

A novel method of bayesian regularization based solar charging station employing maximum power point tracking for electric vehicle applications

Prasanna Moorthy Veerappan

GCT: Government College of Technology

Dineshraj V

GCT: Government College of Technology

Elangovan S

Jansons Institute of Technology

Deepika V

Muthayammal Engineering College

Meenakumari Ramachandran

Kongu Engineering College

Hitesh Panchal

Government Engineering College

Ravita Lamba

MNIT: Malaviya National Institute of Technology

Kokilavani Thangaraj

Sri Krishna College of Engineering and Technology

Suresh Muthusamy (✉ infostosuresh@gmail.com)

Kongu Engineering College

Research Article

Keywords: Electric Vehicles, Solar PV Generation, Battery Energy Storage System, Grid EV Charge, MPPT.

Posted Date: July 29th, 2022

DOI: <https://doi.org/10.21203/rs.3.rs-1870193/v1>

License:   This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Abstract

Any growing country's business development relies on the availability of electricity. Recent years have seen an increase in the development and marketing of electric vehicles (EVs) and hybrid electric cars due to environmental concerns and increasing oil costs (HEV). Electric vehicles are becoming more popular, and their accompanying equipment has become a necessary part of the equation. One module where this has been tried is the charging station. As part of the proposed work, ANN-based MPPT is utilized to monitor the solar panel's maximum power. This approach has the benefit of being more precise. ANN uses the Bayesian Regularization technique for maximum power point tracking. The neural network accustomed to manage the DC-DC converter's duty cycle is trained using this approach. Solar PV, energy storage, and the grid are all included in this electric car charging station. In case of an emergency, the PV and storage systems may draw electricity from the grid. The proposed method's efficiency is simulated and tested using the MATLAB/Simulink programme.

1. Introduction

In today's world, the need for energy is growing at an alarming rate. An electric vehicle (EV) is considered pollution-free because of this. As the world's population grows, so does the need for more electric vehicles. In the move toward electrifying transportation, electric vehicles have taken on a leading role. When the energy used to refuel a battery powered automobile is generated from technologies such as solar, wind, or hydropower option that is both green and clean alternative to the current transportation system may be feasible. Photovoltaic grid growth could be facilitated by deploying solar systems to power battery charging stations for electric vehicles while simultaneously storing energy in the batteries of electric vehicles. As electric car batteries and solar systems become more prevalent, the strain on power grids will be lessened, and photovoltaic systems' self-consumption will be increased (Tran and Islam 2019). The charger's synchronicity and smooth mode shifting regulation ensure that it runs smoothly. does not interfere with EV charging or residential power when transitioning between modes. This means the charger can support the utility grid and V2H (vehicle to the house) power transfer to sustain local loads in an isolated situation (Singh and Verma 2020). The installation of a photovoltaic electric vehicle charging station was completed successfully. To connect the solar array to the grid array, a power converter is necessary (mainly boost converter). A direct DC connection to the solar PV array is made here. Its key advantages include reduced circuit complexity, lower converter costs, and no impact on PV array performance.

This architecture can be added to the current charging infrastructure as a retrofit option as it only requires a little adjustment to the technology (Verma and Singh 2020; Simon and Sood 2019). A pv system electric charging station and a Storage Battery (BESS) are proposed for the existing scheme (Biya and Sindhu 2019). To cope with actual EV recharging and renewable power needs, the Dynamic Charging Scheduling Scheme (DCSS) uses the Model Predictive Control (MPC) technique (Zhang and Cai 2018). This entails a battery charging system that charges the battery during off-peak hours and distributes electricity to the home load during peak hours. In addition, this article investigates the

integration of home solar panels into the existing grid infrastructure, as well as the use of electric vehicles (Akshya and Ravindran 2017). A converter converts the network to a DC bus, which is linked to electric automobiles through battery chargers. Individual automobile charging methods are decentralised, and a separate control handles power transmission from the AC towards the Grid network interface. Linking a photovoltaic Solar producing plant with a fast charger to counterbalance overall grid rapid progress recharging provides a power management strategies focused on optimal reactive power (Ali ,Mahmoud and Lehtonen 2021). In relation to the P&O algorithm, the suggested While obtaining a higher output The ANN approach tackles the slip flow by accurately tracking the optimal true MPP(Tuyet-Doan and Cho 2020; Abdod and Al-Majidi 2019).

The performance of the incremental conductance(IC) approach in comparison in comparison to the usual utilized perturb and observe (P And O) Optimization technique, with the advantages and disadvantages of the various examined(Elgendy and Zahawi 2013; Mei and Shan 2011). The layout of a quick charging point for electric cars grid-connected is adopted in this paper, which offers quality transmission lines with low harmonic currents. A charging station model has been proposed for faster DC charging(Wajahat khan and Furkan Ahmad 2019). The power point tracking mppt approach for a PMSG wind turbine system is described in this study. This study employs adaptive network-based radial basis function (RBF) artificial neural network (ANN) technology to analyze the generator's ideal rotational properties under fluctuating wind velocity conditions. The modeling results prove that the proposed regulator gathers the maximum possible power from the wind turbine system while maintaining the optimum power coefficient for altering the operational settings at will. (Raman and Rahim 2020).

A wind energy conversion system having variable speed has been created in this research. To order to overcome the various restrictions, we used a novel optimized, and accurate MPPT strategy (wind speed conditions). To enhance the traditional PI-based OTC analysis, based on PI, these studies suggest a novel design (MPPT-OTC) according to artificial neural networks (ANN). The proposed approach (OTC-ANN) was tested on a wind turbine with a permanent magnet synchronous connected to the network (Meghni and Chojaa 2020). To address the problem of losing data and latency between entities in a V to G network, this research recommends a fuzzification and ANN-based intelligent controller composed of DICC, ANN, and FLC. This study uses a two intelligence regulator that includes a data integrity and corrective test blocks during the first stage and a regulating fuzzy system (Fuzzy logic control) with in later to manage demand and reduce the danger of EV refueling upon that network (sah and Bose 2020). The effectiveness of a Power Converter as well as a Buck - boost converter for optimum power monitoring of a solar Pv using Artificial Neural Networks (ANN) is investigated in this work because an ANN-based MPPT model allows exceptionally faster increasing monitoring speed and performance. The recommendations of this study will minimize the time and effort required to design an appropriate Converter operation(Islam and Ahmed 2020).

The postulated (neuro-fuzzy) controller was developed to overcome the limitations of conventional (MPPT) solutions, as an illustration the P&O method. To evaluate suggested (Neuro-Fuzzy controller's) system performance, it is important to compare it to that of the (FLC and traditional P&O) based (MPPT

controllers) under fluctuating sun exposure and the temperature of the environment. With the novel approach, voltage variations and output power enable the (MPPT) to be obtained with negligible oscillations and a quick reaction time(Heelan and Al-Qrimli 2020). The study proposes a novel hybrid algorithm that operates in two modes: continual power (CP) model and peak power monitoring mode, and restricts PV formation in CP mode in conformance with the benchmark rated capacity while seamlessly transferring to MPPT mode to enable maximum power eviction from the Pv array. Controlling PV electricity generated at less than full power reduces overburden and improves grid stability, while simultaneously encouraging more PV system adoption.(Bhatia and Mittal 2020).

2. Design Of Charging Station

A block schematic a charger adapter for electric cars is displayed in Fig. 1. Each electric vehicle might be charged by a 48V DC bus with a 250W power outlet. A single power outlet for charging a single electric car is the subject of this article's proposed work.

2.1 Solar PV with Boost Converter

Open-circuit voltage is 38.46V, short-circuit current is 8.89, and the 255W photovoltaic array is the basis of the MATLAB/Simulink charging station design. The voltage of the solar array is raised using a boost converter to meet the Dc link voltage.

2.2 Battery Energy Storage System With Bi-directional DC-DC Converter

A battery energy storage device may be used to charge electric automobiles at night using extra solar electricity. The battery charging of the energy storage system is controlled by a bidirectional Power converter. The charging station is utilized to supply the DC BUS with the maximum amount of energy since both the charge-discharge effectiveness and the bi-directional converter effectiveness are 90%.

2.3 Grid With Rectifier

The 230V AC grid of the charging station has an additional need for power. Matlab/Simulink uses a transformer to reduce voltage to 48V AC, therefore it's called "grid" in this application. The AC voltage is converted to a continuous 48V DC connection in the bus through a controlled rectifier.

2.4 Artificial Neural network

An ANN Bayesian Regularization technique for the given system was designed using an ANN block. An established three-layer feedforward network with linear output neurons and sigmoid hidden neurons may be used to solve multidimensional mapping cases, according to consistent data. The specified solar panel's irradiance, temperature, and produced voltage are utilised to build a neural network. The data collection includes 70 data sets for training and 15 data sets for validation, and 15 testing data sets. In the feedforward network design, the retired layer has 10 neurons.

3. Control Methodology

MATLAB/Simulink is used to simulate the ANN-based solar PV tracking maximum power point as illustrated in Fig. 2. Heating rate (T) and illumination (I) are the two input variables (Ir). The voltage of MPP is the output variable (Vmpp). A neural network can only be trained if it receives input and output data. A set of neuron weights is then determined at different layered depths. In order to extract data from PV models, MATLAB programming is utilised. In order to train neural networks, it is possible to use Bayesian regularisation techniques. Based on (1) and (2), solar panel electricity production relies on irradiance and temperature, respectively, for ANN data.

Irradiance Ir(W/m²):

$$Ir = [(Ir_{Max} - Ir_{Min}) \times Rand] + Ir_{Min} \quad (1)$$

Temperature T (C):

$$T = [(T_{Max} - T_{Min}) \times Rand] + T_{Min} \quad (2)$$

Maximum Voltage, VMP(V):

$$T = [(T_{Max} - T_{Min}) \times Rand] + T_{Min} \quad (3)$$

Maximum Current, IMP (A):

$$T = [(T_{Max} - T_{Min}) \times Rand] + T_{Min} \quad (4)$$

The Vmpp is the output of the ANN after it has been trained and its neuron weights specified for any T and Ir inputs. The modelled PV's V-I characteristic may now be used to determine the maximum power point current (Impp). Vmpp and Impp are multiplied to get maximum power (*Pmax*). Tracker system for maximum power points with neural network-based maximum power point tracking using DC boost converter and neural networkThe following Eq. (5) yields an integral control unit proportional to the chopper's duty cycle:

$$D = 1 - \sqrt{\frac{Vmpp}{Impp} \times \frac{Iout}{Vout}} \quad (5)$$

4. Results And Discussions

For 05 seconds, the proposed concentrated solar power scenario is conducted. in a computer lab to verify that the sequential transmission of 1000 PV array input data correlates with the simulation duration. For the most accurate results, discrete simulation is preferred over continuous simulation. The Bayesian

Regularization approach used to train the ANN has a significant impact on the accuracy of its predictions. The ANN's predictions are often correct because of the enormous amount of data it has been trained on. A lookup table contains the input data (solar radiation and array temperature) and a clock keeps it in sync with the rest of the system.

The performance and correctness of the Bayesian Regularization technique can be evaluated using parameters such as regression, mean square error, gradient, momentum parameter, and a validation check. An error in prediction is derived by subtracting output from the goal, which is a function of inputs in the regression model. The network is trained, verified, and tested using three kinds of samples. Using the training data, the dataset is then trained, and the network is then tweaked to account for any mistakes. Network generalisation stops during error handling when validation is used for generalisation. While training affects the network's performance, testing gives an accurate measure that has no effect on the dataset's performance (figure. 3).

Probabilistic interpretations of network characteristics underlying the Bayesian Regularization procedure for neural networks. The trained dataset does not have to be verified, as can be seen from the regression diagram in Figure. 4. Using correctly trained data, the regression diagram shows that the solar PV system's output and target voltage have a perfect correlation of just one

The above Fig. 5 shows that the voltage and current increases and decreases depending upon weather condition. If there is no solar radiation, the current and voltage will zero.

The above Fig. 6 shows the battery performance of the system where it displays three parameters voltage, current, and SOC (%).When there is no access to the grid or solar electricity, the electric car is recharged using the energy stored in the battery.

Table 1
Comparative analysis of ANN and P & O MPPT Technique

	P & O BASED MPPT		ANN BASED MPPT	
Irradiation (W/m²)	800	1000	800	1000
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

Conclusion

An artificial neural network (ANN)-based system can quickly and precisely identify the maximum power point (MPPT). PV systems that use maximum power point tracking may benefit from using artificial neural networks (ANNs). This device may be used to determine the peak power of a dc-dc power converter. This technique has the ability to maximize the use of solar energy. For any electric vehicle with

an integrated photovoltaic (PV) generator, Artificial Neural Network (ANN) technology is a dependable MPPT solution for tracking rapid irradiance fluctuations.

Declarations

Conflict of interest

The authors declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Data Availability:

The data used to support the findings of this study are available from the corresponding author upon request

Funding information

There was no financial support received from any organization for carrying out this work

Ethical Approval

This material is the authors' own original work, which has not been previously published elsewhere. The paper is not currently being considered for publication elsewhere. The paper reflects the authors' own research and analysis in a truthful and complete manner.

Consent to Participate

I have been informed of the risks and benefits involved, and all my questions have been answered to my satisfaction. Furthermore, I have been assured that any future questions I may have will also be answered by a member of the research team. I voluntarily agree to take part in this study

Consent to Publish

Individuals may consent to participate in a study, but object to having their data published in a journal article

Competing Interests

To the best of my knowledge and belief any actual, perceived or potential conflicts between my duties as an employee and my private and/or business interests have been fully disclosed in this form in accordance with the requirements of the journal

Author contribution

Prasanna Moorthy Veerappan, Dineshraj Saravanan- Drafting the manuscript

Elangovan Karmegam, Deepika Saravanan- Supervision

Meenakumari Ramachandran, Hitesh Panchal- Assisting in drafting the manuscript

Ravita Lamba, Kokilavani Thangaraj, Suresh Muthusamy- project administration

References

1. Tran, V. T., Islam, M. R., Muttaqi, K. M., & Sutanto, D. (2019). An Efficient Energy Management Approach for a Solar-Powered EV Battery Charging Facility to Support Distribution Grids. *Ieee Transactions On Industry Applications*, 55(6), 6517–6526. doi:10.1109/TIA.2019.2940923
2. Singh, B., Verma, A., Chandra, A., & Al-Haddad, K. (2020). Implementation of Solar PV-Battery and Diesel Generator Based Electric Vehicle Charging Station. *Ieee Transactions On Industry Applications*, 56(4), 4007–4016. doi: 10.1109/TIA.2020.2989680
3. Verma, A., Singh, B., Chandra, A., & Al-Haddad, K. (2020). An Implementation of Solar PV Array Based Multifunctional EV Charger. *Ieee Transactions On Industry Applications*, 56(4), 4166–4178. doi: 10.1109/TIA.2020.2984742
4. Biya, T. S., & Sindhu, M. R. (2019). "Design and Power Management of Solar Powered Electric Vehicle Charging Station with Energy Storage System," Proc. 3rd Int. Conf. Electron. Commun. Aerosp. Technol. ICECA pp. 815–820, 2019, doi: 10.1109/ICECA.2019.8821896
5. Zhang, Y., & Cai, L. (2018). "Dynamic Charging Scheduling for EV Parking Lots with Photovoltaic Power System," IEEE Access, vol.6, no.c, pp. 56995–57005, doi: 10.1109/ACCESS.2018.2873286
6. Akshya, S., Ravindran, A., Srinidhi, A. S., Panda, S., & Kumar, A. G. (2017). "Grid integration for electric vehicle and photovoltaic panel for a smart home," Proc. IEEE Int. Conf. Circuit, Power Comput. Technol. ICCPCT pp. 1–8, 2017, doi: 10.1109/ICCPCT.2017.8074358
7. Do, T. D., Tuyet-Doan, V. N., Cho, Y. S., Sun, J. H., & Kim, Y. H. (2020). Convolutional-Neural-Network-Based Partial Discharge Diagnosis for Power Transformer Using UHF Sensor. *Ieee Access : Practical Innovations, Open Solutions*, 8, 207377–207388. doi: 10.1109/ACCESS.2020.3038386
8. Ali, M. N., Mahmoud, K., Lehtonen, M., & Darwish, M. M. F. (2021). An Efficient Fuzzy-Logic Based Variable-Step Incremental Conductance MPPT Method for Grid-Connected PV Systems. *Ieee Access : Practical Innovations, Open Solutions*, 9, 26420–26430. doi: 10.1109/ACCESS.2021.3058052
9. Khan, W., Ahmad, F., & Alam, M. S. (2019). Fast EV charging station integration with grid ensuring optimal and quality power exchange. *Eng Sci Technol an Int J*, 22(1), 143–152. doi: 10.1016/j.jestch.2018.08.005
10. Selvakumar, S., Madhusmita, M., Koodalsamy, C., Simon, S. P., & Sood, Y. R. (2019). High-Speed Maximum Power Point Tracking Module for PV Systems. *IEEE Trans Ind Electron*, 66(2), 1119–1129. doi: 10.1109/TIE.2018.2833036
11. Mouli, G. R. C., et al. ("Economic and CO2 Emission Benefits of a Solar Powered Electric Vehicle Charging Station for Workplaces in the Netherlands," 2016 IEEE Transp. Electrification Conf. Expo, ITEC 2016). 2016, doi: 10.1109/ITEC.2016.7520273

12. Al-Majidi, S. D., Abbod, M. F., & Al-Raweshidy, H. S. (2019). "Design of an intelligent MPPT based on ANN using a real photovoltaic system data," 54th Int. Univ. Power Eng. Conf. UPEC 2019 - Proc., pp. 1–6, 2019, doi: 10.1109/UPEC.2019.8893638
13. Elgendy, M. A., Zahawi, B., & Atkinson, D. J. (2013). Assessment of the incremental conductance maximum power point tracking algorithm. *Ieee Transactions On Sustainable Energy*, 4(1), 108–117. doi: 10.1109/TSTE.2012.2202698
14. Mei, Q., Shan, M., Liu, L., & Guerrero, J. M. (2011). A novel improved variable step-size incremental-resistance MPPT method for PV systems. *IEEE Trans Ind Electron*, 58(6), 2427–2434. doi: 10.1109/TIE.2010.2064275
15. Rahman, M. M. A., & Rahim, A. H. M. A. (2020). "Design and Testing of an MPPT Algorithm Using an Intelligent RBF Neural Network and Optimum Relation Based Strategy," 2020 IEEE Reg. 10 Symp. TENSYP 2020, no. June, pp. 1245–1248, doi: 10.1109/TENSYP50017.2020.9230807
16. Meghni, B., Chojaa, H., & Boulmaiz, A. (2020). "An optimal torque control based on intelligent tracking range (MPPT-OTC-ANN) for permanent magnet direct drive WECS," 2020 IEEE 2nd Int. Conf. Electron. Control. Optim. Comput. Sci. ICECOCS 2020, doi: 10.1109/ICECOCS50124.2020.9314304
17. Sah, B., Kumar, P., & Bose, S. K. (2020). A Fuzzy Logic and Artificial Neural Network-Based Intelligent Controller for a Vehicle-to-Grid System. *Ieee Systems Journal*, 15(3), 3301–3311. doi: 10.1109/jsyst.2020.3006338
18. Islam, O. K., Ahmed, M. S., Rahman, K., & Tahsin, T. (2020). "A Comprehensive Comparison between Boost and Buck-Boost Converters in Solar MPPT with ANN," ETCCE 2020 - Int. Conf. *Emerg Technol Comput Commun Electron*. doi: 10.1109/ETCCE51779.2020.9350867
19. Heelan, M. Y., & Al-Qrimli, F. A. M. (2020). "Design and Simulation of Neuro-Fuzzy Based MPPT Controller for PV Power System," 2nd Int. Conf. Electr. Commun. Comput. Eng. ICECCE vol. 1, no. June, pp. 12–13, 2020, doi: 10.1109/ICECCE49384.2020.9179287
20. Bhatia, P., Mittal, S., Raizada, S., & Verma, V. (2020). "Hybrid ANN based Incremental Conductance MPPT-Current Control Algorithm for Constant Power Generation of PV fed DC Microgrid," Proc. IEEE 1st Int. Conf. Smart Technol. Power, Energy Control. STPEC 2020, 2020, doi: 10.1109/STPEC49749.2020.9297751

Figures

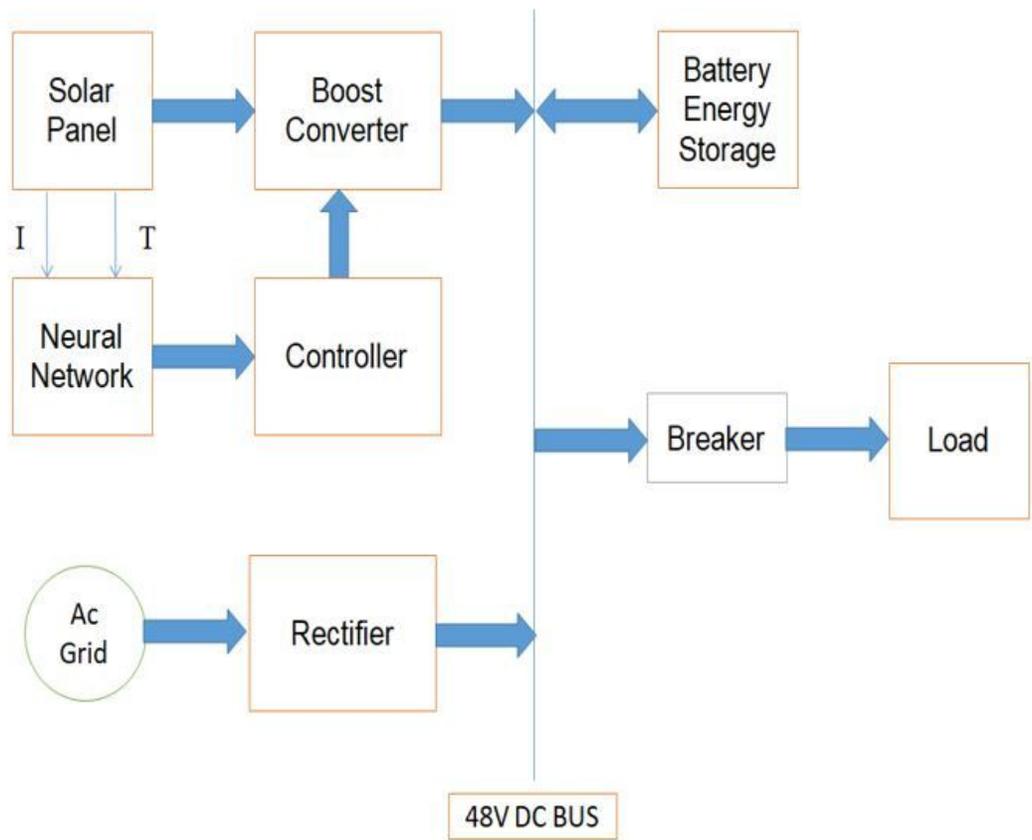


Figure.2.Block diagram of proposed of the system

Figure 1

See image above for figure legend.

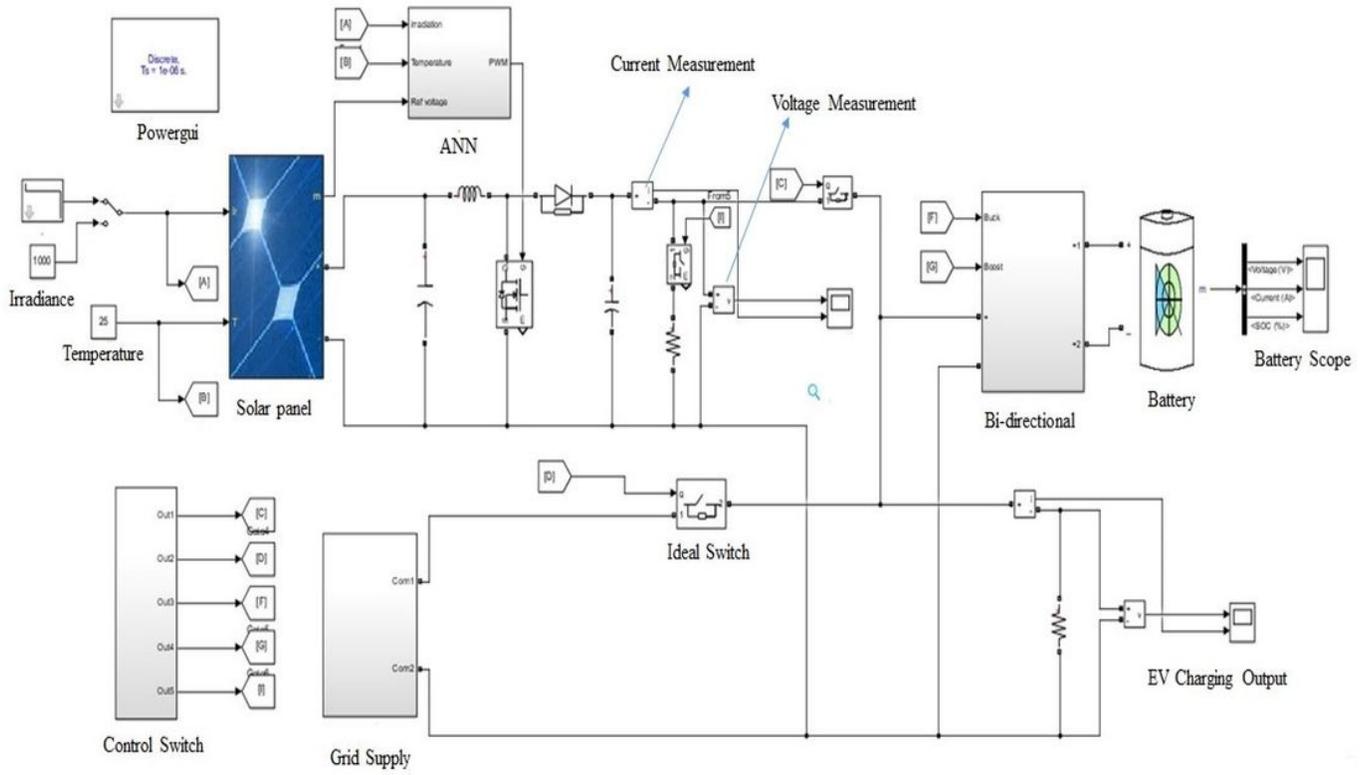


Figure 2

Circuit diagram of the proposed simulation system



Figure 3

Artificial neural network train toolbox

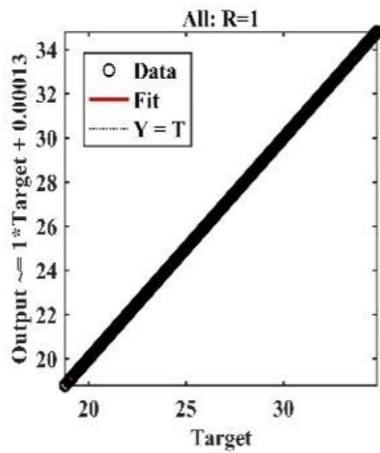
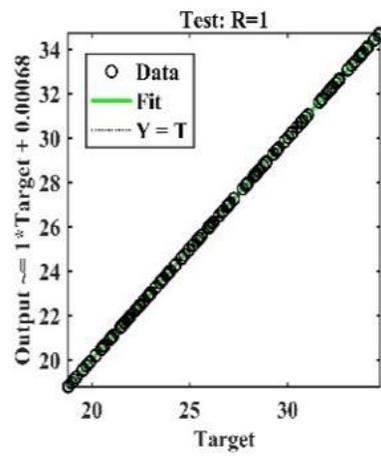
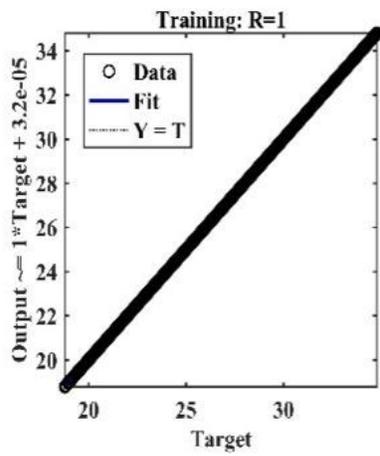


Figure 4

Regression plot of the Bayesian Regularization algorithm

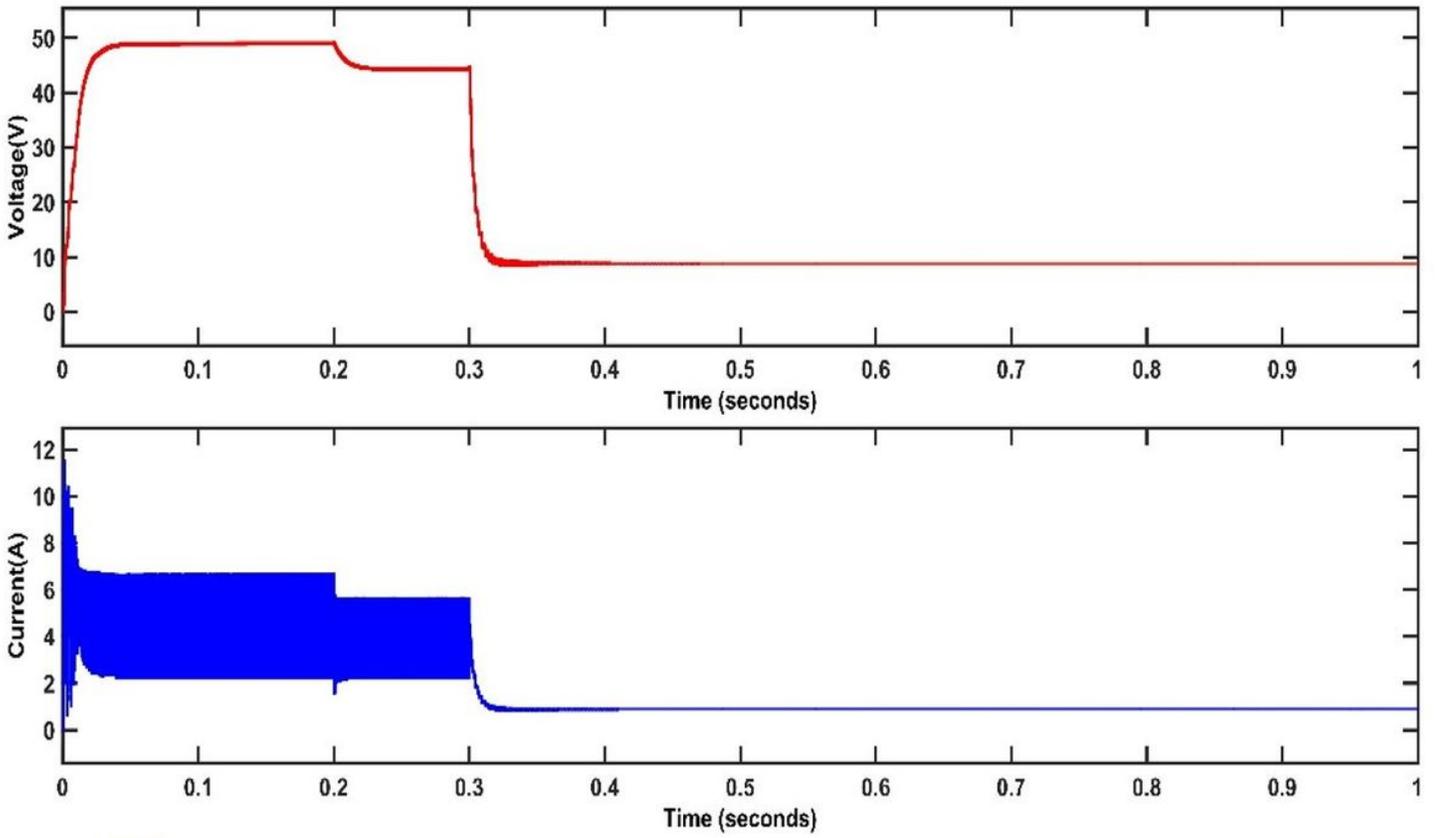


Figure 5

Boost converter output voltage, current at different irradiation levels.

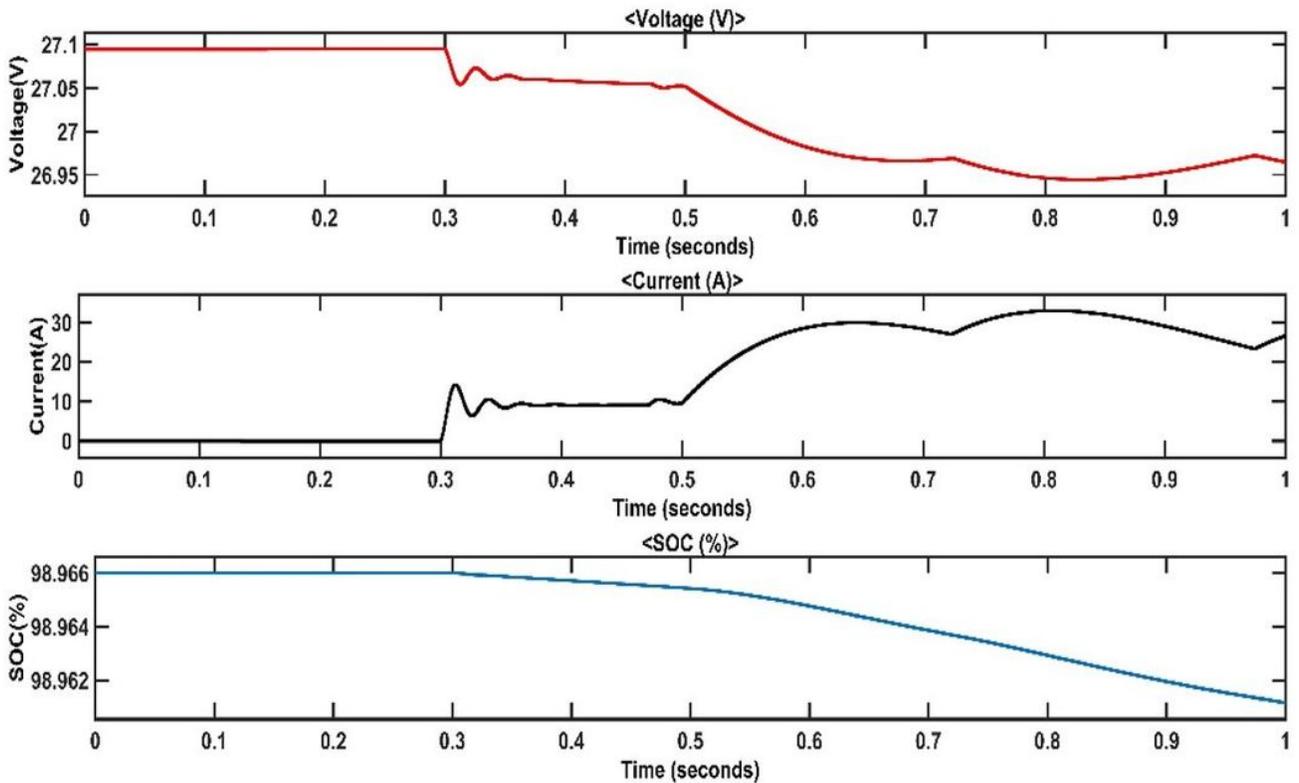


Figure 6

Battery storage system (Voltage, Current, SOC(%))

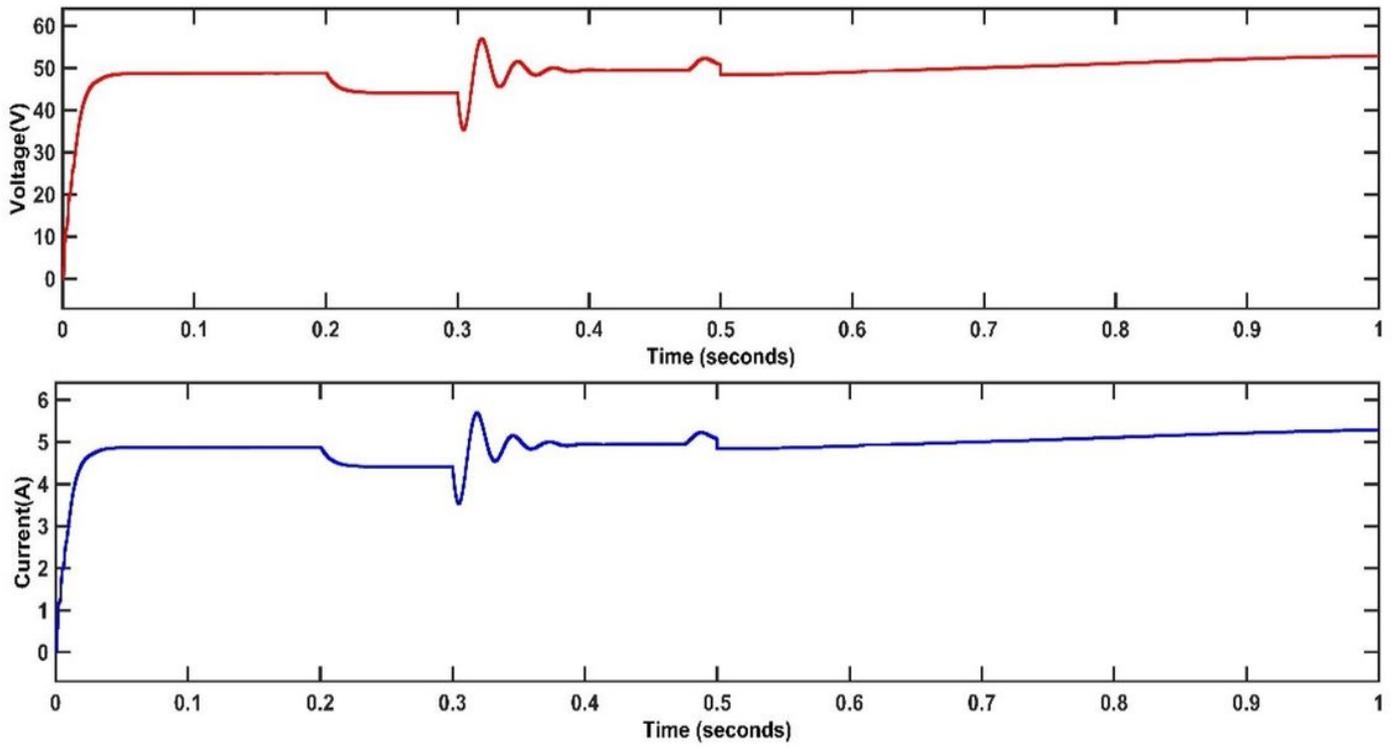


Figure 7

EV charging output(Voltage and Current)