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DESIGNING AND SIMULATING NEURAL NETWORKS FOR MAXIMUM POWER POINT TRACKING AND ACTIVE/REACTIVE POWER CONTROL IN GRID-CONNECTED PV SYSTEMS

Omar Nayyef Rajab RAJAB

Master's Thesis

Supervisor

Asst. Prof. Dr. Zaid HAMODAT

İstanbul, 2024

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The thesis titled DESIGNING AND SIMULATING NEURAL NETWORKS FOR MAXIMUM POWER POINT TRACKING AND ACTIVE/REACTIVE POWER CONTROL IN GRID-CONNECTED PV SYSTEMS prepared by OMAR NAYYEF RAJAB RAJAB and submitted on 12/06/2024 has been **accepted unanimously** for the degree of Master of Science in Electrical and Computer Engineering**.**

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I hereby declare that this thesis meets all format and submission requirements of a Master's Thesis.

I hereby declare that all information/data presented in this graduation project has been obtained in full accordance with academic rules and ethical conduct. I also declare all unoriginal materials and conclusions have been cited in the text and all references mentioned in the Reference List have been cited in the text, and vice versa as required by the abovementioned rules and conduct.

Omar Nayyef Rajab RAJAB

Signature

DEDICATION

To my beloved parents, who have tirelessly worked and dedicated their lives to my education and upbringing, guiding me to this significant milestone. Your unwavering support and sacrifices have shaped me into the person I am today, and I am forever grateful for your love and guidance I also extend my profound gratitude to my supervisor, Dr. Zaid Hamodat, for his invaluable mentorship, wisdom, and patience.

Finally, I wish to thank everyone who has contributed to my journey, no matter how small the contribution. Each word of encouragement and support has left an indelible mark on my academic and personal growth This thesis is not only a reflection of my hard work but also a testament to the collective effort and belief of everyone who stood by me. Thank you.

ABSTRACT

DESIGNING AND SIMULATING NEURAL NETWORKS FOR MAXIMUM POWER POINT TRACKING AND ACTIVE/REACTIVE POWER CONTROL IN GRID-CONNECTED PV SYSTEMS

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This thesis explores the application of Neural Network (NN) in the management of grid-connected Photo Voltaic (PV) system. This study aims to improve the performance and reliability of PV systems using NN capabilities. The controller modelling using MATLAB/Simulink, the first section of the thesis designs and implements a Maximum Power Point Tracker (MPPT) control system based on NN, designed to dynamically adapt to variable solar radiation intensity due to weather conditions. it also raises the voltage from 260 V to 350 V despite fluctuations in radiation intensity. The result obtained indicates that the boost converter effectively raised the PV voltage and maintain it at a certain level while working under the guidance of the NN. The final section discusses active and reactive power control. The algorithm provides local reactive power compensation making it economically viable. We use five different performance scenarios of the proposed control method are tried, and the NN controller shows remarkable flexibility and quickly adapting to fluctuations in load and radiation. The inverter voltage of 230V was equivalent to the mains voltage due to their parallel connection. The Total Harmonic Distortion (THD) of the grid current under all operating conditions was measured at less than 1.86%. In addition, it has been observed that the success rate of NN is more than 99%. This thesis provides insight into the potential of NN in renewable energy applications by using NN, contributing to the development of a more sustainable and stable energy grid, and obtaining an integrated system that can be integrated with the grid.

Keywords: PV, MPPT, Neural Network, Active & Reactive Power, THD.

ÖZET

ŞEBEKE BAĞLI PV SİSTEMLERDE MAKSİMUM GÜÇ NOKTASI TAKİBİ VE AKTİF/REAKTİF GÜÇ KONTROLÜ İÇİN SİNİR AĞLARININ TASARLANMASI VE SİMÜLASYONU

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Bu tez, şebekeye bağlı Foto Voltaik (PV) sistemin yönetiminde Sinir Ağının (NN) uygulanmasını araştırmaktadır. Bu çalışma, YSA yeteneklerini kullanarak PV sistemlerinin performansını ve güvenilirliğini artırmayı amaçlamaktadır. Tezin ilk bölümü olan MATLAB/Simulink kullanılarak kontrolör modellemesi, hava koşullarına bağlı olarak değişen güneş ışınımı yoğunluğuna dinamik olarak uyum sağlamak üzere tasarlanmış, NN tabanlı bir Maksimum Güç Noktası Takipçisi (MPPT) kontrol sistemi tasarlar ve uygular. aynı zamanda radyasyon yoğunluğundaki dalgalanmalara rağmen voltajı 260 V'tan 350 V'a yükseltir. Elde edilen sonuç, yükseltici dönüştürücünün NN'nin rehberliğinde çalışırken PV voltajını etkili bir şekilde yükselttiğini ve belli bir seviyede tuttuğunu göstermektedir. Son bölümde aktif ve reaktif güç kontrolü tartışılmaktadır. Algoritma yerel reaktif güç kompanzasyonu sağlayarak ekonomik açıdan uygun hale getirir. Önerilen kontrol yönteminin beş farklı performans senaryosu denenmiş olup, NN kontrolörü dikkate değer bir esneklik göstermekte ve yük ve radyasyondaki dalgalanmalara hızlı bir şekilde uyum sağlamaktadır. Paralel bağlanmaları nedeniyle 230V evirici voltajı şebeke voltajına eşdeğerdi. Tüm çalışma koşulları altında şebeke akımının Toplam Harmonik Bozulması (THD) %1,86'nın altında ölçülmüştür. Ayrıca NN'nin başarı oranının %99'un üzerinde olduğu gözlemlenmiştir. Bu tez, NN kullanarak yenilenebilir enerji uygulamalarındaki NN'nin potansiyeli hakkında fikir vermekte, daha sürdürülebilir ve istikrarlı bir enerji şebekesinin geliştirilmesine katkıda bulunmakta ve şebeke ile entegre olabilecek entegre bir sistem elde edilmesine katkıda bulunmaktadır.

Anahtar Kelimeler: PV, MPPT, Sinir Ağı, Aktif ve Reaktif Güç, THD.

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ABBREVIATIONS

AC	:	Alternating Current
AI	:	Artificial Intelligence
ANN	:	Artificial Neural Network
APF	:	Active Power Filter
DC	:	Direct Current
DG	:	Distributed Generation
MPP	:	Maximum Power Point
MPPT	:	Maximum Power Point Tracking
NN	:	Neural Network
PECs	:	Power Electronic Converters
PI	:	Proportional Integral
PQ	:	Power Quality
PV	:	Photo Voltage
PWM	:	Pulse Width Modulation
THD	:	Total Harmonic Distortion

1. INTRODUCTION

1.1 OVERVIEW

Solar PV systems have emerged as a fundamental component of sustainable energy methods within the current energy environment. As nations endeavour to attain ambitious renewable energy objectives, the incorporation of PV devices into the electricity grid is experiencing significant growth. These systems are widely preferred owing to their capacity to utilize the plentiful and renewable energy of the sun, which is a clean and limitless resource. Nevertheless, solar energy presents inherent difficulties mostly attributed to its intermittent nature and the fluctuating levels of solar radiation. 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].

The progress made in the field of Artificial Intelligence (AI) has brought forth significant opportunities in effectively addressing the challenges related to grid-connected PV systems. neuronal networks, which are a subset of AI renowned for their capacity to emulate the neuronal architecture of the human brain, have exhibited remarkable potential in this domain. According to Jones and Williams (2021), 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. NN have demonstrated efficacy in the modulation of inverter outputs, a critical process for the conversion of DC generated by solar panels into AC compatible with the electrical grid. According to [2], intelligent systems have the capability to adjust the equilibrium between active and reactive power, hence improving the PQ and overall efficiency of the energy conversion process.

The utilization of control systems based on NN in grid-connected PV systems signifies a significant advancement in smart grid technology. The statement highlights the use of renewable energy sources in conjunction with advanced AI technologies, hence facilitating the development of energy management solutions that are more effective, adaptable, and intelligent. The capacity of NN to engage in ongoing learning from external stimuli and adjust their management techniques is crucial in effectively regulating the intermittent characteristics of solar power generation [3]. The degree of adaptability described is not only crucial for strengthening the economic feasibility of solar energy, but it also plays a pivotal role in bolstering the resilience and long-term sustainability of the worldwide energy system. The expanding amount of scholarly investigation and advancement in this domain highlights the capacity of NN to fundamentally transform the methods by which we capture, distribute, and employ solar energy in a global context that is progressively reliant on sustainable energy sources [4]. The diagram in Figure 1.1. illustrates the design of an adaptive energy management algorithm system that can effectively control both active and reactive power for grid-connected PV installations.

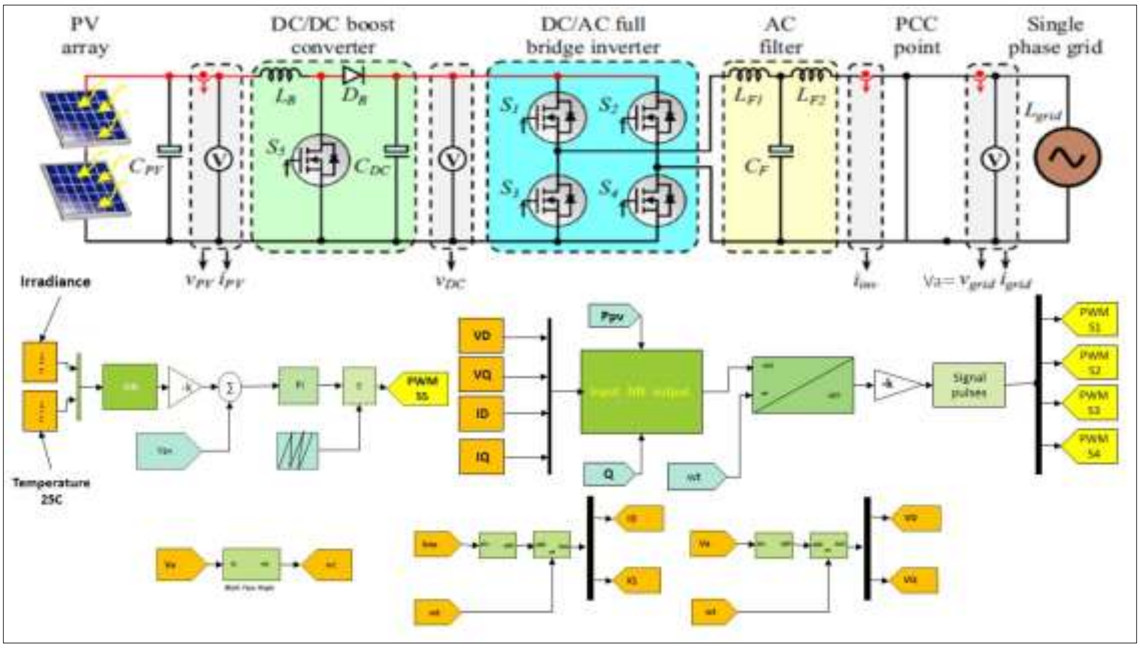

Figure 1.1: The Structure of Adaptive Energy Management Algorithm with PQ.

1.2 THESIS GOALS

The main objective of this thesis is to examine the effectiveness of neural networks in regulating the active and reactive power in photovoltaic systems that are linked to the electrical grid. It attempts to establish the viability of NN as a control approach for inverters within these systems. The purpose of this thesis is to show how sophisticated computational models can improve power output, grid stability, and resiliency in the face of environmental change. Research success in these areas will help further our knowledge of smart grid technology and AI place in the management of renewable resources. It is anticipated that the results will provide a thorough assessment of NN controllers and their potential to change energy distribution in a time when renewable sources of energy are increasingly in demand.

1.3 THESIS OUTLINES

This thesis is organized to provide a clear and extensive analysis of NN applications in PV system control. This paper will begin by providing an overview of the current state of renewable energy integration and the unique difficulties of PV systems. After that, the thesis will go into depth about how a NN controller was built, including its specific settings and the reasoning behind the architecture's selection. Simulation findings demonstrating the NN reaction to variations in solar irradiation and capacity to maintain grid standards will be shown in the following sections. The thesis will also compare these findings to more conventional control approaches in order to emphasize the benefits of NN control.

2. LITERATURE REVIEW

2.1 BACKGROUND OF THE PROJECT

Prakash Prajapat et al. [5]. For PV systems connected to the grid, this research presents a NN-driven MPPT controller that can make efficient use of power even when no storage device is present. The components of the system are a grid, a three-phase voltage source inverter, a boost converter, and a PV array. The NN is trained using the NN toolkit, while MATLAB/Simulink is used for system design and simulation. Based on the results of the comparison, the NN-based controller is more effective than the conventional P&O MPPT controllers. Mateus F. Schonardie et al. [6]. The article suggests a three-phase photovoltaic (PV) generating system that is connected to the grid and maintains a constant power factor in response to solar radiation. The system employs the dq0 transformation for control and emulates the Pulse Width Modulation (PWM) inverter. The technology mitigates the effects of reactive power and harmonic components produced by loads. We present a method for achieving Maximum Power Point (MPP) operating by restricting the input voltage. The methodology is supported by both experimental and computational data. Su-Won Lee et al. [7]. A grid-connected PV system without a transformer is presented in the paper, which has active and reactive power management. In addition to functioning in both solar and night modes, the system may offset reactive power generated by nonlinear loads. To lower harmonic current and raise power factor, it manages power quality (PQ) and produces active power when in sunny mode. M.S. Kandil et al. [8]. This study introduces a smart control mechanism for grid-coupling inverters that use fuel cells for Distributed Generation (DG), which allows for regulation of the unit's active and reactive power. The approach provides a local reactive power adjustment at a reasonable cost. The effectiveness of the controller in increasing power factor is proven by modeling and evaluating its performance using Simpower and MATLAB/Simulink system blocks. Fuel cell technology offers a clean, controlled, and economically feasible alternative to other DG systems. Georgios Tsengenes et al. [9]. This research focuses on a solar power system that is linked to a three-phase grid using a voltage source inverter. The control method relies on the p-q theory to ensure the load's reactive power is evenly distributed during the night and to supply active power to the grid during periods of sunlight. The method utilizes basic algebraic calculations to synchronize the inverter with the grid, eliminating the requirement for a phase-locked loop

(PLL), and maintains continuous operation throughout the whole day. Singh Mukhtiar et al. [10]. Active power filter (APF) capabilities are introduced in this work as a new control mechanism for grid-connected inverters in 3-phase 4-wire distribution systems. The inverter can handle reactive power demand, neutral current, harmonic current, current imbalance, and load current as a power converter. Laboratory tests and simulations in MATLAB/Simulink demonstrate the control idea. ZHU YongLi et al.[11]. This study compares two types of grid-tie PV systems: one including a single stage and the other incorporating a two-stage configuration together with a boost circuit. Diverse types of components are utilized, such as photovoltaic arrays, boost choppers, and grid-tie inverters. This study explores the functioning of the outer-loop controller of a grid-tie inverter and presents perturb and observe techniques for maximum power point tracking (MPPT). The findings demonstrate that the photovoltaic (PV) array is capable of maintaining a consistent and precise maximum power point tracking (MPPT) performance throughout a wide range of environmental circumstances. The inverter is capable of achieving a power factor of one by effectively managing the transfer of reactive power to zero. This study can be utilized by researchers and engineers to gain a deeper comprehension of the advantages and disadvantages of these two topologies in the construction of photovoltaic (PV) systems. Bader N. Alajmi et al. [12]. This PV system's grid-connected design consists of fuzzy logic controllers and a single-phase, single-stage current source inverter. Additionally, the system does not own a transformer. A double-tuned parallel resonant circuit enhances power quality, while a proportional-resonant controller regulates current injection. A modified carrier-based modulation approach is employed to induce magnetization in the dc-link inductor. The system's efficiency is validated by simulation and empirical data. El Fadil et al. [13]. The objective of this study is to regulate a photovoltaic (PV) system that is connected to a single-phase power grid. The system consists of a PV panel, a boost power converter, and an inverter. The control objective seeks to accomplish four main objectives: achieving asymptotic stability, maximizing power point tracking (MPPT), accurately regulating the DC bus voltage, and attaining a unity power factor in the grid. Nilesh Shah et al. [14]. To get the most out of photovoltaic (PV) arrays, we offer an MPPT tracking method that is based on fuzzy logic. The algorithm takes the P-V curve's slope as input and produces a boost converter's duty ratio output. Quicker convergence and precise MPPT are outcomes of this approach. Harmonic and reactive power adjustment, active power, and grid interaction are further features of the two-stage PV system. B. Boukezata et al. [15]. According to the research, a direct power control connection between PV modules and the grid can be established using an APF. In order to optimize the power transfer from the PV array to the grid, the filter compensates for reactive power and harmonic currents. Compared to conventional systems, this one is more efficient. The results of the simulation show that it works. Jaypalsinh Chauhan et al. [16]. The incremental conductance and perturb and observe approaches are compared and contrasted with respect to boost and buck converters in this research. Using the energy point assessment tools in MATLAB Simulink, we record comparisons of voltage, current, and power output. Gitanjali Mehta et al. [17]. A one-stage, three-phase grid-tied PV system that is both efficient and straightforward is suggested based on these results. Making a model of the photovoltaic module and the power conditioning gear that will connect the PV system to the power grid is the first step of the process. The system incorporates reactive power compensation, maximum power point tracking (MPPT), grid synchronization, and output current harmonic reduction. Simulations verify the operation and control theory, revealing a highly efficient and reliable single-stage grid-connected PV system. Ravi bathula et al. [18]. As more and more is learned about PV systems, their future seems promising. Both the temperature and the intensity of the sun's rays affect the power that is produced. A cheap control device can efficiently monitor the input source's MPP. A DC-DC converter device integrated with a Fuzzy Logic Controller is recommended as a sensible way to control MPPT in the study. Lina M. Elobaid et al [19]. Research on solar systems is currently centered around maximum power point tracking (MPPT) approaches, which aim to improve efficiency. In many situations, particularly those with partial shading and quickly changing environmental circumstances, AI-based systems perform better than classic MPPT approaches, even though they are easier to design and execute. The capacity to train the network without an internet connection, nonlinear mapping, fast response time, reliable operation, less computational burden, and clear answers to issues with multiple variables are some of the features of ANN approaches. The study includes a thorough analysis of PV MPPT approaches that rely on ANNs. Considering input variables and controller structure, this research introduces a novel categorization approach. The proposal is subsequently evaluated based on transient/steady-state performance criteria, experimental validation, and ANN building blocks. Layate et al. [20]. This research introduces a novel control technique that utilizes artificial neural networks

(ANN) to regulate the active and reactive power controllers in grid-connected solar production systems. The system consists of two components, each equipped with inverters and control algorithms. To achieve maximum power efficiency for a photovoltaic (PV) array, it is recommended to utilize a DC/DC converter in conjunction with a DC/AC hysteresis inverter. The simulation data has demonstrated the successful implementation of active and reactive power management using neural controllers. Using MATLAB/Simulink, we conduct tests and simulations on the power circuit and control system. Faa-Jeng Lin et al. [21]. In this study, we present TSKPFNN-AMF, a smart controller that can regulate active and reactive power in a three-phase grid-connected solar system even when the grid goes down. By adjusting the reactive power value and keeping the output current below the maximum current limit, the controller ensures compliance with Low-Voltage Ride Through (LVRT) requirements. To maintain a constant voltage on the dc-link bus, a converter and inverter are part of a dual-mode operation control system. Detailed in the article are the TSKPFNN-AMF's design, online learning method, and convergence analysis. Experiment findings clearly show that the proposed control system works. R. N. Tripathi et al. [22]. The Fryzel conductance-based current minimization method is used to model and simulate a grid-connected PV system in this work. Using a PI controller, the control algorithm calculates the average active current component and regulates the DC link voltage. Improving PQ for both linear and non-linear loads is possible, according to the simulation results, by delivering the average active power with low current. I. Abadlia et al. [23]. The study presents a new intelligent control method for grid-connected solar production systems that controls active and reactive power using ANN. To guarantee that the system's sinusoidal current output is in sync with the grid voltage, it consists of two halves that are equipped with inverters and a DC/DC converter. The simulation results show that the controller is successful in responding quickly to power changes and keeping the current and voltage synchronized enough. Adel A. Elbaset et al. [24]. Despite its widespread use and inexpensive cost, the P&O approach has the potential to produce instability in otherwise stable situations or oscillate about the MPP in the event of abrupt weather changes. The study introduces a tweaked P&O algorithm that employs a constant load technique for precise power variation detection and decision-making. Experimental validation with measurements for MPPT systems verifies the technique, which is evaluated using a solar PV module. Faa-Jeng Lin et al. [25]. In order to manage grid-connected three-phase PV systems during grid outages, this article presents a reactive power controller that employs a Probabilistic Wavelet Fuzzy Neural Network (PWFNN). The controller verifies the voltage on the dc-link bus, the current limit, and the reactive current ratio to prevent overcurrent. The controller was able to maintain power balance in numerous grid fault scenarios, according to experimental testing. B.G. Sujatha et al. [26]. This study introduces a hybrid strategy for enhancing PQ in grid-connected PV systems. A PI controller and an RBFNN (radial basis function neural network) work together to form the system. Among other input parameters, the RBFNN is trained to react to changes in grid power and the gain settings of the PI controller. The approach improves PQ by predicting gain parameters using changes in grid side characteristics. The strategy is being tested to see how well it works in compared to more traditional methods. Pradipta et al. [27]. The primary objective of the project is to construct a DG system that is linked to a 20 kV network and includes PV and WT. To get the most out of the system, a boost converter and fuzzy logic controller collaborate. Power supply to the load or grid at 20 kV and 50 Hz can be demonstrated through MATLAB simulations. Priyanka R. Yelpale et al.[28]. In order to improve the grid power transmission capacity, the research introduces a new control method for PV solar farms that are connected to the grid. Using the inverter capacity left over after actual power generation, the method deactivates the PV farm at night through voltage and damping management. M. Nour Ali et al. [29]. The study's primary objective is to find ways to use AI to monitor the places of highest power, with the ultimate goal of making grid-connected PV systems more efficient. The research proposes a better ANN architecture that takes into account alternative inputs like temperature and solar irradiation. The architecture of the ANN is built using genetic algorithm optimization. The improved ANN design outperforms the baseline for MPPT, according to the simulation results. Arsha.S.Chandran et al. [30]. An autonomous hybrid system that stores energy in batteries and generates power from solar PV and wind turbines is the subject of this study's discussion of the operational challenges of such a system. In response to these issues, control mechanisms are developed. For energy storage in batteries, we propose a droop-based method for voltage and frequency management, and for PV and wind power, we propose an active and reactive power control approach that incorporates MPPT. Rivera et al. [31]. Solar power, which is both abundant and environmentally friendly, is a renewable energy source that serves several uses, including the creation of low and medium power. Due to their nonlinear properties, single-stage grid-connected PV systems are gaining popularity as solar systems proliferate. In order to optimize power tracking and manage active and reactive power without the need for an additional power converter, this dissertation proposes a single-stage three-phase grid-connected PV inverter with a nonlinear control approach. A major drawback of single-phase PV inverters, double-line-frequency current ripple, is mitigated by the device's novel method. To anticipate unknown disturbances that can affect system performance, the nonlinear controller is coupled with adaptive control. This work uses Lyapunov stability analysis to demonstrate that systems with three and one phase are stable and that signals are bounded. The results of the simulations demonstrate that the proposed controllers are reliable and efficient in monitoring peak power and controlling active and reactive power in the face of sudden changes in load and air conditions. Sarkar et al. [32]. The reactive power problems caused by renewable energy generators (REGs) connected to electrical power electronic converters (PECs) are impacting both the steady-state voltage and dynamic stability. How reactive electricity is managed by power systems that rely heavily on renewable energy sources is the focus of this research. Research on REG grid codes is explored, with a focus on REGs interfaced with PEC, their control methods, and reactive power compensation capabilities. Both conventional and PEC-based reactive power support devices are compared and contrasted in this research. Finding the right capacity of support devices and coordinating reactive power among them are the main focuses of the study, which examines several ways of reactive power regulation. At the conclusion of the essay, the author offers some technical suggestions to politicians, academia, and the power industry. Ankita Arora et al. [33]. This research presents a functional NN method for shunt adjustment in PV-based grid-connected systems that is based on Legendre. In response to changes in the load current, the controller adjusts the PQ and applies compensating current. This methodology surpasses popular methods like backpropagation multilayer perceptron NN, recurrent NN, and non-adaptive conventional synchronous reference frame theory. It is built with non-linear functional Legendre expansion. Ram Karishan et al. [34]. The integration of DG into a dynamic grid is determined by grid features such as voltage and network strength. One important renewable energy source is solar photovoltaic (PV) power generation, which relies on inverters to offer consistent voltage support. This study offers reactive power control techniques for synchronous inverters that make use of the inverter's reactive power capabilities to improve voltage regulation at the Point of Common Coupling. Wind power integration levels can be increased by 81% using the suggested technique, according to the study, when considering renewable energy sources and network constraints. Karunakaran Venkatesan et al. [35]. This paper introduces a perfect method for managing the power flow in HRESs by integrating ANN with the whale optimization algorithm (WOA). The ANN forecasts control gain parameters by analyzing changes in active and reactive power on the load side, taking into account power balancing restrictions such as the availability of renewable energy sources, the state of charge of storage elements, and the power demand on the load side. This approach reduces operational costs and power flow unpredictability by taking grid electricity tariffs into account on a weekly and daily basis. The plan is put into action and evaluated in comparison to other methods in MATLAB/Simulink. An optimum control strategy for managing power flow in HRESs is presented in this paper by merging ANN with the Whale Optimization Algorithm (WOA). The ANN forecasts control gain parameters by analyzing changes in active and reactive power on the load side, taking into account power balancing restrictions such as the availability of renewable energy sources, the state of charge of storage elements, and the power demand on the load side. This approach reduces operational costs and power flow unpredictability by taking grid electricity tariffs into account on a weekly and daily basis. The plan is put into action and evaluated in comparison to other methods in MATLAB/Simulink. Elhor Abderrahmane et al. [36]. The effect of MPPT algorithms on PV system efficiency is the subject of this thesis. On both the off-grid and on-grid systems, it evaluates multiple MPPT algorithms. Incremental Conductance, P&O, OCV, and a new NN are the algorithms that are simulated to work in different environments. Faster response time, more effectiveness, and less oscillation are all hallmarks of the NN technique compared to more conventional approaches. The impact of external factors on the efficiency of the system's output is also investigated in the research. Mustafa Inci et al. [37]. This work presents a new approach to managing grid-connected fuel cells' energy consumption, with the dual goals of reducing electrical energy demand and eliminating reactive energy consumption. This method guarantees that the grid's voltage and current are consistently aligned with the power factor, and it efficiently avoids demand charge penalties. Both case studies and testing with different inductive load banks show the method's validity. Mithun Madhukumar et al. [38]. In order to maximize array power extraction, satisfy load demands, and feed excess power back into the AC grid, grid-integrated PV systems are the focus of this study. In order to improve performance and reduce error, the research looks at various MPPT control algorithms that use the incremental conductance approach. Power quality, grid synchronization functions, and network stability are all covered in the article. The results produced by the INC algorithm were satisfactory and up to par. Prakash Prajapat et al. [39]. This study presents a NN controller for grid-connected PV systems that optimizes power point tracking. The components of the system are a grid, a three-phase voltage source inverter, a boost converter, and a PV array. We use MATLAB/Simulink for system design and simulation, and the NN toolbox for NN training. Analyzing the proposed controller in contrast to conventional P&O MPPT controllers verifies its efficacy and yields desirable results. Ibrahim Alsaidan et al. [40]. The rising need for power and the associated environmental concerns have contributed to the meteoric rise in the popularity of solar photovoltaic (PV) systems. Using a generalized NN control method based on Kalman filters, this research provides a grid-connected solar PV system that may enhance power quality and sustain a three-phase AC grid. The technology separates the components of the load current in order to effectively lower harmonics, bring the system into grid alignment, and ensure fast responses to quickly changing conditions. P. R. Bana et al. [41]. The research presents an ANN controller for a single-stage grid-connected solar system, which incorporates an enhanced MPPT method. The controller is trained with the Levenberg-Marquardt-based backpropagation method and utilizes basic mathematical equations to calculate the appropriate output modulation signals. The system guarantees efficient power extraction, reduced harmonic content, and consistent output signals during transient conditions, overcoming the constraints of conventional control methods. K. Chandrasekaran et al. [42]. The research presents a complex smart grid model that uses ANN and renewable power sources to improve the voltage profile and keep reactive power levels balanced. For effective reactive power management, the system makes use of solar and wind energy modules in conjunction with DSTATCOM. Controlling the reactive power balance of the system improves voltage profile, reduces power loss, and keeps grid satisfaction maintained. An improved voltage profile of 98.45% was the outcome of the system's performance evaluation using MATLAB/Simulink. Shilaja Chandrasekaran et al. [43]. Renewable energy sources are becoming increasingly popular because of their substantial impact on energy usage. The swift advancement of energy-efficient technology results in energy security and economic advantages, decreasing capital expenditure for electrical systems. Enhancing power system planning can enhance quality and efficiency. Machine learning methods like pattern recognition and ANN can help manage electricity needs. V

Iniya et al. [44]. This study explores the compensation of reactive power supplied to the grid-connected inverter of a solar system, emphasizing the utilization of a LUO converter and a fuzzy logic controller for power transfer regulation. The simulation findings demonstrate regulated reactive power in the grid tied PV system. Kamran Zeb et al. [45]. The solar PV business is advancing quickly, but challenges must be resolved when integrating PV with the grid. The study effectively regulates DC-link voltage, active power, and reactive power in a 3-kW single-phase two-stage transformer less grid-connected inverter by employing Adaptive-PI and Adaptive-Sliding Mode Controller. The controllers are durable, reliable, quick, and resilient, and are not affected by changes in active and reactive power. The results demonstrate enhanced system dynamics. B. Babes et al. [46]. In order to get the most out of a three-phase shunt APF grid-connected PV system that powers an arc welding equipment, this study recommends employing a metaheuristic optimized multilayer feed-forward artificial neural network controller. The ANN-ACO MPPT controller optimizes the ANN by altering the connection weights and biases using an ant colony optimization (ACO) algorithm. When it comes to improving PQ and making distortion-free transmissions, the controller meets grid criteria. Superior MPP tracking, higher efficiency, and less steady-state oscillation were shown in tests conducted on a 12.2 kW PV system in comparison to conventional Incremental Conductance (INC) methods. O. E. Okwako et al. [47]. This study introduces a PV system with battery storage that operates a Unified PQ Conditioner (UPQC) to efficiently resolve PQ concerns. The shunt active filter of the UPQC is regulated by an ANN, which simplifies control intricacies and reduces harmonic issues caused by non-linear grid loads. The model is evaluated in several situations, and the suggested controller achieves a THD percentage that falls within the IEEE-519 standards, guaranteeing efficient power supply and grid stability. Satyajeet Sahoo et al. [48]. Renewable energy sources and sustainable materials are the focus of this study, which examines a PV-based grid-connected hybrid energy system (HES) that also makes use of wind, solar, fuel cells, and hydro/water resources. Using artificial neural networks (ANNs), the study presents a power management approach for a photovoltaic (PV) system that combines lithium-ion batteries with a hybrid energy storage system that features supercapacitors. Testing on a typical PV system demonstrates the efficacy of the method, which increases the lifespan of Li-ion batteries by reducing their stress and peak value. Christian Utama et al. [49]. The growing number of renewable distributed generators, particularly PV systems, has led to operational problems like voltage fluctuations and line congestions. To address these issues, an ANN is proposed to predict optimal reactive power dispatch in PV systems. The ANN-based controllers, based on Shapley Additive Explanations (SHAP), show superior performance in reducing voltage problems and line congestions, while achieving ACOPF-level performance. This approach promotes data privacy and reduces computational burden. Prateeksha Khare et al. [3] In order to track the maximum power output of a solar PV panel, this research uses ANN approach. A boost converter, proportional resonant controller, and synchronous reference frame are all part of the system. Realistic dynamic scenarios demonstrate the effectiveness of the suggested solution. Y. Kırçiçek et al. [50]. For PV systems connected to the grid that operate on a single phase, this study introduces an innovative adaptive energy management algorithm (AEMA) that integrates active and reactive power control. The software analyses the PV system for possible operating situations and keeps an eye on the load's and inverter's active and reactive power. In addition to assisting the grid with reactive power, the PV system is capable of producing active power as well. The inverter receives reference current signals from the AEMA with PQ algorithm, which determines the demands of the reactive power load. Improving grid power reliability and clean energy production are both addressed in the project. Kanchan Bala Rai et al. [51]. This article introduces a controller for shunt correction in PV interfaced grid systems that is based on artificial neural networks (ANNs) and uses Hermite functions. To address PQ issues including load variations, low power factor, reactive power needs, and current harmonics, the HeANN algorithm is employed. At the junction of various electrical systems, the shunt APF injects compensatory current. To fulfill the active power needs of the load, the inverter is connected to the PV system through its DC terminals and supplies electricity. With respect to convergence, computing load, and total harmonic distortion, this control strategy outperforms previous methods. Unal Yilmaz et al. [4]. This paper suggests a way for controlling active and reactive power in a grid-connected single-phase Proton Exchange Membrane Hydrogen Fuel Cell (PEMFC) using an ANN. The control structure is designed to achieve minimal harmonic distortion, excellent power factor performance, and a simple, comprehensible design. The approach was utilized on a 6 KW prototype and evaluated in five situations using nine activation functions, resulting in a power factor of 1 and a total harmonic distortion below 0.99.

2.2 GAP OF STUDY

The research gap addressed by this thesis lies in the integration of NNs for simultaneous control of active and reactive power in grid-connected PV systems under the influence of non-linear loads. Previous studies have separately explored NN applications in MPPT or inverter control but not the combined approach in a singular system. Furthermore, most existing models do not sufficiently address the complexities introduced by non-linear loads on the grid power quality. This research bridges this gap by developing a comprehensive NN framework that ensures optimal power management while maintaining power quality, presenting a significant advancement over traditional control methods in the face of real-world grid conditions.

3. METHODOLOGY

3.1 INTRODUCTION

3.1.1 Overview

This research addresses the complexities of managing power in grid-connected PV systems, particularly when interfaced with non-linear loads. It employs AI, specifically NNs, to optimize and control power management in such intricate scenarios. The study uses a meticulously designed model comprising a PV system, a DC/DC boost converter, and a DC/AC inverter, using MATLAB/Simulink as the primary tool for modelling and simulation. NNs are characterized by their adaptability and learning capabilities, with two interconnected roles explored. The first is their capability in MPPT, which ensures PV systems operate at peak efficiency due to fluctuating environmental conditions. The second role is to control a DC/AC inverter, which manages both active and reactive power, ensuring the reliability and stability of the grid, especially when connected to non-linear loads. The research aims to provide insights into the optimal functioning of grid-connected PV systems under ideal conditions and explore performance under practical, challenging, real-world conditions.

3.1.2 Object

The main goal of this study's methodology is to optimize the performance of a grid-connected PV system that is interfaced with non-linear loads by designing, simulating, and evaluating a control mechanism that is based on neural networks. The NN are intricately developed to achieve MPPT and to optimize the active and reactive power delivered to the grid. By incorporating complex, non-linear load scenarios, the research seeks to extend the conventional boundaries of study, offering insights not just on theoretical or ideal conditions but under practical, real-world scenarios indicative of contemporary power systems.

In essence, the objective is twofold: to validate the efficiency of NN in enhancing power extraction from PV systems and to evaluate their effectiveness in ensuring PQ and reliability when connected to a grid with non-linear loads. Every stage, from the NN design and training to the simulation of the entire system, is methodically planned to extract quantifiable data that would be instrumental in assessing the viability and efficiency of this integrated approach in real-world applications.

3.2 SIMULATION TOOLS AND SOFTWARE

3.2.1 MATLAB/Simulation

MATLAB/Simulink is a flexible modelling, simulation, and analysis utility for multidomain dynamical systems. Using Simulink's block diagramming interface, which offers a set of customizable libraries and integrates seamlessly with MATLAB, users can construct simulation models. One can model systems with characteristics such as electric, mechanical, and fluid flow, and then design simulation control algorithms such as PID and supervisory control for these systems. The libraries in Simulink are a collection of elements that can be utilized across models. Custom libraries can be created for specific requirements or to incorporate frequently used components, as Simulink libraries are immutable [52].

3.2.2 Virgin and Library

By using Deep Learning Toolbox, Simulink Control Design, and Sim’s cape Electrical These libraries are specifically designed for deep learning applications, control system design, and electrical system modelling, respectively. The Deep Learning Toolkit allows deep NN to be designed, trained, and integrated into simulations. Simulink Control Design provides tools for systematically designing and tuning control systems within a simulation environment. Finally, Sim’s cape Electrical specializes in the modelling and simulation of electrical systems and components, which may be particularly useful for any work involving electrical circuits or power systems. These specialized libraries are part of the larger ecosystem of Simulink libraries that provides blocks and subsystems for a wide range of applications, which can be customized or extended by creating custom libraries. This allows a high level of flexibility and specificity in modelling and simulation tasks.

3.3 MODELING OF THE PV SYSTEM

3.3.1 Introduction

The solar cell is the central component of the PV system, serving as the essential section of the PV panel. Its primary function is to convert solar radiation into electrical electricity. The literature presents several modelling examples of solar cells. Various parameters are present in every cell, which vary based on the type of cell and the surrounding circumstances. In the PV module, many cells are connected in both series and parallel, and various protective systems are employed. As the primary component of the PV system, the PV cell's functionality and the various models that are employed both of which are covered in this chapter must be highlighted.

3.3.2 PV Array

PV cells convert the sun's rays into electricity, a process known as solar energy generation. This phenomenon is known as the PV effect [52]. Light energy is converted into electrons—subatomic particles with a negative charge when it reaches a PV cell. The cell's inherent potential barrier facilitates the conversion of electrons into PV energy, which can subsequently be utilized to generate an electric current in a circuit. The PV effect is visually represented in Figure 3.1.

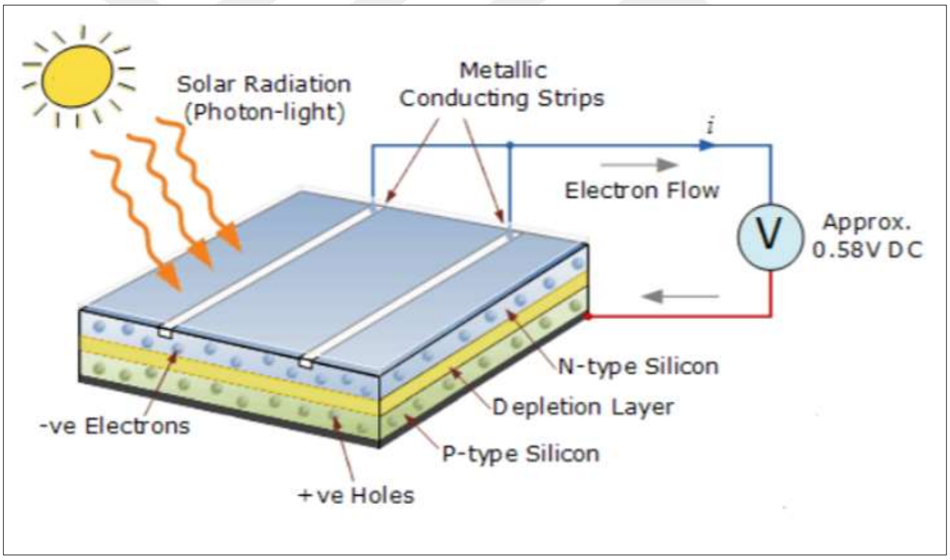

Figure 3.1: The PV Effect.

Silicon forms the junction of a PV cell. Particles called photons make up solar radiation. A photon's energy and wavelength are its defining characteristics.

$$E = h\frac{c}{\lambda} \tag{3.1}$$

Were

E: photon energy [J]

h: Plank's constant ($6,626 * 10^{-34}$ [J.s])

c: the speed of light (299 792 458 [m/s])

λ: wavelength of photon [m].

An electric current can only be generated when the energy of a photon surpasses the energy gap of the material. As a function of both temperature and the amount of sunlight reaching the array, PV cells have non-linear properties. The literature on MPPT describes a number of different PV cell models. The single-diode model describes a circuit that is similar to a PV cell [7]. To combine or merge.

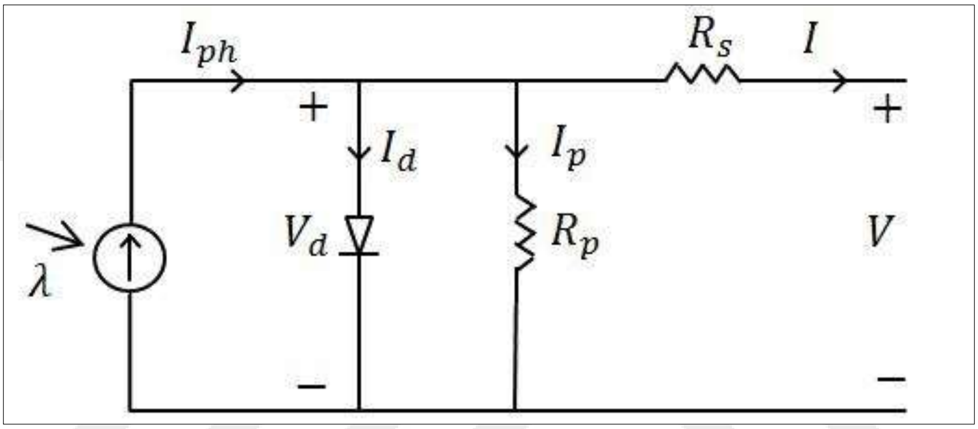

Figure 3.2: Solar Cell Equivalent Circuit.

A series resistance and a parallel resistance must be added to the current model in order to account for these losses in the cell model. Rs, or series resistance, is a measure of the power loss due to a number of factors such as the cell's metal grid, the conductivity of the p and n layers, metal contacts, and current collecting buses. The value of ab has a significant impact on the cell's fill factor. The shunt resistance, abbreviated as Rsh, is mainly responsible for correcting errors and flaws that occur during the cell's production [53]. The equations that represent the current-voltage (I-V) characteristics are as follows [54].

$$I = I_{Ph} - I_d \frac{v_d}{R_d} \tag{3.2}$$

$$V_d = IR_s + V \tag{3.3}$$

$$I_d = I_0 \left[exp\left(\frac{qV_d}{AKT}\right) - 1\right] \tag{3.4}$$

$$I_{ph} = [I_{sc} + K_l(T - T_r)]\lambda \tag{3.5}$$

According to this context, Jph is the photocurrent, $\boldsymbol{Vd}$ is the average current through the diode, and Xd is the average voltage across all PV cells. At reference temperature Tr, the current of reverse saturation [54] While A is the ideal factor of a diode, I0 is the notation for A. The letter T stands for the solar cell panel's temperature in Kelvin. At the reference temperature and radiation, Isc denotes the short circuit current, Kl stands for the short circuit current temperature coefficient, and λ is the solar radiation. K is the symbol for the Boltzmann constant, which is equal to 1.38 x 10-23 J/K. With a value of 1.6 x 10-19 Coulombs, the electron charge is represented as q.

$$I = I_{ph} - I_0 \left[\exp\left(\frac{V+IR_S}{\alpha V_T}\right) - 1\right] - \frac{V+IR_S}{R_{sh}} \tag{3.6}$$

The l-diode/2-resistors circuit is frequently employed to investigate the characteristics and operation of a PV cell. To determine the relationship between voltage V and electric current I [53]. The five unknown parameters in the equation, Jkh, $J0$, ab, and ayh, are used to generate the cellular model. The unknown value of the parameter β is strongly correlated with the cell's material composition. Therefore, using α as an approximation constant is a viable choice. Use of the three aforementioned cell functional points is one way to get unknown parameters. A PV module's current-voltage and power-voltage characteristics at 25°C and different irradiation levels are shown in Figure 3.3. The features of the PV module at 1000 $Ym2/$ at various temperatures are illustrated in Figure 3.4. The power rate dictates the number of solar modules that must be linked in parallel within the PV array. N modules linked in a succession create each string. The PV array's output current (Ipv) and voltage (Vpv) can be calculated using the following equations.

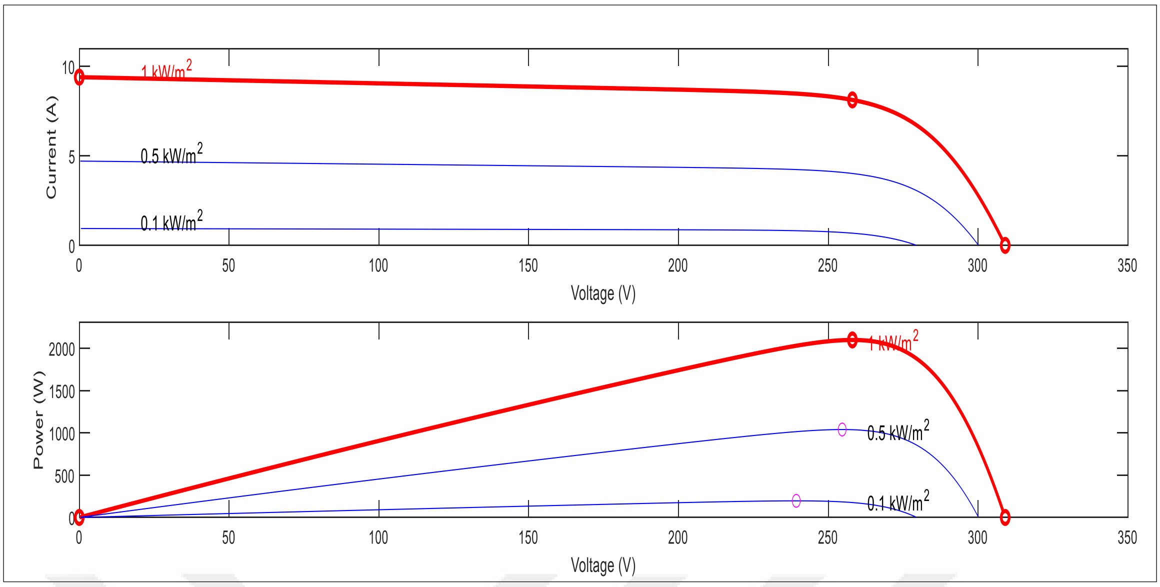

Figure 3.3: Solar Cell Characteristics At 25ºc.

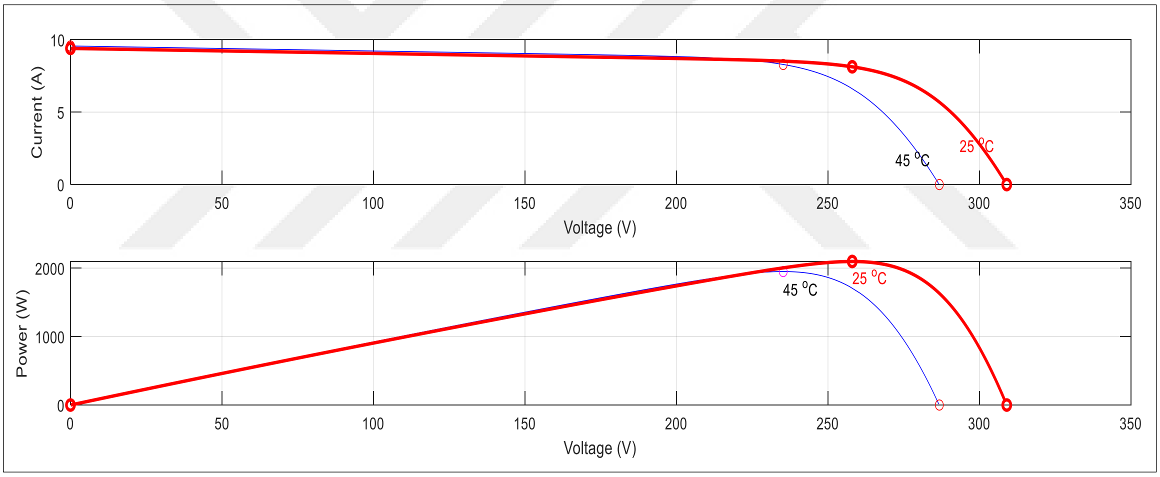

Figure 3.4: Solar Cell Characteristics At 1000 Wm^2.

In accordance with the short circuit condition, the current passing through the cell's short, circuited terminals is$\boldsymbol{U}su$, resulting in an absence of voltage at those terminals. By substituting the given values into Equation 3.6, one obtains Equation 3.7.

$$I_{sc} = I_{ph} - I_0\left[\exp\left(\frac{I_{sc}R_s}{\alpha V_T}\right) - 1\right] - \frac{I_{sc}R_s}{R_{sh}} \tag{3.7}$$

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 [55]. Consequently, the equation (3.8) is expressed as follows:

$$I_{ph} = \frac{R_{sh}+R_s}{R_{sh}} I_{sc}, Rsh \gg Rs \text{ so } Iph \cong Isc \tag{3.8}$$

The operational point for this particular example is represented by the coordinates (I, V) = (0, Voc). When this is inserted into equation 6, the following outcome is obtained in equation (3.9):

$$0 = I_{ph} - I_0 \left[\exp\left(\frac{V_{oc}}{\alpha V_T}\right) - 1\right] - \frac{V_{oc}}{R_{sh}} \tag{3.9}$$

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 Iph into equation (3.10):

$$I_{ph} = I_{ph-ref}\left(\frac{G}{G_{ref}}\right) \tag{3.10}$$

we arrive at the resultant expression for I_0.

$$I_0 = \frac{G I_{sc,T_r} - \frac{V_{oc}}{R_{sh}}}{G_{ref} \exp\left(\frac{V_{oc}}{\alpha V_T}\right)} \tag{3.11}$$

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.

Modelling the solar array is an essential component in the simulation study of PV systems, as it establishes the groundwork for evaluating the performance of the system across diverse operating conditions. A prominent technical computing software, MATLAB, was employed to select a pre-configured model that served as the simulation framework for the solar array module. By doing so, a targeted examination of the solar array's performance was feasible through the modification of model parameters to correspond with empirical data.

Consequently, this customized the simulation environment to mirror the attributes of the solar array being studied.

The efficacy of a solar array is heavily influenced by its electrical characteristics, which determine its maximum power output, efficiency, and ability to meet load or grid demands. The parameters that are established in the MATLAB model establish the operational parameters and limitations that govern the solar array's functionality. To ensure an exact depiction of the system's potential output and response to environmental changes, these parameters were rigorously allocated values in accordance with the solar array's datasheet specifications or derived from empirical measurements. The table (3.1) below encapsulates the key electrical parameters inputted into the MATLAB model for the solar array.

Table 3.1: Parameters of the Model PV When For 25°*c*, 1000 W/M^2.

Parameter	**Value**
Maximum Power (Pmax) (W)	349.59
Cells per module (N_{cell})	80
Open circuit voltage (V_{oc}) (V)	51.5
Short-circuit current (Isc) (A)	9.4
Voltage at MPP (Vmp) (V)	43
Current at MPP (Imp) (A)	8.13
Temperature coefficient of Voc (%/ºC)	-0.36
Temperature coefficient of Isc (%/ºC)	0.09

The chosen submissions were meticulously selected to accurately represent the performance of the solar module under standard test conditions (STC). Pmax represents the peak wattage output of a PV module under STC. The number of cells per module (Ncell) indicates the physical size of the PV module and its ability to harness solar energy. Voc and Isc provide crucial data on the open-circuit and short-circuit conditions, essential for safety and maximising power efficiency. The Vmp (maximum power voltage) and Imp (maximum power current) are the critical operational stages at which the module can generate its maximum power output. These parameters are crucial for the progress of MPPT algorithms. Understanding the temperature coefficients of Voc (open-circuit voltage) and Isc (short-circuit current) is essential for grasping how voltage and current change with temperature.

The coefficients have a substantial impact on the module's performance in various environmental conditions.

By utilizing the MATLAB simulation, one can dynamically examine the impact of these parameters on the output of the solar array. Maintaining an optimal power transfer to the load or grid while adapting to changing environmental conditions is of particular significance for such systems. Simulation studies enable the prediction of system performance, identification of potential problems, and optimization of operation—all while obviating the necessity for expensive field investigations. Moreover, in a controlled and repeatable environment, the simulation permits the examination of the solar array's integration with additional system components, including inverters, storage units, and grid interfaces.

3.4 DC/DC BOOST CONVERTERS

3.4.1 Introduction

Electronic circuits for the precise management and transformation of electrical power are fundamental building blocks of the power electronics industry. The DC/DC Boost Converter is a key topology among power conversion methods, particularly in situations when a greater voltage must be achieved from a lower one. The inductor at the heart of a boost converter stores and releases energy to aid the voltage conversion.

The Boost Converter is based on a modified version of the power-transmission concept; in this case, the current path between the energy storage and load components is changed via switching elements. The converter is a time-varying system since the process is not continuous but rather occurs at intervals indicated by the switching frequency. The intrinsic nature of the boost converter provides for a small design, excellent efficiency, and the flexibility to offer a controlled output voltage over a wide variety of input voltages and load situations.

The boost converter is adaptable both in terms of design and use; it may be applied to a wide variety of systems, from PV and fuel cell applications in renewable energy systems to the battery voltage control in automobiles and portable gadgets. Better performance, longer battery life, and reliable power delivery are all possible thanks to the inverter's capacity to take advantage of control techniques.

3.4.2 Modeling of the DC/DC Boost Converters

To model a DC-DC boost converter mathematically, a series of equations and representations must be created to describe the converter's behaviour and efficiency. A DC boost converter is an electrical circuit that decreases current and raises voltage from input to output. Mathematical modelling is a crucial technique used to analyse and simulate systems governed by the principles of physics. The strategy relies on many assumptions that are specifically suited to each scenario. For instance, state space modelling is used to address optimum control problems, while the transfer function technique is employed to analyze transient or frequency responses. The transfer function modelling technique is the preferred option among several modelling strategies. After formulating the mathematical model, many computational techniques can be employed for synthesis and analysis. To simplify the complexity of modelling. The fundamental boost converter comprises an IGBT and a diode that cooperate during the switching operation. When incorporating a DC-DC boost converter into a PV system, the mathematical equations must take into account the properties of both the boost converter and the PV cells. Equation 3.12 represents the PV system.

$$I = I_{ph} - I_0 \left[\exp\left(\frac{V + IR_s}{\alpha V_T} \right) - 1 \right] - \frac{V + IR_s}{R_{sh}} \tag{3.12}$$

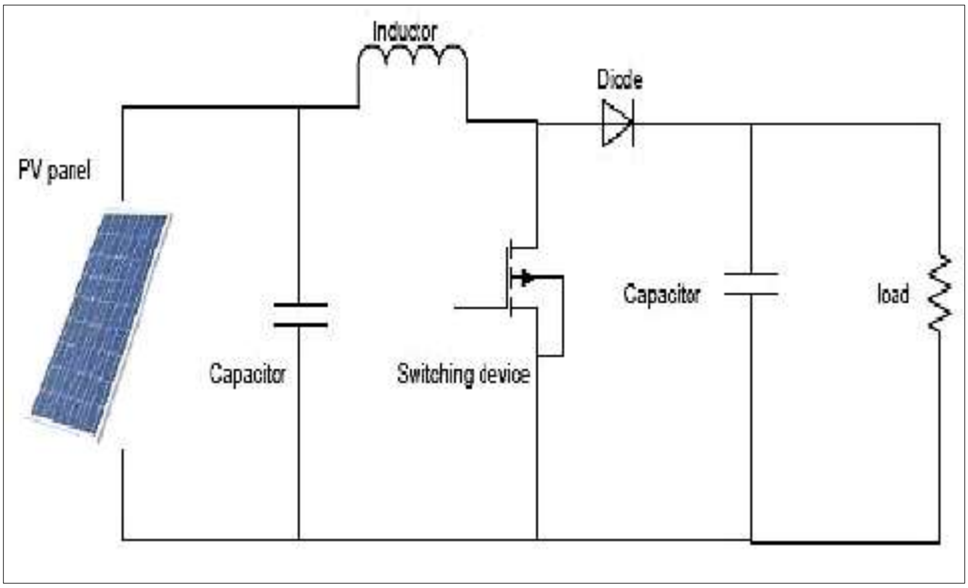

Figure 3.5: The Boost Converter Equivalent Circuit Connected to PV.

The mathematical modelling of the boost converter starts with the inclusion of storage devices such as capacitors and inductors, as depicted in Figure 3.4. Equations (3.13) and (3.14) provide the inductor voltage and capacitor current, respectively.

$$V_L = L\frac{dI_L}{dt} \tag{3.13}$$

$$I_c = c\frac{dV_c}{dt} \tag{3.14}$$

Figure 3.5 and Figure 3.6 illustrate two distinct circuit configurations resulting from the boost conversion process initiated at the onset of the switching operation. Inductor VL is depicted for the ON and OFF switching conditions in equations (3.15) and (3.16) respectively [56].

$$V_L = V_{in} * PWM \tag{3.15}$$

$$V_L = (V_{\text{in}} - V_{\text{out}}) * PWM \tag{3.16}$$

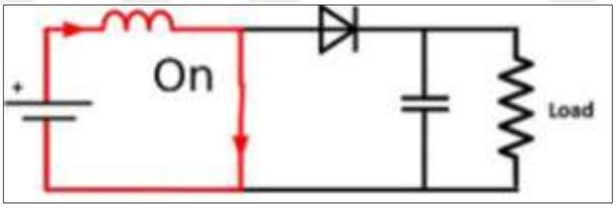

Figure 3.6: Boost Converter in ON State.

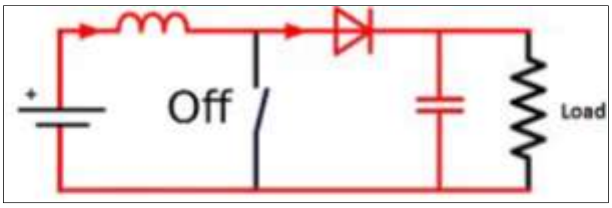

Figure 3.7: Boost Converter in OFF State.

The duration of the transition between states (3.15) and (3.16) is influenced by the PWM switching frequency. The duty cycle, as indicated in (3.17), represents the ratio of the difference between V_0 and V_{in} to V_0.

$$PWM = \frac{(V_o - V_{in})}{V_o} f_{pwm}^{-1} \tag{3.17}$$

The current flowing through can be determined by integrating in (3.18).

$$I_L = \frac{1}{L} \int V_L dt \tag{3.18}$$

The current through the capacitor is given by (3.19), where is the current through the load resistor, once has been obtained.

$$I_C = I_L - I_R \tag{3.19}$$

In the ideal model, the boost converter's load voltage may be determined from the capacitor voltage using the formula (3.20), which can be found by solving for I_C.

$$V_C = \frac{1}{C} \int I_C dt \tag{3.20}$$

The mathematical modelling process involves graphically implementing data flow on the Simulink platform. Figure 3.8 visually illustrates the connection between the differential equation that represents the boost converter system. The fundamental laws of Kirchhoff's Voltage Law (KVL) and Kirchhoff's Current Law (KCL) are employed to analyse the ON and OFF states of the boost converter. States: 3.20 Figure 3.8 displays the outcome of constructing a graphical computational model using these two equations.

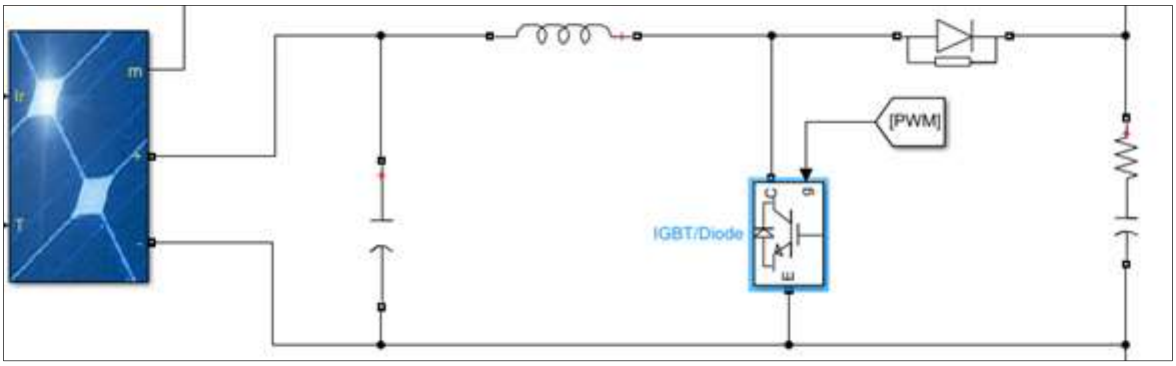

Figure 3.8: Mathematical Model Boost Converter MATLAB/Simulink.

The duty cycle D of the converter is defined as the ratio of the switch-on time to the total switching period T (where ($T = t_{on} + t_{off}$)) in equation (3.21).

$$D = \frac{t_{on}}{T} \tag{3.21}$$

The relationship between the input and the output voltages in steady state (ignoring losses) can be expressed as (3.22).

$$V_O = \frac{V_{PV}}{1 - D} \tag{3.22}$$

Specifications used in this model, the basic elements of the boost converter include an inductor (L), an IGBT with an anti-parallel diode, a capacitor (C), and an input voltage (Vi). The table (3.2) shows the parameters in the boost converter.

Table 3.2: Parameters in the Boost Converter.

Parameters	**Value**
Input voltage (V)	280 V
Inductor (L)	20 mH
Capacitor (C)	500 μF
Diode voltage	0.8 V
Output voltage	390 V
Snubber resistance Rs (Ohms)	$1*10^5$ Ω
Internal resistance Ron (Ohms)	1m Ω

In conclusion, a DC/DC boost converter added to this PV system circuit is a major boon for voltage management and flexibility. Since grid or load needs typically call for a stable and higher voltage level than what solar panels can offer directly, the PV array's voltage must be increased by the boost converter. It is essential for optimising the energy transfer from renewable sources to the power grid or storage systems to reduce losses and enhance the efficiency of the energy conversion process. The system can enhance its adaptability and responsiveness to fluctuations in solar irradiation and load requirements by adjusting the output voltage through the duty cycle of the IGBT switch. The boost converter is crucial for facilitating a seamless transition of power from the PV array to the power grid.

3.5 DC/AC INVERTERS

3.5.1 Introduction

The inverter circuit, which is connected to PV panels and integrated with a boost converter, is an innovative technological component that is critical for the functioning of renewable energy systems. The AC produced by this system transforms the DC generated by the solar panels into the voltage format utilized by most household appliances and the power grid. To elevate the voltage from the PV panels to a level that the inverter can process, the boost converter stage is utilized. It is state-of-the-art to operate the inverter using NN. NN are data-learnable computational models, which renders them highly suitable for managing the intricate and fluctuating circumstances inherent in solar power generation, including fluctuations in temperature and light intensity. Through the integration of NN into the control system of the inverter, it becomes possible to dynamically optimize the inverter's operation in terms of both PQ and efficiency.

3.5.2 Modeling of the DC/AC Inverters

This project also focuses on the design and simulation of a single-phase solar inverter using NN techniques for PWM. THD in an inverter circuit can be decreased by employing PWM. The model was constructed using a computer simulation program called MATLAB and the SIMPOWER SYSTEM block set. The design, analysis, and evaluation of PEC and their controllers all benefit greatly from the use of computer simulation. When analysing PWM inverters, MATLAB proves to be a useful tool. The benefits of utilizing MATLAB include quicker reaction time Having access to a wide range of simulation programs Various building blocks of functionality, etc.

In use is IGBT. Although there are numerous other devices available, the IGBT exhibits a greater number of advantages that are evident when compared to them. Critically, this IGBT conversion and toggling is accomplished via a variety of PWM techniques. NN are utilized in this instance to convert AC power. This technique is significantly more efficient than alternative approaches and substantially reduces harmonics in the output [57]. The schematic representation illustrates that solar panels are subjected to thermal energy derived from the sun DC power is generated by the solar panels through the process of heating. The power allocation will be managed by the MPPT system to enhance the transfer of maximum power to the DC-DC boost adapter. The DC-DC boost converter raises the voltage to the specified DC level to make it compatible with the inverter. The inverter converts DC voltage into AC voltage required for the specific purpose. Yet, the alternating voltage will show pulsations and contain harmonics, requiring the use of a filter to reduce its impact. After the AC power passes through the filter, it will be purified and ready for use by the load.

There are two separate categories of inverters. The Voltage Source Inverter (VSI) is a device in electrical engineering that transforms a constant DC voltage into an AC voltage with adjustable magnitude and frequency. The Current Source Inverter (CSI) is a frequently utilised technology in the field of power electronics. VSI is used in this context. A voltage source inverter (VSI) is an electrical device designed.

To transform a constant voltage obtained from a power supply, such as a DC power source, into an AC source with a variable frequency. Converting AC voltage to DC voltage is generally considered to be a more straightforward process compared to converting DC voltage to AC voltage. To fully optimize the performance of this topology, it is imperative to conduct meticulous study and make accurate choices regarding the high-side and low-side combination of the IGBT. In accordance with the specified criteria, we will now examine a 2 Arm Bridge - 4 single phase pulse converter for a solar inverter. In the figure 3.9, above it appears that there is a total of four IGBT transformers, namely T1, T2, T3, and T4. T1-T2 and T3-T4 are alternately turned on and off.

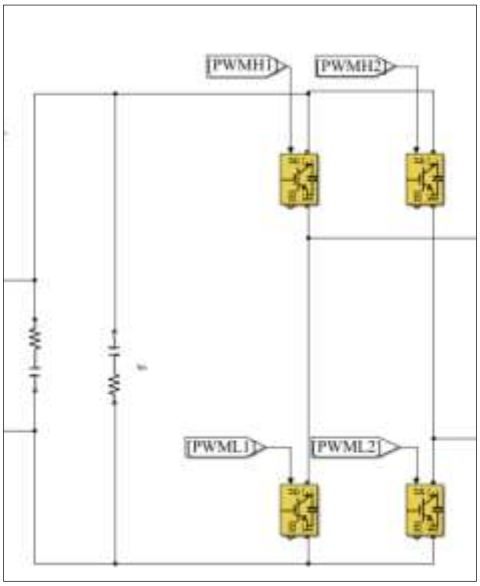

Figure 3.9: Modelling of the DC/AC Inverters.

Modelling a single-phase grid-connected DC-AC inverter involves several key equations that describe the DC-AC conversion process and the interaction with the grid. Here are the fundamental equations for such a system. In a full-bridge inverter, the output voltage is controlled by the switching states of the four switches in the bridge. The basic equation (3.23) for the output voltage (V_{out}) can be represented as:

$$V_{\text{out}} = V_{dc} \times (T_1T_4 - T_2T_3) \tag{3.23}$$

Where:

V_{pv} is the DC input voltage of PV.

T_1, T_2, T_3, T_4 are the states of the switches (either 0 or 1).

For a typical square wave inverter:

When T_1 and T_4 are ON (1) and T_2 and T_3 are OFF (0), $V_{out} = V_{dc}$.

When T_2 and T_3 are ON (1) and T_1 and T_4 are OFF (0), $V_{out} = -V_{dc}$.

When employing PWM control in inverters to provide a more sinusoidal output, the equation governing the output voltage becomes more intricate. PWM entails the manipulation of pulse widths in a manner that closely resembles the shape of a sine wave. The output voltage in this particular scenario can be expressed as a mathematical function of the duty cycle in (3.24).

$$V_{\text{out}}(t) = V_{dc} \times D(t) \tag{3.24}$$

Where: *D(t)* is the duty cycle that varies to create a sinusoidal waveform. To establish a connection with the grid, it is necessary for the inverter to synchronize its output with the voltage and frequency of the grid in equation (3.25).

$$V_{\text{grid}} = V_{rms}\sin(\omega t) \tag{3.25}$$

Where:

V_{grid} is the instantaneous grid voltage.

V_{rms} is the root mean square voltage of the grid.

ω is the angular frequency of the grid.

t is time.

The instantaneous output power P_{grid} can be calculated as:

$$Pgrid = Vgrid * Iinverter \tag{3.26}$$

Where $I_{inverter}$ is the current supplied by the inverter to the grid.
For RMS (Root Mean Square) values, which are more useful in AC analysis, the equations are (3.27), (3.28) and (3.29).

$$v_{rms} = \frac{V_{peak}}{\sqrt{2}} \tag{3.27}$$

$$I_{rms} = \frac{I_{peak}}{\sqrt{2}} \tag{3.28}$$

$$P_{rms} = V_{rms} \times I_{rms} \tag{3.29}$$

When all of the system's components, including the PV module and inverter, are operating at peak efficiency, the result is the system's overall efficiency. After taking into consideration any losses that may occur within the system, the ideal power output (Ppv) of the PV module should match the power input (Pgrid). The following equations provide the groundwork for simulating a single-phase full-bridge inverter with a boost and PV input, with the AC current passing through the filter after leaving the device. After connecting to the grid, this filter cleans up the waveform.

3.6 NEURAL NETWORK

3.6.1 Introduction

The NN algorithm, which takes its cues from the human nervous system, is a cutting-edge MPPT method. AI includes this subfield. This chapter will cover the fundamentals of NN, how they are applied to MPPT, and the several systemic stages required for their full realization.
There are a few procedures that must be completed before the network can be used. There are many elementary components operating in tandem. A network is formed by the relationships between these parts. The purpose of the network is to make predictions about the outputs by learning from the inputs and the desired outcomes. The network is fine-tuned by tweaking the weights, or values assigned to each neuron connection, until the outputs

meet the targets. Current applications for NN include voice, vision, and control, as well as identification and classification systems.

3.6.2 Modeling of the Neural Network

The artificial neuron operates at the fundamental processor level. The input is established by means of a weight. One output (a) is associated with each neuron and is accompanied by a transfer function (f) [50]. Certain neurons are additionally linked with bias (b), which is represented as a basic scalar or a weight (W) with a single input value [48]. The subsequent diagram illustrates the configuration of a synthetic neuron in figure (3.10).

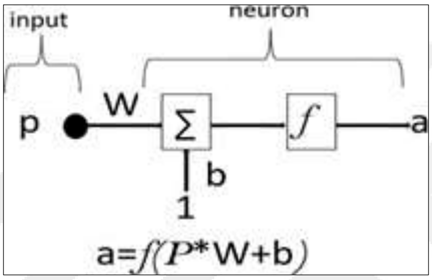

Figure 3.10: The Structure of the Neuron with one Input.

The structure of neuron with multiple inputs is shown in the next figure 3.11.

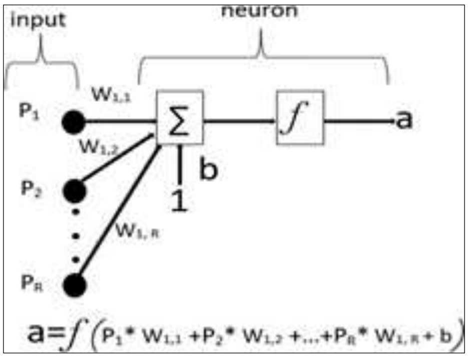

Figure 3.11: The Structure of the Neuron with R Inputs.

There exists a multitude of transfer functions, with the most employed ones being:
Figure 3.12 displays the hard-limit transfer function, which yields a binary output of either 0 or 1.
The linear function can be classified as a neural transfer function. Transfer functions are mathematical functions that determine the output of a layer based on its net input.

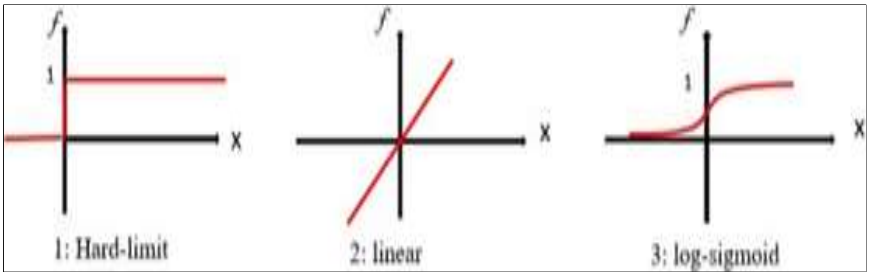

Figure 3.12: The Most Transfer Functions Used.

The variable X, denoted as X = [x_1, x_2, x_3, ..., x_n], represents the Hermite functional expansion of the input variable. The weights coefficient of the Hermite function, denoted as W_{ji}(n) = [w_1, w_2, w_3, ..., w_K], is represented by the vector W_{ji}(x). In the context of NN, the variable $y'(n)$ represents the calculated or estimated amount, which is dependent on the input variable. The summation S is obtained by multiplying the weights W_{ji} with the enlarged input vector $\phi_i(x)$ The sum obtained via computation is subjected to an activation function, namely the hyperbolic tangent function (tanh), which is non-linear in nature. This activation function is utilized to determine the estimated output signal, denoted as y', in the context of this article [51].

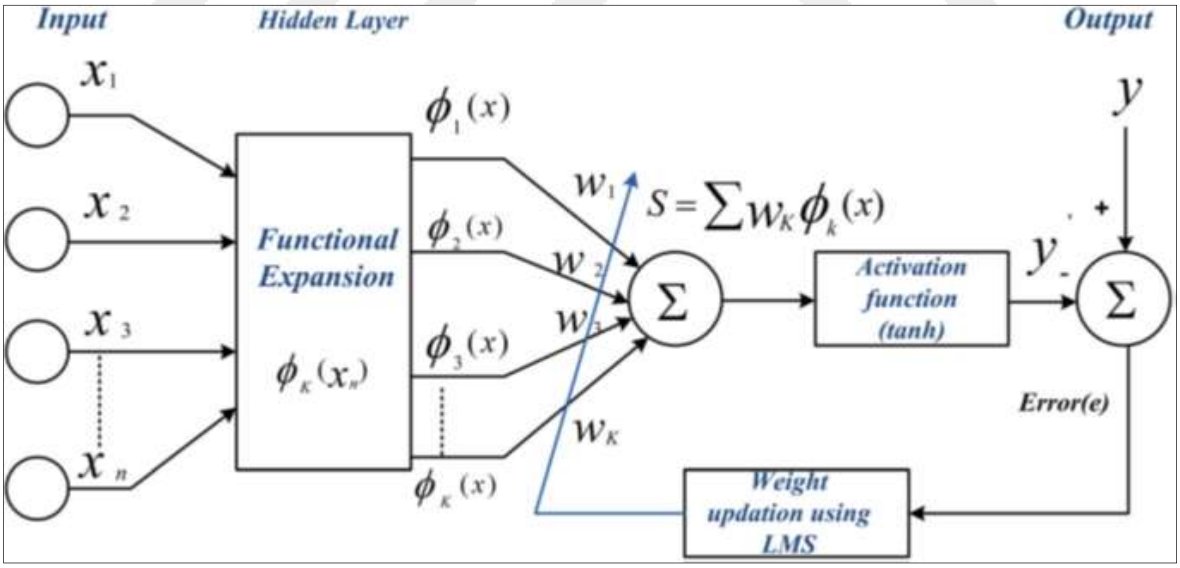

Figure 3.13: Single-Layer NN with Functional Expansion Layer Structure.

$$y' = tanh(s) \qquad (3.30)$$

The learning methodology is employed to adjust the weights using the least mean square (LMS) algorithm in order to minimize the error term "e."

$$e(n) = y(n) - y'(n) \quad (3.31)$$

$$e(n) = y(n) - y'(n) \quad (3.32)$$

$$w(n) = w(n-1) + \mu e(n) \sin\theta \quad (3.33)$$

"n" is a variable, μ is the step size, sin(θ) is the synchronizing signal, y'- is the predicted output signal, e(n) is the calculated error at each time instant, and "n" is truly a variable. Multiple neurons make up a layer. A network is formed by the interconnection of the tiers. The data that is input into the system is first processed by the input layer. To communicate with the outside world, data must pass through the output layer. There are n invisible layers that make up the hidden layers. The original network architecture is called Feedforward, and it involves connecting all of the neurons in one layer to all of the neurons in the layer below it. In contrast, the neuron is able to communicate with other neurons across numerous layers in the feedforward with shortcut connections network [49]. The Feedforward network and the Feedforward network with shortcut links are shown in figures 3.13 and 3.14, respectively [36].

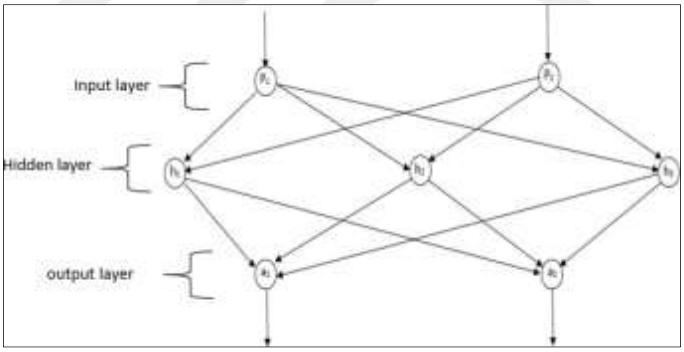

Figure 3.14: Feedforward Network.

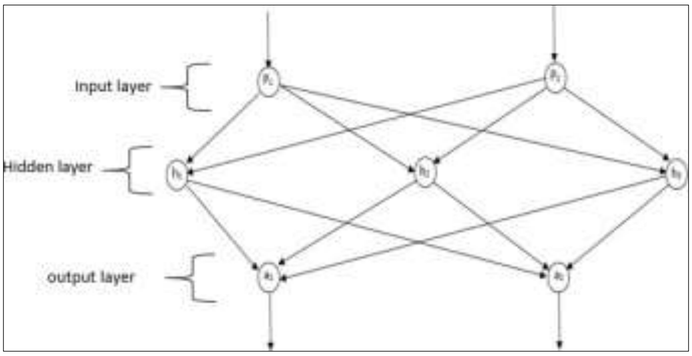

Figure 3.15: Feedforward Network with Shortcut Connections.

3.6.3 Neural Network Architecture

The topology of the NN is a critical aspect in influencing the performance of a NN designed to manage and optimize the DC/DC boost converter of a PV and inverter system. A NN structure is made up of its layers, the number of nodes (or neurons) in each layer, the activation functions used, and the way in which the neurons in each layer communicate with one another. What follows is a description of the typical features that can be recognized:

a. Input layer: The number of neurons in the input layer is proportional to the total number of inputs expected from the network. Voltage, current, temperature, radiation levels, and load demand are all possible inputs for a PV system.
b. Hidden layers: The number of hidden layers is typically proportional to the problem's complexity. A single hidden layer can theoretically mimic any function, but richer networks (those with two or more hidden layers) can capture complex interactions more efficiently. The number of nodes in each hidden layer is variable. The optimal trade-off between the network's generalizability and its tendency to overshoot is typically used to decide the number, which is set depending on the specific application and through empirical testing. Rectified linear unit (RLU), tanh, and sigmoid functions are all popular alternatives. Because of its computing efficiency and its potential to mitigate the vanishing gradient problem, RLU has gained a lot of traction in deep networks.
c. Layer of Output: The type of expected output should guide the selection of an activation function. Linear activation can be used to solve a regression problem, like forecasting a continuous number. If it is important to classify the output, the SoftMax function might be utilized for this purpose.
d. Output layer: The number of neurons in the output layer is proportional to the number of outputs needed. This could refer to the boost converter's duty cycle or the modulation index of an inverter in a PV system machine. The most common technique is called backpropagation, and it employs gradient-based optimization techniques including stochastic gradient descent (SGD), Adam, and RMSprop.

Mean squared error (MSE) is a popular loss function for regression tasks, while cross-entropy loss is utilized for classification challenges.

Overfitting can be avoided using methods like L1 and L2 regulation, dropout, and early halting. during training, the weights connecting each neuron in one layer to those in the next layer are tweaked until the loss function is minimized. The success of a network's convergence relies heavily on how well it is initialized. Initialization techniques like Xavier and He are widely utilized.

Among these are the momentum (for some optimizers), learning rate, number of periods, and batch size. Important to network performance, tuning these parameters is often accomplished through a combination of network search and random search techniques.

Using the PV system's past data as training, the network will learn to map inputs to the required output control signals and then use those signals in real time to fine-tune the boost converter or inverter's parameters for maximum efficiency.

3.6.4 Neural Network Control the DC/DC Boost Converters

For MPPT, an ANN control mechanism is designed. Two input variables—solar radiation and panel temperature—are used by an ANN control system to generate the reference voltage. By combining two signals, we found that the PV system is affected by two identical variables, such temperature and sunshine. By contrasting the measured PV with the reference PV. The Proportional Integral (PI) controller receives the error signal and uses it to generate control signals that regulate the boost converter's PWM. The MATLAB programming language was used to implement the ANN algorithm. Figure 3.15 is used to select the composition for training.

Figure 3.16: Shows the Block for Training.

When discussing PV systems, the idea of the MPP is essential. It refers to the point on the current-voltage (I-V) characteristic curve of a PV cell or module where the product of current (I) and voltage (V) is maximum. The MPP is the point when the PV system generates the most power, which is equal to the product of the MPP voltage (V_{mp}) and the MPP current (Imp).

To maximize efficiency, a NN regulates a DC/DC boost converter connected to a PV array, as shown in the figure 3.16.

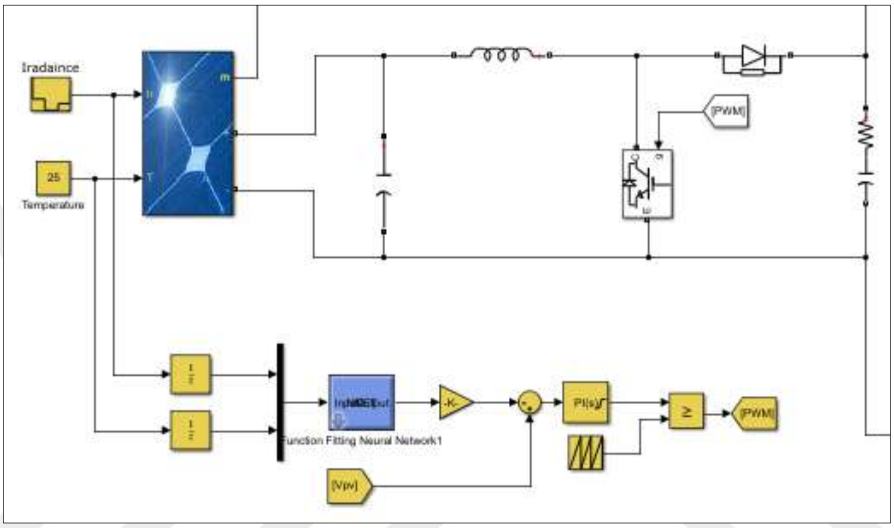

Figure 3.17: Boost Converter NN Controller.

The majority of the circuit's power comes from PV cells, which transform sunshine into electricity. The inputs to the system—radiation and temperature—the intensity of solar radiation was entered into the PV in variable proportions according to the table (3.3) that simulates weather fluctuations and changes in the intensity of solar radiation. Influence the efficiency of PV output is adjusted using real-time data collected from sensors that measure radiation and temperature. A capacitor, an inductor, a diode, and an IGBT switch make up the boost converter. This is achieved by boosting the PV output voltage until it satisfies the inverter's requirements.

Table 3.3: The Intensity of Solar Radiation Entering the PV Over Time.

Time (sec)	**Radiation (W/m^2)**
0	1000
0.3	500
0.6	250
0.9	400
1.2	750

Solar PV systems maintain a constant voltage output regardless of changes in temperature or sunshine intensity. There is no text provided. It is possible that the voltage requirements of the inverter exceed the DC output. The boost converter regulates the output voltage of the PV array. When the switch is closed, the inductor accumulates energy. When the switch is in the open position, the energy is transmitted to the load, resulting in an increase in voltage. After receiving data from the PV panels and other environmental factors, the NN controller processes the information and adjusts the duty cycle of the boost converter accordingly. The amount of power transferred during each switching cycle determines the implications for the output voltage.

An essential component is the NN controller. It is typically trained using historical data to identify patterns in the impact of radiation and temperature on PV output, among other environmental conditions. Cycle of duty We characterize the ratio of on time to off time for a switch in each cycle. In other words, the voltage produced is proportional to the duty cycle. The circuit in the figure shows a control system that uses a NN to synthesize functions, resulting in improved energy production. The circuit consists of a group of blocks.

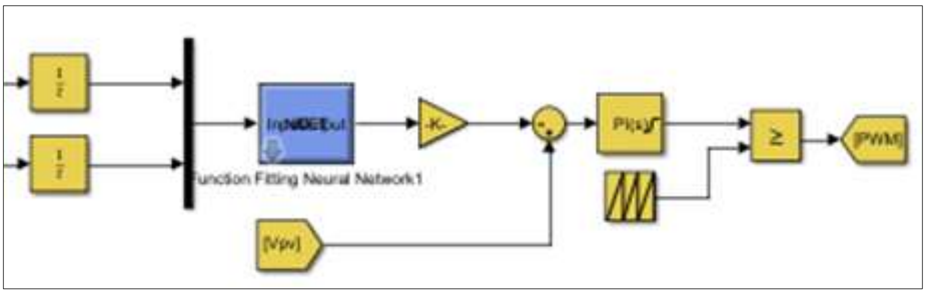

Figure 3.18: NN Blocks.

The ambient temperature and the amount of solar radiation that can be used by the PV system both play a role in how effective the PV cells will be. The data is then sent to a pre-trained NN algorithm block that can make predictions or exert control over the signal based on its inputs. Predicting the MPP of a PV system based on current environmental variables or providing direct control signals to optimize system performance are both examples. A system that sums the output from an MPP control will have a summation block (∑). Synergistic NN comprising several control mechanisms. A PWM signal is created from the combination block output. PWM is widely employed in power electronics because it allows for precise regulation of power delivered to a load with minimal thermal impact. The duty cycle of the PWM signal will regulate the switching of power electronic devices, such as transistors or IGBTs, within the actual devices of the PV system. The goal of the control system is to keep the PV system running in the MPP, increasing its efficiency and energy output in the process.

A NN is used to learn the connection between input factors and output variables, such as temperature and sunlight, to predict the optimal duty cycle for a booster converter. By training on historical data, the network minimizes variance between predictions and observed data. This information is then used to control the IGBT switching gate, which is controlled by a PWM signal. The NN constantly evaluates system performance and adjusts the duty cycle to maintain the MPP despite changes in solar radiation, temperature, or load demand.

The MPP is a crucial aspect of PV systems, where the sum of current and voltage is at its highest value. MPPT technology is essential in ensuring the PV system generates its maximum power output, which is equal to the product of the MPP voltage (Vmp) and the MPP current (Imp). The efficiency of a PV cell is nonlinear in the input voltage (I), and it varies over time due to variations in solar radiation, ambient temperature, and electrical demand. MPPT controllers are high-tech electronic gadgets that can swiftly locate the MPP, maintaining peak efficiency in PV systems. This technology ensures maximum energy output, improving system performance and increasing economic benefits for solar producers.

3.6.5 Neural Network Control the DC/AC Inverter

To improve efficiency and reliability in the field of renewable energy, inverter control is a crucial component. Since energy systems, and PV arrays, are inherently dynamic, traditional approaches, which are generally static and linear, have difficulty keeping up. The use of NN for inverter control represents an early experiment with machine learning. These cutting-edge algorithms have completely changed our strategy for optimizing inverters; they were inspired by the structure and function of the human brain. The inverter's operational parameters are determined by NN after processing a variety of inputs, including voltage, current, and temperature, to ensure that the conversion of DC to AC power is not only effective but also in sync with the grid's requirements. NN are ideally suited for this job because of their flexibility in learning from data and their capacity to handle non-linear systems. The use of NN to control inverters is a step toward a more responsive and intelligent energy environment, one that can better ensure grid stability and maximize energy usage. This breakthrough has the potential to release the full power of solar arrays, ushering in a world where clean energy is always there when we need it and always adapts to our lifestyles. This topology converts the DC power obtained from the Boost converter into the form of AC power, allowing the power to be injected into the grid.

3.6.6 Simulation Neural Network in The Inverter Control

The conversion system depicted in the figure 3.19 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 ($\alpha\beta 0$). Subsequently, these values are further transformed into a rotating reference frame ($dq0$). This rotating reference frame is utilized as input for the NN responsible for controlling the inverter.

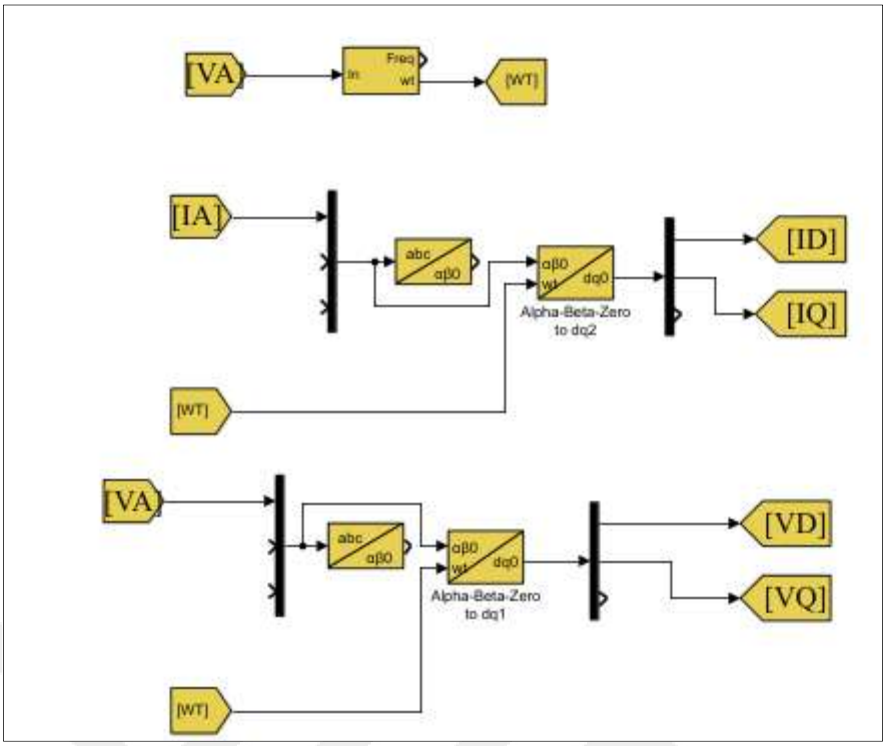

Figure 3.19: Transformation Block.

The blocks labelled as [VA], [IA], and [WT] represent the inputs of voltage, current, and angular frequency to the system, respectively. The voltage and current are usually represented in the form of three-phase AC. The symbol ωt represents the angular frequency of the system in this context, crucial for the transformation to the rotating reference frame dq0.

The output of the Clark transform is represented by the variables [ID][IQ][VD] and [VQ]. The variables ID and IQ denote the direct and quadratic components of the current, respectively, whilst VD and VQ represent the direct and quadratic components of the voltage in the rotating reference frame. The signals possess a DC characteristic and offer the benefit of being decoupled, hence enabling autonomous manipulation of the output voltage's amplitude and phase. This feature holds significance in the context of inverter control.

The utilization of these shunts in inverter control is of utmost importance due to their ability to enable the NN to process AC signals as if they were DC. The control algorithm is significantly simplified due to the absence of time-varying DC signals in the steady state. The NN utilizes the converted signals ([ID][IQ][VD][VQ]) as input and computes the optimal switching actions for the inverter to generate the desired AC output, while considering the prevailing situation and load specifications.

Figure 3.20 illustrates the recommended control strategy utilising a full bridge voltage source inverter. The phase angle reference value is determined by combining the grid voltage with pulses from the control signal(s). The ab/dq conversion supplies the control block with reference values for active and reactive power, along with the current and voltage values produced by ANN. The single-phase full-bridge voltage source inverter generates switching signals by passing the acquired reference voltage value at the output to the PWM block. When the system is functioning, all actions are carried out in a repetitive manner.

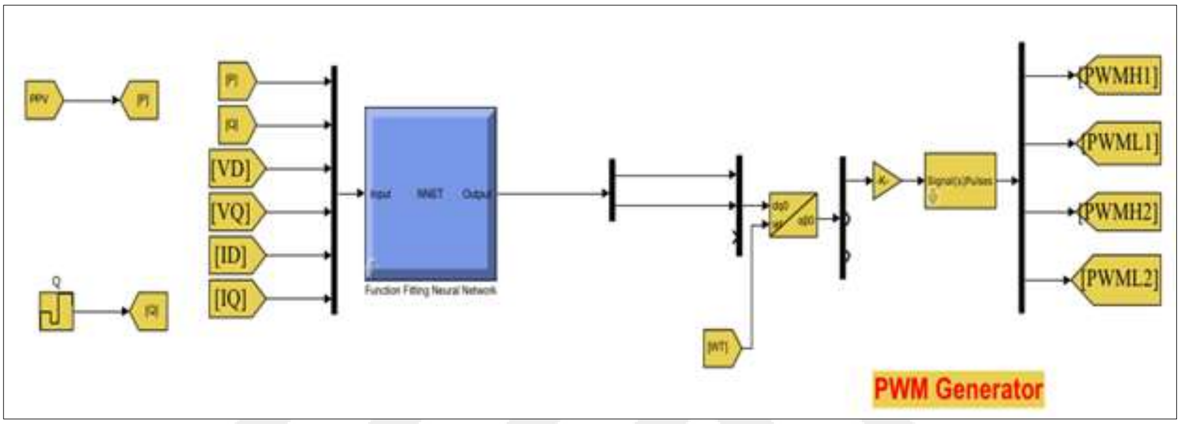

Figure 3.20: NN Design and Proposed Control Method.

Figure 3.21 displays power factor, active power, and reactive power as a vector. S1 and S2 denote the complex power input to the gride, P and Q represent the active and reactive power, and the phase angle between the current and voltage values a1 and a2 is used to regulate the amplitude of the reactive power injected into the network [4]. D-Q conversion involves converting AC waveforms into DC signals to mitigate the influence of time-varying factors. The AC signals are converted to DC and then subjected to basic computations. Equation (3.7) provides the matrix representation of the d-q transformation. "X" can represent either voltage or current depending on the situation [58].

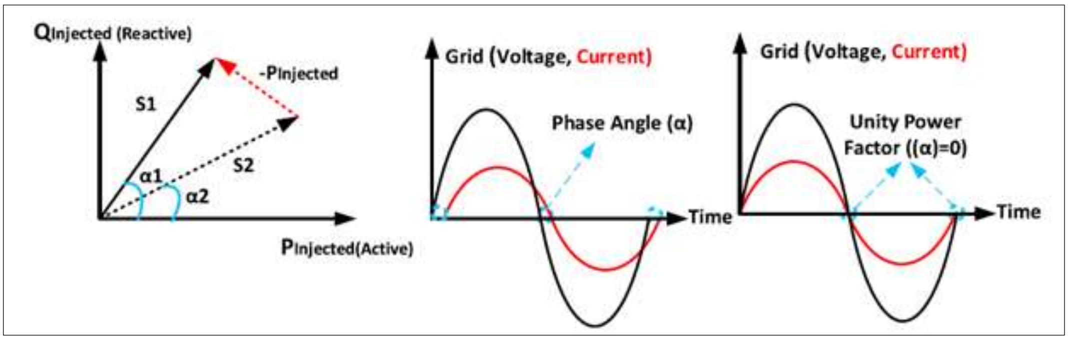

Figure 3.21: Active Reactive Power Relationship and Power Factor.

Where the P value is taken from Ppv, and the Q values are given from the table (3.4) that represents the power values to be injected into the controlled gride.

Table 3.4: Reactive Power Injected into The Gride Over Time.

Time (sec)	Reactive Power (VAR)
0	0
0.3	300
0.6	100
0.9	600
1.2	400

The inverter's control mechanism functions based on a NN structure, with PV representing the intended active power value and Q representing the desired reactive power value. The inverter must achieve the target values, which are the desired objectives.

The variables Vd, Vq, Id, and Iq are being mentioned. The power system input is converted into the dq0 reference frame to provide the NN with information about the electrical state of the system. The NN used for the function takes PV, Q, Vd, Vq, Id, and Iq as inputs and calculates the best control signals for the inverter. The model has been trained to predict the best inverter output using the given active and reactive power levels.

The inverter's operation is determined by the control signals it generates, which directly affect how the inverter adjusts its outputs to achieve the desired power transmission. Using a signal processing block in the NN allows for adjusting the outputs to match the input requirements of the PWM generator. Adjustment may require the use of scaling or filtering procedures. The variables [PWMH1] [PWML1] [PWMH2] and [PWML2] represent the high and low PWM signals of the inverter switches. The inverter controls the voltage and current output to efficiently handle the transmission of active (P) and reactive (Q) power. The NN efficiently controls the inverter's delivery of active and reactive power to the grid by adjusting the phase for active power and magnitude for reactive power of the inverter's output voltage in respect to the grid. This method enables the real-time implementation of adaptive control by utilising a NN to learn from past data. This knowledge is used to predict control actions that help preserve the stability and efficiency of the power system.

3.7 PV MODEL IN AB & DQ0 TRANSFORMER

The switching functions of a single-phase inverter are responsible for the nonlinearities and discontinuities that characterize its functioning. Converting control variables into DC values makes the controller easy to build and utilize in a synchronously rotating dq0 frame. A popular technique in three-phase systems, the dq0 conversion, is incorporated into the design of the proposed single-phase system. The conversion of dc in systems with only one phase is not easy. The dq transformation base proposed by [59], was utilized in this study.

The standard procedure before running the dq transform is to create an imaginary part, called the β component, that is 90 degrees out of phase with the original signal. The application of a phase delay equal to one quarter of the original signal's phase yields the β component, which is perpendicular to the original signal (α component).

Assuming the grid voltage is sinusoidal in shape and significantly lower in frequency than the switching frequency [60] the equations that represent the PV system in the αβ frame can be derived from Equation (3.31), Equation (3.32) and Equation (3.33). These equations are as follows:

$$L\frac{dI_\alpha}{dt} = -RI_\alpha + d_\alpha V_{pv} - V_{g\alpha} \tag{3.34}$$

$$L\frac{dI_\beta}{dt} = -RI_\beta + d_\beta V_{pv} - V_{g\beta} \tag{3.35}$$

$$c\frac{dV_{pv}}{dt} = I_{pv} - \left(d_\alpha I_\alpha + d_\beta I_\beta\right) - \left(I_{r\alpha} + I_{r\beta}\right) \tag{3.36}$$

Alpha and beta, denoted as IA and IB, respectively, constitute the inverter's output current. The inverter's control functions within the αβ frame are $d\alpha$ and $d\beta$. The beta and alpha parts of the grid voltage are denoted by Vga and Vgb, respectively. Voltage (Vpv) and current (Ipv) are the two variables that represent the PV array's performance. The terms Irα and IrH stand for the αH parts of the second harmonic current ripple. The second harmonic current ripple's αβ components can be calculated using Equation (35) and Equation (34).

$$I_{r\alpha} = -\frac{V_{gm}I_{am}}{2V_{pv}}\cos 2\omega t \tag{3.37}$$

$$I_{r\beta} = -\frac{V_{gm}I_{am}}{2V_{pv}}\sin 2\omega t \tag{3.38}$$

Once the two Clarke components, which are perpendicular to each other, have been obtained, the single-phase PV system model may be represented in the dc reference frame, which rotates at the σ angular frequency of the grid. To accomplish this, one can apply the trigonometric relationships shown in Figure 3.18 to generate the transformation matrix T. [31]. The formulae for the d-axis and q-axis components are as follows:

$$V_d = v_\alpha \cos\theta + v_\beta \sin\theta \tag{3.39}$$

$$V_q = -v_\alpha \sin\theta + v_\beta \cos\theta \tag{3.40}$$

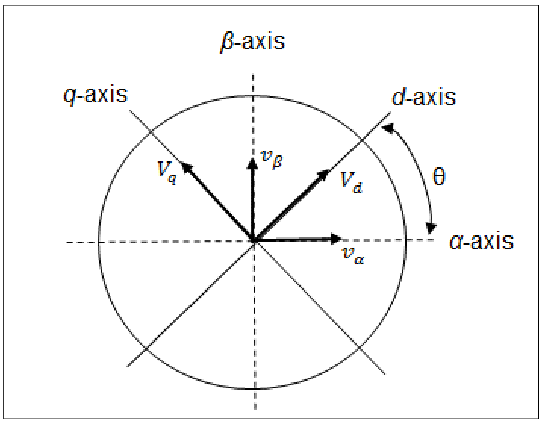

Figure 3.22: $\alpha\beta$ and dq Components Relationship.

Equation (3.41), in conjunction with Equation (3.42), yields the following expression for the transformation matrix $T \in \mathbb{R}2x2$. [46].

$$T = \begin{bmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{bmatrix} \tag{3.41}$$

where Equation 3.42 gives the displacement angle θ. Here is the expression for the transformation matrix's inverse.

$$T^{-1} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \tag{3.42}$$

The versions that are more broadly applicable for the change from α β components to dq components and back again are.

$$\begin{bmatrix} F_d \\ F_q \end{bmatrix} = T \begin{bmatrix} F_\alpha \\ F_\beta \end{bmatrix} \tag{3.43}$$

$$\begin{bmatrix} F_\alpha \\ F_\beta \end{bmatrix} = T^{-1} \begin{bmatrix} F_d \\ F_q \end{bmatrix} \tag{3.44}$$

$[Fdc]$ represents the voltage or current in the dq frame, while $[F\alpha\beta]$ stands for the current in the αβ frame.

3.8 MODELLING THE FILTER

The depicted circuit is an LC low-pass filter that is linked to the output of an inverter. Its function is to attenuate high frequency switching noise generated by the inverter, so ensuring that the current supplied to the grid is free from such disturbances. In the realm of power electronics, the filter is commonly denoted as an output filter or an electromagnetic interference (EMI) filter. The filter components comprise two inductive coils, denoted as L1 and L2, along with a single capacitor, referred to as C. Both inductors possess a value of 4.06 mH, while the capacitor is characterized by a value of 6.0172μF. The inductors are arranged in a series configuration with the line, while the capacitor is linked in parallel with the line and grounded. The arrangement described exhibits a "pi" structure, as it has resemblance to the Greek letter "π" in its shape.

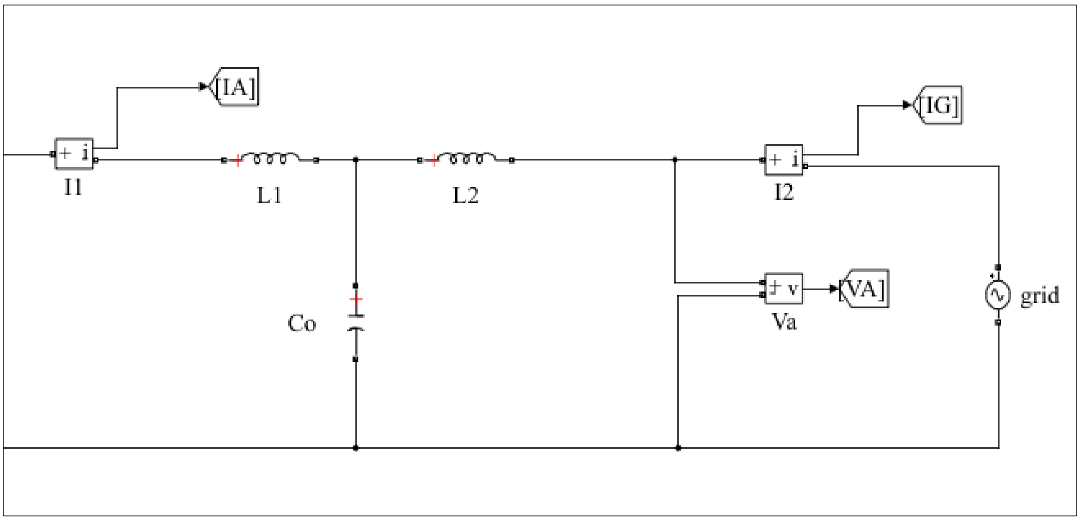

Figure 3.23: LC Low-Pass Filter is Connected to the Grid.

During the operational phase, inductors impede the passage of high-frequency current components by augmenting their impedance in direct correlation with the frequency. At higher frequencies, inductors exhibit increased impedance to the flow of electric current, resulting in the attenuation of said frequencies. The capacitor functions to establish a pathway of low resistance to the ground, specifically for high-frequency noise. This effectively results in the suppression of undesired frequencies, while permitting the intended low-frequency current to flow through the network. The grid voltage is denoted as $230\sqrt{2}$ V, representing the peak voltage of a sinusoidal waveform with a root mean square (RMS) value of about 230V. This value is commonly observed in residential power systems throughout various regions globally.

The utilization of this filter is crucial for optimizing the efficiency and durability of both the inverter and the electrical network. The filter aids in conforming to regulatory criteria for electromagnetic interference by attenuating high-frequency components. Additionally, it safeguards against potential harm to interconnected equipment and upholds the integrity of the power system's quality. The selection of inductance and capacitor values is based on the matching of the inverter's switching frequency and the network resistance, with the aim of optimizing the performance of the filter in this application. The figure 3.22 shows a networked PV system with a NN circuit to control active and reactive power.

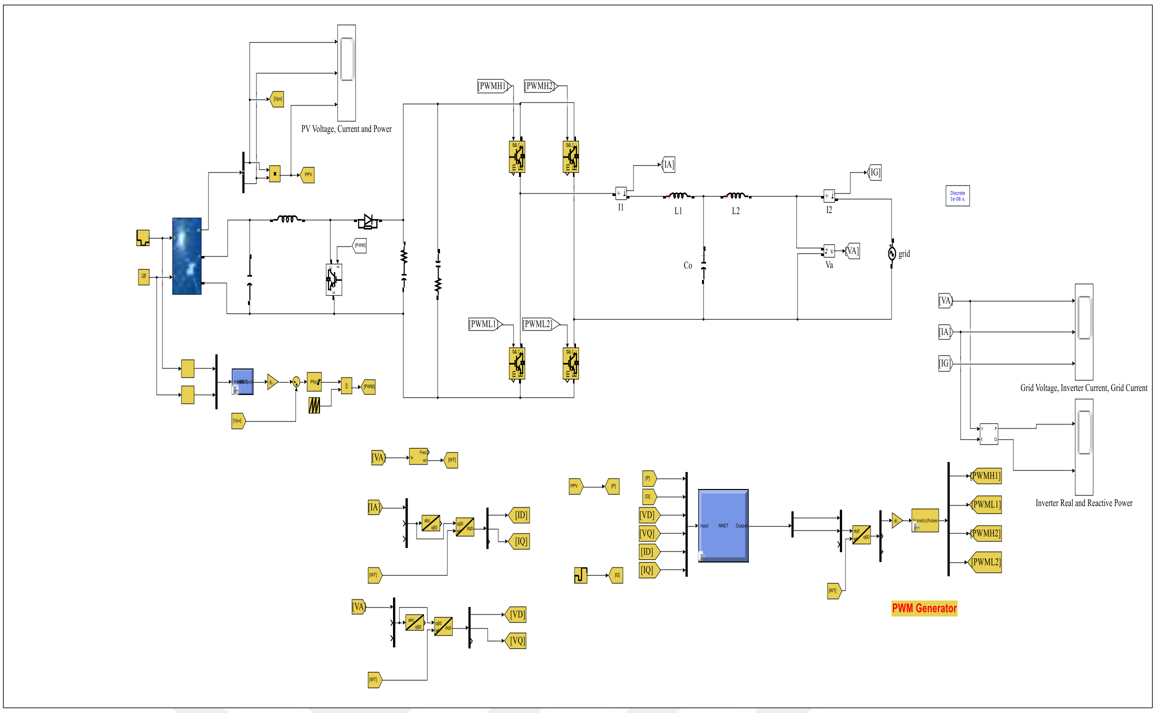

Figure 3.24: Simulation of PV System to Control Active and Reactive Power.

4. SIMULATION AND RESULT

4.1 INTRODUCTION

This thesis relies heavily on the results chapter, which provides a comprehensive presentation of the outcomes and data obtained from the extensive calculations and experimental work performed. Specifically, it details how well the NN controller handles the active and reactive power of a solar system that is connected to the grid. In this section, we examine the efficacy of the suggested control technique under a variety of variables that mimic the dynamic and frequently unpredictable nature of real-world settings. Graphs and tables illustrate the system's reaction to load and environmental changes, with emphasis on the reliability and precision of power supply. Smart inverter control for renewable energy systems takes a giant step forward with the validation of the hypotheses presented in this chapter, as well as the provision of crucial insights into the robustness of the NN model. Following sections will provide a systematic breakdown of these findings, clarifying the effect of the NN on inverter performance and grid compatibility.

The figure 4.1 shows a grid-connected PV with a boost converter and an inverter controlled by a NN. The solar panel generates DC power, which is then processed through a series of conversions to control the inverter's output to the grid.

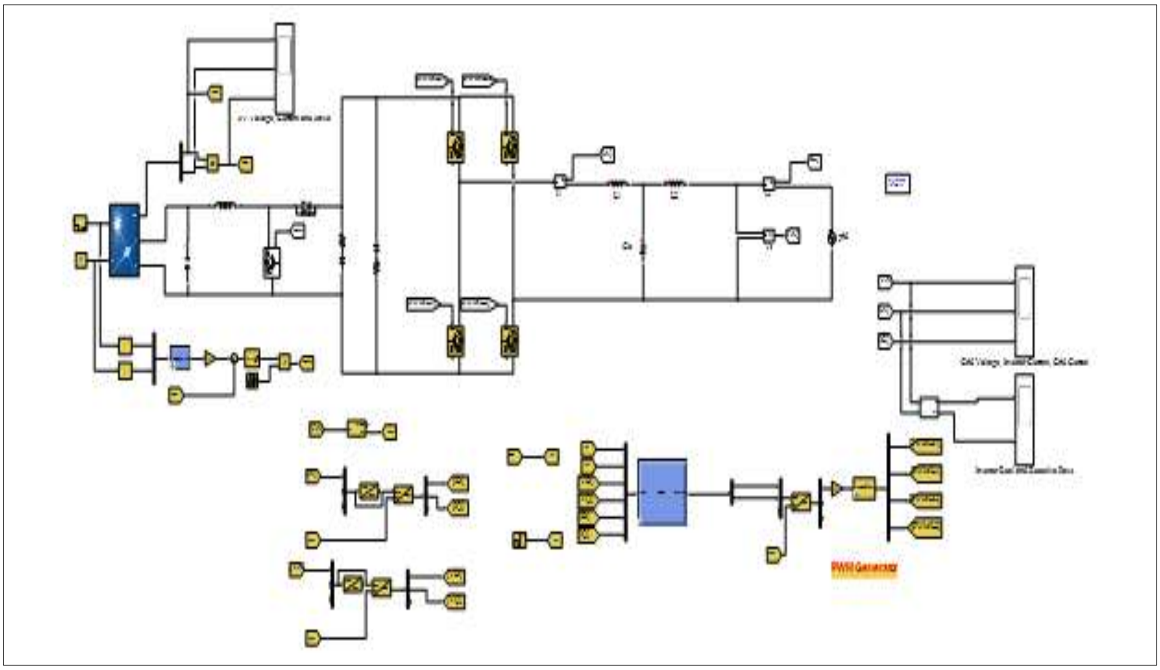

Figure 4.1: Simulation of PV System to Control Active and Reactive Power.

The DC power from the solar panel is initially directed through the boost converter to optimise power extraction from the PV system. The pure DC power is subsequently transformed into AC power via the inverter. The NN is crucial in this process as it receives inputs related to PV power characteristics and grid requirements, analyses the data, and generates control signals. The signals are inputted into a PWM generator, which controls the inverter's output by regulating the switching of its transistors.

The inverter is responsible for converting DC power from PV power into AC power matching the grid voltage, frequency, and phase. It also manages active and reactive power supplied to the grid, ensuring efficient power transmission and meeting grid regulations. The filter in the circuit is part of the filtration system that cleans the AC output before it reaches the grid.

4.2 MATLAB SIMULATION RESULT ANALYSIS

First, simulate the electrical components of the PV system and Boost converter using the settings listed in table (3.1) table (3.2) table (3.3) and table (3.4)

Secondly, simulation results demonstrate the connection of the NN to regulate the Boost converter and inverter, illustrating the control of active and reactive power. Five scenarios were utilised at various time intervals to illustrate the impact of active and reactive power on energy efficiency and quality.

4.2.1 Simulation Result Maximum Power Point Tracker (MPPT)

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 NN, MPPT becomes even more efficient. By constantly evaluating patterns in voltage and current from the solar panel, the NN learns and predicts the ideal operating voltage that accomplishes MPPT. By communicating this information to the boost converter, the duty cycle of the converter may be dynamically adjusted to match the output of the solar panels with the MPP. By boosting the voltage of the energy coming from the solar array, it is better prepared to be used by the load or stored in batteries. Since the NN can adjust to new variables on the fly, the system can reliably keep the MPP and so maximize the efficiency of the energy conversion process as it happens in real time.

The graph in the figure 4.2, shows the voltage measurement of the PV system over time when inputting data representing fluctuating solar radiation intensity with weather conditions that transitions from one state to another every 0.3 seconds while maintaining a constant temperature at 25 C^{o}. The voltage reaches its operational level quickly and then remains relatively stable thereafter. This indicates that upon start-up 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 behaviour 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.

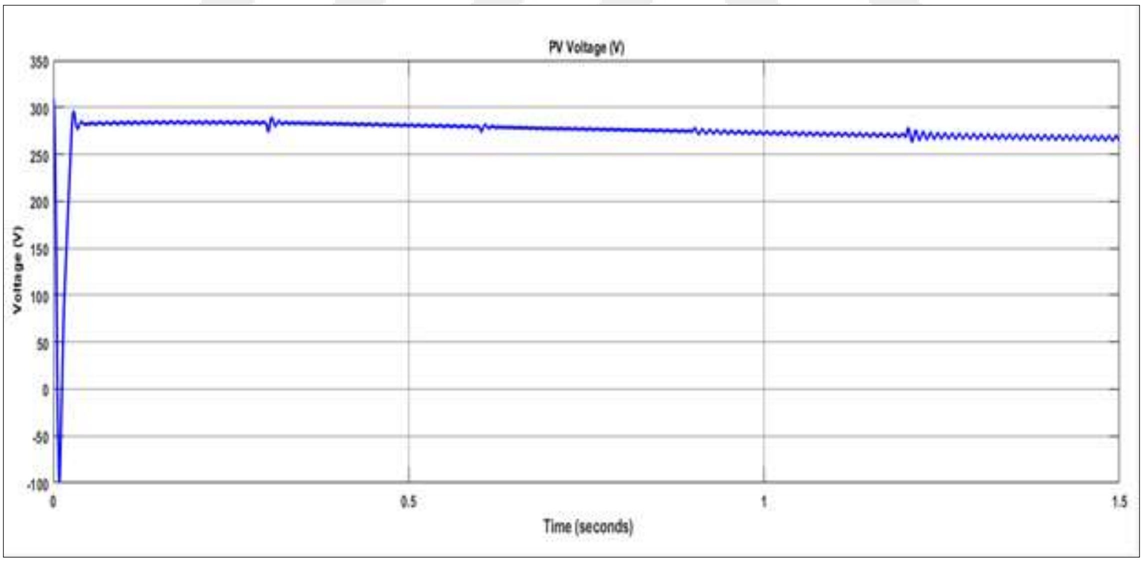

Figure 4.2: PV Voltage (V).

The graph in the figure 4.3, 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.

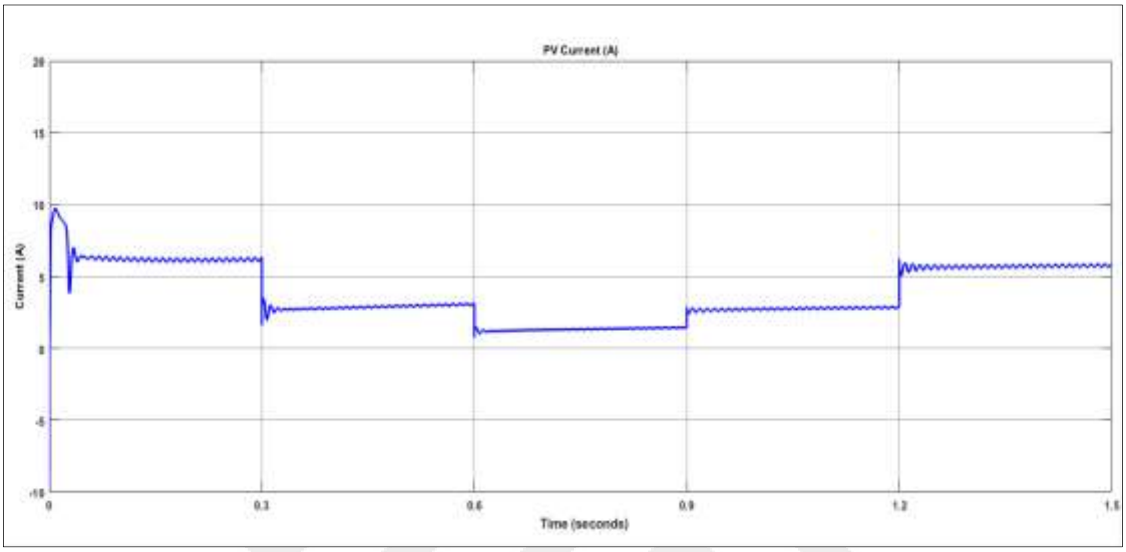

Figure 4.3: PV Current.

The graph in the figure 4.4 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. After the graphs for PV have been reviewed, we will review the graphs after linking the post converter with PV, which is controlled using the NN to obtain the MPPT so that we know if the NN succeeded in finding the greatest possible power. The voltage output of the boost converter, which is regulated by a MPPT NN, is depicted in the figure 4.5 graph. Following conversion, the PV panel's initial voltage of 260V was maintained at approximately 350V. The obtained outcome suggests that the boost converter effectively elevated the PV voltage while operating under the guidance of the NN.

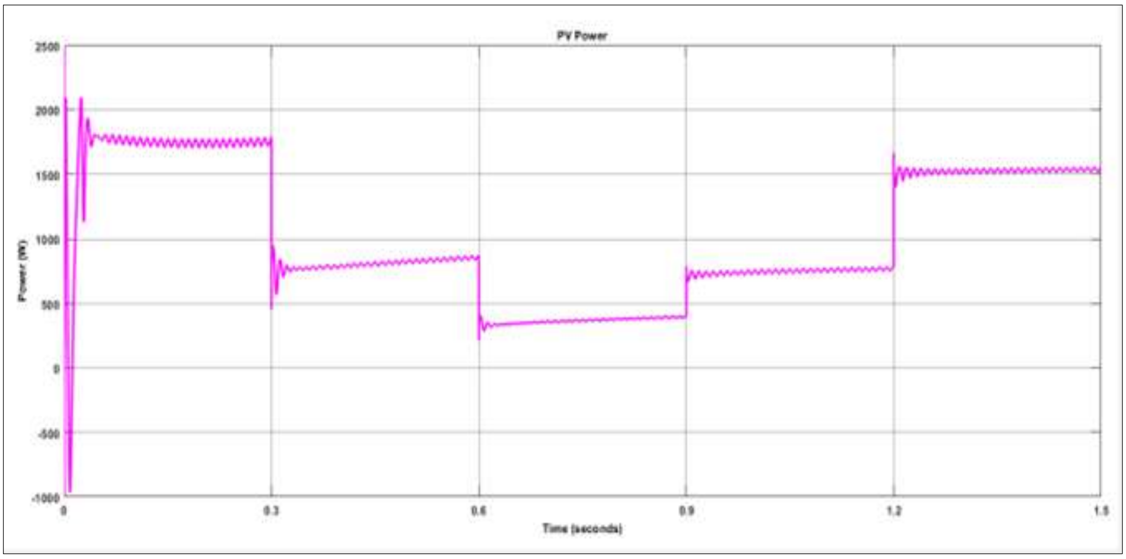

Figure 4.4: PV Power.

Successful MPPT operation is indicated by the NN effectively maintaining the output voltage at the desired level, which is greater than the input, as indicated by the relatively stable line at 350 V. A marginal voltage ripple may be ascribed to the NN control process or minor variations in the PV power output. When an MPPT system is operating effectively, substantial spikes or declines are absent. The increase in voltage from 260 to 350V signifies that the NN has accurately identified the optimal duty cycle for the inverter, which maximizes power output in accordance with MPPT principles and PV panel capabilities.

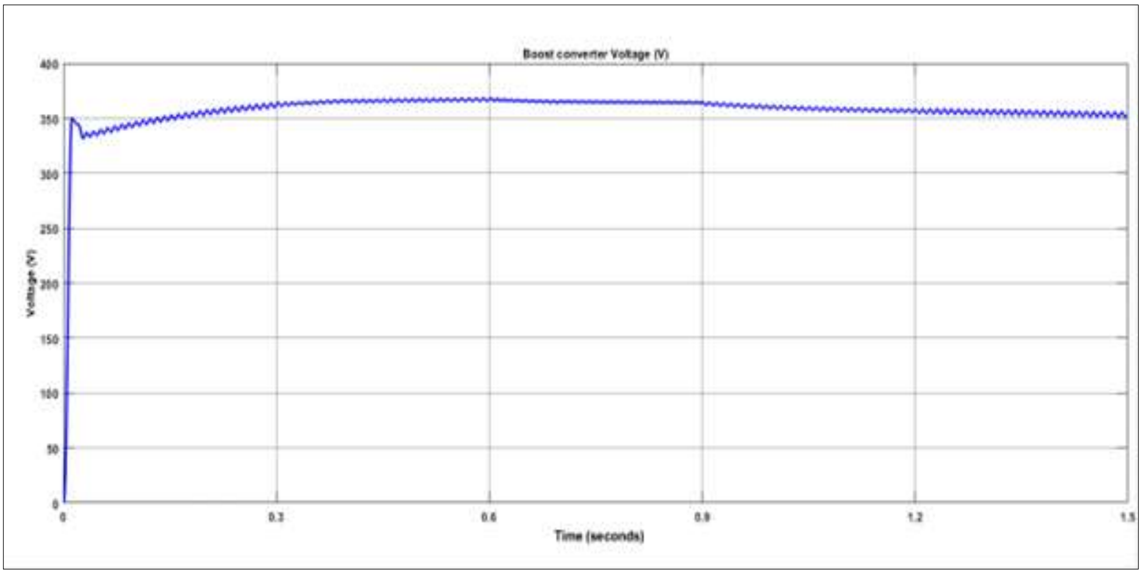

Figure 4.5: Boost Converter Voltage.

The figure 4.6 depicts the electric current passing through the boost converter element of the photovoltaic (PV) system. The initial current surges are likely caused by the launch conditions. Subsequently, the present state becomes stable, but there are little variations that indicate changes in the input from the PV panels. Two noticeable decreases in current are noted due to the neural network's adjustments to changing conditions and the boost converter's electronic circuitry consuming less current. As evidenced by the consistent flow of electricity after the initial variations, the neural network is efficiently readjusting the boost converter to sustain the highest level of power. This is demonstrated by the speedy stabilization that occurred following these decreases. The NN plays a crucial function in this situation by adaptively modifying the control parameters to guarantee that the system works close to the well-regulated MPP, while also taking into account the overall stability of the current during the monitoring period.

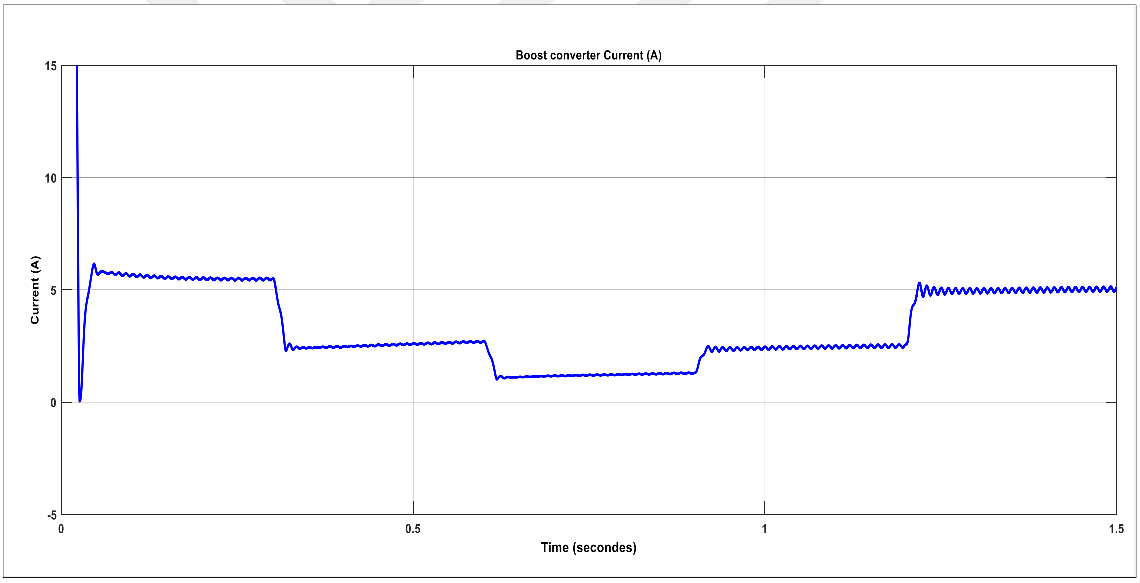

Figure 4.6: Boost Converter Current.

The provided graph in the figure 4.7 illustrates the power output of a boost converter within a PV system, which is overseen by a NN specifically engineered for the purpose of MPPT. Following a brief transitional phase, the power becomes stable, but with noticeable oscillations. These oscillations may suggest that the NN continuously adapts the converter parameters to sustain MPP as environmental or loading circumstances change.

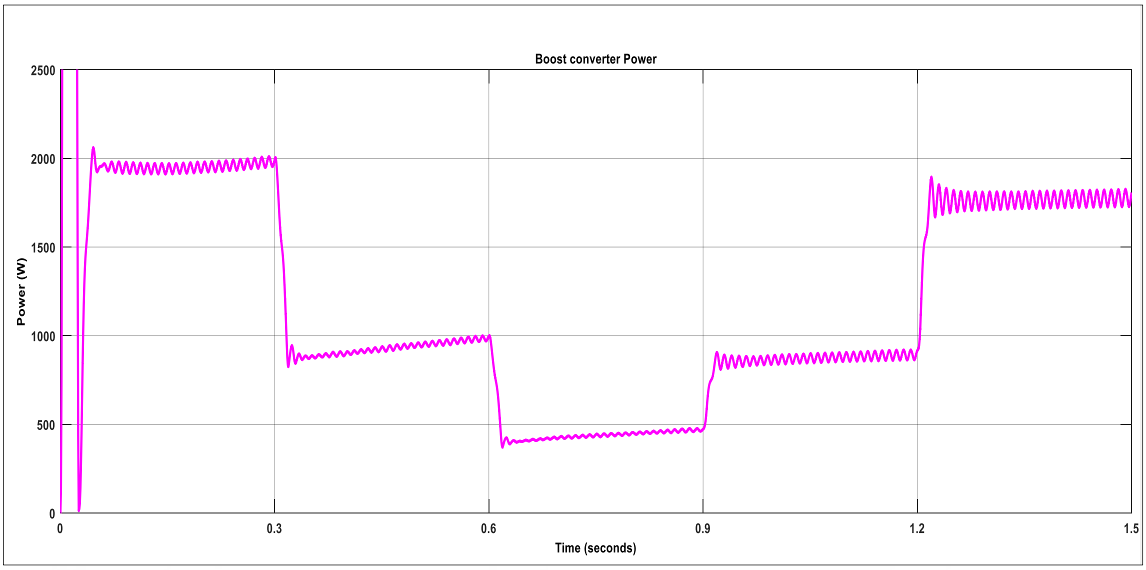

Figure 4.7: Boost Converter Power.

The graph illustrates that the energy value is more than the values in PV. Specifically, between the time intervals of 0 and 0.3 seconds, the energy value is 2000 watts Between 0.3 seconds and 0.6 seconds, the energy value is 1000 watts. Between 0.6 seconds and 0.9 seconds, the energy value is 500 watts. Lastly, between 0.9 seconds and 1.2 seconds, the energy value is 9000 watts. This indicates that the NN is effectively and efficiently performing its function by maximizing the electricity output from the PV system. Following each drop, the energy reverts to a stable condition, indicating that the NN possesses the capability to rapidly restore the system to its ideal operational state.

4.2.2 Simulation Result Inverter (Active & Reactive)

The incorporation of NN into the control of inverters for grid-connected solar systems is a noteworthy advancement in the field of renewable energy management. The intelligent systems have the capability to dynamically adjust their operations in real-time, hence enhancing the optimization of the active and reactive power equilibrium. NN provide the capacity to acquire knowledge and make predictions, enabling them to optimize inverter operations. This optimization facilitates efficient energy transmission, sustains grid stability, and maximizes the utilization of solar resources. This strategy exemplifies the forefront of smart grid technology, pushing the limits of solar energy harnessing and distribution. The graph depicted in Figure 4.8 illustrates the output voltage emanating from the inverter within a single-phase grid-connected PV system that is governed by a NN. The observed voltage output has a sinusoidal waveform, which is indicative of the transmission of AC electricity to the power grid. The system's peak voltage of roughly 325 V suggests that it is intended for usage in a grid with an RMS voltage of around 230 V. This conclusion is drawn from the understanding that the peak value of a sine wave is √2 times the RMS value, and that the inverter voltage is equivalent to the grid voltage due to their parallel connection. The primary function of the NN is to effectively control the output of the inverter, hence maintaining its alignment with the voltage specifications of the grid. A waveform that remains steady and constant suggests that the NN is successfully maintaining the inverter's operation at the intended voltage level, while also adjusting to variations in inputs from the PV system or requirements from the electrical grid. The confirmation of a 325 V peak signifies that the inverter, operating under the guidance of a NN, is functioning within the anticipated parameters of a single-phase network connection.

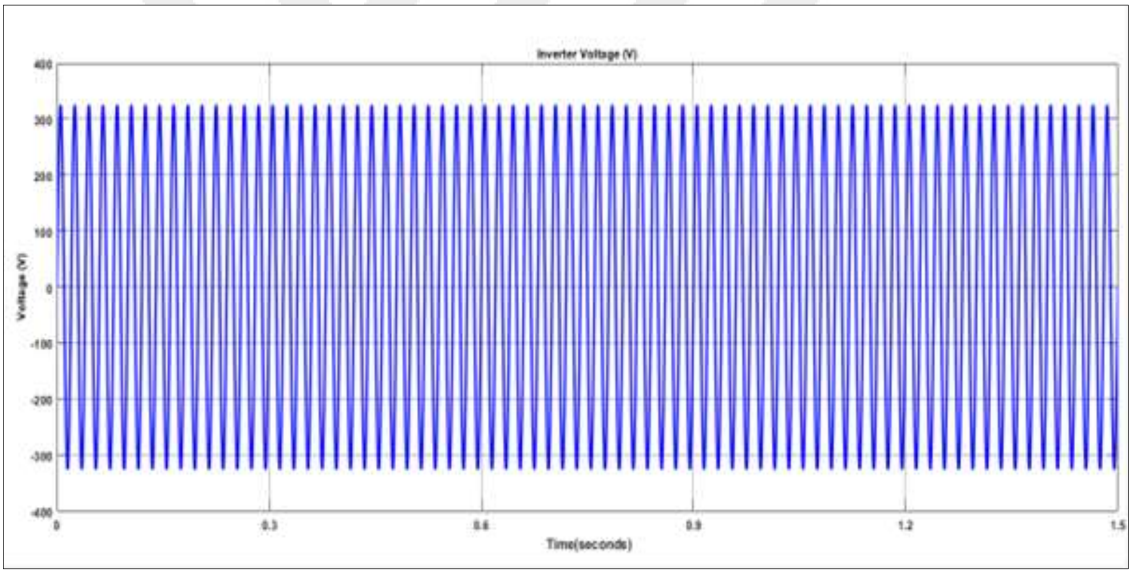

Figure 4.8: Inverter Voltage.

The current waveform output from the inverter prior to undergoing filtration is depicted in Figure 4.9, whereby the control system employs a NN. The waveform depicted illustrates 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. In this particular case, the NN assumes the responsibility of modifying the functioning of the inverter in order to uphold the appropriate current waveform. This is crucial in order to align with the load or network prerequisites. The fluctuations in the magnitude of the current waveform, which are discernible when the current undergoes increments and decrements, may arise from the NN reaction to alterations in stimuli. As previously indicated, the PV system is subject to the influence of solar radiation intensity. The process of converting DC to AC is accompanied by the presence of harmonic content or high-frequency noise. To mitigate the impact of these harmonics, it becomes necessary to employ a filter.

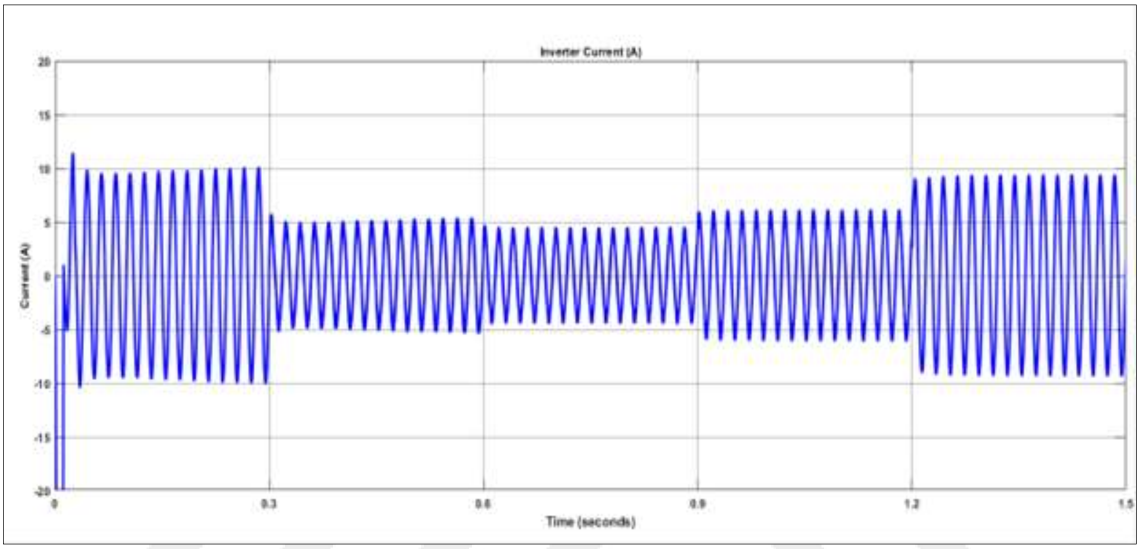

Figure 4.9: Inverter Current (A).

The waveform of the grid current after passing through the LCL filter, which is regulated by an inverter controlled by NN, is depicted in figure 4.10. The waveform exhibits sinusoidal characteristics, as is commonly observed in AC supplied to the electrical grid. The primary function of the LCL filter is to mitigate the presence of noise and high-frequency harmonics in the output of the inverter, thereby yielding a waveform that is characterized by enhanced cleanliness and improved compatibility with the power grid. The existence of residual ripples in the waveform may suggest that the filter is not achieving complete elimination of higher frequency components, or it could potentially signal that the control system is dynamically adjusting to ensure PQ is maintained amidst changing conditions. The objective of NN control is to guarantee that the present satisfies the network's prerequisites, including phase, frequency, and amplitude, in order to achieve efficient synchronization and power transmission. The observed phenomenon of a steady amplitude following an initial transient suggests that the NN demonstrates good management of these parameters subsequent to the application of filtering techniques.

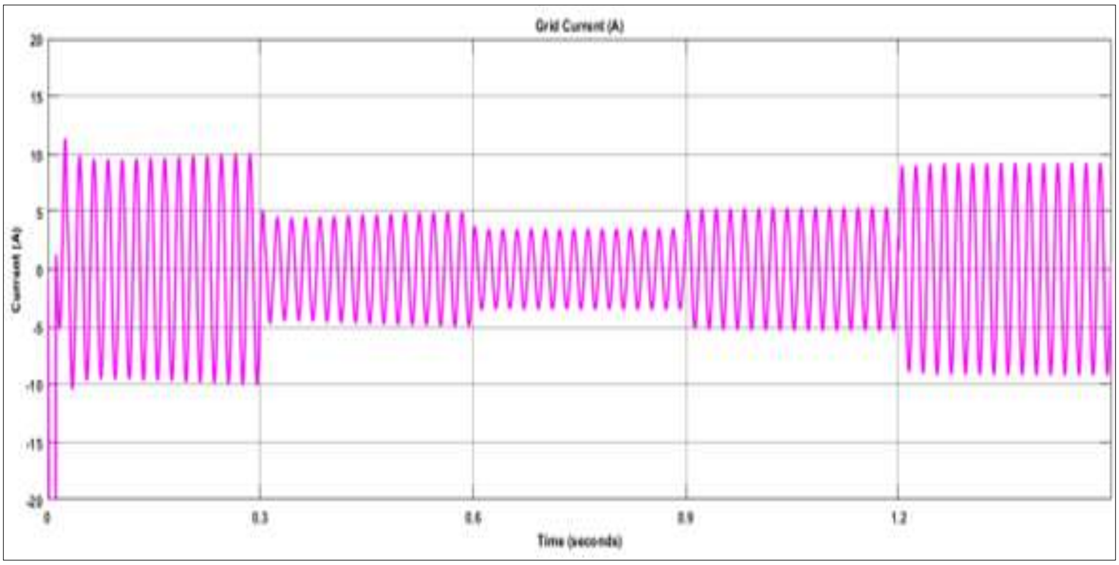

Figure 4.10: Grid Current (A).

In Figure 4.11, the image shows a graph with superimposed sine waveforms representing the inverter's output voltage and current over a short time period from 0 to 0.3 seconds. The two waveforms being in phase indicate that the inverter is converting DC power to AC power efficiently with minimal reactive power, indicating a near-unity power factor that is ideal for grid-connected systems. The constant amplitude and frequency of the waveforms reflect stable operation and efficient control by the NN over the observed time interval.

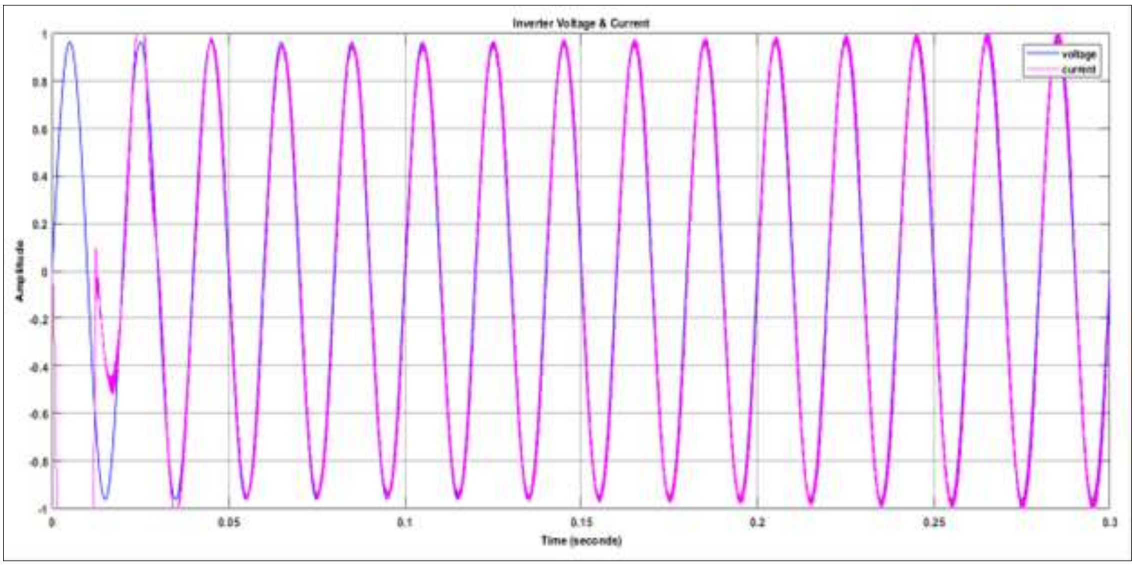

Figure 4.11: The Voltage and Current in Same Phase from 0 to 0.3 Second.

Figure 4.12 depicts the waveforms of the inverter's output voltage and current within the time interval of 0.2 to 0.5 seconds. The NN responsible for controlling the inverter modifies the phase angle between the voltage and current in order to regulate the reactive power, as per the designated control strategy. This adjustment is necessary due to the current leading the voltage and their lack of phase alignment. Phase shift is a deliberate outcome resulting from the functioning of a NN that is reliant on the reactive power setpoints it receives. It is important to acknowledge that the current power factor is 0.9 due to the presence of a negligible amount of non-reactive power. The evaluation of control effectiveness in NN can be conducted by examining the consistency of the phase shift over time. This consistency indicates the network's capacity to inject or absorb the necessary reactive power in order to attain the desired control objectives.

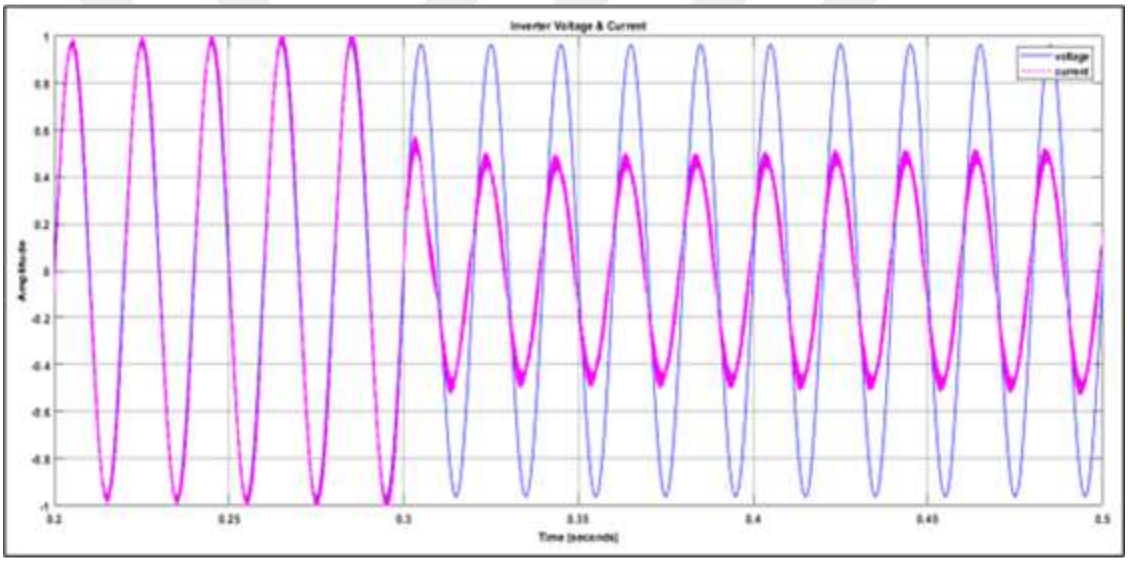

Figure 4.12: NN Injecting the Reactive Power in the Grid.

The figure 4.13, shows overlapping waveforms of inverter voltage and current between 0.6 and 0.9 s. Since the current waveform lags the voltage waveform, this lag represents the presence of reactive power, resulting in a power factor of less than 1. A power factor of 0.6 indicates that the system is highly reactive, and the job of the NN is to control the power. The magnitude of this interaction. The phase shift between current and voltage indicates that the NN effectively adjusts the inverter output to manage reactive power according to the required power factor,

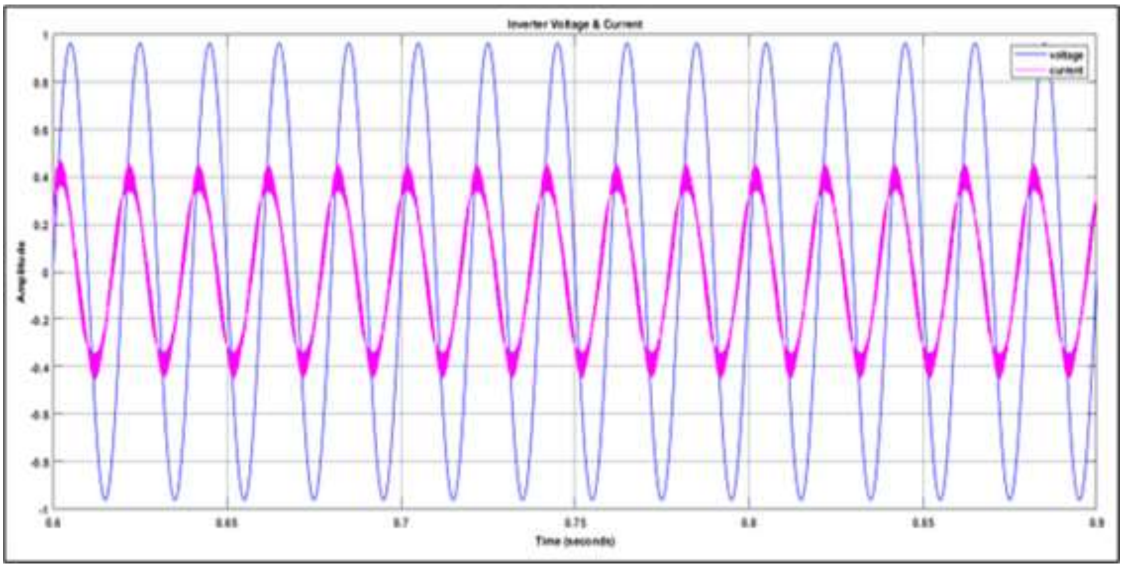

Figure 4.13: The Current Lags Behind the Voltage.

The graph shows in the figure 4.14, the Real power being delivered to the grid from a solar PV system. The power output shows large variations at several time points, which is consistent with the changes in solar radiation data we mentioned previously. Where the power value is 1.6 kW between the period 0 to 0.3 seconds, after which it becomes a value of 0.8 kW until it reaches 0.6 seconds, where the power decreases and becomes a value of 0.4 kW and after 0. After 9 seconds, the power goes back up to reach 0.75 kW, after which the power increases and becomes 1.35 kW in an instant of 1.2 seconds. This happens due to a decrease in radiation, which will lead to a decrease in the power output of the PV system. The recovery in power output after each drop indicates that the system is responding to changes in radiation and adjusting its output accordingly. The ability of the system to return to a higher Real power level after each decrease indicates that the control mechanism of NN is working well.

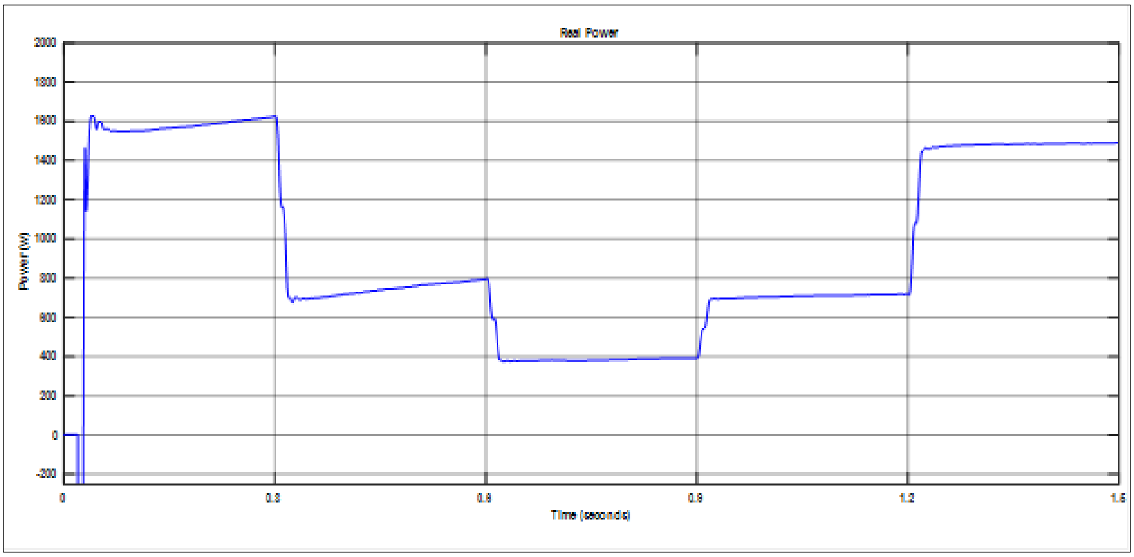

Figure 4.14: Real Power in the Grid.

The graph in Figure 4.15, indicates the reactive power in the network over time. The system adjusts the reactive power at specific time intervals, which is a feature of a control strategy designed to maintain compliance with network requirements. The value of passive power is -0.01 KVAR and the pf 1 between the interval from 0 to 0.3 seconds, after which it becomes a value of 0.22 KVAR, and the pf is 0.9, until it reaches 0.6 seconds, and then it begins to increase, so that the effective power becomes a value of 0.5 KVAR, and the pf is a value of 0.6 until it reaches 0.9 seconds, after which the ineffective power increases to 0.59 KVAR and the pf is 0.79. Between the period 1.2 seconds and 1.5 seconds, the ineffective power value is 0.2 KVAR and the pf is 0.95.

The role of the NN in controlling and managing reactive power is to adjust system parameters to inject or absorb reactive power, thus ensuring that the power factor remains within the range that meets the network standards. The precise moments when reactive power levels change correspond to the specific control strategy of the NN, which depends on network conditions or operational requirements.

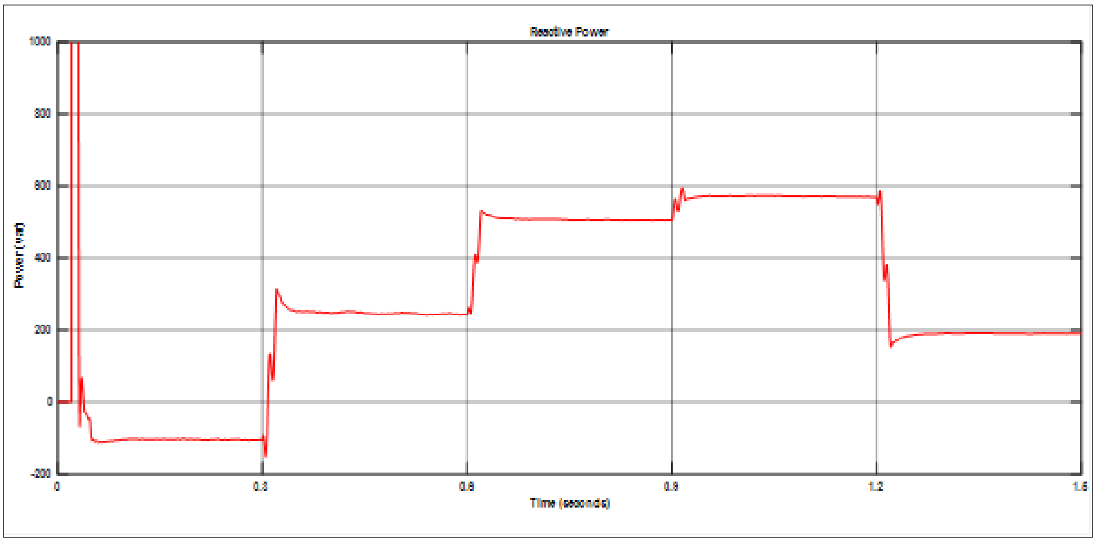

Figure 4.15: Reactive Power.

4.2.3 Simulation Result Training Neural Network

The data is supervised and trained using the Levenberg-Marquardt method (Trainlm), renowned for its effective tracking skills. The importance of the MPPT algorithm is in its rapid convergence, efficient tracking, and ability to handle nonlinearity. Details regarding the training data are outlined in table (4.1).

Table 4.1: Details of Function Fitting ANN.

ALGORITHM USED	DATA	VALUES
Trainlm	Training data	70%
Trainlm	Validation Data	15
Trainlm	Test Data	15
Trainlm	Layer Size	10

Regression plots (RP) are a form of supervised learning technique that primarily focuses on the relationship between input data and a target variable. These plots are commonly used as command to ANN. The results of the trained algorithm are depicted in Figure 4.16.

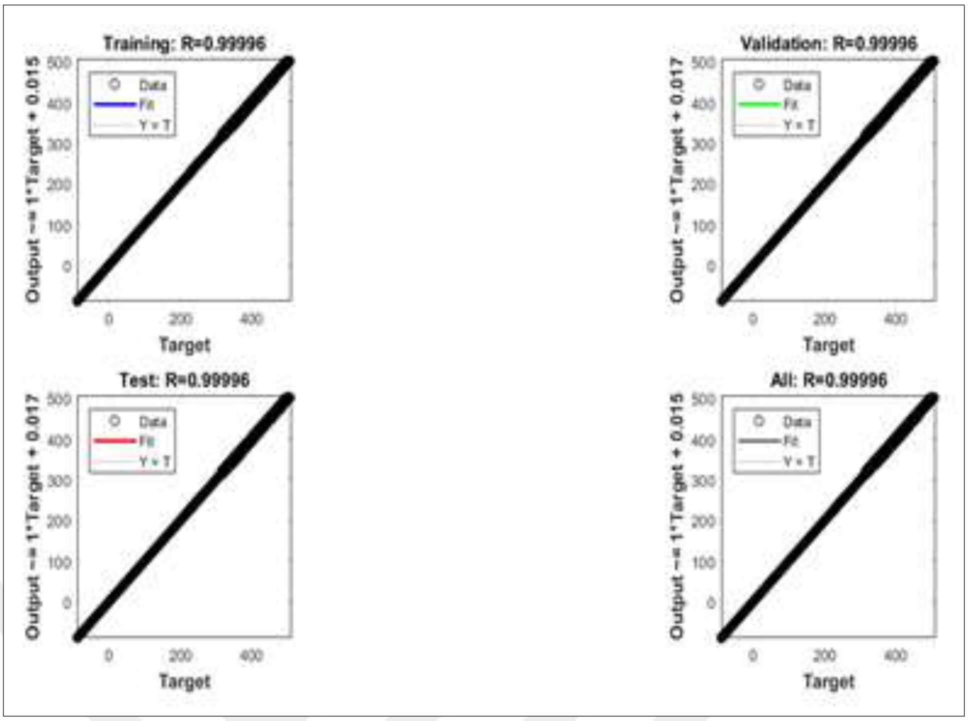

Figure 4.16: Regression Plots for ANN.

The trained data is supplied in the form of a MATLAB function that fits a NN block. table (4.2) 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 4.2: Ann 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

5. CONCLUSIONS AND THE FUTURE WORKS

This chapter presents the findings and contributions of this thesis. Additionally, this chapter includes suggestions for future directions.

5.1 CONCLUSIONS

This work proposes a new technology to obtain an integrated PV system by controlling it using a NN, which can be connected to the gride. This system consists of two main parts, where the first part is MPPT, which extracts the maximum power from PV through the instructions NN gives it, where the voltage of the solar panels was $260V_{dc}$ and MPPT, which raises the voltage and makes it constant at $350V_{dc}$ despite changes in the intensity of solar radiation at a constant temperature of 25^oC. The second part is the inverter, which controls the active and effective power using NN The PV system is connected to the grid, and through the PV system it is possible to obtain a good power factor, reduce fault, and economic benefits. The peak voltage was about $325V_{ac}$. There were several cases in which the active and reactive power was changed according to the circumstances to be worked on. Proving the efficiency of the NN control method through the extent to which the system adapts to short-term changes and the extent of its ability to continue operating continuously despite these changes. By maintaining a constant inverter output across a variety of operating conditions, the neural network training success rate was 99% and a THD of 1.86% was obtained.

5.2 FUTURE WORKS

Several methods can be followed to continue this study:

a. Verify the scalability of the NN model for larger or multi-stage systems to meet industrial or utility scale applications.
b. Enhancing the NN algorithm with deep learning methods to enhance its predictive capabilities and real-time control efficiency.
c. Using information from weather forecasts in a NN to make proactive adjustments to upcoming shifts in solar radiation.
d. To improve production consistency and collect excess energy during peak production times, the integration of energy storage solutions is being studied.

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