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Design of Power Control Circuit for Grid-Connected PV System-Based Neural Network

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***Abstract*—This research explores the application of neural networks in managing grid- photovoltaic (PV) systems. this paper aims to improve the performance and reliability of PV systems using artificial intelligence capabilities, specifically neural networks. The main emphasis of this system is to control active and reactive power and to track the maximum power point (MPPT). This study introduces an intelligent control technique for fuel cell distributed generation (DG) grid connection inverters. The algorithm allows for the management of both active and reactive power for the unit. The algorithm provides local reactive power compensation, making it economically viable. The controller modeling and performance validation are conducted using MATLAB/Simulink and Sim power system blocks, demonstrating its capacity for enhancing power factor. This makes fuel cell technology a clean, highly controllable, and economically viable option for DG systems. The system maximizes the energy extraction of PV panels and maintains them at their ideal PowerPoint across various environmental conditions. It also raises the voltage from 260 volts to 350 volts. Simulations and practical evaluations validate the proposed control system. The obtained results indicate that the total harmonic distortion (THD) of the grid current under operating conditions was less than 1.86%. This demonstrates significant improvements in the efficiency and reliability of PV systems. The neural network controller shows remarkable flexibility and the ability to quickly adapt to fluctuations in load and radiation, which contributes to developing a more sustainable and stable energy network.**

Keywords*—PV; Neural Networks; Maximum Power Point Tracking (MPPT); Grid Active Power Control; Reactive Power Control.

I. INTRODUCTION

The variability in power supply might result in instability within the electrical grid, requiring the implementation of sophisticated measures to guarantee a consistent and dependable delivery of electricity [1]. Individuals possess a high level of proficiency in effectively handling substantial volumes of data, acquiring knowledge from intricate patterns, and implementing anticipatory modifications in real time [2][3][4][5]. Neural networks have demonstrated efficacy in the modulation of inverter outputs, a critical process for the conversion of direct current generated by solar panels into alternating current (AC) compatible with the electrical grid. According to [6], intelligent systems have the capability to adjust the equilibrium between active and reactive power, hence improving the power quality and overall efficiency of the energy conversion process. The capacity of neural networks to engage in ongoing learning from external and adjust their management techniques is crucial in effectively regulating the intermittent characteristics of solar power generation [7][8][9]. In reference [10], a study conducted in (2015) which aimed to achieve maximum efficiency MPPT of the input source indicates that a low-cost controller, based on a single chip, can adjust the output voltage of a solar cell array based on an intelligent control method using a fuzzy logic controller implemented on a DC-DC converter device. in reference [11], a study of using the artificial neural network (ANN) as a technology to improve efficiency was established. This paper outlined several benefits of ANN, including the ability to train offline, perform nonlinear mapping, respond quickly, operate reliably, need less computational effort, and provide compact solutions for multivariate issues. However, there is limited research on ANN techniques used in MPPT.

The efficiency of the MPPT in the input source must be tracked. A low-cost controller, based on a single chip, can adjust the output voltage of a solar cell array. In reference [12], a paper proposes an intelligent control method using a fuzzy logic controller implemented on a DC-DC converter device. It is important to note that fuzzy logic controllers have certain disadvantages such as limited accuracy, difficulty in design and control, lack of interpretability, and difficulty in dealing with complex systems [13][14][15].

In references [16][17][18][19][20][21] some studies have been conducted by using ANN as a technology to improve efficiency. This research has noted several advantages of ANN, including offline training, nonlinear mapping, fast response time, reliable operation, reduced computational effort, and efficient solutions for multivariate issues. However, there is limited research on ANN techniques used in MPPT.

In reference [22], a study proposes a new classification based on the controller structure and input variables, as well as a detailed comparison of these techniques. An intelligent controller using ANN was used for active and reactive power controllers in grid-connected PV power generation systems. In this study, the authors proposed a two-part system with inverters and control algorithms, ensuring optimal power and synchronization of the sinusoidal current output with the grid voltage. The simulation results confirmed the validity of the efficiency control, ensuring a good response to changes in active and reactive power. However, the use of the neural controller only on the MPPT and not on both parts of the solar system. Elbaset, Adel A. Ali, Hamdi Abd-El Sattar, Montaser Khaled, and Mahmoud (2016) [23] conducted a conventional Perturbation and Observation (P&O) algorithm modified with a constant loading technique to recognize power changes and make correct decisions on a large-scale due to its simplicity and low cost. The algorithm was simulated using a solar PV module and validated experimentally. However, it suffers from instability during rapid climate changes and oscillates around the MPPT in a steady state [24]. M. Nour Ali [25] discusses an increase in the efficiency of grid-connected PV systems.

An important component for improving the performance of artificial augmentation in creating a superior MPPT control system is the optimization of the ANN design. This optimization aims to maximize the power output of the grid-connected PV system. In the majority of ANN-based MPPTs discussed in the literature [26-35], solar radiation and temperature have been utilized as inputs. However, this research proposes other inputs that successfully enhance the performance of the ANN as an MPPT system. Chandran, A.S., and P. Lenin [36] propose an enhancement that utilizes genetic algorithm (GA) optimization to determine the optimal design of the ANN topology. This includes determining the number of neurons in the hidden layer, selecting the appropriate learning algorithm, and choosing the suitable activation function for each neuron. The simulation results are showcased and compared to illustrate the exceptional performance of the MPPT-optimized ANN design. The integration of renewable energy resources improves voltage stability and reduces harmonics. Provides stability to the network. Traditional compensation methods are no longer suitable, so local reactive and harmonic compensation is needed.

AI (heuristic) methods can distribute computing and communications tasks between control devices, enhancing power quality in low-voltage distribution networks [37-45]. Abderrahmane, E., (2020) [46], Developed a neural network model to analyze the effects of varying temperature and radiation levels in different environmental circumstances. The simulation demonstrates that the neural network approach exhibits rapid responsiveness, meaning it takes less time to achieve the MPP. Additionally, it showcases good efficiency and reduced oscillation as compared to conventional methods. This algorithm is also effective for two-stage systems under all conditions [47]. The ANN-based approach used in this research offers the benefit of eliminating the need to calculate the intricate mathematical relationship between output power, irradiance of the solar PV system, and temperature of the solar PV system [48].

The proposed ANN-based the MPPT system is capable of rapidly and accurately identifying the MPPT in response to variations in environmental variables. The controller is trained using a backpropagation method based on the Levenberg-Marquardt algorithm. It guarantees the most efficient extraction of power in various environmental situations, reduces the presence of harmonics, and maintains steady output signals during temporary conditions.

II. Methodology

The circuit under consideration has two stages, namely a DC/DC boost converter and a DC/AC inverter. In order to maximize the efficiency of converting solar energy from PV units, a DC/DC boost converter is employed to improve the ratio between output power and installation cost.

This converter exhibits minimal input current ripple and possesses a high-power tracking capability. Several techniques have been devised to control the duty cycle of the converter for MPPT. However, most of these systems lack precise convergence analysis, leading to only approximate MPPT. ANN techniques provide superior convergence for MPPT. It efficiently monitors energy points, hence improving the system's efficacy by maximizing efficiency and accuracy [49].

The current is then transferred to the DC/AC inverter unit, which converts the current from DC to AC, in addition to controlling active and reactive power, and this is controlled by neural networks. Furthermore, it is crucial for DC/AC inverter unity system to generate power of superior quality while maintaining a reasonable cost [50]. By employing high-frequency switching using PWM (Pulse Width Modulation) technology in semiconductor chips, it is feasible to attain a high-power factor and reduce harmonic distortion. Modelling PV cells and the process of optimizing power output [51]. Fig. 1. shows the structure of the adaptive energy management algorithm with PQ.

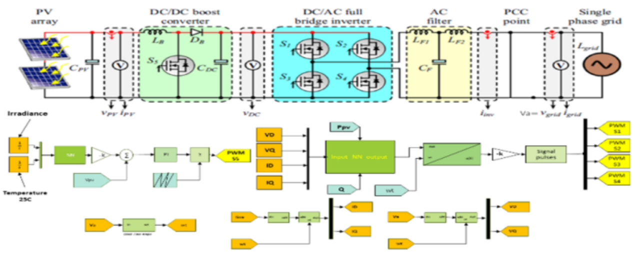

Fig. 1. The architecture of the adaptive energy management algorithm incorporating PQ

The aim of this paper is to obtain an integrated approach to improve energy management and control in PV systems by integrating MPPT techniques with neural network-based algorithms. The primary objective includes studying existing MPPT methods, designing neural network based MPPT control algorithms, integrating them into a power management system, and exploring their effectiveness in controlling both active and reactive power. In addition, control strategies based on DC/AC inverter neural networks have been developed to ensure efficient power conversion and management. Performance evaluation is performed under various operating conditions to verify the robustness and efficiency of the proposed approach.

We used neural network control on the two-stage system in solar systems to be an integrated system in terms of extracting energy from solar panels and managing energy in the grid.

By incorporating complex, nonlinear load scenarios, the research seeks to extend the conventional boundaries of study, offering insights not just on theoretical or ideal conditions but also on practical, real-world scenarios indicative of contemporary power systems in two folds: to validate the efficiency of neural networks in enhancing power extraction from PV systems and to evaluate their effectiveness in ensuring power quality and reliability when connected to a grid with nonlinear loads. Every stage, from the neural network design and training to the simulation of the entire system. The simulation circuit has been conducted by MATLAB Simulink [52].

A. Modeling of the PV System

Solar energy is produced through the conversion of sunlight into electrical energy by PV cells. The phenomenon that describes this occurrence is known as the PV effect. When light interacts with a PV cell, it supplies enough energy to release electrons, which are negatively charged subatomic particles. The conversion of these electrons into a voltage, known as the photovoltage, occurs due to the cell's inherent potential barrier. This voltage can then be harnessed to generate a current in a circuit. [52]. Fig. 2 illustrates the PV operation principle [53].

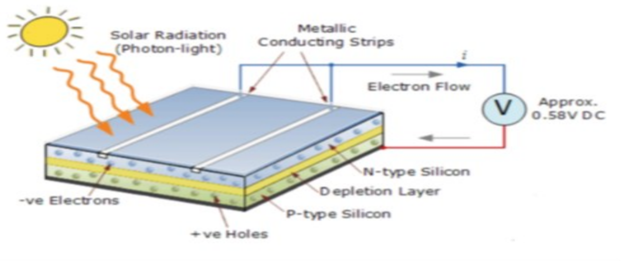

Fig. 2. The PV operation principle

A PV cell is a semiconductor junction formed by combining p-type and n-type semiconductors, often silicon. Photons are the constituent particles of solar radiation. A photon is defined by its wavelength (λ) and energy (E) [54]:

$$E = h\frac{c}{\lambda} \tag{1}$$

where, E is photon energy [J], h is the Plank's constant ($6{,}626 * 10{-}34$ [J.s]), c is the speed of light (299 792 458 [m/s]), λ is Wavelength of photon [m].

The equations that represent the current-voltage (I-V) characteristics are as follows [55]

$$I = I_{Ph} - I_d \frac{v_d}{R_d} \tag{2}$$

$$V_d = IR_s + V \tag{3}$$

$$I_d = I_0\left[exp\left(\frac{qV_d}{AKT}\right) - 1\right] \tag{4}$$

$$I_{ph} = [I_{sc} + K_l(T - T_r)]\lambda \tag{5}$$

The reverse saturation current at the reference temperature T_r [58] A is denoted as I0, while the diode ideal factor is represented by A. The Boltzmann constant, denoted as K, is equal to 1.38×10^{-23} J/K [56]. On the other hand, the electron charge, represented by q, is equivalent to 1.6×10^{-19} Coulombs.

$$I = I_{ph} - I_0\left[\exp\left(\frac{V + IR_s}{\alpha V_T}\right) - 1\right] - \frac{V + IR_s}{R_{sh}} \tag{6}$$

By substituting the given values into Equation (6), one obtains Equation (7).

$$I_{sc} = I_{ph} - I_0\left[\exp\left(\frac{I_{sc}R_s}{\alpha V_T}\right) - 1\right] - \frac{I_{sc}R_s}{R_{sh}} \tag{7}$$

Experimental investigations demonstrate that under the short circuit condition, the magnitude of the second term on the right-hand side of the aforementioned equation is inconsequential in comparison to the magnitudes of the other two terms; thus, it is possible to eliminate this term. Consequently, the equation is expressed as follows [57]:

$$I_{ph} = \frac{R_{sh} + R_s}{R_{sh}} I_{sc}, Rsh\ "Rs \text{ so } Iph \cong Isc \tag{8}$$

The operational point for this particular example is represented by the coordinates (I, V) = (0, V_{oc}). When this is inserted into (6), the following outcome is obtained [58]:

$$0 = I_{ph} - I_0\left[\exp\left(\frac{V_{oc}}{\alpha V_T}\right) - 1\right] - \frac{V_{oc}}{R_{sh}} \tag{9}$$

Experimental experiments have once again demonstrated that the -1 in the second term on the right-hand side of the equation can be disregarded. Upon putting the derived expression for I_{ph} into (10) [59],

$$I_{ph} = I_{ph-ref}\left(\frac{G}{G_{ref}}\right) \tag{10}$$

we arrive at the resultant expression for I_0.

$$I_0 = \frac{GI_{sc,T_r} - \frac{V_{oc}}{R_{sh}}}{G_{ref}\exp\left(\frac{V_{oc}}{\alpha V_T}\right)} \tag{11}$$

The symbol "I_{ph}" represents the photocurrent produced by the current source in the corresponding circuit.

The variables G_{ref} and G represent the reference value of the irradiance and the irradiance on the cell/solar panel, respectively. The mathematical modeling of the boost converter starts by considering the storage parts, namely the capacitor and inductor. The voltage across the inductor is denoted by (12), while the current across the capacitor is represented by (13) [60].

$$V_L = L\frac{dI_L}{dt} \tag{12}$$

$$I_c = c\frac{dV_c}{dt} \tag{13}$$

Meanwhile, inductor V_L for switching conditions of ON and OFF are shown in (14) and (15) respectively [61].

$$V_L = V_{in} * PWM \tag{14}$$

$$V_L = (V_{\text{in}} - V_{\text{out}}) * PWM \tag{15}$$

The duty cycle, as indicated in (16), represents the ratio of the difference between V_0 and V_{in} to V_0 [61].

$$PWM = \frac{(V_o - V_{in})}{V_o} f_{pwm}{}^{-1} \tag{16}$$

The current passing through can be calculated by performing an integration with respect to (18).

$$I_L = \frac{1}{L}\int V_L dt \tag{17}$$

The current through the capacitor is given by (18), where the current through the load resistor once has been obtained.

$$I_C = I_L - I_R \tag{18}$$

In the ideal model, the boost converter's load voltage may be in Fig. 3 shows the Mathematical model Boost converter by using MATLAB/Simulink.

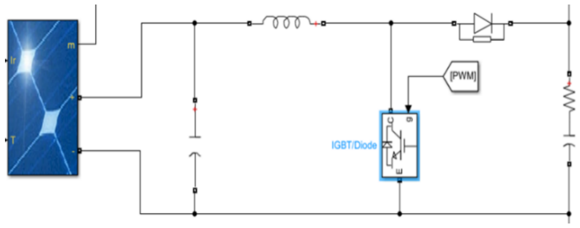

Fig. 3. Mathematical model Boost converter MATLAB/Simulink

B. *Neural Network*

The artificial neuron operates at the fundamental processor level. The input is established utilizing a weight. One output (a) is associated with each neuron and is accompanied by a transfer function (f). Specific neurons are also associated with bias (b), which is expressed as a fundamental scalar or a weight (W) with a solitary input value. The following diagram depicts the arrangement of an artificial neuron. The configuration of neurons with numerous inputs is depicted in Fig. 4, whereas Fig. 5 illustrates the architecture of the neuron with R inputs.

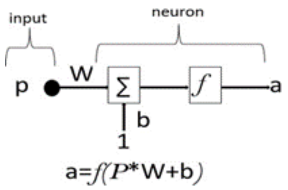

Fig. 4. The structure of the neuron with one input

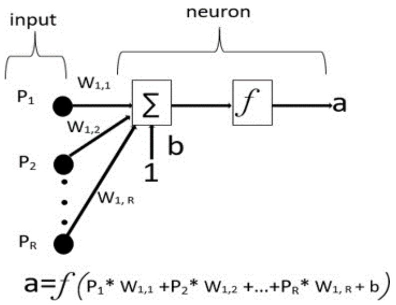

Fig. 5. The structure of the neuron with R inputs

C. *Simulation Neural Network in Inverter Control*

The conversion system depicted in Fig. 6 illustrates a widely employed conversion method utilized in the regulation of power electronics, particularly inverters. The process of conversion involves the transformation of three-phase currents and voltages, originally represented in the conventional three-phase coordinates (ABC), into a stable two-dimensional reference frame (αβ0). Subsequently, these values are further transformed into a rotating reference frame (dq0). This rotating reference frame is utilized as input for the neural network responsible for controlling the inverter.

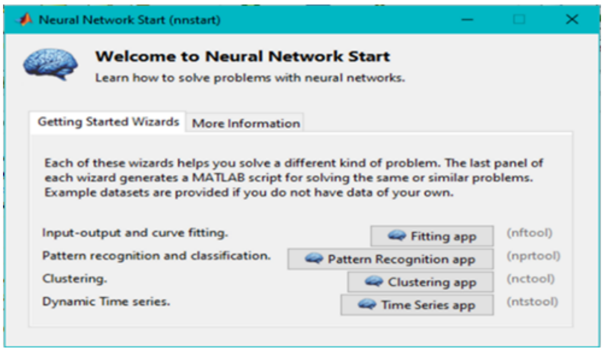

Fig. 6. The block for training

The blocks denoted as [VA], [IA], and [WT] symbolize the inputs of voltage, current, and angular frequency to the system, respectively. Typically, the voltage and current are expressed in the form of three-phase AC. The symbol ωt represents the angular frequency of the system in this context. This angular frequency is crucial for converting to the rotating reference frame dq0. The variables [ID], [IQ], [VD], and [VQ] reflect the result of the Clark transform. The variables ID and IQ represent the direct and quadratic components of the current, respectively. Similarly, VD and VQ designate the direct and quadratic components of the voltage in the rotating reference frame.

III. Results and Discussion

MPPT technology is a sophisticated way to ensure that solar panels perform at their optimum power output regardless of shifting sunshine conditions. When coupled with a boost converter employing neural networks, MPPT becomes even more efficient. By constantly evaluating patterns in voltage and current from the solar panel, the neural network learns and predicts the ideal operating voltage that accomplishes MPPT.

Fig. 7 shows the voltage measurement of the PV system over time when inputting data representing fluctuating solar radiation intensity with weather conditions that transition from one state to another every 0.3 seconds while maintaining a constant temperature at 25 Co. The voltage reaches its operational level quickly and then remains relatively stable thereafter.

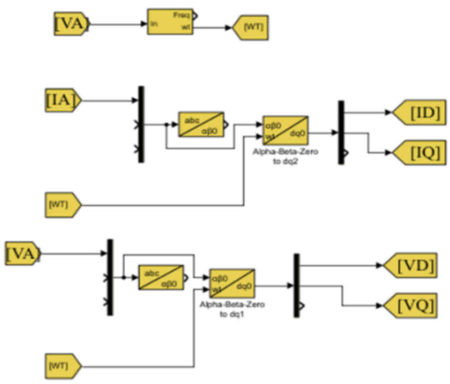

Fig. 7. Transformation Block

This indicates that upon startup or when conditions change, the PV system quickly reaches the operating voltage. An initial rise is observed when the voltage exceeds a threshold, followed by a gradual return to a steady state. This is the usual behavior of an operating system that stabilizes once it reaches equilibrium. During its operation, the voltage shows tiny variations (ripples) with respect to its steady-state value. This phenomenon can be attributed to the variation in the amount of solar radiation received by PV cells, as well as the transition between states due to weather fluctuations and changes in the intensity of solar radiation. After the initial surge, the PV system maintains a constant voltage, which is an excellent indicator that the system is operating properly and is not susceptible to significant voltage drops. Disturbances in the system or radiation. When the voltage stabilizes at approximately 260 V, the maximum PV voltage is indicated.

Fig. 8 shows how a PV system's current output changes over time. A sharp apex appears initially, signifying the flow of current during the startup phase. The current stabilizes with discernible ripples following this apogee; these ripples are caused by variations in solar radiation or system noise. Two times, at approximately 0.6 and 1.2 seconds, the current decreases marginally, which could indicate that system adjustments have been modified. The current appears relatively stable on the whole, indicating that the PV system generates electricity continuously. Minor fluctuations in the current output are indicative of adjustments to the operating environment or the dynamics of the feedback control.

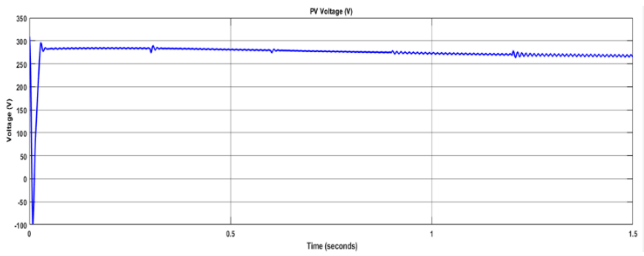

Fig. 8. PV voltage (v)

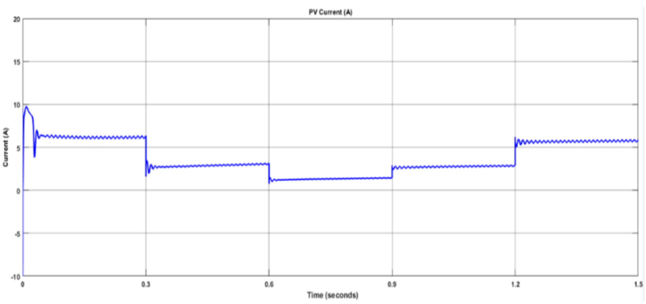

Fig. 9. PV current

Fig. 9. represents the power output of a PV system over time, which settles into a constant output with minor fluctuations. It is worth noting that there is a change in the power value, where from the period 0 to 0.3, it is about 1750 W; after 0.3 seconds, it is 850 W; after 0.6 seconds, it is 474 W; after 0.9 seconds, it is 750 W, and then increases in 1.2 seconds to the value 1500 W. These decreases are due to solar inputs representing changes in environmental conditions such as the passage of cloud cover over the PV panels or modifications in the system itself. Aside from momentary lapses, the PV system appears to provide consistent energy production.

The voltage output of the boost converter, which is regulated by an MPPT neural network, is depicted in the graph in Fig. 10 Following conversion, the PV panel's initial voltage of 260V was maintained at approximately 350V.

The data is supervised and trained using the Levenberg-Marquardt method (Trainlm), renowned for its effective tracking capabilities. The MPPT algorithm is significant due to its rapid convergence speed, high tracking efficiency, and ability to withstand nonlinearity. The details of the training data are presented in Table I. Regression plots (RP) are a type of supervised learning method that specifically examines the correlation between input data and a target variable. These plots are frequently employed as a directive for ANN. Fig. 10 displays the outcomes of the algorithm that has been trained.

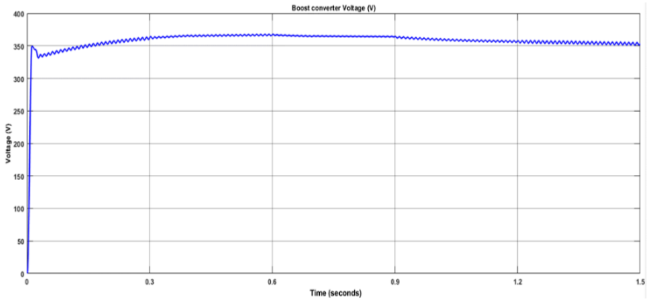

Fig. 10. Boost converter voltage

Table I shows details of the function of fitting of ANN. Table II displays the recorded iterations and corresponding mean square error (MSE) data. The Mean Squared Error (MSE) quantifies the discrepancy between the observed output and the desired target values. The findings improve when the Mean Squared Error (MSE) value decreases.

TABLE I. DETAILS OF THE FUNCTION OF FITTING OF ANN

Algorithm Used	Data	Values
Trainlm	Training data	70%
Trainlm	Validation Data	15
Trainlm	Test Data	15
Trainlm	Layer Size	10

TABLE II. THE TRAINING ALGORITHM

	SAMPLES	MSE	R
Training	105001	1.71780e-0	9.99961e-1
Validation	22500	1.73009e-0	9.99960e-1
Testing	22500	1.75659e-0	9.99959e-1

Fig. 11 and Fig. 12 represent the simulation results of inverter voltage and inverter current respectively.

Fig. 11 depicts the output voltage generated by the inverter in a single-phase grid-connected PV system controlled by a neural network. The measured voltage output exhibits a sinusoidal waveform, which suggests the transfer of AC electricity to the power grid. The system's maximum voltage of around 325 V indicates that it is designed for use in a power grid with an RMS voltage of approximately 230 V.

The waveform illustrated in Fig. 12 represents the characteristic AC produced by the inverter, exhibiting a sinusoidal pattern. Under the assumption that the inverter is working with a somewhat constant load, it can be observed that the current exhibits peaks that are directly correlated with the output voltage.

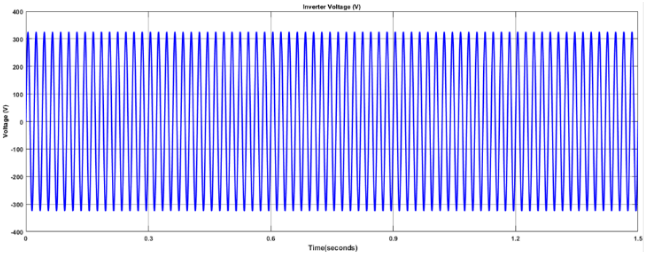

Fig. 11. Inverter voltage

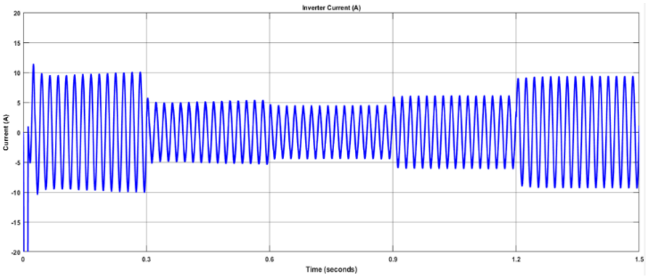

Fig. 12. Inverter Current

The waveform of the grid current after passing through the LCL filter, which is regulated by an inverter controlled by neural networks is illustrated in Fig. 13. This waveform exhibits sinusoidal characteristics, as is commonly observed in AC supplied to the electrical grid.

Fig. 14 represents the waveforms of the inverter's output voltage and current within the time interval of 0.2 to 0.5 seconds.

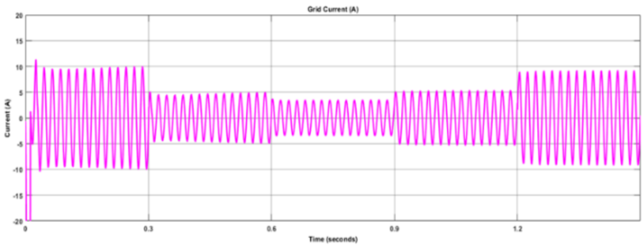

Fig. 13. Grid Current

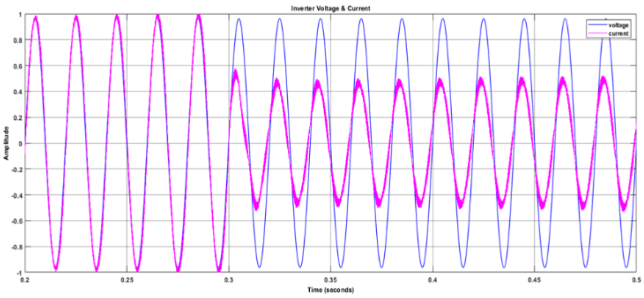

Fig. 14. Neural Network injecting the reactive power in the grid

The neural network that governs the inverter adjusts the phase angle between the voltage and current to regulate the reactive power, in accordance with the selected control strategy. This correction is necessary because the current is leading the voltage, and they are not in phase alignment. Phase shift is an intentional consequence that occurs when a neural network relies on the reactive power setpoints it gets. It is crucial to recognize that the existing power factor is 0.9 because of the presence of a minuscule amount of non-reactive power. Control effectiveness in neural networks can be evaluated by analyzing the temporal consistency of the phase shift. The network's ability to inject or absorb reactive power to achieve the desired control objectives is demonstrated by this consistency.

IV. Conclusion

The aim of this project is to develop, model, and assess a control mechanism based on neural networks to enhance the efficiency of a PV system connected to the power grid and interacting with non-linear loads. The neural networks are elaborately designed to accomplish MPPT and to maximize the active and reactive power transmitted to the grid. This steady voltage is proof that the neural network efficiently controls the inverter, keeping the voltage and current outputs within the specified ranges despite variations in solar light. After an initial period of peaks and valleys, the system's energy output quickly stabilized, demonstrating its capacity to rapidly adapt to changes in solar input, hence minimizing downtime and optimizing energy harvest. Since the neural network regulates the reactive power injection into the grid, efficiency, and compatibility are both preserved throughout the process. The efficacy of the neural network control technique is evidenced by the system's ability to promptly adapt to transient alterations and sustain uninterrupted operation in spite of these alterations. The capacity of neural networks to improve the dependability and performance of renewable energy systems is demonstrated by the consistency in inverter output over a wide range of operating situations.

V. Future Work

The study suggests checking scalability for bigger systems, improving deep learning for better prediction, using weather forecasts to make energy production more efficient, and looking into energy storage options to make production more consistent and collect extra energy. These research avenues could enhance fuel cell DG systems' performance and practical applicability.

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