NN Controller

The illustration in Figure 14 illustrates simulation outcomes for EV battery systems with minimized distortions. It demonstrates the connection of a controlled rectifier to a step- down transformer to decrease voltage. A DC regulator, shown by feedback from grid parameters, adjusts the voltage to the required level. A three-phase inverter with an LC filter powers residential loads, with its output voltage illustrated in the figure.

Table 1: THD Comparison Table

Parameter	% of THD obtained using PI Controller	% of THD obtained using NN Controller
Load Voltage	1.20%	0.51%

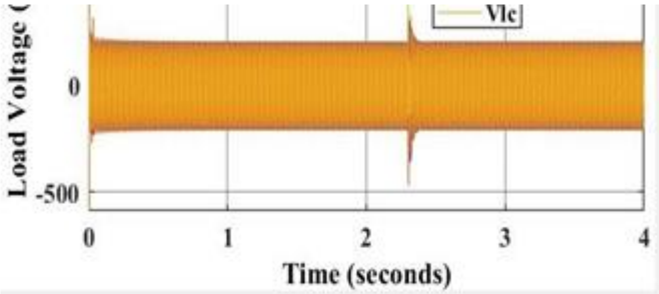


Figure 15: Load voltage

Comparison:

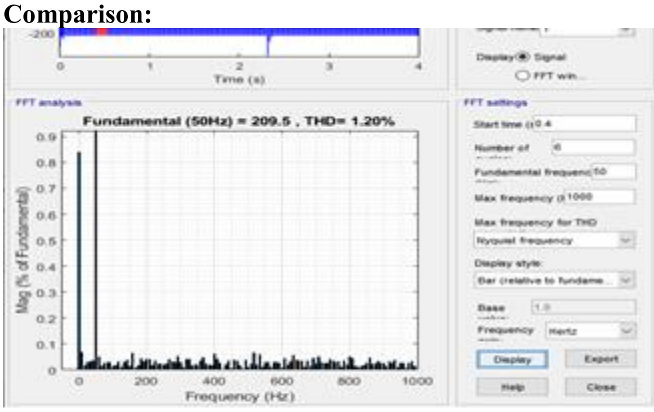


Figure 16: Load Voltage THD graph obtained using PI Controller

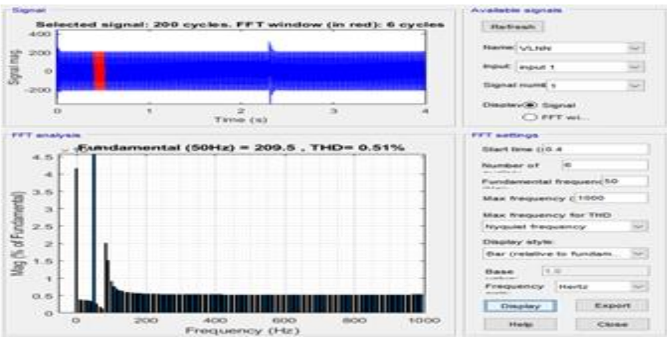


Figure 17: Load Voltage THD graph obtained using NN Controller

By observing the Table-1 it can be noted that the % THD obtained in load voltage by using PI Controller is 1.20%, whereas it is reduced to 0.51% by using NN Controller. It can be concluded that the NN based System has reduced THD with improved power quality. It enhances the system performance without power losses. Neural networks can handle the nonlinear dynamics and complex interactions in multi-renewable sources, leading to optimized control actions and reduced THD in the charging station. Unlike PI controllers, neural networks adapt to changing conditions and make data-driven decisions for accuracy is improved by reducing THD values, as shown in the comparison between PI and ANN controllers in the table

IV. CONCLUSION

In conclusion, the integration of neural network controllers into grid-connected wind-solar PV charging stations marks a significant advancement in renewable energy management. Through the application of sophisticated algorithms, these controllers optimize the performance of such stations by dynamically adjusting energy generation and storage based on real-time data and forecasted conditions. This results in improved efficiency, reliability, and stability of the charging stations, enhancing their overall functionality and contribution to the grid. Additionally, neural network controllers enable intelligent decision-making, allowing for better utilization of renewable energy resources and smoother integration into existing power systems. As renewable energy continues to play a crucial role in combating climate change and achieving sustainability goals, the implementation of neural network controllers represents a promising approach to maximizing the potential of wind-solar PV charging stations and advancing the transition towards a cleaner energy future.

REFERENCES

1. W. Zhou, C. Lou, Z. Li et al., “Current status of research on optimum sizing of stand-alone hybrid solar-wind power generation systems,” Ap- plied Energy, vol. 87, no. 2, pp. 380- 389, Feb. 2010.
2. M. Nehrir, C. Wang, K. Strunz et al., “A review of hybrid renewable/ alternative energy systems for electric power generation: configura- tions, control, and applications,” IEEE Transactions on Sustainable En- ergy, vol. 2, no. 4, pp. 392- 403, May 2011.
3. C. Zhou, K. Qian, M. Allan and W. Zhou, "Modeling of the Cost of EV Battery Wear Due to V2G Application in Power Systems", IEEE Trans. Energy Convers, vol. 26, no. 4, pp. 1041-1050, December 2011.
4. A. Arancibia and K. Strunz, "Modeling of an electric vehicle charging station for fast DC charging", Electric Vehicle Conference (IEVC) 2012 IEEE International, pp. 1-6, 2012.

5. Ciprian Vlad et al., "Using renewable energy sources for electric vehicles charging", Electrical and Electronics Engineering (ISEEE) 2013 4th International Symposium on, 2013.
6. H. Li, H. Liu, A. Ji, F. Li and Y. Jia, "Design of a hybrid solar-wind powered charging station for electric vehicles", IEEE Int. Conf. Materials for Renew. Energy and Env., pp. 977-981, 2013.
7. S. Li, K. Bao, X. Fu and H. Zheng, "Energy Management and Control of Electric Vehicle Charging Stations", Electric Power Components and Systems, vol. 42, pp. 339-347, 2014.
8. M. O. Badawy and Y. Sozer, "Power Flow Management of a Grid-Tied PV-Battery System for Electric Vehicles Charging", IEEE Proceedings of 2017 Winter Simulations, vol. 53, no. 2, pp. 1347-1357, 2017.
9. A. Verma and B. Singh, "Multi-functional charger for electric vehicle operating with grid and SPV generation", 6th IEEE Int. Conf. on Comp. App. In Electrical Engineering- Recent Advances (CERA), pp. 252-257, 2017.
10. A. Verma and B. Singh, "Energy Management Strategy of Solar PV-Battery and Diesel Generator Based Electric Vehicle Charging Station", IEEE Energy Conversion Congress and Exposition (ECCE), pp. 1043-1050, 2018.
11. L. Bokopane, K. Kusakana and H. J. Vermaak, "Energy Management of a Grid-Integrated Hybrid Peer-to-Peer Renewable CS for Electric Vehicles", 2018 Open Innovations Conference OI 2018, pp. 275-280, 2018.
12. T. Alharbi, K. Bhattacharya and M. Kazerani, "Planning and Operation of Isolated Microgrids Based on Re-purposed Electric Vehicle Batteries", IEEE Trans. Ind. Informat. Early Access.
13. Stanislav I. Koval, "Data preparation for neural network data analysis", Young Researchers in Electrical and Electronic Engineering (EIConRus) 2018 IEEE Conference of Russian, pp. 898-901, 2018.
14. S. Kamat and S. Jadhav, "Design and Simulation of Low Power Charging Station for Electric Vehicle", 2019 International Conference on Advances in Computing Communication and Control (ICAC3), pp. 1-4, 2019.
15. B. Singh, A. Verma, A. Chandra and K. Al-Haddad, "Implementation of Solar PV-Battery and Diesel Generator Based Electric Vehicle Charging Station", IEEE Transactions on Industry Applications, vol. 56, no. 4, pp. 4007-4016, July– Aug. 2020.