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Intelligent Controller Based on Artificial Neural Network and INC Based MPPT for Grid Integrated Solar PV System

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ABSTRACT

Solar photovoltaic (PV) systems have become an integral part of today's advanced energy infrastructure due to its low kinetic energy, its abundance availability, and its freedom from human interference. Solar PV systems have the potential to greatly reduce our reliance on fossil fuels, but their intermittent nature means they cannot provide a constant source of electricity. The system's security should be well thought out, and it should be able to withstand a lot of abuse. The current energy system faces a significant difficulty in ensuring continuous supply. In this study, a three-phase, two-stage photovoltaic system that is managed by artificial neural networks (ANN). A DC-DC boost converter with maximum power point tracking (MPPT) based on the incremental conductance (INC) method is incorporated in the first stage. In the next step, an ANN-based controller optimizes the performance of a three-phase switching PWM inverter that is connected to the grid by controlling currents along the d-q axis. Comprehensive simulations were carried out using MATLAB or Simulink to evaluate the system's performance under various illumination and temperature conditions. Results show that the suggested approach outperforms the baseline in a number of areas. Better dynamic reactions, accurate tracking of reference currents within permissible bounds, and quick settling periods after startup are all displayed by it. These findings show that our method has the potential to greatly improve the efficiency and dependability of solar PV systems. The results of this study have implications for renewable energy in general and present a viable path toward enhancing the resilience and sustainability of energy infrastructure.

1. Introduction

These days, the high expense of building new or expanded facilities is offset by the integration of renewable energy sources (RES) including photovoltaic solar systems, wind turbines, and others into traditional power systems [1]. DC-AC inverters make up the last piece of the puzzle when it comes to PV system integration. To maintain the reliability of the network and to get a good voltage and frequency dynamic performance, careful planning of the inverter topology and controls is necessary [2]. In prior research [3][4], researchers have explored the use of several controllers for micro-grid inverters in both grid-connected and islanded modes of operation. Linear, non-linear, resilient, adaptive, predictive, and intelligent controllers are all possible varieties of inverter system controllers [5], each of which corresponds to a certain set of behaviors and operational situations in the electrical grid. Classical controllers, Proportional Resonant (PR) controllers, and Linear Quadratic Gaussian (LQG) controllers were all shown to work as linear controllers for micro-grid inverters [6]-[8]. Sliding mode controllers, feedback linearization controllers, and hysteresis controllers are just a few examples of non-linear controllers for grid-connected inverter systems (GCIS) that have been presented in [9]–[13]. Voltage-source inverters are the focus of [6], which proposes a current-control using the H robust control technique.

Also, in [7]-[9], both grid-connected and stand-alone inverters with adaptive control approaches and model predictive controllers are described. All of the cited research found that the proposed non-linear controllers outperformed the linear controllers. PV generators, however, can only generate DC power. As a result, connecting the PV generator and AC loads requires an electrical interface mechanism known as a power inverter. The power inverter supplies connected loads with clean, high-quality power when a standalone PV generator is used. Under the inverter's standalone mode of operation, the output voltage and current waveforms should be managed based on the reference values. This necessitates the use of a voltage source inverter (VSI) and a suitable voltage control method. No matter what kind of load it is connected to, a good power inverter can deliver sinusoidal voltage and frequency with constant amplitude. Additionally, the power inverter must be able to swiftly recover from transients brought on by outside disturbances without compromising power quality. However, the widespread usage of PV generators presents numerous difficulties, including harmonic pollution, poor energy conversion efficiency, output power fluctuations, and the dependability of power electronic converter. Nonlinear control methods have one major drawback: they need a mathematical model and parameters to be available in order to work. This distributed power system can operate independently or in conjunction with the grid, with the system load using a portion of the available power and the remaining power being delivered to the grid only in the event that there is a surplus of available energy. There are several control approaches that have been discussed in the literature to improve the steady power flow and power quality at the grid side. Grid-connected operation is strongly advised over stand-alone operation in order to meet the local load feeding standards and maintain a constant power supply. Also, it is essential that the grid's voltage and frequency be synced. The type of converters utilized between the source and grid will determine how the microgrid is configured. In order to connect the grid with the energy sources, converters like DC/DC and AC/DC are used in addition to inverters because the outputs of PV and wind are different. Each system will require a different sort of converter, which will depend on a variety of technical specifications, configurations, and power ratings.

The use of intelligent control systems, such as neural network controllers, repetitive controllers, fuzzy logic controllers (FLCs), and autonomous controllers are presented as means of handling nonlinear systems dynamics. Intelligent controllers are useful because they can deal with a wide variety of non-linear and unpredictable systems without needing a mathematical description of the system. To enhance the output current and get around the issue of employing a linear proportional integral (PI) controller when non-linearity exists in the system, a discrete repeatable controller (RC) was presented in [10]. A complementary control loop built on radial basis function neural networks (RBFNNs) was developed by the authors of [11]. One or more loads can have many renewable energy sources integrated into them via a non-isolated direct link connection or the idea of time-sharing of devices. Along with the traditional droop control method, this was done. RBFNNs were incorporated into droop control, which improved micro grid (MG) stability and increased the power-sharing ratio by making power calculations more accurate and quick.

The drawbacks of traditional vector control techniques were addressed in [12] by the development of an ANN-based vector control methodology. In the direct connection approach, numerous sources are joined to a common bus by converter cells. A two-input buck-boost type converter with the resulting dynamic operational characteristics and steady-state responses were shown using device time-sharing. The multi-input controller concept was further validated by the experimental converter setup and operation.

The AC-MG system has a new energy management method that was created in [13]. A battery and a grid backup system operate together to maintain the stability of a system where solar panels are the main power source. Additionally, simulations for the bidirectional converters in an AC-MG in a challenging environment were run. The limitation is that power cannot be delivered from two input sources to a load at the same time.

This AC-MG was used to power a DG in the study [14] using nonlinear autoregressive network with exogenous inputs (NARX). The proposed controller is based on an upgraded artificial neural network. This study evaluated the dynamic behavior under various source and load conditions and employed a non-isolated multiport topology with parallel-connected inputs to monitor the maximum power point of the PV sources for a stand-alone load.

An ANN-based energy management system (ANN-EMS) was suggested in [15] for the aim of managing the flow of power. The ANN-EMS that has been shown selects an effective mode of operation by gathering information on things like the quantity of power being used, the amount of load that is being demanded, and the state of charge. The quantity of energy that an ESS charges and releases in various power distribution network scenarios should be profiled in order to train the ANN.

The relationship between power quality and its non-linear characteristic was found by the authors of [16]. The research to date indicates that while assessing and regulating the power quality of AC-MG systems that are powered by PV, the aforementioned factors are not taken into account all at once. To reduce the impact of these variables, a novel ANN based control approach that can regulate the power quality in compliance with IEEE and IEC standards has been proposed.

A Particle Swarm Optimization (PSO) based ANN strategy was recommended by the authors of [17]. A multi-input and multi-output boost controller structure that can connect 'n' sources with 'm' loads was introduced in this study. But the inclusion of too many diodes and passive components makes the circuit less trustworthy. These converters' limited voltage increase is a result of their reliance solely on the duty cycle and not also on the inverter's turn ratio.

The authors of [18] proposed an EMS-based artificial neural network for hybrid AC MG with DG, ESS, and variable loads. An ANN is utilized to determine the appropriate operating mode for the MG and the power reference for the ESS using the power data from unanticipated DGs and loads. The controller has the ability to draw continuous current from inputs and also supports operating multiple sources concurrently. Additionally, the genetic algorithm (GA), Particle Swarm Optimization (PSO) [19], and Artificial Bee Colony (ABC) based regulating techniques are commonly used in EC-DER and systems.

The article presents an intelligent controller for grid integration solar PV systems. The research includes comprehensive solar PV modeling and aims to enhance energy harvesting and grid stability. The contribution also holds practical significance for improving the performance of real world solar PV installations. The development and evaluation of intelligent control systems, such as ANN controllers, to maximize the performance of grid-connected solar PV systems is main focus of this paper. The motive is to solve problems with quick transients, power quality, and nonlinear features that affect grid-integrated solar PV systems' performance. In this way, this research supports the development of dependable and sustainable energy infrastructure, which is in line with the changing requirements of the renewable energy industry. This paper's remaining sections provide a thorough analysis of intelligent controller for grid-integrated solar PV systems, covering modeling, simulation, and real-world installation implications.

2. Proposed PV Power System & Solar PV Modeling

Modern AC-MG control systems update the ANN parameters using the hidden weight optimization (HWO) rather than the conventional gradient technique. Using MATLAB platform the dynamic characteristics and closed-loop behavior of the system with the aforementioned controller for resistive load while subject to disturbances to both the supply and the load can be obtained. The control challenges in such a scenario revolve around maintaining a constant load voltage in spite of fluctuations in both the power source and the load. Reference currents, one from the maximum power point tracking algorithm for the d-axis current and the other set to zero for the q-axis current, are fed from the three-phase inverter currents. The ANN controller functions like the human brain; it has a number of synthetic neurons that function like those in the human brain. Power electronics equipment has advanced in recent years and now supports a wide variety of voltage, current, and switching frequencies. The most electricity is used by fans, pumps, fans, electric drives, battery chargers, uninterruptible power supply, and other equipment. The distribution network experiences a significant demand for reactive power as a result of some of the loads taking current with lagging power factor. Also, the situation gets worse when there are uneven loads. The majority of these power devices may experience problems like harmonics generation and reactive power due to the non-linear nature of such loads. Harmonic current and reactive current both increase power losses and lower power factor when present. Moreover, the active power flow capacities of the distribution system will be diminished. The reference tracking error data is delivered as input to the ANN through a suitable scaling factor in order for it to generate the control pulses for the inverter. Both offline and online methods of managing the inverter are effective at keeping the operating frequency constant. The ANN controller's functional mapping estimation offers a high level of fault tolerance. The inverter model is not essential for the construction of ANN controllers, but comprehensive understanding of the inverter's functional behavior is necessary. The mathematical structure of the ANN intelligent controllers, which consists of connected artificial neurons that imitate neurons on a much smaller scale, is what gives them their fundamental advantages. Such intelligent controller designs don't require a precise mathematical representation of the system. Additionally, adding more semiconductor switches increases the cost of the entire system. The designer must learn about the system in order to construct an intelligent control system. The management of the PV grid-connected system involves regulating the number of hidden layers. ANN was initially designed as an effort to simulate how the brain works and operates. The controller's goal was to build an artificial model using hidden layers, input, and output. This motivates a lot of academics to create ANN-based PV system controllers. Automation is accomplished by intelligent control, which imitates intelligence. One advanced control is ANN. The three phase PV-grid connected system is managed by it. NNs have been employed successfully in a variety of domains, including associative memories, pattern recognition, and optimization. Fig. 1 shows the block diagram of proposed photovoltaic power system.

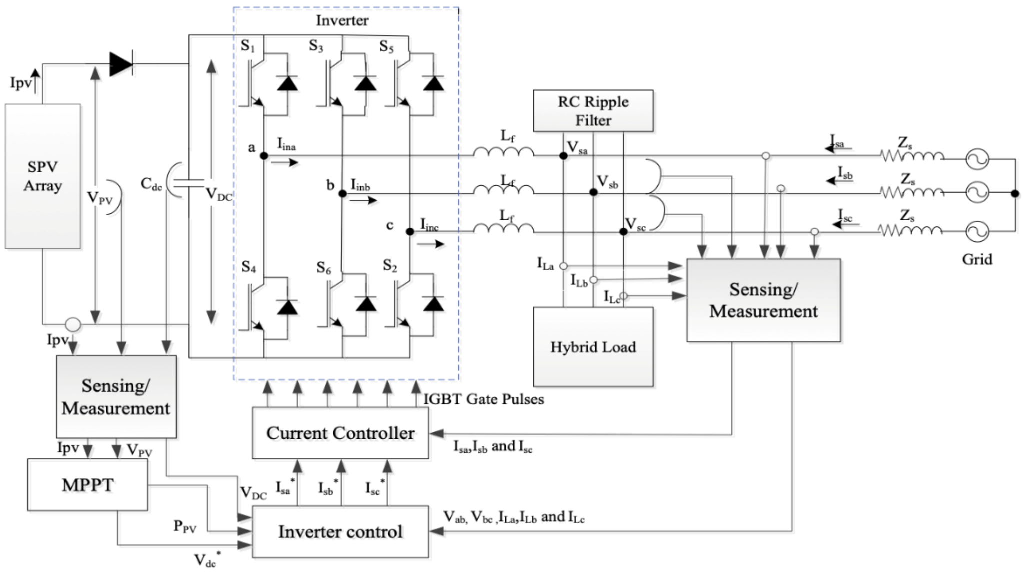

Fig. 1. Architecture of proposed PV power system

To comprehend solar cell performance, current-voltage relationships are necessary. As a result, a MATLAB script file was used to implement the solar cell's single diode model. A PV cell is represented by a PN diode that is linked in parallel with the current source. The simulation findings show that the current increases with increasing irradiation but drops with increasing temperature. Fig. 2 depicts solar cell equivalent circuit. Solar PV Module modeling in MATLAB/Simulink is shown in Fig. 3.

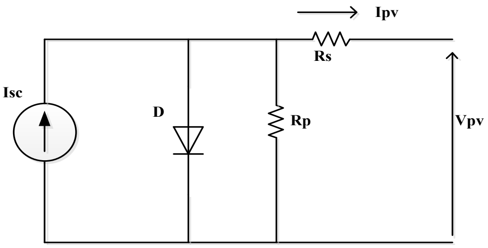

Fig. 2. Solar cell equivalent circuit

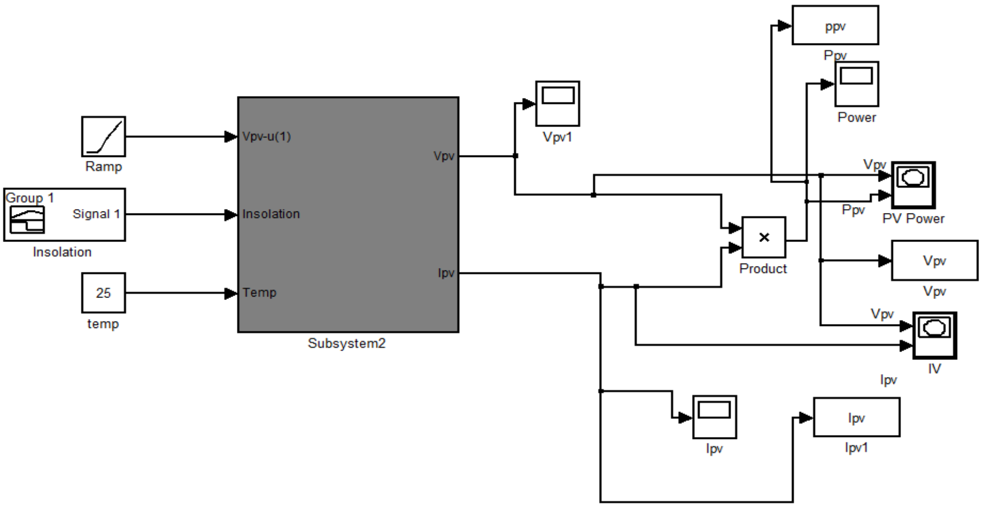

Fig. 3. Solar PV Module modeling in MATLAB or Simulink

The following equation gives the fundamental equation that characterizes the current output of the photovoltaic module of the single-diode model:

$$I_{PV} = I_{sc}N_p - N_s I_o \left[exp\left\{ \frac{q(V_{PV} + I_{PV}Rs)}{N_s AkT} \right\} - 1 \right] V_{PV} + \frac{I_{PV}Rs}{Rp} \tag{1}$$

Fig. 4 depicts current-voltage curve for solar panel at 0.4, 0.6, 0.8, and 1 kW/m^2. Current-voltage curves for solar panel at different temperature are shown in Fig. 5.

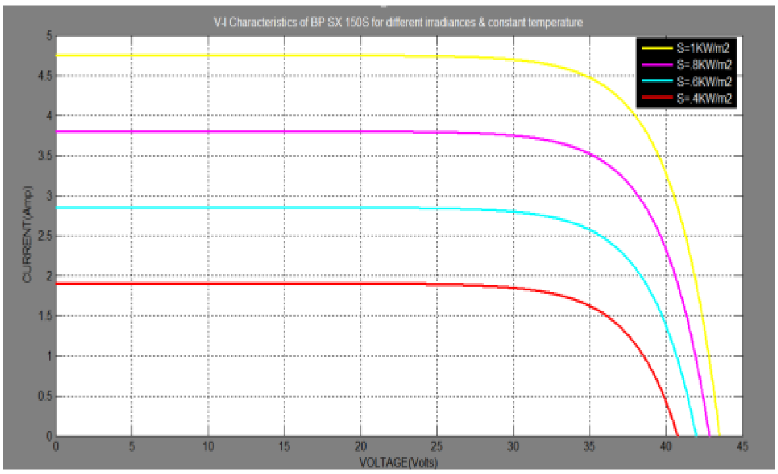

Fig. 4. Current-voltage curve for solar panel at 0.4, 0.6, 0.8, and 1 kW/m^2

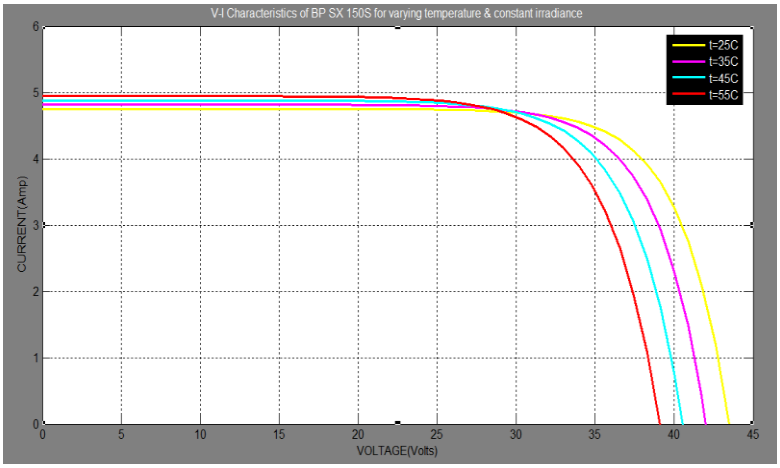

Fig. 5. Current-voltage curves for solar panel at 25°, 35°, 45° and 55°C

3. INC Based MPPT Algorithm with DC to DC Boost Converter

The incremental conductance method is based on the observation that the highest power point of the PV module curve has a slope of zero. For values of output power less than maximum power point (MPP) and for output power greater than MPP, this slope will be positive. The derivative of PV output power with respect to voltage can be used to calculate the maximum output power and is equal to zero. The maximum power point is tracked by comparing the instantaneous conductance to the incremental conductance. Once reaching the MPP, the PV module's operation is compelled to stay there unless a change in current happens as a result of changing meteorological factors that affect MPP. Following equation is therefore derived:

$$\frac{\mathrm{dP}}{\mathrm{dV}} = \mathrm{I} + \mathrm{v}\frac{\mathrm{dI}}{\mathrm{dV}} = 0 \tag{2}$$

Equation (2) can be used to get the following equations:

$$\frac{dI}{dV} \cong \frac{\Delta I}{\Delta V} = -\frac{I_{MPP}}{V_{MPP}} \tag{3}$$

$$\frac{dP}{dV} = 0 \quad \frac{\Delta I}{\Delta V} = -\frac{I}{V} \quad at\ MPP$$

$$\frac{dP}{dV} > 0 \quad \frac{\Delta I}{\Delta V} > -\frac{I}{V} \quad left\ side\ of\ MPP$$

$$\frac{dP}{dV} < 0 \quad \frac{\Delta I}{\Delta V} < -\frac{I}{V} \quad right\ side\ of\ MPP$$

Fig. 6 depicts the flowchart for the incremental conductance technique, a method used in photovoltaic systems for maximum power point tracking. It outlines the sequential steps involved, starting with initialization and proceeding to measurement, calculation of incremental conductance, checking for the maximum power point, and adjusting the operating voltage accordingly. Fig. 7 illustrates the first stage modeling using MATLAB or Simulink 2011b, enabling researchers to simulate and analyze the behavior of a photovoltaic system by representing its components and interconnections. This modeling approach facilitates performance evaluation, parameter optimization, and control strategy development for efficient photovoltaic systems.

Fig. 8 provides a visual representation of a system's performance under more practical circumstances, considering factors like environmental conditions, solar irradiance variations, temperature fluctuations, and load changes. It serves as a valuable tool for evaluating the system's robustness, identifying challenges, and optimizing parameters to ensure reliable power output, efficient operation, and effective maximum power point tracking in real-world scenarios.

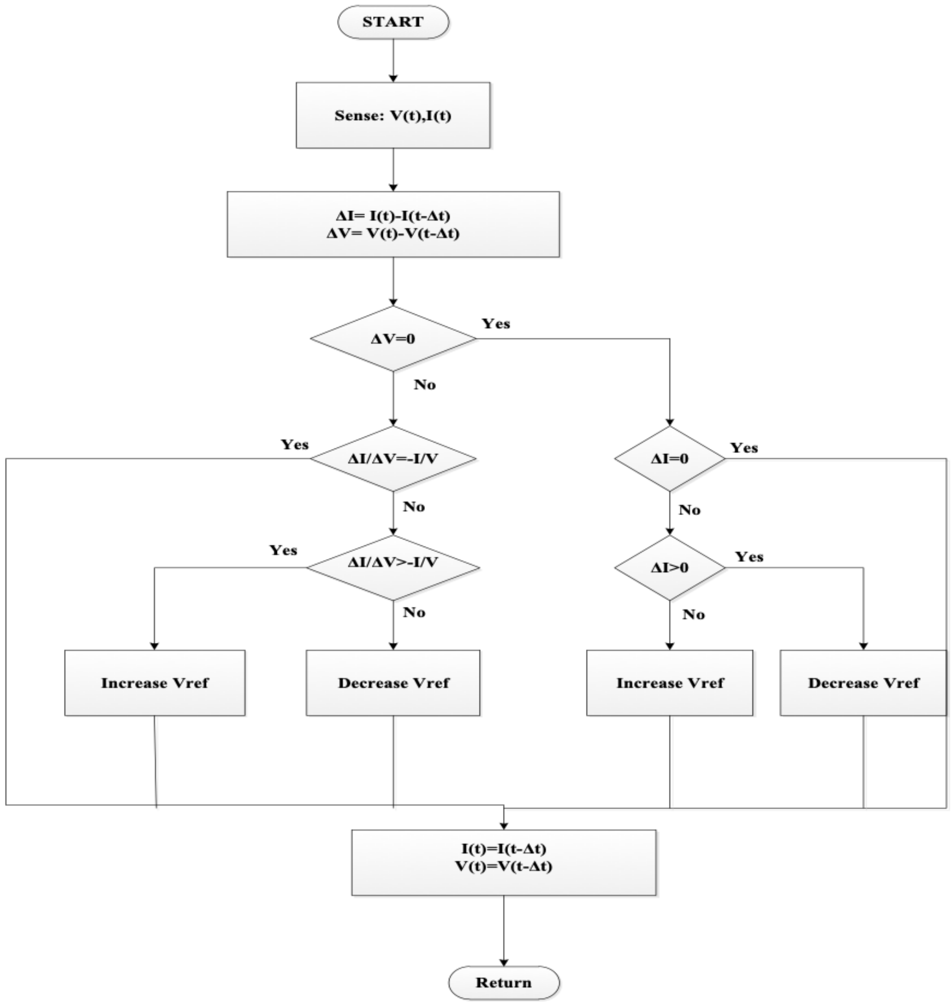

Fig. 6. Flowchart of the MPPT algorithm

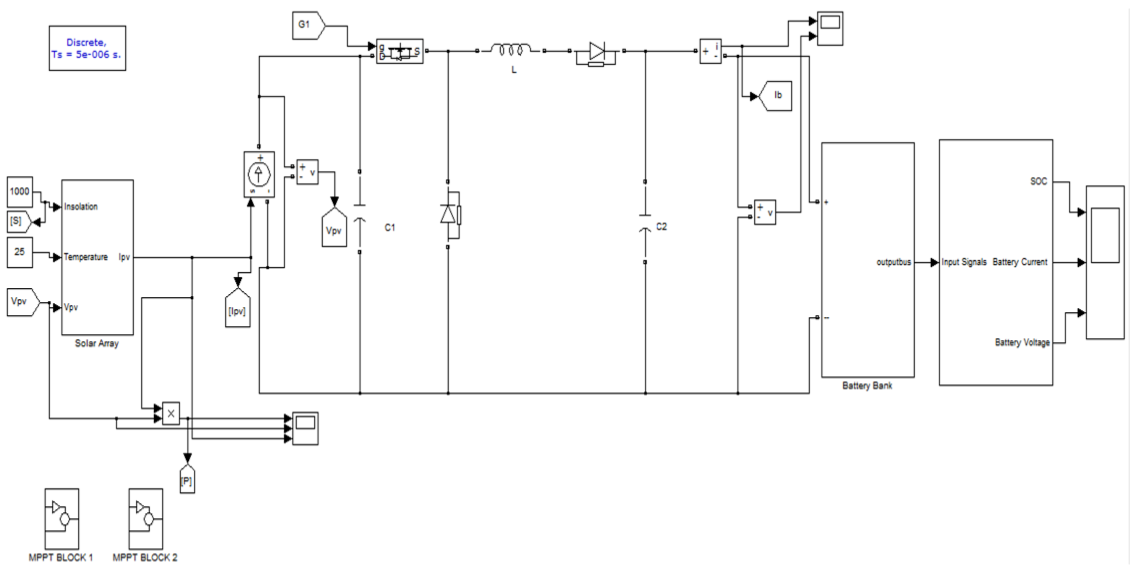

Fig. 7. First stage modeling using MATLAB or Simulink

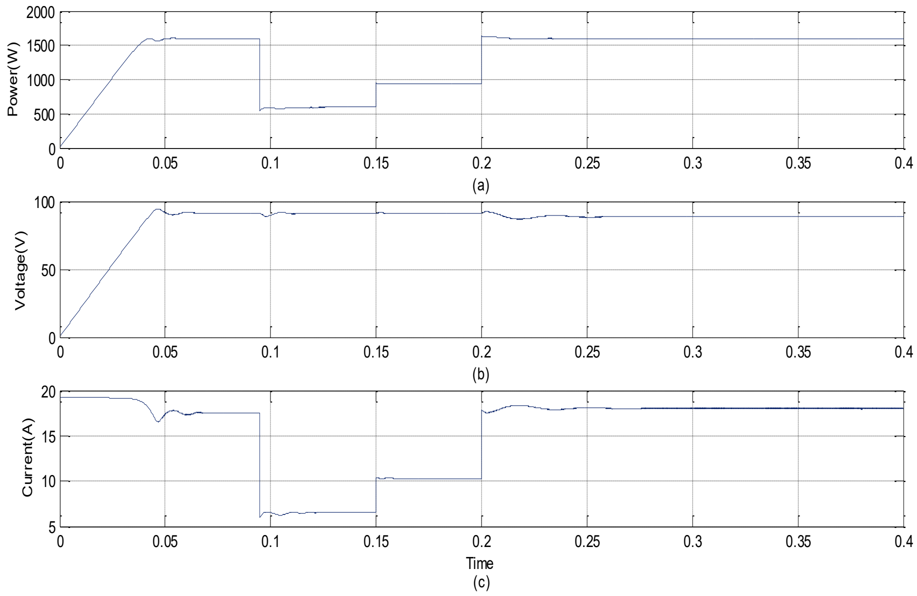

Fig. 8. Performance under more practical circumstances

4. Inverter Current Controller

In control systems utilized in the real world, artificial neural networks play a crucial role in augmenting existing operations and attaining the operations that are planned. The most advanced AI, ANN, has the capacity to optimize any system by offering the best end-to-end training, for instance from input to output. ANN was developed with a large number of hidden layers so that it could deliver dependable results; these layers are coupled to one another via the usage of weight maps. The equation (4).

$$F(\vec{x}) = h\left(w_0 + \sum_{i=1}^{M} w_i . x_i\right) \; Illustrates\ the\ ANN\ process \tag{4}$$

The symbol h in this instance represents the nonlinear activation function (x). The activations are often carried out using the logistic sigmoid or the hyperbolic tangent. The entered data is represented by the variable x, which has a range from x_1 to $x_{M,}$ where M is the total number of samples. Further, each element x_i with weights given by w_i. Depending on the situation, the weight w_0 may represent either the bias or the corrective factor.

In this a feed-forward ANN model of the "shallow" sort is used. In order to function properly, it follows the theory of layered perception. Therefore, a lesser total number of hidden layers is adequate to conduct the controlling strategy while consuming a less quantity of memory. Following the determination of the total number of variables, the input and output layers are furnished with the appropriate settings to carry out the application-specific function. Therefore, by employing the ANN training technique in the appropriate order, the optimum weight coefficients (w_i and w_0) may be ascertained.

In order to accomplish an accurate selection of the most effective controlling features, the smart grid-based tuning technique was devised and deployed. Twenty units are used in each hidden layer throughout this technique. After that, Scaled Conjugate Gradient (SCG), which has high level convergence properties, was used to conduct the training. This was carried out in order to enhance conjugate gradient optimization.

Traditional PI controllers are unable to produce results that are sufficient. Hence, there are two layers in the ANN, each with a unique set of neuron interactions. A "1" neuron at the input layer receives the inputs; the middle layer, which is made up of ten neurons, receives the input after processing.

One neuron is used in the output layer, and its output is taken into account while calculating reference current. Each layer is given a unique set of activation transfer functions to train. The activating function used by the input layer is the hyperbolic tangent sigmoidal transfer function, whereas the activating function used by the output layer is the identity transfer function.

4.1. Training Procedure

The Neural Network (NN) Fitting tool is employed, when it comes to training the network. As a result, the projected harmonic and reactive power levels were calculated. In order to achieve the greatest outcomes, artificial neural network training must be done with caution. The training data samples, which made up 60% of the whole data (the output of the DFT), the validation data samples, which made up 20% of the total data, and the testing data samples, which made up 20% of the total data, were all taken into account by the NN tool.

A single hidden layer in the ANN training process has 20 weights. The controller is given these weights, which range from (1,0) to (1,20), with the aim of producing a better output function and enhancing the functionality of grid-connected system.

4.2. ANN Operation and Control

Discrete Fourier Transform outputs are taken into account for several input processing parameters in order to train and test artificial neural networks. The EC-DERs system generates these parameters, which comprise the reference voltage ($v \times c\ (k)$), filter current ($i_{sabc}(k)$), output current ($i_{dc}(k)$), and output voltage ($v_{sabc}(k)$).

Based on design requirement, there must be an output link. Furthermore, the input link, output link, as well as ground link, must be assigned on different link, the output link must not be adjacent to the ground link with a revolute joint, the input link and the output link must be in different loops. In addition, according to design constraint, all the other links, except the input and the output links, must be a link with three joints or more. The value of k in this case reflects the sample time for both training and testing with gain. The optimal voltage vector $xopt$, which is produced by the ANN, serves as a representation of the outcome. The IGBT inverter bridge receives these ideal output voltages as input, which finally causes the output to be divided into the three switching states of Sa, Sb, and Sc. The three-phase IGBT inverter bridge's ANN-based controller is depicted for the three phases of the bridge in Fig. 9. As a result, it produces a high-quality sinusoidal voltage after passing through the LC filter and reduces overall harmonic distortion for a variety of load configurations. The controlling strategy that the ANN controller employs at each and every sampling time k is described as follows: For each time k spent sampling, calculate the voltages and currents $i_f(k)$, $vc(k)$, and $i_o(k)$. In this instance, i_o stands for the measured value inverter output current.

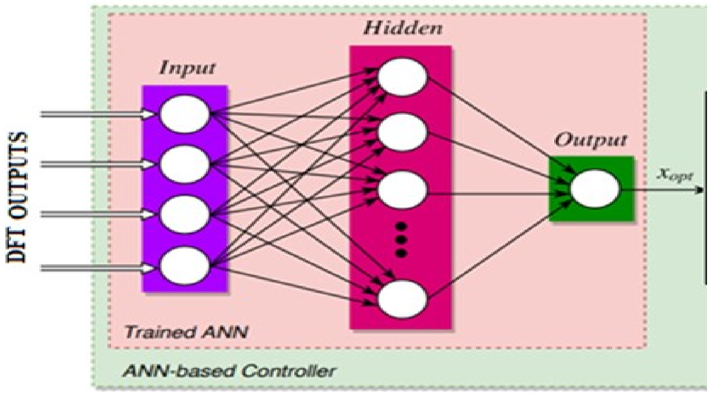

Fig. 9. ANN-based controller

Fig. 10 showcases the Simulink model of an implemented prototype, providing a detailed representation of the system's configuration and interconnections. This model offers a comprehensive view of the prototype's components, including sensors, actuators, controllers, and any other relevant subsystems. By utilizing Simulink, engineers can simulate the behavior and performance of the implemented prototype, allowing for in-depth analysis, performance evaluation, and validation of the system's functionality. The Simulink model of the implemented prototype serves as a powerful tool for refining design choices, optimizing control algorithms, and assessing the overall system performance before actual deployment. The ANN layer and the weights and bias are depicted in Fig. 11 and Fig. 12 respectively.

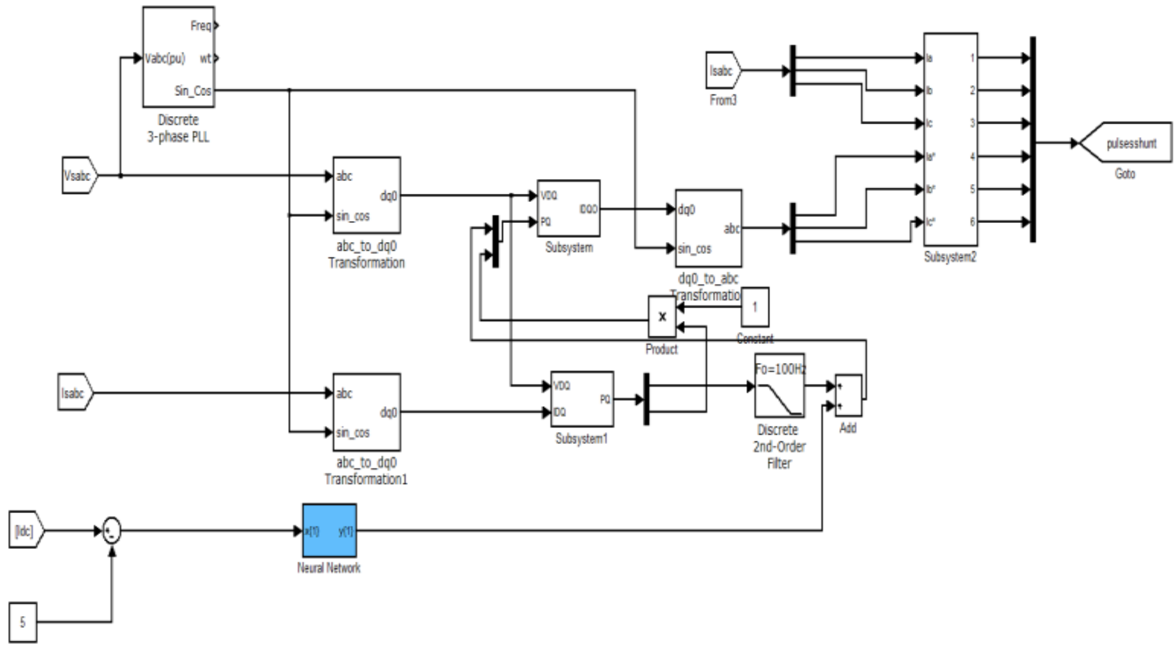

Fig. 10. Simulink model of implemented prototype

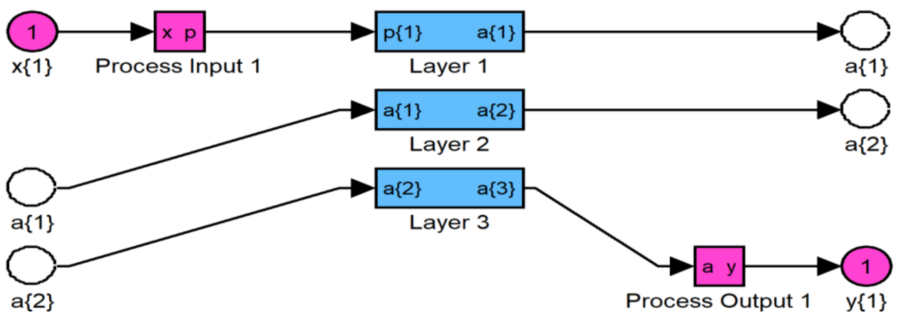

Fig. 11. ANN layers

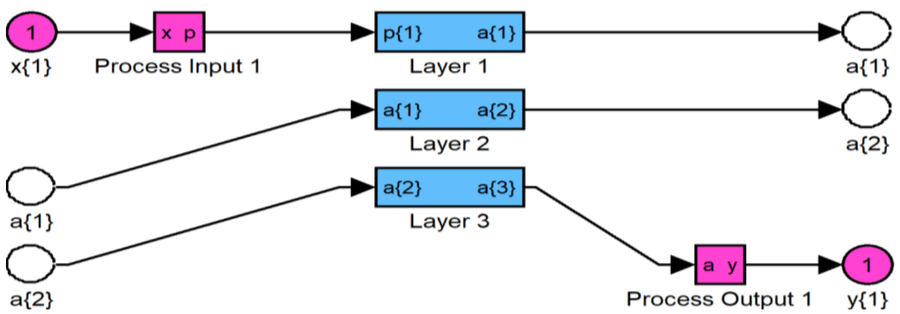

Fig. 12. Depicting weights and bias

5. Simulation Results

The proposed control helps to maintain sinusoidal grid currents when phase "c" of the load is removed at 1.1 s as can be seen in Fig. 13. The behavior of the designed system under nonlinear loads that are dynamic in character is shown in Fig. 14.

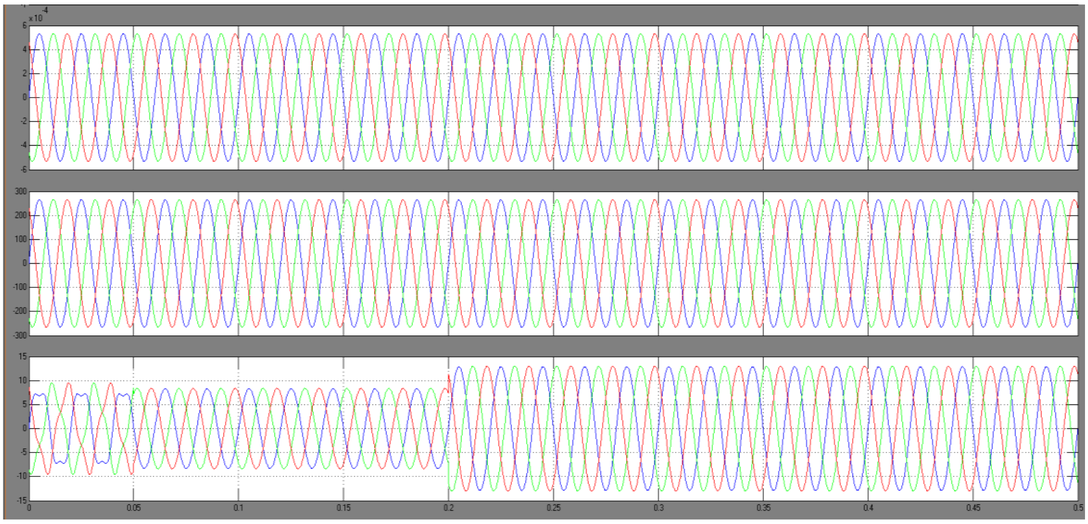

Fig. 13. Improved Current waveforms using proposed controller

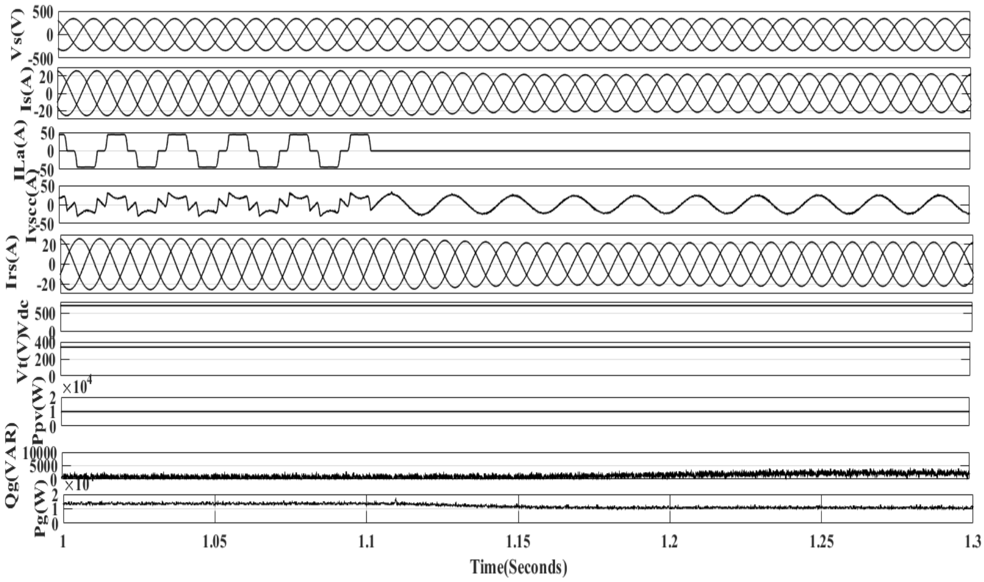

Fig. 14. Performance for non-linear type of load

Under conditions of varying solar irradiation, the system exhibits dynamic behavior as well. At 0.5 seconds, the solar irradiation increases from 600 W/m^2 to 1000 W/m^2. The SPV system is supplying the electric grid with extra generation while also feeding the load. In order to examine how variations in weather affect the system's output performance, a simulation is run under various combinations of solar irradiance and temperature as exposed. As the SPV power (P_{pv}) increases in Fig. 15, the grid power (P_g) declines after 0.5 seconds. The proposed system will continue to function at the SPV array's maximum power point and maintain a unity power factor under fluctuating solar irradiation. The voltage at the DC link is also kept at the fixed point, and the grid side current is maintained to be sinusoidal. The performance of the ANN controller, for total harmonic distortion (THD) value is 1.07%, is shown in Fig. 16.

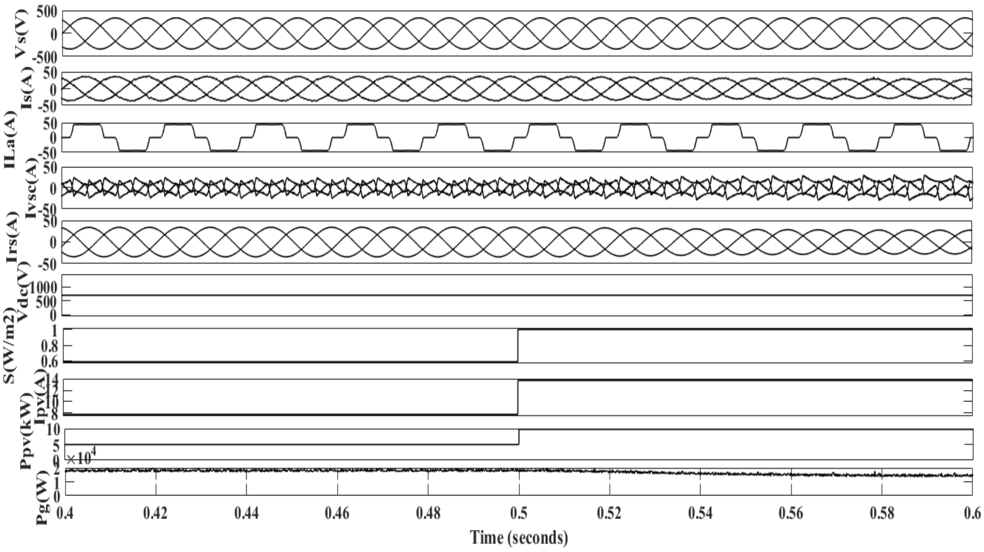

Fig. 15. Performance under changing solar irradiance

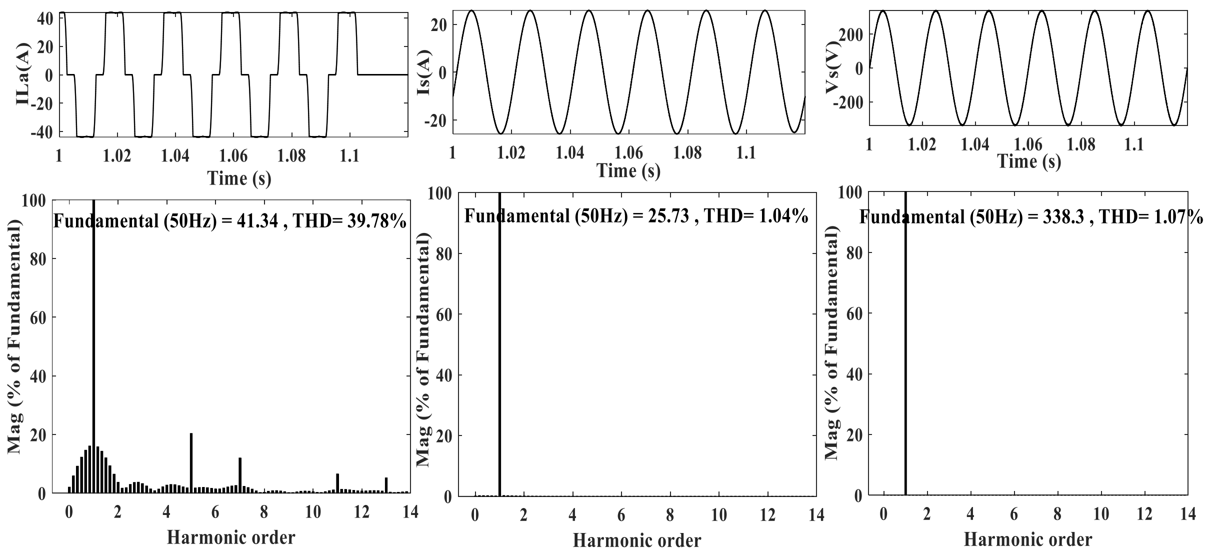

Fig. 16. Improved THD of overall system using proposed controller

6. Conclusion

As part of this research, ANN based inverter controller is introduced to improve the quality of the PV power supply and address the issues with output fluctuation and nonlinearity in the AC outputs of the PV inverters. Using the developed controller optimize the duty cycles of IGBTs, the inverter controller described in this study produces optimum PWM control signals for the inverter gate drive, resulting in a stabilized inverter output. The proposed controller is verified and validated through simulation and experimental tests using a variety of control signals, including PWM switching signals, phase voltages and currents, output voltage waveform, controller direct and quadrature voltages, error value change, and THD of the PV inverter's load current and output voltage. The control signals, output voltage, and current responses found in the simulation findings showed good agreement with the experimental data. Additionally, in terms of voltage and current THDs, the suggested PV inverter controller performs better than the other current approaches listed in the literature. The created controller is founded on two tenets: how close a guess the ANN based system can make, and the notion of input-output feedback linearization. The suggested controller is robust to parametric uncertainties because of its capacity to predict unknown parameters for different operating circumstances.

Compatibility between catalogue values and theoretical principles is demonstrated by the produced simulation results. Looking at the numbers, it's easy to see that the proposed controller has a fast-settling time and follows the reference currents reliably.

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