INTL JOURNAL OF ELECTRONICS AND TELECOMMUNICATIONS, 2025, VOL. 71, NO. 3, PP. 1-6
Manuscript received September 23, 2024; revised July 2025. doi: 10.24425/ijet.2025.153630

An evaluation of a medium-power grid-Integrated Solar Photovoltaic System MPPT Energy Capturing Capability Using ANN

Vijaychandra Joddumahanthi, Vedaprakash Kakinada, Vanajakshi Bammidi, and Łukasz Knypiński

***Abstract*—Technologies centered around renewable energy are now feasible options for providing everyone with quick and dependable access to electricity. Solar energy, in which photovoltaic (PV) cells can convert directly into electricity, is one of the most efficient renewable energy sources. The sun irradiation and temperature are the two factors that affect how much power photo voltaic systems can produce. In order to increase power, maximum power point tracking techniques have been developed and applied to PV systems. The proposed model was trained on a total of 1000 datasets containing information on voltage, temperature, and sun irradiation. Training, validation, and testing are the three categories into which the data are divided. The Artificial Neural Network (ANN) model was compared with the classical method like the perturb and observe method (P&O).**

***Keywords*—Artificial Neural Network; Maximum power point tracking; solar PV system; Perturb and Observe method; DC-DC converter**

I. Introduction

SOLAR photovoltaic from renewable energy is the most ecological type of energy to use. It is centered on efficient contemporary technologies, giving promise for a future based on environmentally friendly and pollution-free technology [1]. The significance of leveraging renewable energy systems, especially solar photovoltaic, has grown substantially in recent decades, as global electricity demand has gone up dramatically. Each type of PV module has distinctive characteristics that correspond to the underlying factors like irradiance and temperature, rendering tracking the maximum power point (MPP) a challenging endeavor [2-4]. To tackle such a problem, several maximum power point tracking (MPPT) control approaches have been developed. An MPPT is used to extract the most power feasible from the solar PV module and transfer it to the load. A DC/DC converter (step up/step down) translates the solar PV module's maximum power to the load and establishes a bridge between the load and the module. When the duty cycle adjustments are made, the maximum power can be transferred by adjusting the load impedance as seen by the source equivalent it to its peak power. Different MPPT procedures must be used to keep the PV arrays that operate at their maximum power point. The applications of various renewable energy sources were addressed in Table I.

TABLE I
APPLICATIONS OF THE RENEWABLE ENERGY SOURCES

No	Types of RE sources	Applications
1	Solar energy	Heat, cooling, natural lightening, electricity
2	Wind energy	Wind electricity generation, wind pumps
3	Tidal energy	It is used to produce tidal electricity. Energy storage, alternative to fossil fuels.
4	Bio energy	To produce transportation fuels, heat, electricity
5	Hydropower energy	Flood control, irrigation support, and cleaning deinking.
6	Biomass energy	Heating buildings and water, for providing industrial process heat, and for generating electricity in steam turbines.
7	Geothermal energy	Cooling, Heating, electricity generation.

Another critical aspect of renewable energy networks is the power we use, which is produced by solar photovoltaic cells. PV modules are becoming less expensive as technology advances quickly and solar panels gain greater dependability. Evaluation of solar panel maximum power extraction through experimentation using various converter topologies was discussed [1]. An active filter that operates in a single phase and connects renewable energy sources to the electricity grid was presented [2]. Photovoltaic power stability is dependent on solar radiation levels and a number of environmental conditions. Grid integration's significance for achieving attainable reductions in greenhouse gas emissions from alternative vehicle technologies was discussed in [3]. Power networks are facing significant challenges as a result of complex grid-connected solar PV systems, including issues with energy balance, device flexibility, and efficiency. MATLAB Simulink modelling of a photovoltaic array and neural network-based maximum power point tracking was presented by the authors in [4]. PV networks need to forecast solar output energy in order to provide a consistent power supply. The accuracy of predictive models limits the impact of solar photovoltaic performance, enhances device reliability, and reduces the expenses associated with additional equipment maintenance. Various soft computing and conventional MPPT methods for high step-up boost converter solar PV systems were reviewed by the authors in [5]. Temperature and irradiation are two components of a PV

First Author, Second Author and Third Author are with Department of Electrical & Electronics Engineering, Lendi Institute of Engineering and Technology, Vizianagaram, AP, India, (e-mail: vijaychandrajvc@gmail.com, vedha016@gmail.com, vanajakshi.eee@gmail.com).

Fourth Author is with Faculty of Automatic Control, Robotic and Electrical Engineering, Poznan University of Technology, 60-965 Poznan, Poland (e-mail: lukasz.knypinski@put.poznan.pl)

module's I-V properties. For best utilization performance, MPPT controllers are employed after solar cell arrays. A TE-PV Hybrid Energy Harvesting System with Adaptability was discussed [6]. Several studies in the literature discuss different MPPT designs and algorithms to improve PV device performance. Besides the performance of incremental conductance under non-linear conditions was presented [7]. The various MPPT methods like P&O, INC, FLC, ANN, PSO and other popular techniques were discussed by the authors and the merits and demerits have been presented in [8]. Impact of weather on PV system performance was outlined in [9] by the authors. ANN-assisted sequential Monte–Carlo and quickest change detection technique MPPT was presented in [10]. It is challenging for the controller to initially overcome the MPP because a sudden shift in irradiance distorts the P&O algorithm and the operating parameters of PV systems. A comparative analysis was made on ANN and P&O MPPT techniques. However, the controller fixes the algorithm's mistakes before continuing to follow the MPP after a little pause. Moreover, the MPP experiences variations in terminal voltage during a power outage. Artificial Neural Networks retrieve many inputs, including temperature, irradiance, input voltage, input current, and continually train to enhance the overall performance of the solar power system [11-13].

II. MODELING OF PHOTOVOLTAIC CELL MODULE

In this study, we have used a single diode equivalent model of a PV cell for modeling as shown in the below Fig. 1. It include of a current source, diode, shunt and series resistances and the modeling equations are given in this section.

The equation for photon current (i_{ph}) can be given as,

$$i_{ph} = i_d + i_{sh} + I \tag{1}$$

where i_d is diode current, i_{sh} is current through the shunt resistance and I is the terminal current.

The terminal current can be written as,

$$i = i_{ph} - i_d - \left(\frac{v+i_{Rse}}{R_{sh}}\right) \tag{2}$$

Now, the diode current (i_d) in reference to PV Junction theory can be written as,

$$i_d = i_0\left(e^{\left(\frac{v+i_{Rs}}{nV_t}\right)} - 1\right) \tag{3}$$

where i_0 is the reverse saturation current and it depends upon the material and the temperature and doping of P and N junctions and V_t is Volt equivalent of temperature.

Finally, the entire model of photovoltaic current can now be written as,

$$i = i_{ph} - i_0\left(e^{\left(\frac{v+i_{Rs}}{nV_t}\right)} - 1\right) - \left(\frac{v+i_{Rse}}{R_{sh}}\right) \tag{4}$$

The single-diode model is a mathematical representation of commonly used to analyze the behaviour of the photovoltaic cells or modules. It simplifies the complex physical processes occurring within a solar cell into a circuit with one diode. In this model, the solar cell is represented by a current source in parallel with a diode, a series resistance, and a shunt resistance. The current source models the light-generated current, while the diode represents the non-ideal behaviour of the semiconductor material in the conversion of the light into electricity. The series resistance accounts for the resistive losses within the cell, and the shunt resistance represents the leakage paths. The diode equation governs the current-voltage relationship in the model, expressing the diode current as a function of voltage, temperature, and cell parameters. The series and the shunt resistances introduce additional voltage drops and losses, influencing the overall performance of the PV device [4]. The model is particularly useful for the siFig 9lating and optimizing PV systems under various operating conditions by adjusting various operating conditions parameters like the identity factor, saturation current, and series resistance, etc. Furthermore, the single diode model allows the calculation of the maximum power point, which is crucial for optimizing the energy extraction from a PV system. The MPP corresponds to the operating point where the product of the voltage and current is maximized, representing the highest achievable power output.

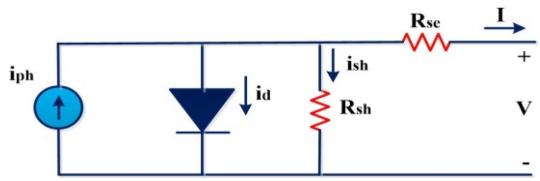

Fig. 1. Single-diode equivalent model of the PV cell

III. PROPOSED DC-DC BOOST CONVERTER STRUCTURE

A DC-DC boost converter which is generally called as boost converter is used to boost the output voltage for a given DC input voltage. A boost converter is widely used in the electronics to step up or increase the voltage of a direct current power source [5]. The structure of proposed DC-DC converter id proposed in Fig. 2.

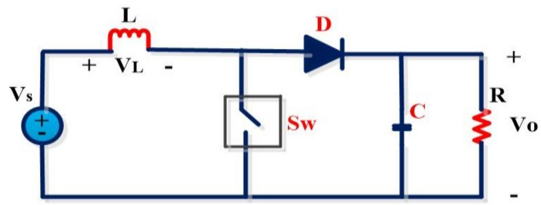

Fig. 2. Proposed DC-DC boost converter structure

Its primary function is to take a lower voltage input and produce a higher voltage output. This makes the boost converters essential in the various applications including the renewable energy systems, battery-powered devices and power supplies. The basic structure of the boost converter consists of an inductor, a diode, a switch, a capacitor and finally a load.

IV. MPPT USING ANNS

ANNs are frequently employed across different power electronics applications, such as MPPT in solar PV systems. For the purpose of maximizing the power production from a photovoltaic system, maximum power point tracking (MPPT) adjusts the operating point to the MPP under various conditions of the environment. An analytical model of a PV system's MPP is challenging due to its nonlinear and time-varying nature. Given their shown efficacy in simulating this nonlinear relationship, ANNs are a widely-selected possibility for MPPT in photovoltaic systems [4]. The adapted ANN scheme is presented in Fig. 3.

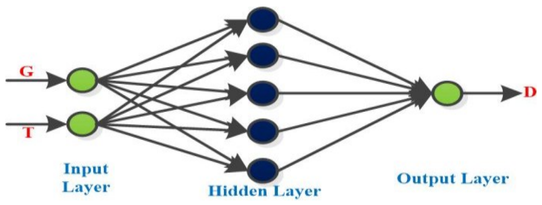

Fig. 3. Design of ANN

The P&O algorithm continuously adjusts the operating point by perturbing the operating voltage and observing the resulting change in the power. If the power increases, the controller continues in that direction, then adjusts the opposite direction but this method has encountered with several drawback like maximum power point tracking failure during variations in the irradiation levels. In this method, the size of the perturbation defines the accuracy which is the extreme limitation of this approach. The incremental conductance method calculates the derivative of the power with the respect to voltage and compares it to the zero [16, 17]. The specifications of 1Soltech 1STH-215-P module used in this study was presented in Table II.

TABLE II
APPLICATIONS OF THE RENEWABLE ENERGY SOURCES

No	PV specifications	Parameter readings
1	Parallel strings	28
2	Series strings	11
3	Open-circuit voltage V_o (V)	36.3
4	Voltage for maximum power point V_{mp} (V)	29
5	Short-circuit current I_{sc} (A)	7.84
6	Current for maximum power point I_{mp} (A)	7.35
7	Maximum power (W)	301.05

The controller adjusts the operating conditions based on whether the derivative is positive or negative, ultimately reaching the maximum power point but possess some demerits like Increased complexity, computational costs etc. To overcome the demerits of both P&O and INC MPPT methods we use advanced controller that is Artificial Neural Network (ANN) controller.

A comparator that is embedded in the ANN MPPT subsystem, as depicted in figure 4, compares the voltage produced by the PV array with the output voltage of the ANN. The comparator will use this generated voltage as a reference. A duty cycle signal is produced by a PID controller in response to the error that is produced. The gate signal generated by the PWM generator activates the IGBT in the switching block, which has a boost converter integrated into it. The comparator's observation of the voltage difference governs the PWM's duty cycle [11]. Smooth IGBT switching operations are accomplished because of the ANN algorithm's perfect correlation between the target and training values, which guarantees a constant duty cycle for PWM. Furthermore, to guarantee that the simulation duration matches the time required for transferring the input data, the solar data subsystem feeds the PV array input data (G and T) in a sequential manner. The solar panel (1Soltech ISTH-215-P)'s rated voltage, rated current, and temperature coefficient served as a baseline for the input and output datasets used in the MPPT technology design process. It is assumed that the sun's standard irradiance (G_s) is 1000 W/m^2 and that the standard temperature (T_s) is 25°C. The maximum and minimum irradiance levels, denoted as $G_{\max}$ and $G_{\min}$, respectively, are 1000 W/m^2 and 0 W/m^2 [12].

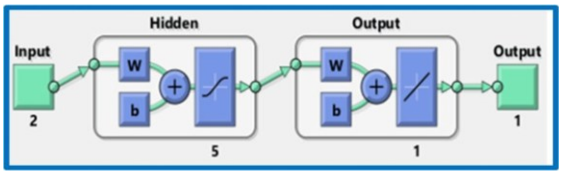

Fig. 4. Block diagram of the ANN MPPT controller

It is discovered that the values of Tmin and Tmax represent the lowest and greatest temperatures, respectively, at 15 and 35 degrees Celsius. Applying MPPT technology, Figure 6 shows the flowchart of the proposed ANN algorithm. Building the ANN method, gathering data, building and training a network, and assessing the network's performance are all accomplished with the help of the MATLAB/Simulink neural network toolbox function.

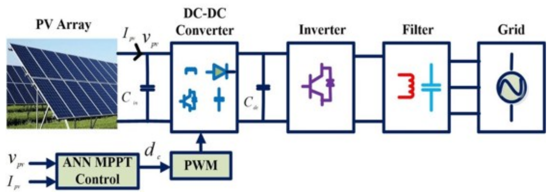

Fig. 5. Block diagram of proposed architecture

The flowchart representing ANN MPPT algorithm is shown in the figure 6. One thousand data sets, including details on the temperature, irradiance, and generated voltage of a selected 1Soltech ISTH-215-P solar panel, are utilized to train the neural network. After that, the data are haphazardly divided into three categories: 10% are used for testing, 80% are used for training, and 10% are for validation. The neural network was designed using MATLAB/Simulink software.

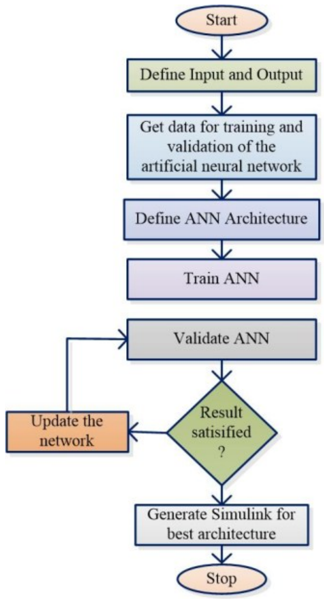

Fig. 6. Flowchart for Artificial Neural Network

V. RESULTS AND DISCUSSIONS

The model that is recommended for solar energy gathering simulates 1000 seconds of data transfer from a PV array in order to evaluate the best analysis. Instead of taking a continuous approach, this simulation takes a discrete one. Both the volume of training data set and the training algorithm chosen affect how accurate an artificial neural network (ANN) is. ANN error is typically lower for bigger training datasets. A lookup table with a clock for synchronization is used to supply the solar panel's input data, which consists of solar irradiance and temperature of the panel. A single cycle is often referred to as an "epoch" when going over the training dataset. It takes several epochs to train a neural network.

Figure 7 presents regression chart for ANN model and Fig, 8 presents error histogram chart.

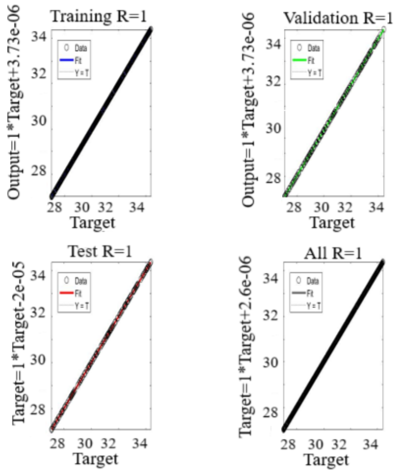

Fig. 7. Regression chart for ANN model

Figure 7's regression (R = 1) reveals how accurately the ANN estimated the output in relation to the input. The bin containing the error value of 0.000278 for one hundred samples extracted from the validation dataset is situated in the middle of the error histogram. When using ANN MPPT, Figure 8 offers the error histogram with 0% error and 20 convergence bins.

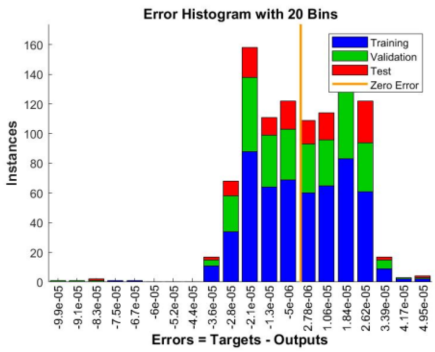

Fig. 8. Error histogram chart

The number of divided training data batches or steps needed to finish an epoch, known as the iteration, is associated to the epoch. Heuristically, the network may view the previous data and adjust the model's parameters. During training, the model is unencumbered toward the last few data points. In order to prevent the local minimum issue, which occasionally causes the ANN to fail to converge, the $M_u(\mu)$ is added to the weight update phrase. Its value, which is between 0 and 1, therefore, has a direct impact on the convergence error during dataset training. In training data, the validation check is represented as error minimization. A neural network (ANN) model for prediction will be examined and validated using one or more predefined error metrics. The ANN algorithm uses a continuous error matrix, such as mean square error (MSE), mean absolute error (MAE), or root mean square error (RMSE), to approximate a function. The results of MES after training, validation and testing are listed in Table III.

The errors are put together for each input and output in the validation set, and the results are then scaled according to the set size. To maximize the prediction model's final efficacy, a squared and then averaged loss function is applied to each data instance throughout the whole dataset. Through the process of error reduction, which is often referred to as "backpropagation," the ANN adjusts the difference between its expected and actual outputs.

TABLE III
VALUES OF MSE AFTER TRAINING, VALIDATION AND TESTING

Results	Samples number	MSE	R
Training	700	9.21e-11	9.89e-1
Validation	150	9.54e-11	9.89e-1
Testing	150	9.67e-11	9.89e-1

The proposed system was simulated using MATLAB/Simulink software. The simulation results shown in Fig. 9 represent the grid voltage, grid current, inverter voltage and currents when the ANN MPPT technique was employed. The grid side voltage and currents are almost sinusoidal in nature where the grid current has little spikes at the beginning and turns into sinusoidal. This is the advantage when ANN MPPT technique is employed.

The same grid current when P&O MPPT control is incorporated in analyzing the system shows more spikes at the beginning and moreover, it turns out to be a huge distortion in the waveform as shown in the Fig. 10. The solar PV system with a multi-stage conversion process has been utilized alongside a three-phase grid. The grid side and inverter side voltages and currents of all three phases are shown in Figures 9 and 10 immediately following MATLAB software simulation of the suggested system.

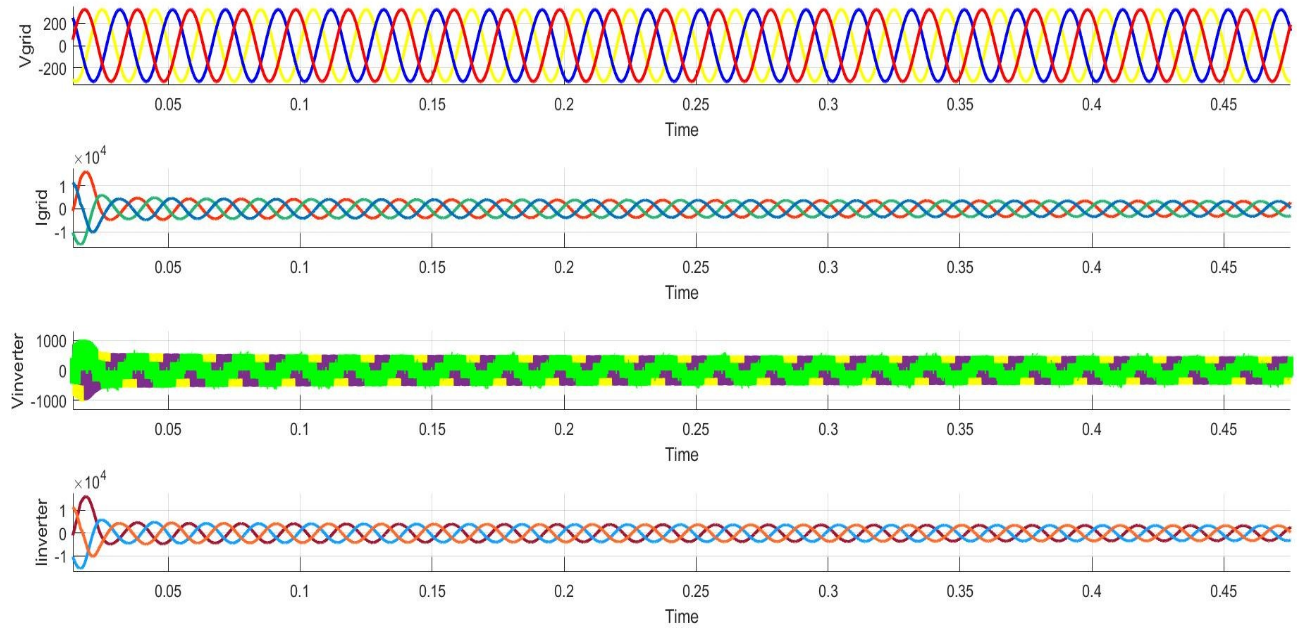

Fig. 9. Grid side voltage, grid side current, inverter voltage and inverter current obtained after incorporating ANN MPPT control.

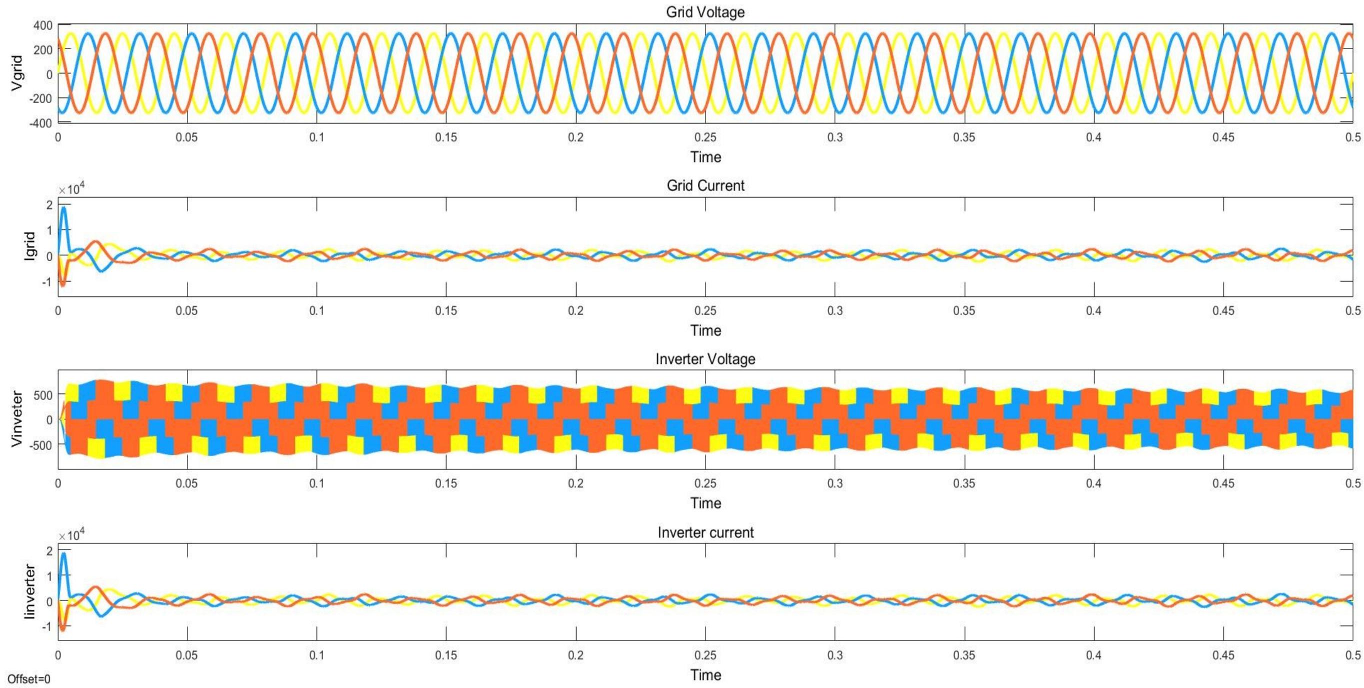

Fig. 10. Grid side voltage, grid side current, inverter voltage and inverter current obtained after incorporating P&O MPPT control.

VI. Conclusion

In this paper, the primary focus is on the analysis of solar PV modules under maximum conditions. To achieve this, we employed Artificial Neural Networks. Initially, we created input values for factors like irradiance and temperature. Since neural networks tend to perform better with more inputs, we generated a higher number of input values. The outcomes of our predictions are detailed in the paper, and we assessed the performance using ANN in MATLAB software. Large-scale issue solving is possible with the suggested ANN-based MPPT energy harvesting idea, which is also extremely adaptable since it can be integrated into multilayer neural networks. The proposed ANN-based MPPT energy harvesting model is applicable in multiple domains and is harmonious with multiple technologies. The model can also be used to forecast solar radiation and temperature, estimate energy, manage energy in smart cities and houses, and estimate solar radiation and temperature. Future potential for solar PV MPPT based on ANN seems vivid providing a number of possibilities for investigation and improvement. Investigating the application of reinforcement learning algorithms to improve MPPT control in solar PV systems is one such path.

REFERENCES

[1] T. V. Dixit, A. Yadav and S. Gupta, "Experimental assessment of maximum power extraction from solar panel with different converter topologies", Int. Trans. Electr. Energy Syst., vol. 29, no. 2, pp. 1–33, 2019, https://doi.org/10.1002/etep.2712

[2] P. Neves, D. Gonçalves, J. G. Pinto, R. Alves and J. L. Afonso, "Single-phase shunt active filter interfacing renewable energy sources with the power grid", IECON Proc. (Industrial Electron. Conf., pp. 3264–3269, 2009, https://doi.org/10.1109/IECON.2009.5415208

[3] B. Tarroja, B. Shaffer and S. Samuelsen, "The importance of grid integration for achievable greenhouse gas emissions reductions from alternative vehicle technologies", Energy, vol. 87, pp. 504–519, 2015, https://doi.org/10.1016/j.energy.2015.05.012

[4] J. Khanam and F. Sy, "Modeling of a Photovoltaic Array in MATLAB Simulink and Maximum Power Point Tracking Using Neural Network", J. Electr. Electron. Syst., vol. 07, no. 03, pp. 1–8, 2018, https://doi.org/10.4172/2332-0796.1000263

[5] C. H. Basha and C. Rani, "Different conventional and soft computing MPPT techniques for solar PV systems with high step-up boost converters: A comprehensive analysis", Energies, vol. 13, no. 2, 2020, https://doi.org/10.3390/en13020371

[6] M. Khatun Mishu, M. Rokonuzzaman, J. Pasupuleti, M. Shakeri, K. Sajedur Rahman, S. Binzaid, S. Kiong Tiong and N. Amin "An Adaptive TE-PV Hybrid Energy Harvesting System for Self-Powered IoT Sensor Applications", Sensors, vol. 21, no. 8, pp. 1–21, 2021, https://doi.org/10.3390/s21082604

[7] P. Sivakumar, A. Abdul Kader, Y. Kaliavaradhan and M. Arutchelvi, "Analysis and enhancement of PV efficiency with incremental conductance MPPT technique under non-linear loading conditions", Renew. Energy, vol. 81, pp. 543–550, 2015, https://doi.org/10.1016/j.renene.2015.03.062

[8] N. Karami, N. Moubayed and R. Outbib, "General review and classification of different MPPT Techniques", Renew. Sustain. Energy Rev., vol. 68, 2015, pp. 1–18, 2017, https://doi.org/10.1016/j.rser.2016.09.132

[9] M. G. De Giorgi, P. M. Congedo and M. Malvoni, "Photovoltaic power forecasting using statistical methods: Impact of weather data", IET Sci. Meas. Technol., vol. 8, no. 3, pp. 90–97, 2014, https://doi.org/10.1049/iet-smt.2013.0135

[10] L. Chen and X. Wang, "Enhanced MPPT method based on ANN-assisted sequential Monte–Carlo and quickest change detection", IET Smart Grid, vol. 2, no. 4, pp. 635–644, 2019, https://doi.org/10.1049/iet-stg.2019.0012

[11] I. Chtouki, P. Wira, and M. Zazi, "Comparison of several neural network perturb and observe MPPT methods for photovoltaic applications", Proc. IEEE Int. Conf. Ind. Technol., vol. 2018-Febru, pp. 909–914, 2018, https://doi.org/10.1109/ICIT.2018.8352299

[12] C. Vimalarani, N. Kamaraj and B. Chitti Babu, "Improved method of maximum power point tracking of photovoltaic (PV) array using hybrid intelligent controller", Optik, vol. 168, no. 2010, pp. 403–415, 2018, https://doi.org/10.1016/j.ijleo.2018.04.114

[13] M. Khatun Mishu, M. Rokonuzzaman, J. Pasupuleti, M. Shakeri, K. Sajedur Rahman, F. Azlee Hamid, S. Kiong Tiong, N. Amin, "Prospective efficient ambient energy harvesting sources for IOT-equipped sensor applications", Electron., vol. 9, no. 9, pp. 1–22, 2020, https://doi.org/10.3390/electronics9091345.