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Innovative Smart Inverter Design for Enhanced Integration of Distributed Energy

Bushra Mahmood[1], Ahmed Ghanim Wadday[2] , Ahmed Kareem Abdullah[3]*

Department of Electrical Engineering Techniques, Al-Furat Al-Awsat Technical University Al-Mussaib Technical College Babylon, Iraq. E-mail: (*abushraa.mahmood.tcm.18@student.atu.edu.iq*)

[2] *Department of Communication Engineering Techniques Al-Furat Al-Awsat Technical, University Engineering Technical College Najaf, Iraq* 2. E-mail: (*ahmadghw@atu.edu.iq*)

[3] *Department of Electrical Engineering Techniques, Al-Furat Al-Awsat Technical University, Al-Mussaib Technical College, Babylon, Iraq* 3. E-mail: ahmedalbakri2012@atu.edu.iq

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Abstract. *This comprehensive exploration delves into the innovative field of smart inverter design, with a particular focus on the role of artificial intelligence (AI) in enhancing the integration of Distributed Energy Resources (DERs) into power grids. The rapid evolution of energy systems and the increasing reliance on renewable energy sources have necessitated the development of more sophisticated technologies for power system management. Smart inverters, at the heart of this transformation, are crucial for integrating DERs like solar panels and wind turbines into existing power grids. The integration of AI into smart inverters represents a significant advancement in managing and optimizing these complex systems. This study demonstrates how these advanced technologies can lead to substantial improvements in inverter reliability, power distribution efficiency, and overall management of renewable energy sources. Realistic models highlight the resilience of smart inverters to fluctuating grid conditions and their ability to maintain system reliability and efficiency. Furthermore, the study critically assesses the current challenges facing this field, such as the need for standardized communication protocols, robust cybersecurity measures against digital threats, and the ongoing requirement for innovation to keep pace with rapid technological advancements. Finally, the exploration forecasts future developments and areas that will further enhance smart inverter technology, emphasizing the essential role of continued research and development in fully realizing AI's potential to transform power grids. The examination concludes by highlighting the promising future of AI in smart inverter design, particularly in contributing to the development of more efficient, reliable, and sustainable energy systems.*

Keywords: *AC Micro-Grid, Renewable Energy, Smart Incerters, Distributed Energy Resources (DERs), Photovoltic Cells, Wind Tubines, ANN Technology.*

1. INTRODUCTION

Small networks activated through transformers and switches connected to infinite distribution energy resources (DERs) or clean energy sources have made significant progress in recent years, driven by the spread of smart technologies and artificial intelligence (AI) algorithms. These advancements have enabled better integration of renewable energy sources like solar panels and wind turbines into existing power grids through smart inverters [1, 2].

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However, these PV systems and smart inverters face several challenges, including improving energy conversion efficiency, ensuring grid stability, and managing the variable power output due to changing weather conditions. Traditional control methods, such as the Kalman filter, sliding mode, and least-square-based techniques, often require complex computations and additional assessments. There is a pressing need to enhance control techniques to ensure optimal performance and minimize losses caused by sudden changes in power generation [3, 4].

Recent years have seen various proposed solutions to address these challenges, including flexible limit predictive control and model-based technologies. Despite these advancements, many existing methods are limited by their complexity and the need for continuous tuning to adapt to changing operating conditions. One promising approach is the use of AI-based techniques, such as neuro-fuzzy control and artificial neural networks (ANNs), which offer higher accuracy and adaptability over conventional controllers[5, 6]

This research aims to present an innovative control model based on Artificial Neural Networks (ANN) to improve the performance of smart inverters in PV systems. The proposed model includes an auto-tuning mechanism for predictive control using dual techniques: an initial evaluation method and an ANN-based assessment of limit variations. It is expected to enhance energy conversion efficiency, improve grid stability, and reduce losses caused by variable weather conditions [7]. Additionally, this paper provides a comparative study to evaluate the performance of the proposed model against traditional control algorithms, demonstrating significant improvements in efficiency and stability[8] .

Figure 1. shows a typical micro-grid smart inverter-PV structure.

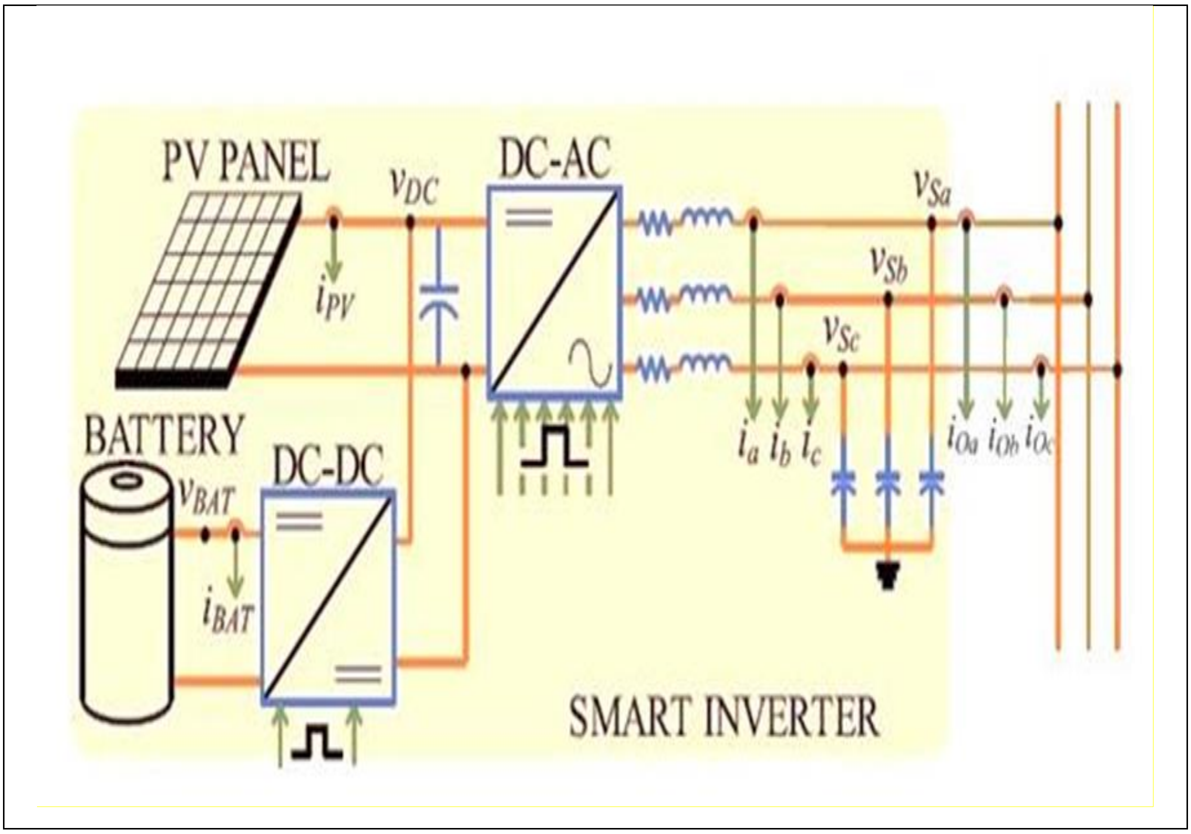

Fig. 1. Common micro-grid smart inverter-PV model[9].

1.1 Photo Voltaic Cells Power Supply

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The solar board includes a homogeneous mass of solar-absorbing glass sheets, succeeded by electronic cells, which are a photovoltaic array those operates to implement a group of photovoltaic (PV) units to convert the sun's rays into a continuous electric current. The matrix consists of series of units attached in parallel, and each series consists of units linked in an integral series. Such block permits modeling of pre-selected PV modules with the System Advisor Model, National Renewable Energy Laboratory (NREL) against PV modules we select. The PV array block is a five-parameter model that utilizes a light-generated current supply (IL), a diode, a series resistance (Rs), against a shunt resistance (Rsh) to produce the radiation- and heat-dependent I-V properties of the modules as presented in Figures 2.

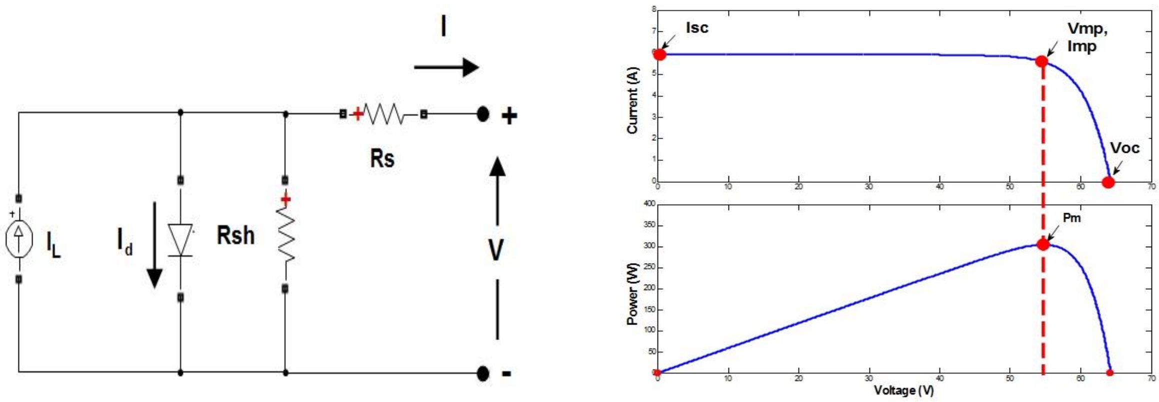

Fig. 2. The PV cell unit model, (a) Equivalent circuit, (b) Power and current characteristics [10] .

The I-V diode characteristics are *shaped* for a specific module by the below equations:

$$I_d = I_o e^{\frac{V_d}{V_T}} - 1 \qquad (1)$$

$$V_T = \frac{KT}{q} \times nl \times N_{cell} \qquad (2)$$

I_d: Diode Current
I_o: Reverse Saturation Current
V_d: Diode Voltage
V_T: Thermal Voltage
K: Boltzmann Constant
T: Temperature
nl : Ideality Factor
N_{cell}: Number of Cells

This PV cells will be the essential power supply of the system that will produce the network against the needed power. The illustration of such unit is as follows:
PV array implemented over a series of PV modules is parallel attached. Every series consists of units attached in series. Such unit allows modeling of a diversity of pre-selected PV modules possible along the NREL System Advisor Model against a user-defined PV module. Input 1 = sun radiation in W/m2 and input 2 = cell heat in degrees Celsius. The circuit diagram of the PV array unit implemented using MatLab2020b simulink structure.

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The impact of PV energy in the electric ebergy scheme is ultimately finite by the electricity requisted which does not match the typical solar PV energy construction, yielding in impractical PV energy production. Also, and in order not insuring too much cost by advancing the solar PV generation utility, the electrical energy model will need conversion to accommodate excess solar PV production.

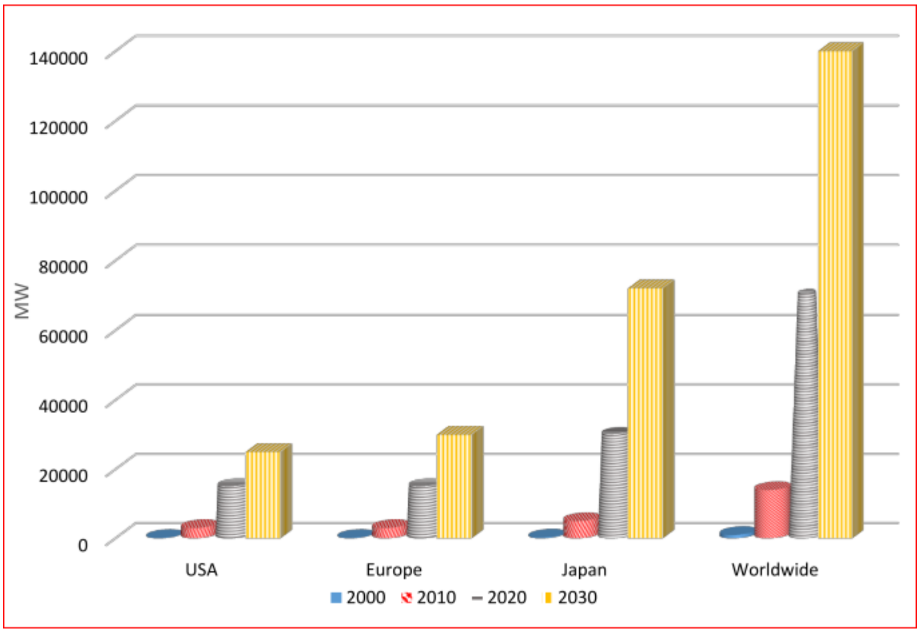

Fig. 3. The projected development and establishment of sun powered PV energy in certain nations and overall till 2030 [11]

Opportunities for generating electrical energy might be better increased through some of the following methods:

1) Augmentation: Allows more natural load to be met by PV energy by completely reducing defects.
2) Load conversion: The normal load is converted into larger PV output.
3) Electrical energy generated by solar energy is stored, this energy stored in Newtons where solar energy production can be significant or non-existent.

1.2 DC to AC Power Inverter System

Inverters are a class of power electronics devices that control the electrical power flow. They perform DC-to-AC conversion by rapidly switching the DC input's orientation. Figure 4 shows a standard DC-to-AC inverter. The switching process is crucial for the quality of the converted AC voltage signal[12] .

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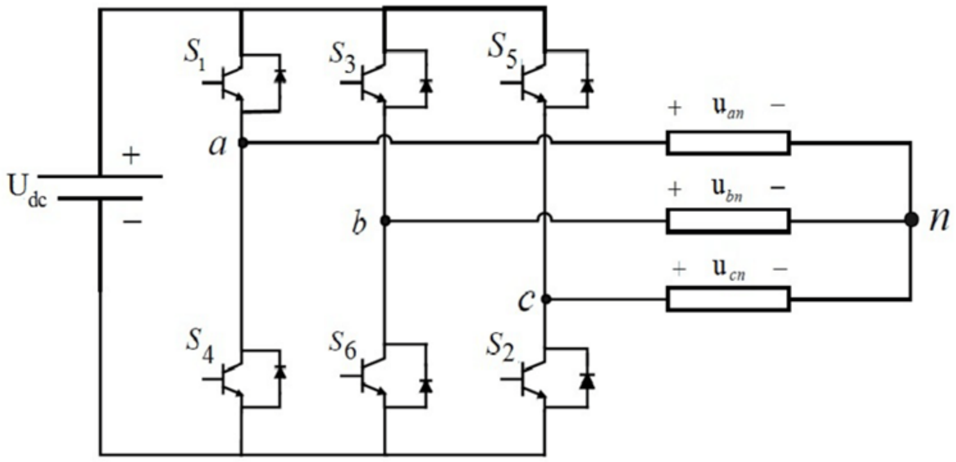

Fig. 4. A standard DC-to-AC inverter circuit diagram [14 ,13] .

Usually, DC to AC inverters are efficiently designed utilizing Neutral Point Clamped (NPC) inverters. Such type of inverters are a group of multi-level transducers that feature the use of stabilization diodes to ensure proper voltage sharing across the power switches. NPC adapters were simultaneously introduced in literature. The NPC inverters circuit diagram is presented in Figure 5. [15].

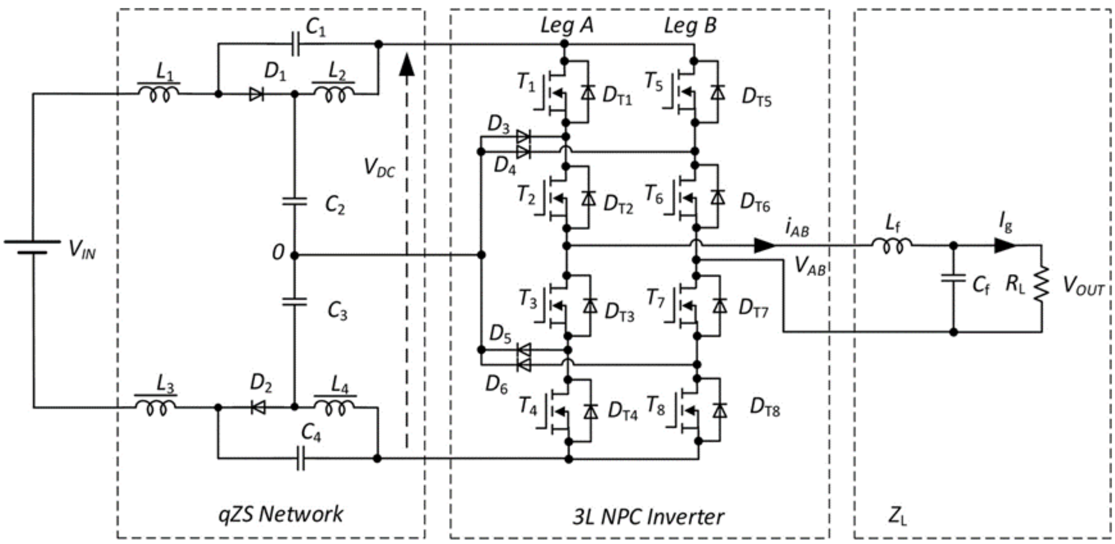

Fig.5. The NPC inverters circuit diagram[16].

1.2.1 The Boost Dc Power Converter Circuit

Boost converters are also defined as schemes to increase the solar panel's AC voltage to a greater DC voltage. It applies voltage feedback to keep the output voltage constant. This section is absolutely essential to obtain maximum DC supply voltage and maintain constant DC power available to the scheme. The circuit diagram of the Boost Dc Power Converter module implemented along the MatLab2021b simulink model is shown in Figure 6.

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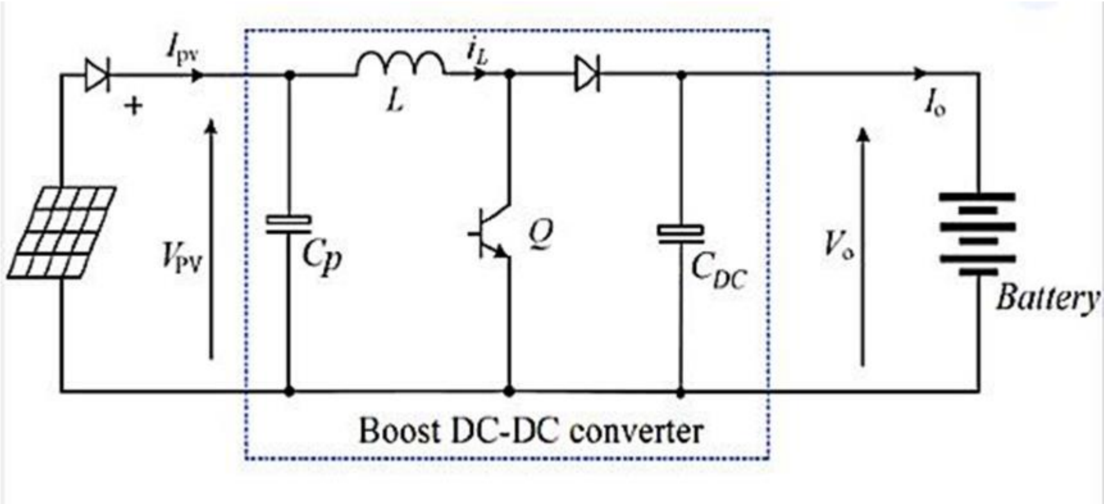

Fig. 6. The typical boost converter circuit.[16]

The boost converter connects the PV cells with the DC to AC inverter and act to increase the DC voltage to its maximal values and prevent or reduce their fluctuations to achieve the best obtained DC amount in for AC conversion preparations. The boost converter might be controlled with various techniques and controllers in order to obtain the maximum point power tracking (MPPT) which insures the best DC voltage performance from the PV arrays. The MPPT concept with the common applied controllers will be discussed in the following sections.

1.2.2 Maximum Power Point Tracking Controllers

Usually, DC to AC inverters are effectively optimized utilizing optimum maximum power point tracking (MPPT) controller. Such kind of controllers are applied to perform the maximum power even if the current or the voltage of the photo voltaic cells have been reduced. Figure 7. displays the MPPT performance for PV panels

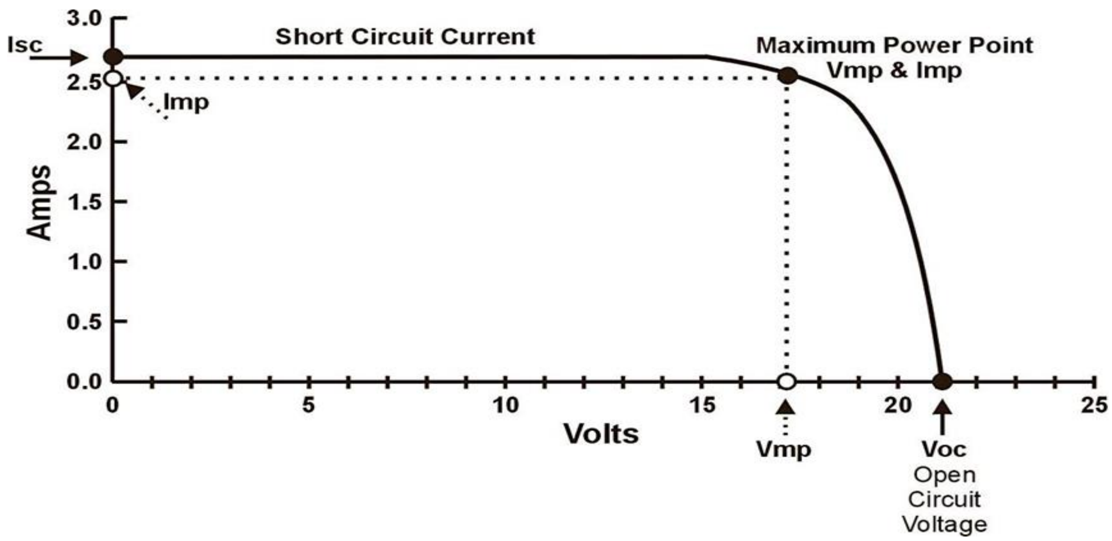

Fig. 7.The MPPT performance for PV panels [17] .

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Several types of the MPPT controllers are available in literature, such as; perturb and disturb (P&O) controller, artificial neural networks (ANN) controllers, voltage source converter (VSC) controller, and so on. Such controllers are all support the boost converter circuit to perform the ultimatev MPPT performance. The boost controllers for MPPT will be discussed and illustrated in details in separate section in order to understand their properties and principles of operation.

1.3. Boost Types Controllers for MPPT Performance

As presented in the previous section, there are various kinds of boost MPPT controllers existing in literature which acting for maximizing the DC voltage from PV cells and enhancing the DC voltage fluctuations also the overall performance. In this project, several schemes of the boost MPPT controllers have been presented such as; perturb and disturb (P&O), voltage source converter (VSC), PQ, and artificial neural networks (ANN) smart controllers[18]. Figure 8. outlines general MPPT boost circuit diagram[19].

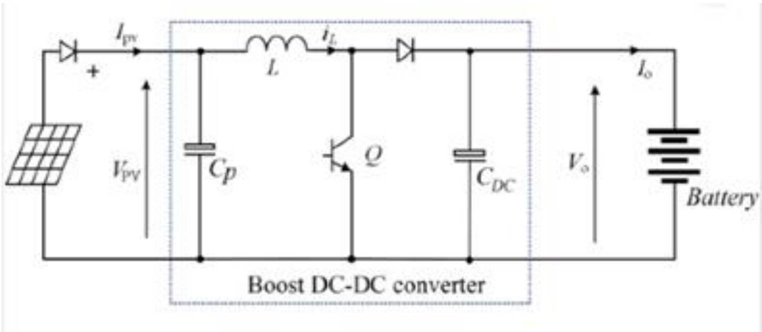

Fig. 8. General MPPT boost circuit diagram [17] .

1.3. Voltage Source Converter (VSC) Controller

Self-switching transformers called voltage selected controllers (VSCs) are used to connect high-voltage alternative current (HVAC) and high-voltage direct current (HVDC) systems using IGBTs and other high-power electronic devices. VSCs have the ability to switch on themselves, producing AC voltage without the need for an AC system. Independent control of active power and reactive power, AC voltage compensation, and a suitable installation size are among the advantages of VSC[14, 20]. Figure 9. depicts the phase locked loop (PLL) circuit diagram for the VSC controller .

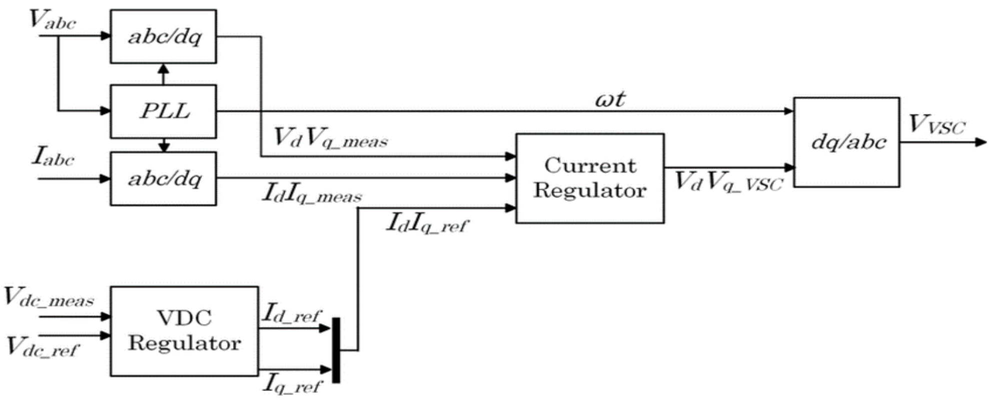

Fig. 9. The VCS using PLL controllers circuit diagram for MPPT [21 ,16].

1.5 The Smart Inverters

The utilization of brilliant grid devices and advancements in the electrical grid foundation allows the bidirectional progression of energy with correspondence amidst the grid also the PV panels. Such capabilities could yield toward achieving further developed safety, interoperability, effectiveness, and reliability. The development of innovation along administrations in regards to brilliant grid has been rising and was assessed to increment somewhere in the range of 2009 and 2014 to almost 43 billion bucks in the US and overall increment more noteworthy than 171 billion bucks. The impacts of environmentally friendly power on the activity and arranging of the system are known very well. Nonetheless, the investigation of existing brilliant grid capacities, for example, correspondence and controls for dealing with the impacts of coordinating and enhancing the future energy system with elevated degrees of sunlight based and wind energy isn't palatable. The target representing things to come grid is to build the combination of RES at an exceptionally quick rate to be driven by cost enhancements, great strategies, and so on. Nonetheless, the irregularity in load type is a significant worry in brilliant grid innovation. The significant kinds of burdens that influence energy effectiveness, request reaction, and burden control of the smart grid comprise of private, business, modern, agrarian, and module electric vehicles[14]. The smart inverter activity is acknowledged by means of a two-way correspondence organization to send and get data between the smart inverter and the principal administrator. The inverter needs first to screen its genuine information circumstance and send such information to the focal controller. The focal controller then, at that point, gathers these data and presents an order sign to every inverter to change the current activity point of the system. The order signal is sent in light of a predefined multifunction in the essential administrator. Such capabilities are characterized in light of the requirement for the heap and the primary grid. These capabilities are fit for working at brought together and decentralized systems as well as any microgrid association modes. Figure 10 shows the multifunction highlights of a smart inverter.

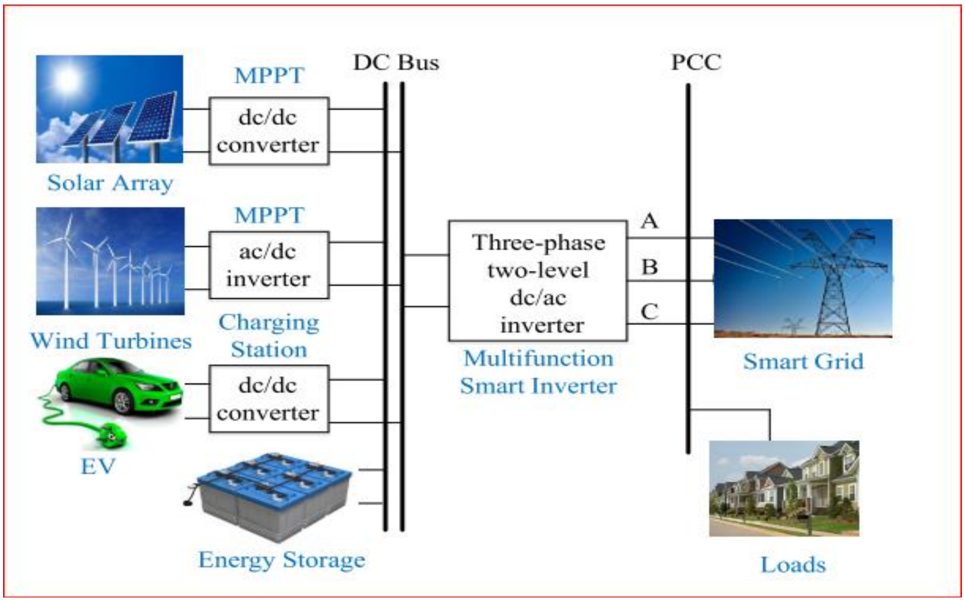

Fig. 10. Multifunction highlights of the smart inverter[14]

The smart elements of VSC presented in Figure 10 might decrease the system topology as well as direction multiple DERs in single microgrid. It is worth to specify that the capability of smart inverter is as

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it were acknowledged through two-way correspondence transport between the inverters and the fundamental administrator. The job of smart inverters surpasses the fundamental elements of customary inverters, for example, maximum power point tracking, islanding location, and power transformation. They could uphold the voltage and frequency of the grid as well as give the system's stability. In genuine applications, the suspicion of consistent and stable powers isn't exact by thinking about the surprising way of behaving of the system. For instance, adding new miniature sources, flaws, and disturbances in the fundamental grid, and associating and detaching the DER and loads are regular circumstances that influence the stability of the microgrid[11]. In this way, planning a proper controller to deal with these circumstances and characterizing multifunctions will guarantee the stability prerequisites of the heap. The future improvement patterns of smart inverter and fostering its capabilities can help the microgrid become cutthroat with traditional age resources. The approach to smart inverters incorporates the coordination of PV, Battery, and electric vehicles, through a smart grid for power quality. Furthermore, a comparison among the functions of smart inverter and VSC has been achieved as listed in Table 1.

Table 1 : Comparison among different smart inverter and VSC functions[14] .

Situation	***Conventional Inverter***	***Smart Inverter***
Ride-through Utility Faul	***Avoid contribution to the fault.***	**Involve in ride-through utility fault.**
Utility Disturbance	***Disconnect PV system from the grid.***	**Support and enhance grid V/F stability.**
Power Generation	***No capability to control power overproduction***	**Monitor and limit power generation.**
V/F variation	**No contribution in supporting V/F. Only disconnected.**	**Monitor V/F fluctuation and generate action for stability**
Anti-island detection	**Not implemented yet.**	**Investigate transient fault based on defined scheme.**
Flicker	**No contribution**	**Mitigate voltage and frequency flicker.**
Power factor	**No contribution.**	***Active load balancing power factor and reactive power control.***

1.6 Artificial Neural Networks (ANN) Smart Controllers

smart controllers such as artificial neural networks, are efficient data-driven modeling equipment those are widely employed in the dynamic modeling as well quantification of nonlinear schemes, due to their global approximation abilities with their flexible structure that allows capturing complicated nonlinear responces. Artificial Neural Networks (ANNs) are biologically inspired computer programs analyzed to simulate the technique that the human brain analyzed data. ANNs combine their knowledge by discovering patterns and relationships in data and learned (or are trained) along practice, not along automation. Figure 11 outlines typical ANN controller for PV power model[19, 22].

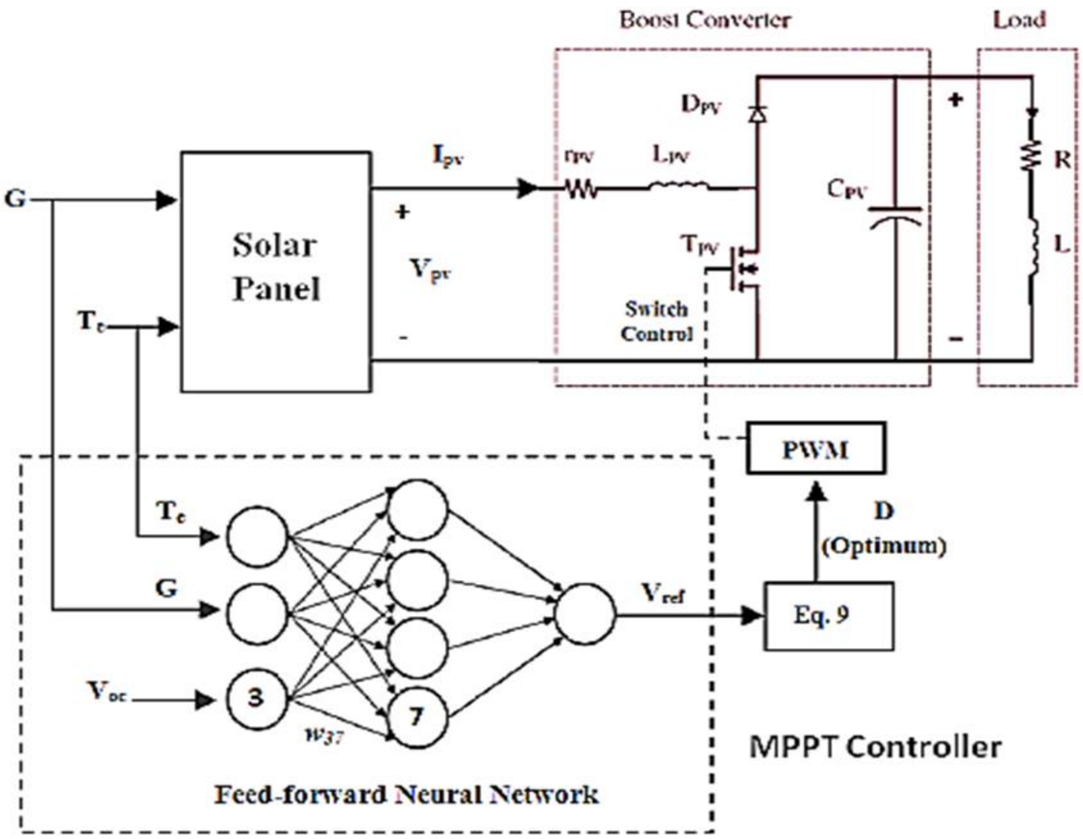

Fig. 11. Typical ANN controller for PV power mode. [23] .

Intelligent control depends on computing along with artificial intelligence simulation (ANN) that is considered part of modern control techniques. It is used for controlling the model connected to the 3-phase PV grid through such ANNs. They have been successfully employed in advancement, for associative memories, pattern recognition, and numerous further fields[23] . ANN is employed in such schemes since it has various advantages similar to neural networks (NN). The types of artificial intelligence could be also considered as part of the advanced controlling classes. Moreover, no force is needed for system description, NN includs input layer, output layer also hidden layers sum as introduced in Figure 11. The input layer is based on controlling the current that includes of two axes (d axis and q axis) with the outcome layer expressed by control signal axis [19].

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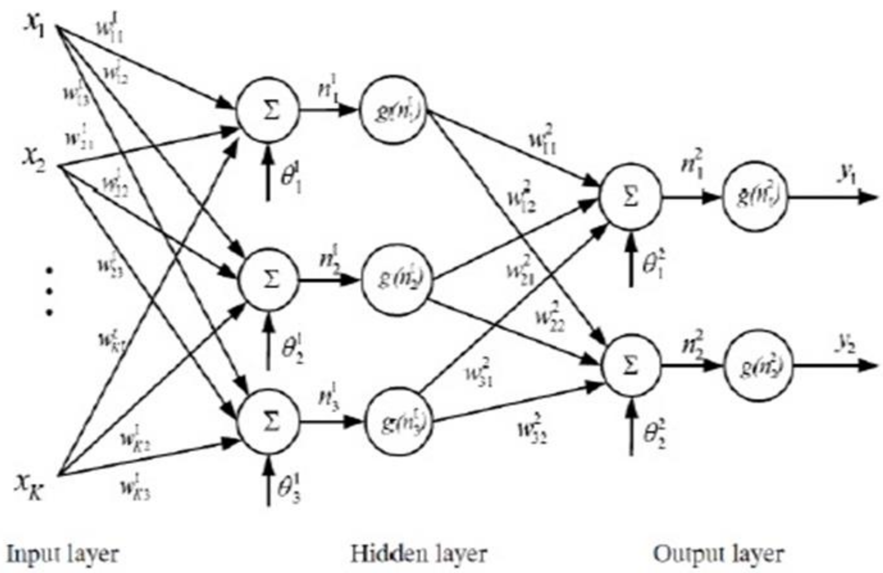

Fig. 10. Schematic diagram of Neural network internal model[24].

The hidden layer details in the ANN algorithm structure contain many neurons organized in layers. Each neuron in one layer is connected to all parts of the neurons and branches through the non-shared layer. Figure 10 presented a scheme of the modern feed-forward neural network. It includs 10 hidden internal neurons, a single output and a single input sections for the input and output layer. The data layer of such network is the present error of the reference frame in the d-axis component[25].

The decision to use 10 hidden layers in the ANN network design is based on balancing model complexity and computational efficiency. Fewer layers may result in insufficient modeling capacity, while more layers could lead to overfitting and higher computational demands. The number of layers was determined through empirical testing and optimization.Figure 10 shows an ANN diagram with three inputs, which are:

Input Voltage (V_in)
Input Current (I_in)
Temperature (T)
obtained simulation ANN model is shown in Figure 11

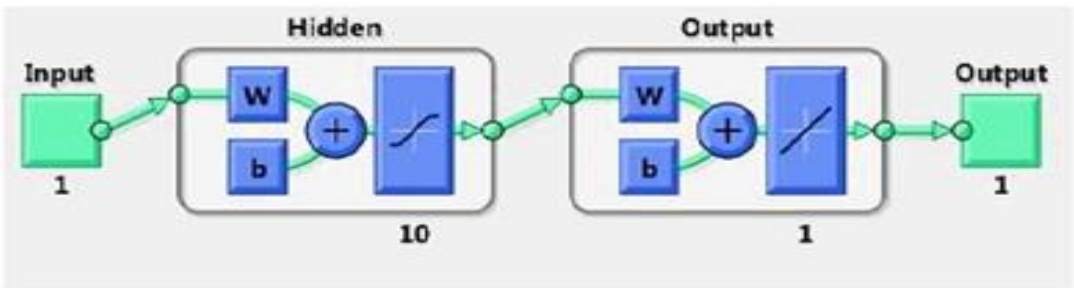

Fig. 11. Example of simulated neural network internal structure [7]

In fact, the ANN algorithm controllers are nominated and selected and presented as a proposed model in this thesis, where the details, categories and types of ANN algorithm models are discussed, in addition to defining the activation functions with analytical equations and illustrative graphs in many references and recent studies.

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ANN, a number of artificial neurons are linked together to form a robust computer-based tool that can handle a lot of data and run huge simultaneous calculations on input data. ANN operations are not guided by clear rules, and sequential computations are used to trial and error generate outputs. In contrast to conventional computers[25], the ANN is also referred to as "connectionism" because the given data is encoded in a complex, interconnected network of neurons rather than being transmitted from one neuron to another.

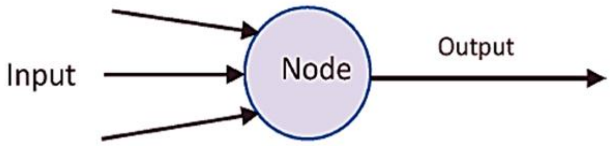

Fig. 12. Essential ANN node structure [25].

To appreciate the essential design of ANN, first and foremost, the comprehension of 'hub' is vital. Figure 12. depicts the node's generic model. Through connections, each node transmits various inputs to adjacent nodes. Figure 2.26 addresses the general model of ANN, which is invigorated by a organic neuron. The nodes are arranged in layers, which are linear arrays. Figure 13 shows that there are three layers in ANN called the info layer, the result layer and the secret layer. In fact, Xn denotes a number of network inputs in the input layer (X1, X2, X3, etc.). W1, W2, W3,... Wn, on the other hand, are connection weights that indicate a node's strength. Weights are the most important factors in ANN because they are numerical parameters that affect the output by converting the input and determining how neurons interact with one another. The hidden layer of the ANN performs the processing portion. The summation function and the transfer function—also known as an activation function—are the two operational functions that are carried out by the hidden layer. The first step is the summation function, in which each Xi input to ANN is multiplied by its weight (Wi), followed by the products Wi. The summation function = Wi is created when Xi is added up. Xi. Also, B is a value for bias. The neuron's output is controlled by this parameter in conjunction with the weighted sum of the inputs as expressed bellow

$$Output = \sum(Input \times Weights) + Bais \qquad (3)$$

The structure of the ANN scheme is presented in Figure 13 .

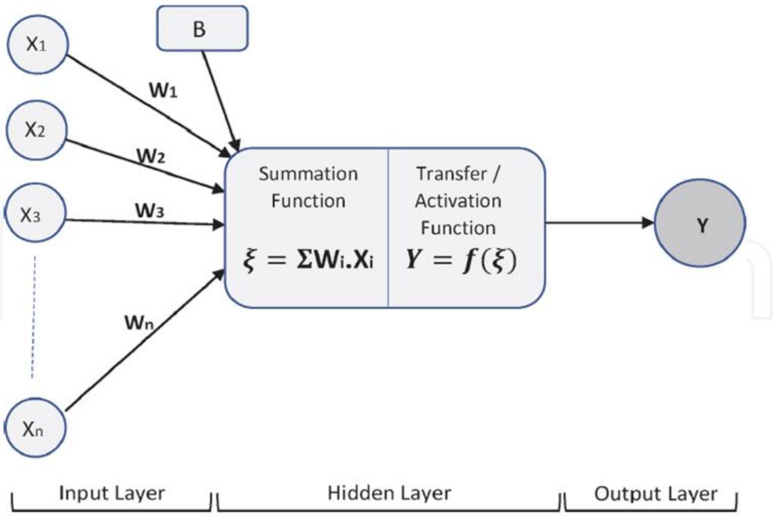

Fig. 13.The structure of the ANN scheme [22].

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The second step is the activation function; which transforms the input signal from the summation function module into an ANN model's ANN model's output. Hence, ANN has three fundamental parts, i.e., hub character, network geography and the learning rules. The activation function, the associated weight for each input and output, and the associated number of inputs and outputs are all determined by the node character, which controls the processing of signals. The starting and changing of weights are determined by learning rules. In contrast, the ways in which the nodes will be connected and organized are defined by the network topology. The ANN model operates by calculating the output of all neurons, which is a completely deterministic process[22, 25].

2. LITERATURE REVIEW

In the literature, there is a variety of research articles and studies related to the subject of smart control of photovoltaic micro-grids utilizing ANN techniques. In this study, recent papers will be summarized and presented according to the research title to provide a comprehensive view of the latest advancements and improvements in this field. The goal is to understand the research problem, define the objectives, and establish the basis for this work, while also suggesting potential solutions.

In 2017, De Santis et al.[7] proposed a fuzzy logic-based control scheme for the battery energy storage system (BESS), demonstrating the effectiveness of the fuzzy controller in regulating the DC bus voltage. They also proposed an EMS based on fuzzy logic to limit oscillations and manage small grid-related peak energies. The framework was tailored to manage the maximum power point tracking (MPPT) and reduce peak power along the grid through a fuzzy logic-based EMS.

In 2018, Lee et al. [8] suggested an energy management system (EMS) that operates independently of the main grid. This system can synchronize with various sources to shave load power during peak times. The system uses air as the primary energy source, combined with PV to enhance reliability in different weather conditions. The battery module is used as an energy storage system during backup energy needs when there is excess energy or demand. A self-restoring algorithm manages optimal power flows to achieve minimum power costs depending on power tariffs and expected load demand.

In 2018, Elgammal et al. [26] aimed to maximize energy generation from each source and reduce the operating cost of the micro-grid. They developed a hybrid algorithm using PSO with golden wolf optimization (GWO) and proposed a day-ahead scheduling energy management strategy.

In 2019, Carlet et al.[27] suggested a PID control scheme for an ANFIS-based PV interface inverter with an ANFIS-based controlled power management system for PV system integration. They addressed potential fluctuations in the low-voltage distribution grid caused by PV energy overflow.

In 2019, Jafari et al. [28] used a fuzzy interface system (FIS) in a scheme with renewable energy sources and a load unit for managing the power storage plan. The proposed structure was compared to a rule-based control methodology and demonstrated that the suggested FIS could effectively reduce variance by extending the lifecycle of the energy storage system (ESS).

In 2020, Bordons et al. [29]recommended a model predictive control (MPC) methodology based on weather forecasts to decrease power demand and increase the use of renewable energy sources for power management in domestic micro-grids. The MPC control methodology addressed an optimal control problem for a specified time horizon, showing improvements in home comfort and a 14.5% reduction in fossil fuel use. The system included wind, PV, and battery components, aiming to select the appropriate supply and generate optimal capacity based on demand.

In 2020, Omar Feddaoui et al.[30] proposed a hybrid power board algorithm by modifying the fuzzy inference system rule base using a hierarchical genetic algorithm (HGA). The fuzzy HGA algorithm outperformed the traditional fuzzy GA method, using only 47% of the rules in the rule base. This simpler soft logic controller could be implemented in real-time on low-cost embedded electronic devices. The grid-connected micro-grid included wind, PV, SOFC sources, BESS, and both DC and AC loads.

In 2020, Stellato et al. [31] provided a solution for convex quadratic programs using the operator section solver for quadratic programming (OSQP), which is typically ten times faster than interior point methods. However, these methods are limited to linear MPC problems or the linear form of the original nonlinear problem.

In 2021, Hannan et al. [12] utilized an artificial neural network (ANN) for load box assessment and battery state of charge (SOC) control, ensuring voltage stability. They also proposed a grid-connected MPC-based EMS. By increasing the use of wind power and batteries, the power obtained from the grid and energy costs were reduced.

In 2021, Prof. Dr.-Ing. Rolf Findeisenm et al. [32] suggested an MPC power board using Gaussian process (GP) estimation to minimize the energy cost from the grid. The GP estimated PV output power and load demand, employing optimization-based MPC techniques.

The studies reviewed above demonstrate various methods and algorithms developed to enhance the management and efficiency of photovoltaic micro-grids using ANN and other AI techniques. However, these methods often face limitations such as high computational complexity, limited adaptability to varying operational conditions, and challenges in real-time implementation on low-cost hardware.

The proposed method in this research aims to address these limitations by providing a more robust and adaptive control mechanism leveraging the strengths of ANN for improved energy management and system stability. Specifically, the proposed method includes:

An auto-tuning mechanism for predictive control to adapt to varying operational conditions in real-time.
Integration of ANN-based assessments to enhance the accuracy and efficiency of energy conversion.
Implementation on low-cost embedded electronic devices to ensure practicality and feasibility for widespread deployment.
By addressing the limitations of previous methods, the proposed approach aims to achieve higher efficiency, better stability, and more reliable energy management in photovoltaic micro-grids.

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Table 2. List of the recent modern publications concerning the proposal title.

Reference	***Technology***	***Contribution***	***Limitations***
In 2020, Omar feddaoui, et. al., [30]	*Proposed a half power board algoritm by altering the standard base of the fuzzy derivation framework against hierarchical genetic algorithm (HGA).*	*The fuzzy HGA algoritm seems, by all accounts, to be preferable over the traditional fuzzy GA technique, utilizing just 47% of the guidelines inside the rule base. By having a sensitive and less difficult logic controller, the entire control system can be progressively implemented at a lower cost than implantable electronic devices.*	*The essential limitation of fuzzy control is time-consuming tuning of the controllers.*
In 2019, Jafari, M., et. al., [28]	*utilized a fuzzy interface system (FIS)*	*A scheme implemented with sustainable energy sources is presented along with a load module to manage the energy storage scheme.*	*The suggested model contrasts with the standard control methodology, which showed that the proposed FIS can indeed reduce the variability by extending the existence pattern of the energy storage (ESS) frame.*
In 2020, Bordons, C., et. al., [12]	*Suggested a model predictive control (MPC) methodology, based on weather gauges*	*Reduce the power demand and increment the utilization of sustainable power hotspots for power the board in homegrown miniature grids. The planned MPC control methodology is based on addressing a restricted ideal control issue for a certain period frame skyline. Such suggested framework was contrasted as well the typical rule-based control rationale. An enhancement in home solace constrains with a normal of 14.5% decrease in the utilization of essential fossil power are noticed.*	*The MPC is designed with construction, use and battery value constraints for a grid-tied framework consisting of wind and PV with battery. Along with this review, it was expected to select the appropriate display as well as produce an ideal capacity for the display of interest.*
In 2020, B. Stellato, et. al., [31]	*Provides the solution for convex quadratic programs implemented in the operator section solver for quadratic programming (OSQP)*	*This proposed technique is usually ten times faster than interior point methods.*	*Such methods are limited to linear MPC problems or the linear form of the original nonlinear problem. Collision-free MPC paths involve navigating through several non-exhaustive WMRs that evaluate the nonlinear optimal control problem.*
In 2021, Prof. Dr.-Ing. Rolf Findeisenm, et. al., [32]	*An MPC power board has been suggested*	*A Gaussian Interaction Evaluation (GP) is employed to limit the cost of energy obtained along the grid against GP, and the PV energy production energy is evaluated with the burden need energy.*	*Reinforcement based MPC techniques are used.*

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3.METHODOLOGY

In this suggestion, we present an effective controller for adjusting the photovoltaic micro-grid smart inverter power system with the help of the ANN technique to solve the issue of floating energy and improve the efficiency of the system as a whole. The suggested model should be capable of eliminating the losses and disadvantages caused by LC filters and other control technique limitations. The necessary software chosen to employ the proposed technique relies on using MATLAB 2020 simulation software. This software provides efficient tools necessary to simulate the problem and present the necessary evaluation packages. The MATLAB 2020 toolbox consists of robust built-in programmed functions that have been utilized in our proposed simulation methodology.. Figure 14, illustrates the proposed model for global DER smart inverter.

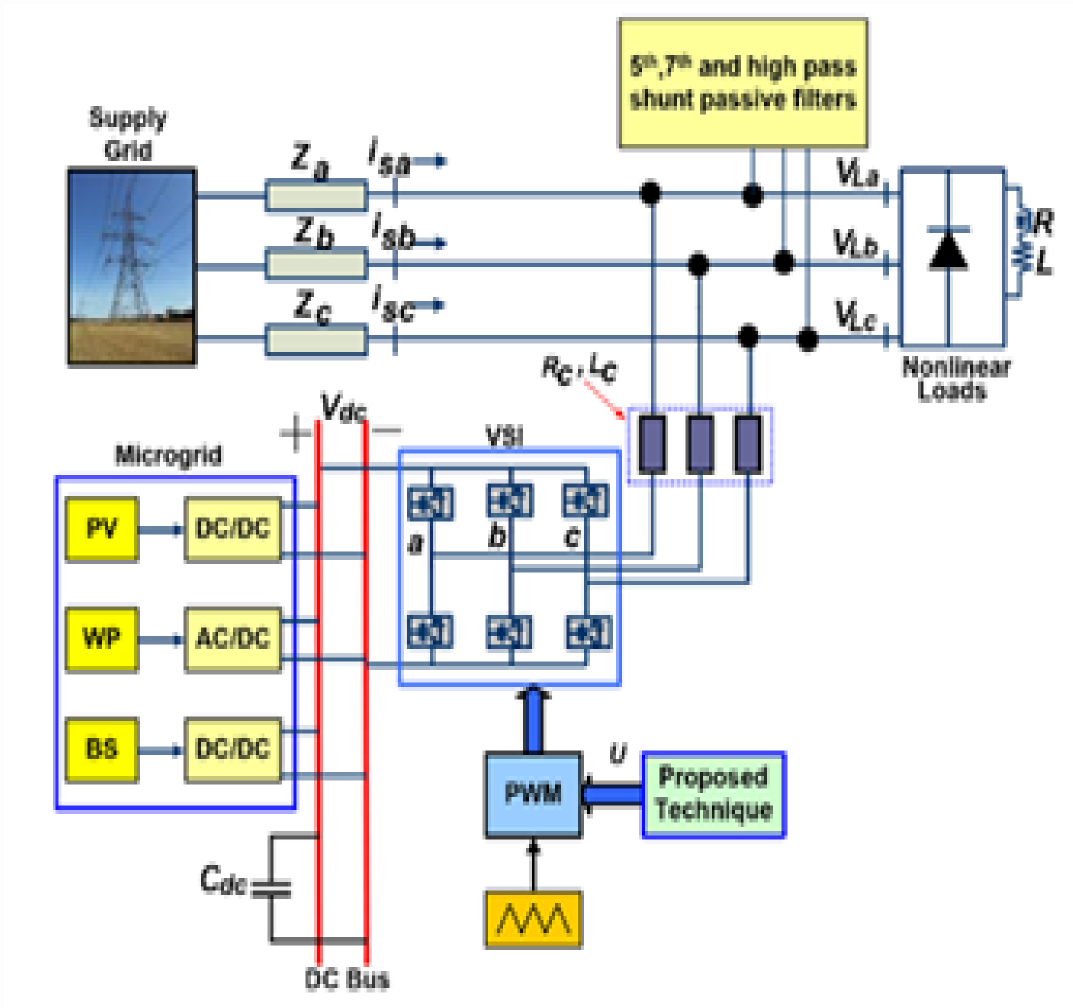

Fig. 14. The proposed general DER smart inverter model.[14]

The proposed model is illustrated in Figure 14, showing the general DER smart inverter. The system consists of three main units: the photovoltaic cells, the boost controller, and the Smart Inverter with ANN controller

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unit. Each unit has a specific mission to perform in favor of achieving the overall optimum response for the scheme

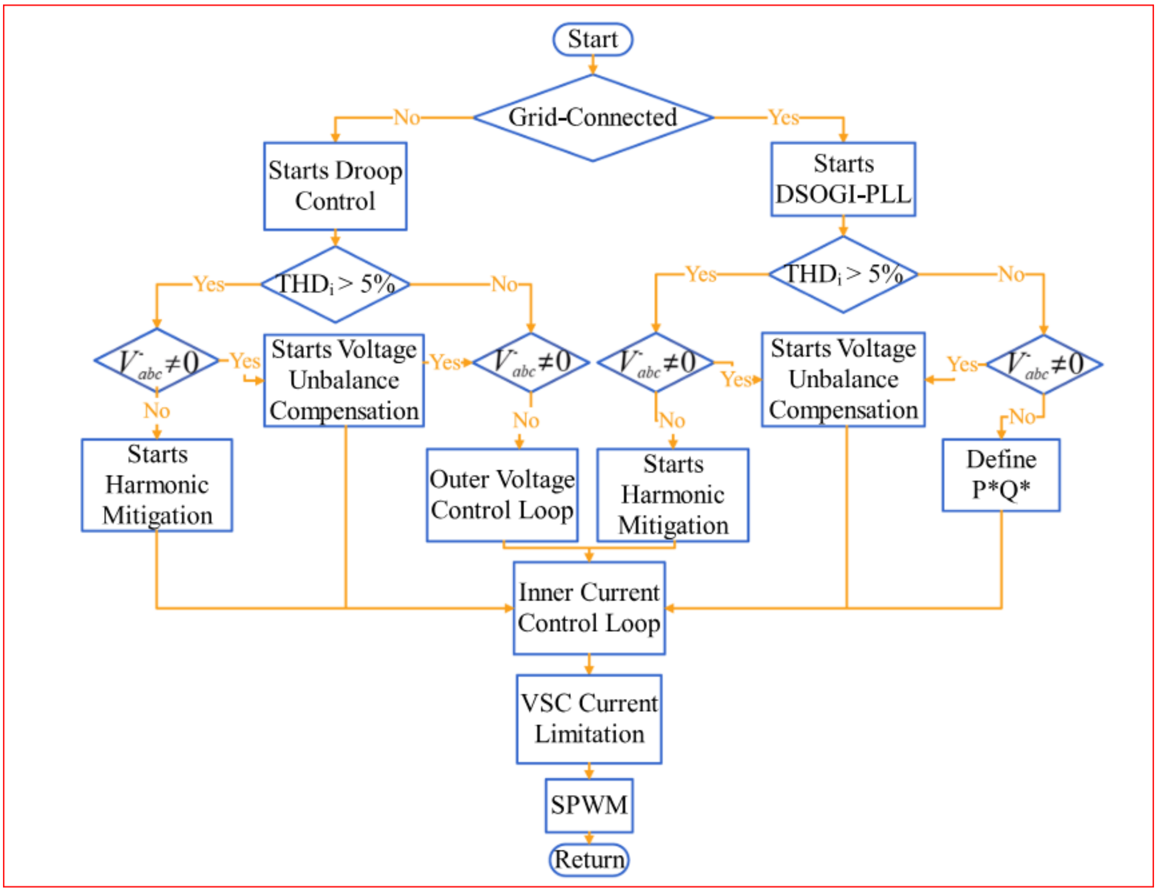

Fig. 15. Flow chart methodology of proposed smart inverter model.[9]

Depending on the operation mode, the algorithm is executed with a various approach to obtain current references. but, every operating modes ccouldan work in parallel, for example, an active shunt filter can work together Voltage imbalance compensation. Therefore, in all cases, connected to the network or island mode, internal current controller employee. While placing the grid formation, it is important to do this start droop control to stabilize voltage and frequency/regulation, utilizing an external AC voltage control loop. In network feeding mode, it is only necessary to set the active and reactive mode power references, through PV system and battery (energy manager).

The suggested model simulation diagram has been presented in Figure 16 to illustrate the methodology of its operation.

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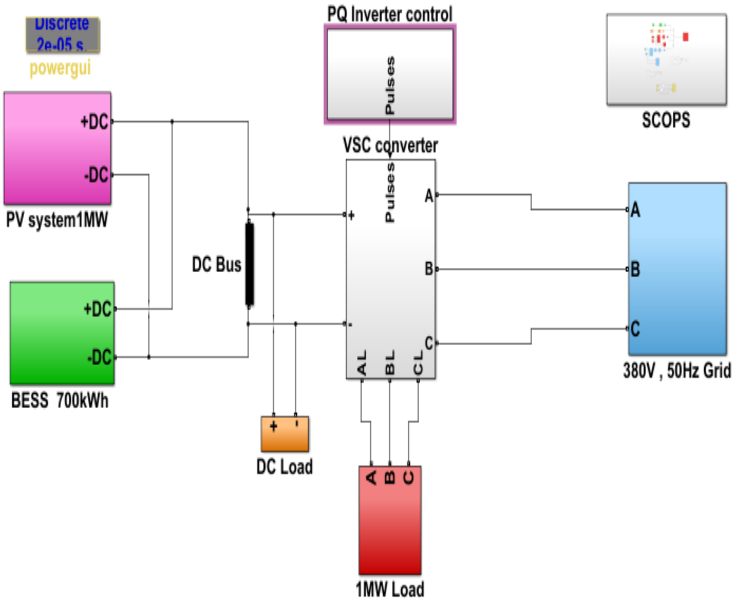

Fig. 16. The suggested simulated scheme employed in the project.

The above displayed simulated model consists of three main units, the photo voltaic cells, the boost controller, and the Smart Inverter with ANN controller unit. Such units each will have a specefic mission to perform in favor of achieving the overall optimum response for the scheme.

3.1 Explanation for Choosing Traditional ANN

The decision to use a traditional Artificial Neural Network (ANN) over deep learning or other machine learning algorithms was driven by several key factors:

1. Complexity and Computational Efficiency:

Traditional ANNs are less complex and require fewer computational resources compared to deep learning models. This is particularly important in real-time control systems where computational efficiency is crucial. Implementing deep learning models would necessitate more powerful hardware and could introduce latency in the control loop, which is undesirable in PV micro-grid applications where timely responses are critical.

2. Simplicity in Implementation:

The architecture of traditional ANNs is simpler and easier to implement and tune for specific tasks compared to the more complex architectures required for deep learning. This simplicity translates to faster development cycles and easier maintenance, which are significant advantages in engineering applications where rapid deployment and reliability are essential.

Sufficient Performance for the Task:

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Traditional ANNs have been shown to provide sufficient accuracy and performance for the control tasks required in PV micro-grids. The tasks such as predicting power output, optimizing energy conversion, and managing grid stability can be effectively handled by traditional ANNs without the need for the additional layers and complexity of deep learning models.

3. Scalability and Adaptability:

Traditional ANNs offer a balance between scalability and adaptability. They can be easily scaled up or down based on the requirements of the specific application without a significant increase in complexity. This adaptability is useful in PV micro-grids where conditions and requirements can change dynamically.

4. Avoiding Overfitting:

Deep learning models, due to their complexity, are more prone to overfitting, especially when the available data is limited or not diverse enough. Traditional ANNs, with their simpler structures, are less likely to overfit the data, making them more robust for practical applications where the data may not always cover all possible scenarios.

5. Training Time and Data Requirements:

Traditional ANNs generally require less training time and fewer data samples compared to deep learning models. In the context of PV micro-grids, where historical data may be limited and the need for rapid deployment is high, the lower data and time requirements of traditional ANNs make them a more practical choice.

By selecting a traditional ANN for this application, we strike a balance between performance, simplicity, and computational efficiency, ensuring that the control system is both effective and practical for real-world deployment in PV micro-grids.

3. 2 The Voltge Source Controller (VSC) Unit

The voltage source controllers (VSC) are self-switching converters for connecting high voltage alternative current (HVAC) with high voltage direct current (HVDC) models utilizing apparatus better for huge-energy electronic implementation, like IGBTs. VSCs have the ability to self-switch, capable of generating AC power regardless the need of rely on an AC model. Figure 17 shows MATLAB simulation circuit diagram of the VSC controller unit used in the proposed smart controller model.

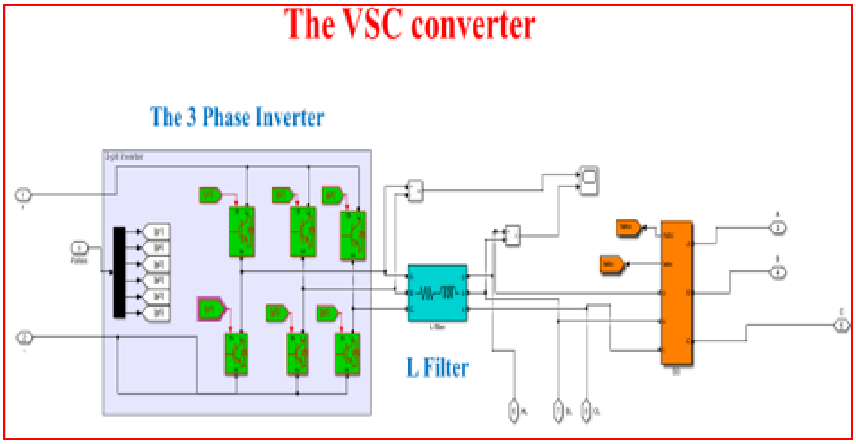

Fig. 17. The MATLAB simulation circuit diagram of the VSC controller unit utilized in the proposed smart controller model.

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From the figure above, we could recognize the details of the design of the voltage control unit, that is also called the alternating voltage control unit or the alternating current regulator. As we explained in the theoretical aspect in the second chapter, this system is an electronic unit that relies either on thyristors, or triodes for alternating current, or rectifiers that are controlled using silicon elements, or bipolar transistors with an insulated gate, which regulate energy in the form of a constant voltage and current. Constant frequency alternator (AC). In fact, the high voltage direct current (HVDC) electrical power transmission system uses direct current (DC) to transmit electrical energy, in contrast to the more common alternating current (AC) transmission systems. As a conclusion for the VSC operation, it will convert the entered DC power to an efficient output AC power.

3.3 The Smart Inverter Controller Unit

As explained theoretically in Section 1, the PQ inverter control is widely used in several types of energy conversion, for example, motor control (electrical energy to motive energy) of air conditioning systems or washing machines, etc., cooking machines (Electricity for heating), and power conditioners, which transfer electrical energy generated from solar energy to the home. Also, "Smart inverters" are a more advanced version of power electronics which might make autonomous decisions to maintain grid stability and reliability as more energy resources become distributed across the distribution network. Instead of simply feeding power to the grid, smart inverters are able to make bi-directional connections to it. Figure 18 shows the designed MATLAB Simulink smart inverter controller unit employed in the suggested model..

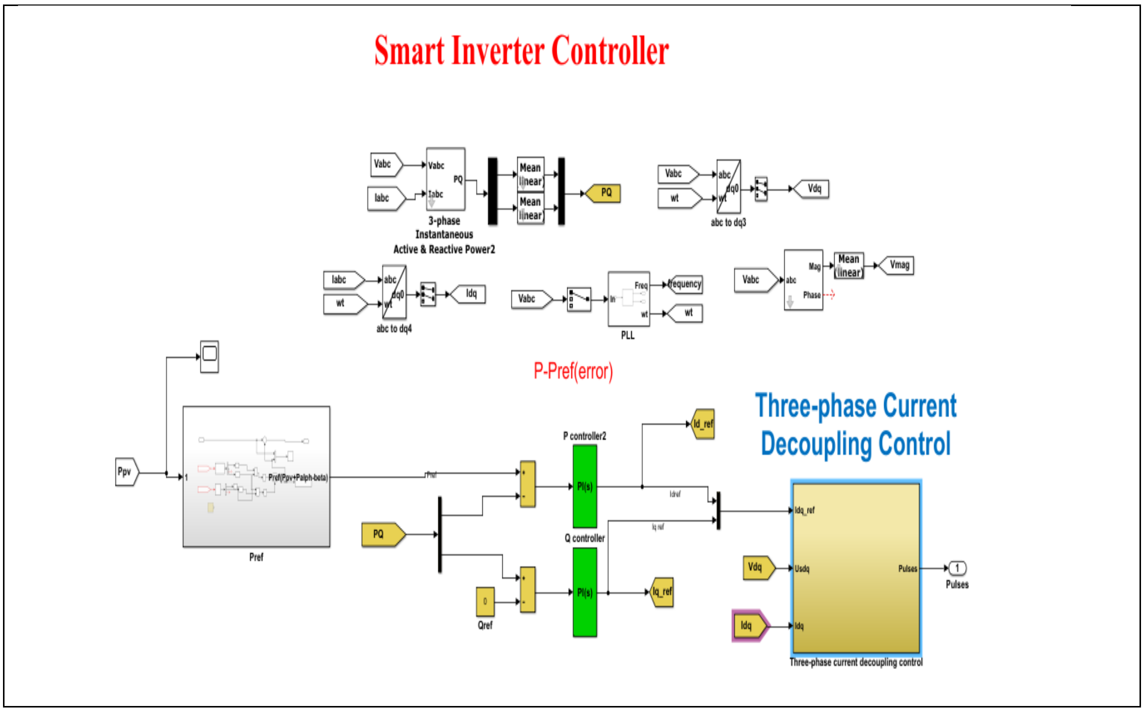

Fig. 18. The designed MATLAB Simulink smart PQ inverter controller unit employed in the suggested model.

As illustrated in Figure 18, and also as we explained in Chapter Two, the PQ-type control system operation includes detecting the three-phase voltage and alternating current signals (Vabc, and Iabc) generated by the three-phase inverter and analyzing them into d- and q-axis components, where vd and vq represent the d-axis and q-axis components of the AC voltage for each phase; Likewise, id and iq represent the d-axis and q-axis components of the armature current for each phase. Such axial components d, q are used to produce the values of the reactive power P and the apparent power Q to find the difference between them and know the changes that occur in the voltage and current values Vabc, Iabc and improve and process them by controlling the cut-off signals of the three-phase inverter diodes. Figure 19 demonstrates the three-phase current decoupling controller.

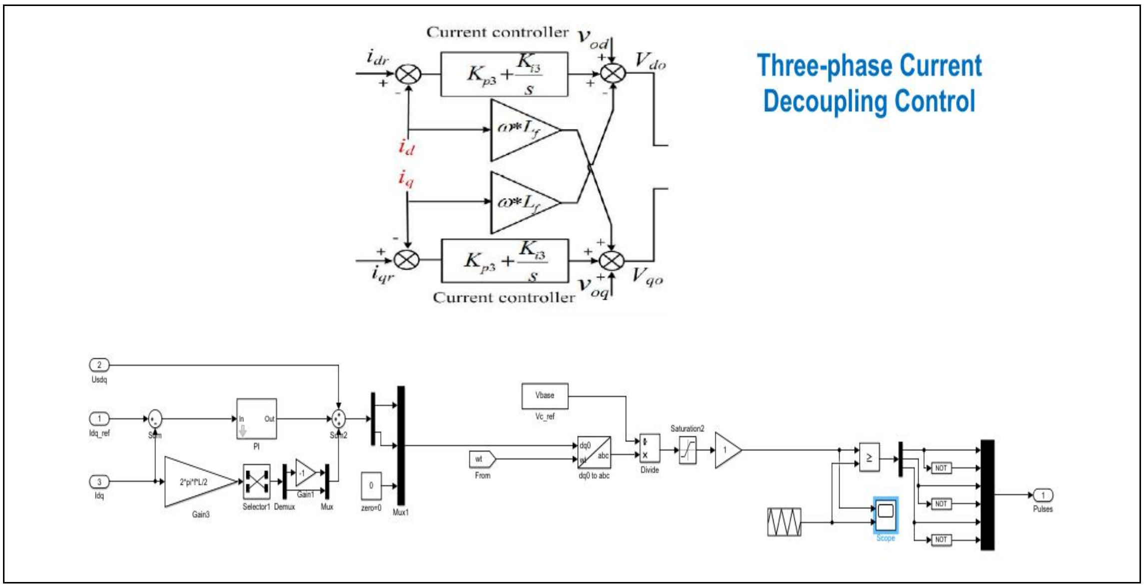

Fig. 19. The designed MATLAB Simulink of the three phase current decoupling controller employed in the suggested model.

By reviewing the details of the three-phase current separation control system, the reference potential waveforms are expressed in the dq framework of SVPWM through the equations described in literature [16-28]. Where the ANN smart controller is utilized instead of the PID controller to carry out the process of intelligent control of the changes in the power differences resulting from the return wave from the three-core inverter to produce cutting control signals that improve power production and equalize the changes in the voltage and current of the three-phase alternating generator inverter.

3.4 The Employed Dataset

In this part, we will introduce and understand the generation tools utilized to represent and implement the entered dataset utilized in this project. In this study, in order to design and implement the systems of the proposed model for intelligent control of electrical energy distribution using artificial intelligence techniques, the tools of the MATLAB environment libraries were used, which are rich in ready and efficient functions for use in generating and processing the dataset used in tests to implement the work of this project. Figure 20 shows the MATLAB Simulation block diagram for the tools utilized to support and generate the model dataset.

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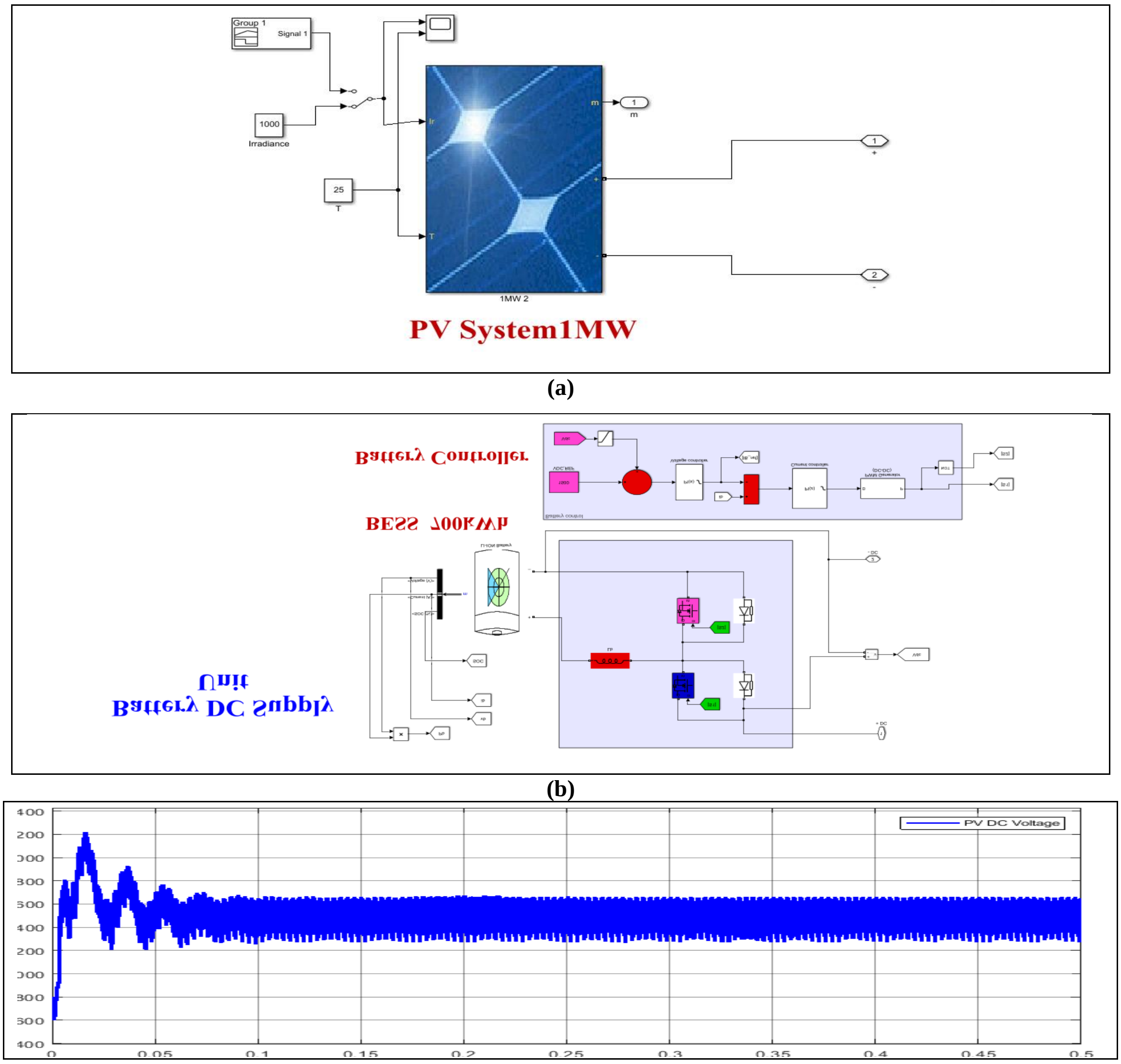

(a)

(b)

(c)

Fig. 20. The MATLAB dataset generation schemes, (a) MATLAB Simulation block diagram for PV dataset model, (b) The MATLAB Simulation block diagram for Battery dataset model, (c) The generated dataset.

As we could notice from Figure 20 above, the prepared dataset used to test and implement the systems of the proposed smart controller model is prepared and generated from a group through the MATLAB program tools shown in Figure 20(a), which represent solar cell data processing tools, and Figure 20(b), which represent tools for preparing dry battery table data. We can also see the generated and processed data used in implementing the project in Figure 20(c), which represent continuous voltage signals that flow with units of time.

3.4 The Model Design Flow Chart

Next, in this section, the operating mechanism of the subject idea of the suggested model will be demonstrated and discussed, with the implementation steps and their details will be outlined, starting with generating and processing the data set and ending with the required results. Figure 21 displays the flow chart for the design and implementation parts of the proposed model for the smart controller for the electrical distribution network.

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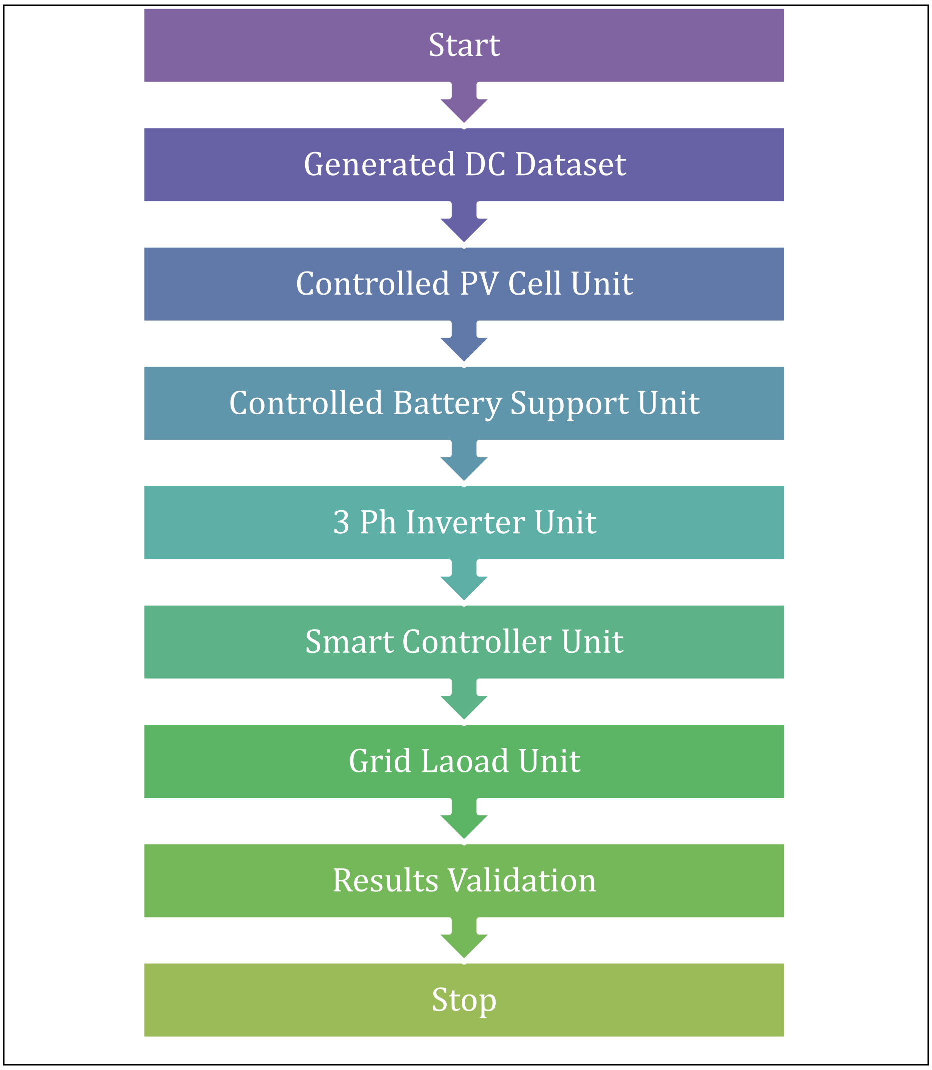


Fig. 21. The flow chart for the design and implementation units in the proposed model of the smart controller for the electrical distribution network.

By looking at the details of the flow chart shown in Figure 21, we could conclude that the program begins by defining the used data set, which was created through the use of a controlled photovoltaic unit as well as a battery support unit to prepare the DC voltage and current supplying the system. This is followed by the implementation of the three-phase inverter unit, which reflects voltages from continuous to alternating power and is controlled through the most important unit in the project, which is the smart control unit, which monitors the work of the outputs from the three-phase inverter unit to output the required signals to the network load unit. Then the results are verified and the program is stopped.

3.6 The Model Design Settings

Finally, the design parameters and variables utilized to settle the operation of all the units in the suggested smart inverter controller model will be demonstrated. Table 3 diasplays the model design components and variables utilized in the construction.

Table 3: The design parameters and variables utilized to control the design and implementation of the suggested system

<table>
<tr><th>Model Components Defenition</th><th colspan="8">Model Parameters Values</th></tr>
<tr><td rowspan="2">PV Cell Unit</td><td>Cin</td><td>Rin</td><td>Lin</td><td>Rout</td><td>Switching frequency</td><td>Ts</td><td>Irradiance</td><td>Temerature</td></tr>
<tr><td>6e-3</td><td>2e-3</td><td>10e-6</td><td>10</td><td>5e5</td><td>1e-5</td><td>1000</td><td>5</td></tr>
<tr><td rowspan="3">VSC Converter Unit</td><td colspan="3">IGBT Diode</td><td colspan="2">L Filter</td><td>3 Phase VI Measurements</td></tr>
<tr><td>Internal Resistance Ron (Ohms)</td><td>Snubber Resistance Rs (Ohms)</td><td>Snubber capacitance Cs (F) :</td><td>Inductance L (H)</td><td>Resistance R(Ohm)</td><td>Voltage Measurement</td></tr>
<tr><td>700</td><td>1e5</td><td>inf</td><td>L=0.01</td><td>5e-7</td><td>Phase-to-Ground</td></tr>
<tr><td rowspan="2">Battery Unit</td><td>Nominal voltage (V)</td><td>Rated capacity (Ah)</td><td>Initial state-of-charge (%)</td><td>Battery response time (sec)</td><td>PID Control Proportional (P):</td><td>PID Control Integral (I):</td></tr>
<tr><td>700</td><td>1000</td><td>80</td><td>1</td><td>0.9</td><td>100</td></tr>
<tr><td rowspan="3">PQ Smart Controller</td><td colspan="3">PLL System</td><td colspan="2">1st Order Filter</td><td colspan="2">Repeating Sequence</td></tr>
<tr><td>Minimum frequency (Hz):</td><td>Regulator gains [Kp, Ki, Kd]</td><td>Time constant for derivative action (s)</td><td>Time constant (sec)</td><td>AC initial input [Mag, Phase (degrees), Freq (Hz)]</td><td>Time Values</td><td>Output Values</td></tr>
<tr><td>45+5</td><td>[180, 3200, 1]</td><td>1e-4</td><td>30e-3</td><td>[0 0 60]</td><td>[0 1/4 0.75 1] /Fpwm</td><td>[0 1 -1 0]</td></tr>
<tr><td rowspan="3">ANN Unit</td><td rowspan="2">Input Layer</td><td rowspan="2">Hidden Layer</td><td rowspan="2">Output Layer</td><td rowspan="2">Training Function</td><td colspan="3">Training Options</td></tr>
<tr><td>Train</td><td>Test</td><td>Validate</td></tr>
<tr><td>1</td><td>10</td><td>1</td><td>Back-Propagation</td><td>70%</td><td>15%</td><td>15%</td></tr>
</table>

4. SIMULATION RESULTS

In this chapter, the simulation model of the proposed PV system inverter characteristics improvement using ANN controlling technique system has been implemented using MatLab2020b Simulink tool box. The simulation structure of the suggested model has been repeated and illustrated in Figure 22.

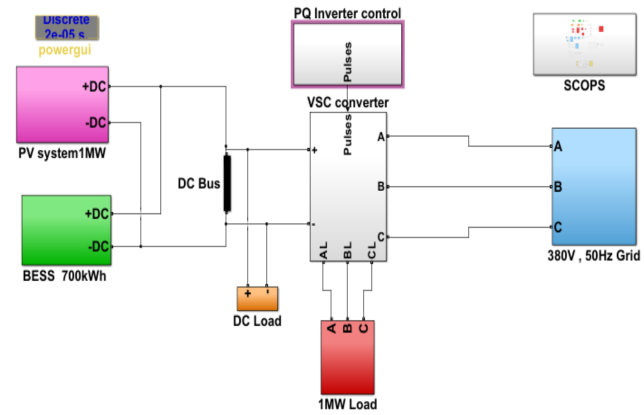
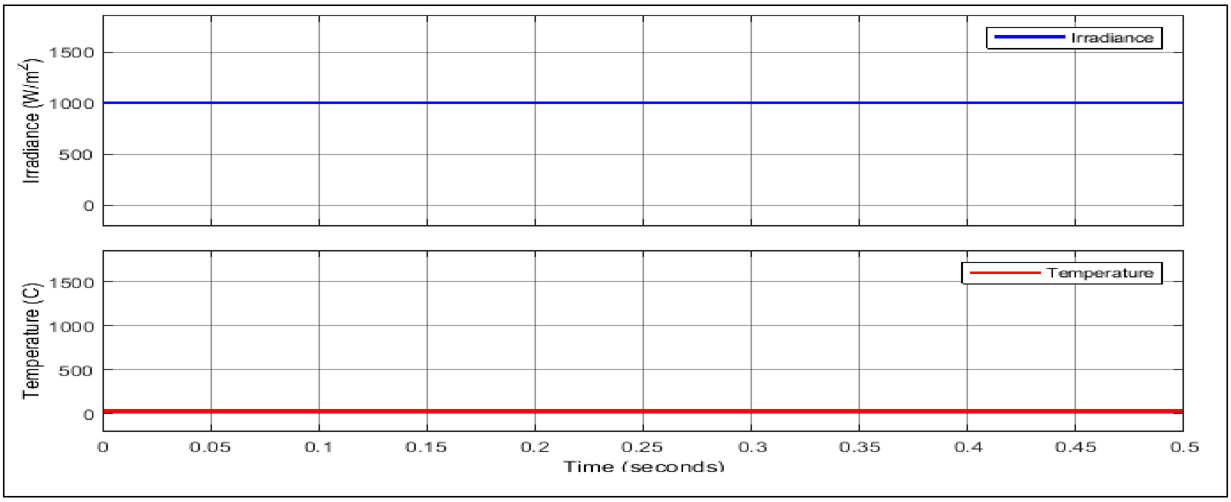


Fig. 22. The proposed simulated model implemented in the studt.

The above displayed simulated model consists of three main units, which are; the photo voltaic cells, the boost controller, and the Smart Inverter with ANN controller unit. Such units each will have a specefic mission to perform in favor of achieving the overall optimum response for the scheme. In the incomming sections, these units will be discussed in details.

4.1 Simulation Results

The generated PV cells signals with obtained voltages, currents, and power waves are presented in Figure 23.



(a)

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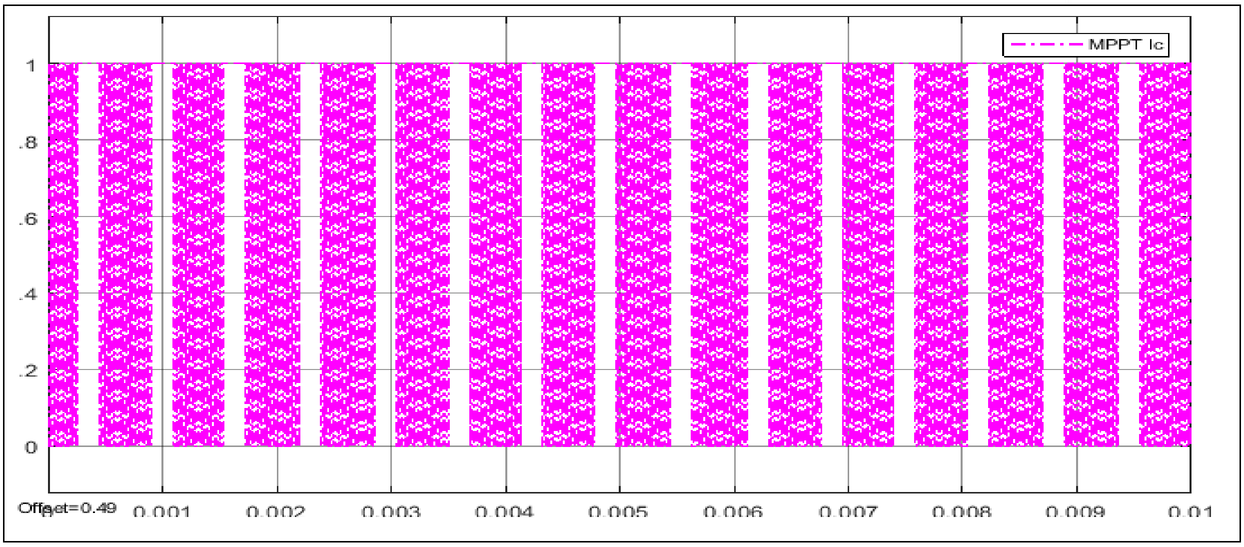
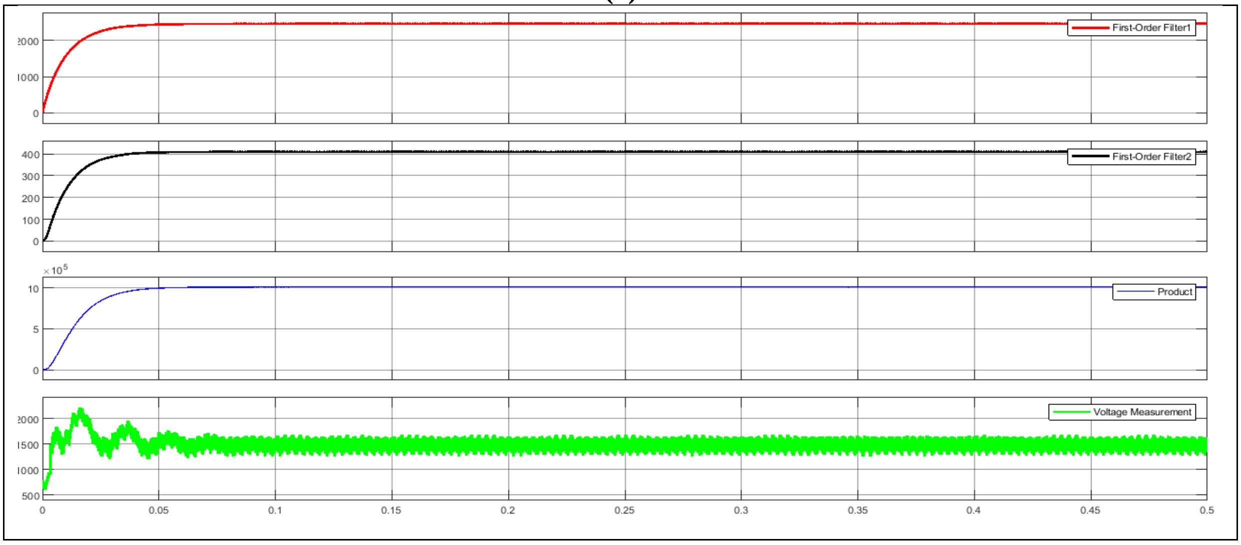


(b)



(c)

Fig. 23. The generated PV panel unit signals of the proposed model, (a) PC cells settings, (b) PWM wave, (c) PVcurrent, voltage, and power signals.

By examining the results in Figure 23, we observe the details of the outputs of the solar cell unit in the implemented model. This system offers the greatest converted cross-power point to ensure that photovoltaic (PV) displays under partial shade (PSC) conditions can always produce maximum power quickly and effectively. The next strategy is called Maximum Power Point Tracking (MPPT), involving specialized disturbance and observation (P&O) monitoring. Instead of utilizing expensive light intensity sensors on the spot, the light intensity of each photoelectric array unit is switched on, and set points can be checked using cheaper voltage and current sensors. As discussed in Section 1, the P&O controller predicts the optimal voltage areas of the Global Maximum Power Point (GMPP) by utilizing background light intensity. The P&O controller operation produces the best tracking of overall power, since part of the slight differential variation in PV voltage and current that the P&O controller might not sense will be detected by adjusting the remainder of the control model. It is evident from the obtained results that the PV voltage and current amounts are unstable, and the resulting PV power is fluctuating below the maximum designed value. The amounts of supplied current are also fluctuating below 400 A, while the voltage reaches further than 2000 V with a maximum power of 100 KW.

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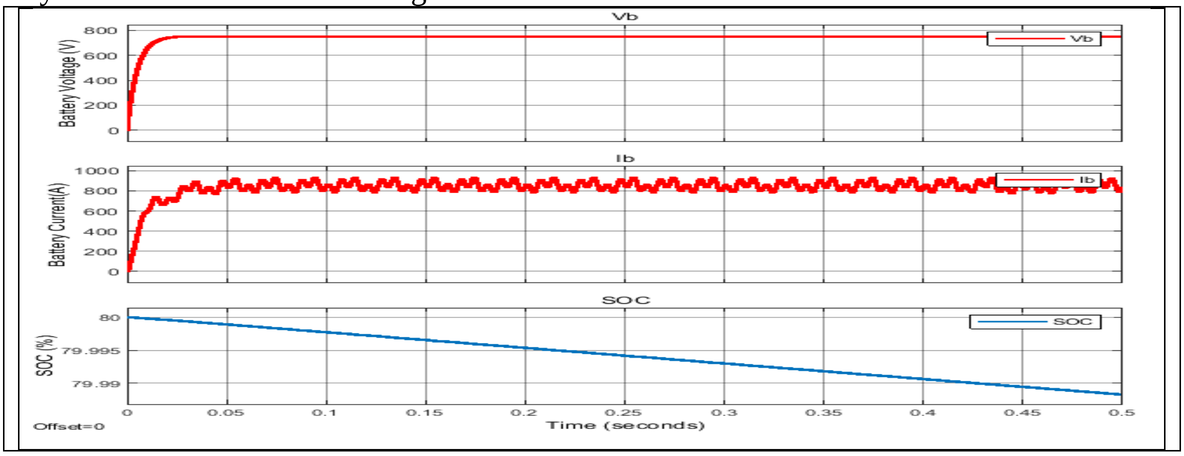
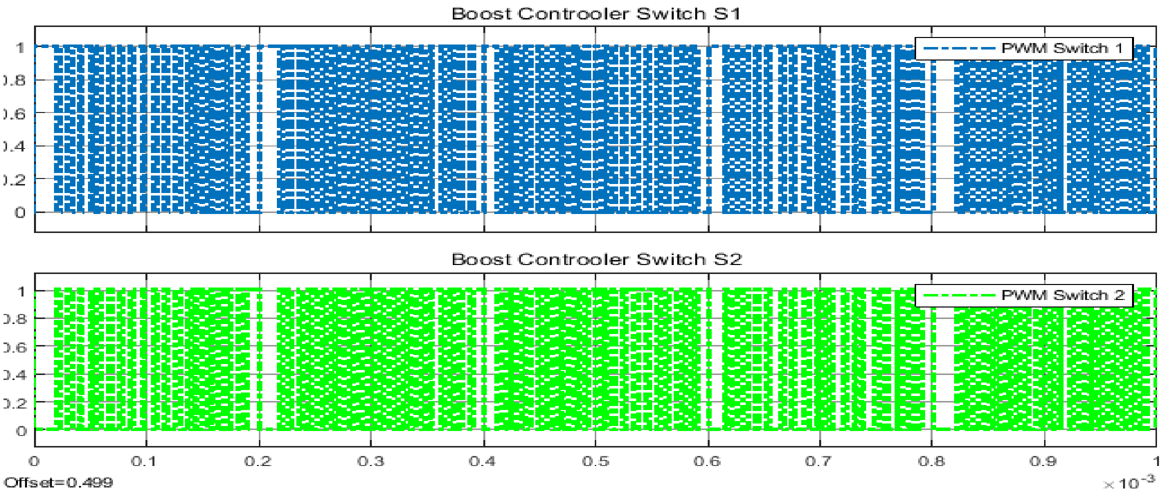
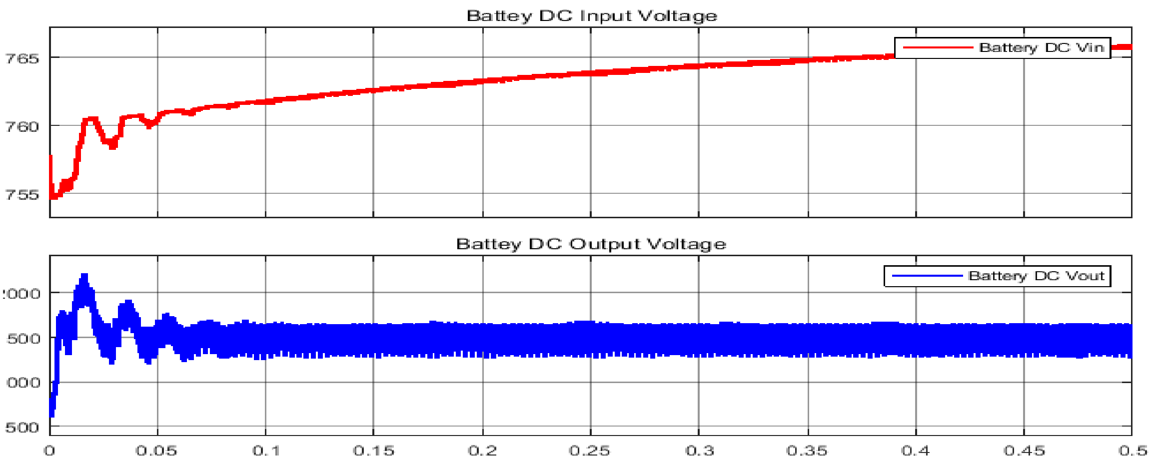
The battery unit results are shown in Figure 24.



(a)



(b)



(c)

Fig. 24. The obtained battery unit results, (a) Battery cell signals, (b) The boost controller switch signals, (c) The Boost resulting voltage.

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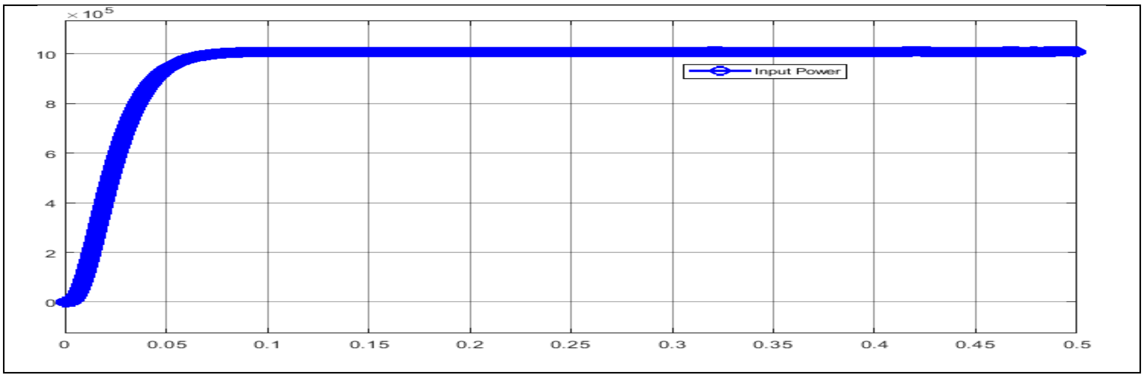
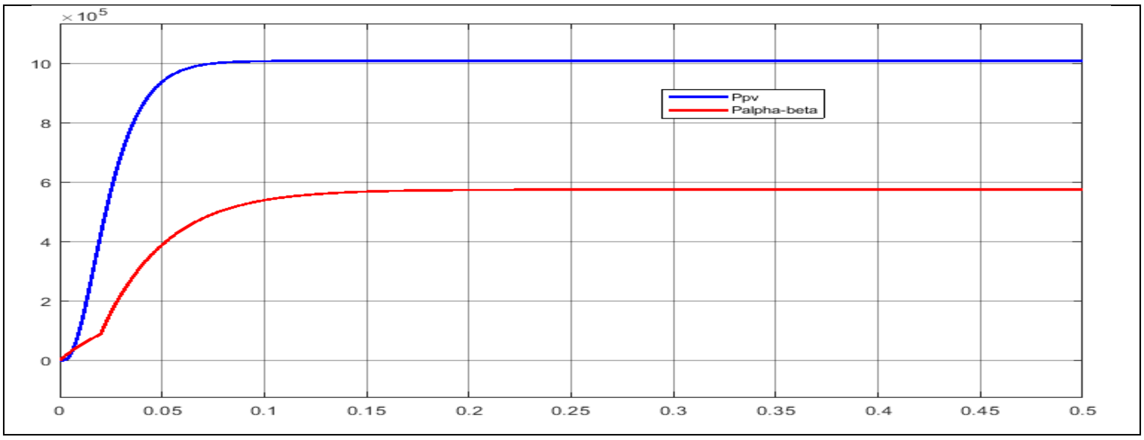
From the results of the signals presented in Figure 24 describing the operation of the battery module, we infer the battery boost control circuit operation as a P&O algorithm, which includes voltage disturbance and power production monitoring. Implementing such a technique results in increased power if operated on the left side of the MPPT and decreased power when operated on the right side of the MPPT. For DC applications, an MPPT algorithm is needed to maximize the use of generated power. MPPT algorithms ensure that the charger extracts maximum power from the battery pack or solar panel and delivers it to the load or to recharge the battery without voltage collapse at the dry table outlet of the battery. The boost converter, with its P&O control circuits, can be utilized for both the battery and the photovoltaic cells to boost the MPPT in the resulting DC voltage signals. The voltage resulting from the battery unit, specifically from the booster block, stabilizes at a value of 500 volts by controlling the booster block with the controller circuit. The operation of this unit is adjusted to obtain a constant continuous voltage that enhances the voltage of the solar panel unit with a stable state of charge of the battery cell by 80%. This battery DC voltage will be an enhanced and alternative voltage to supply the system with power in the event of failure or low voltage of the power panel unit.

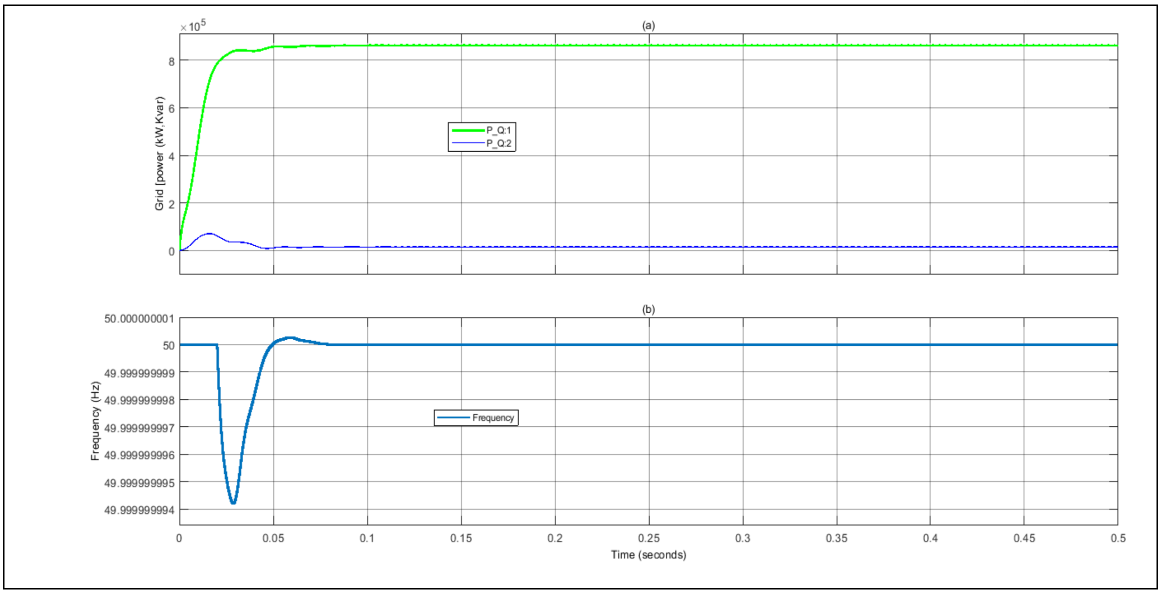
Concerning the results of the smart controlling unit, the achieved signals of voltages, currents, and controlling switches signals are presented in Figure 25..



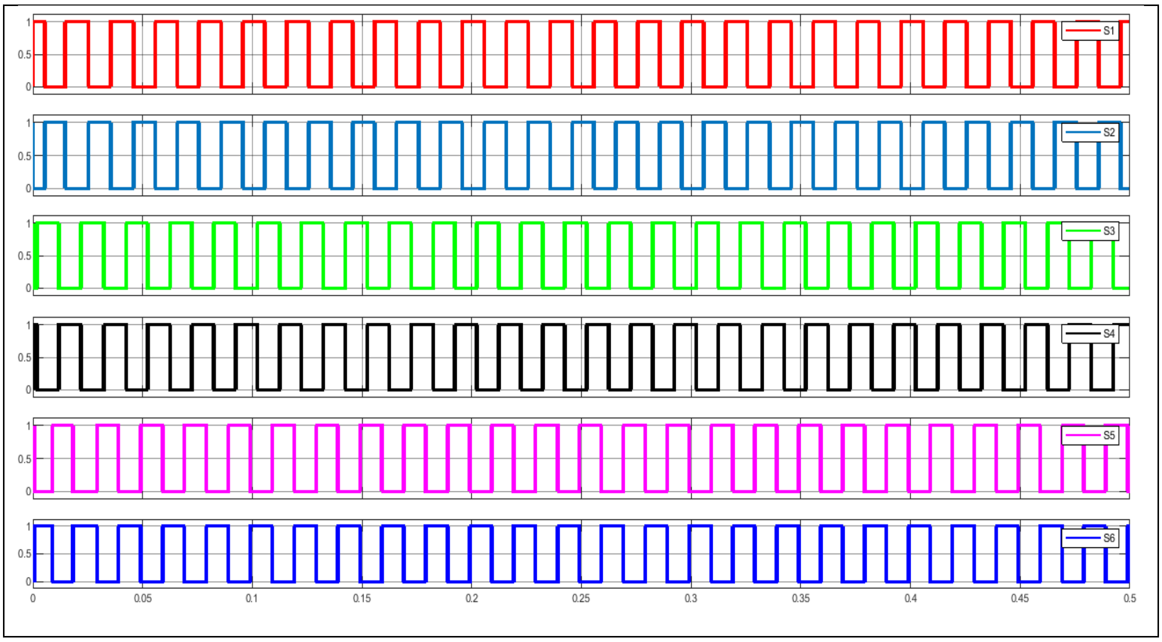
(a)



(b)



(c)



(d)

Fig. 25. The results of the smart controlling unit, (a) Input power, (b) Alpha-beta power, (c) PLL (P_Q and ω_t) , (d) Smart 3-phase current decoupling control switch signals.

The details of the signals and outputs in Figure 25 show the mechanism and details of the operation of the PQ controller, besides the three-phase current control system, through which the reference potential waveforms might be expressed in the dq frame of the SVPWM using the equations described in the literature. As previously explained, the mechanism of operation of the PQ type control system includes detecting and controlling the three-phase voltage and alternating current signals (Vabc and Iabc) generated by the three-phase inverter and analyzing them into d and q axis components, where vd and vq represent the d axis components. The q-axis represents the alternating current voltage for each phase, and similarly, id and iq represent the components of the d-axis and the q-axis of the armature current for each phase. These axial components (d, q) are used to produce the values of the reactive power (P) and the apparent

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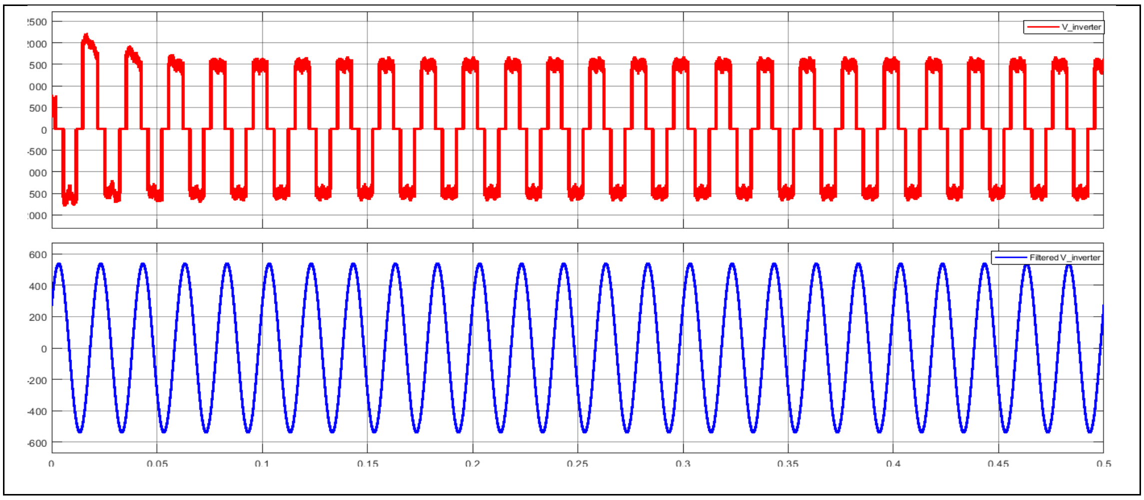
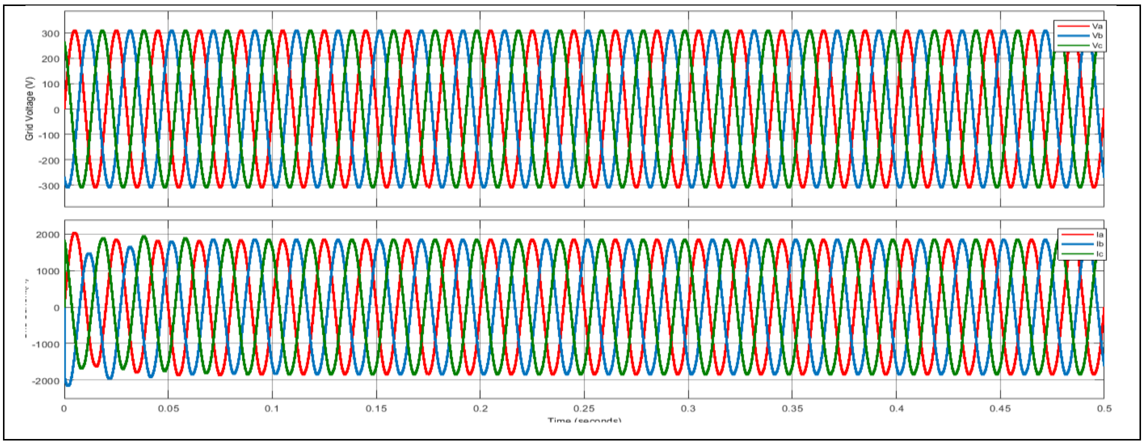
power (Q) to find the difference between them and understand the changes in voltage and current, Vabc, Iabc, and their improvement and processing by controlling the cut-off signals for three-phase inverter diodes. The ANN intelligent controller's role, instead of the PID controller, is evident in the process of intelligently controlling the changes in the power differences resulting from the return wave from the three-phase inverter to produce cutting control signals that improve the power production and equalize the changes in voltage and current of the three-phase generator inverter. The smart controller system works to segment the input power values and take advantage of slight changes and the amount of error between the total power and the apparent power to produce axial current and voltage values (dq) through which the key signals of the three-phase inverter could be controlled to convert the continuous voltage signal to alternating. The basic synchronous DQ framework is a time-domain method derived from space vector transformations of three-phase systems. These methods are widely used for analyzing three-phase circuits, as this particular method is suitable for active filtering.
The achieved signals from the three-phase inverter unit are displayed in Figure 26.



(a)



(b)

Fig. 26. The three phase inverter unit achieved signals, (a) Inverter output voltage, (b) Three phase inverter resulting voltages and currents.

By examining Figure 26, we observe the details of the voltage controller design, also called the AC voltage controller or AC regulator. As explained in the theoretical aspect in the second chapter, this system is an

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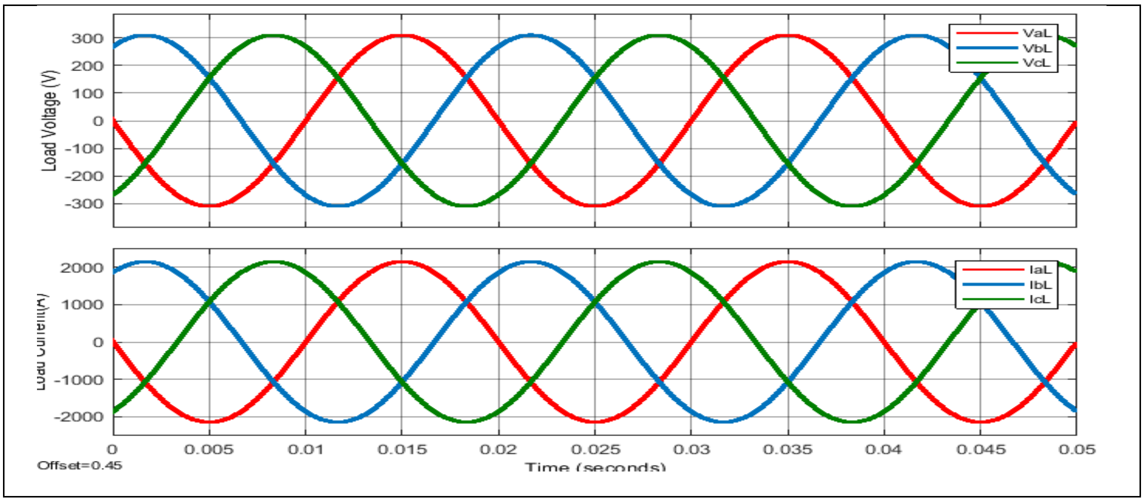
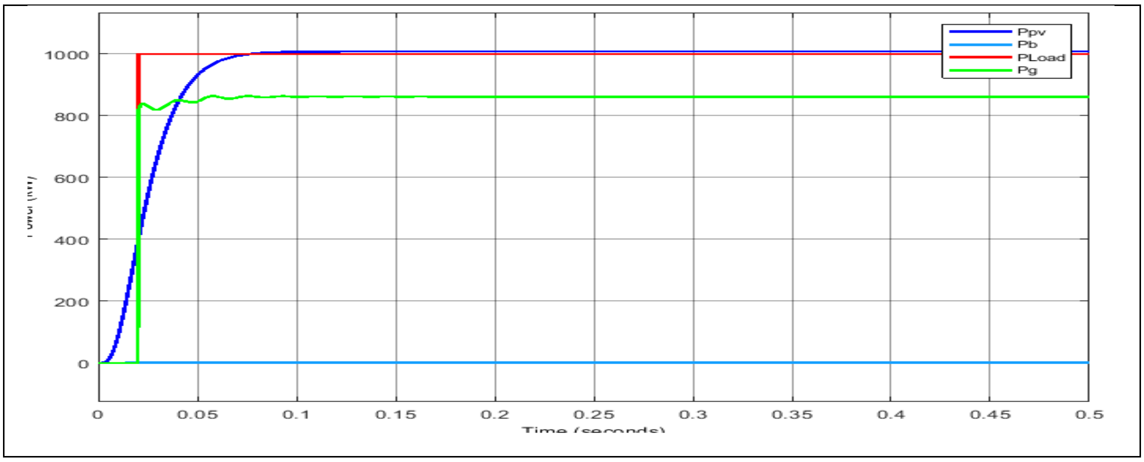
electronic unit that relies either on thyristors, alternating current triodes, or rectifiers controlled using silicon elements or bipolar transistors with an insulated gate, which regulate energy in the form of voltage and constant current. An AC generator is a converter for a high-voltage direct current (HVDC) electrical power transmission system to transmit electrical power, as opposed to the more common alternating current (AC) transmission systems. As a result of the VSC process, the input DC power will be converted into effective AC power. The obtained AC voltage from the three-phase inverter reaches a peak voltage of 500 V, as shown in Figure 26(a). The resulting three-phase inverter AC voltages and currents have been obtained as displayed in Figure 26(b) with Vabc=500 V, and Iabc=2000 A. Furthermore, the load (grid) final achieved three-phase AC voltages and currents with the overall model power signals are shown in Figure 27.



(a)



(b)

Fig. 27. The load (grid) final obtained results, (a) Three-phase AC voltages and currents, (b) Total model power signals.

By viewing the outputs of the work unit and the supply network shown in Figure 27, we notice the AC voltage and current signals obtained from the 3-phase inverter and the feeder to the load network with peak values of Vabc = 500 V, and Iabc = 2000 A. Figure 27(b) shows a comparison of all forms of energy obtained from various simulation units of the proposed model of the smart controller system, including the PV cell power (Ppv), the battery unit power (Pb), the load power (PLoad), and the grid unit power (Pg).).

4.2 Results Discussion & Validation

By comparing the results obtained from simulating the proposed model of the smart controller using neural network technology with the results of the same system using a PID controller, we can notice the difference in the results of the voltage and three-phase current coming out of the triple inverter. The final power obtained and the state of charge of the battery show a noticeable improvement of up to 25%, as a result of the efficiency of the ANN controller, which forces the switch signals of the three-phase inverter to close and open the thyristors of the inverter to produce more stable three-phase voltage and current waves. Table 4 shows a comparison between the PID controller scheme and our suggested ANN smart controller model.

Table 4: Acomparison review between the PID controller scheme against our suggested ANN smart controller model.

	Model Results & Measrements							
Smart Controller Type	V_{DC}	V_b	P_{PV}	V_{abc}	I_{abc}	P_{Load}	P_g	SOC
PID	900 Volts	500 Volts	1000 KWatt	300 Volts	2000 A	1000 KWatt	850 KWatt	80 %
	± 10 V	± 10 V	± 500 W	± 2 V	± 2 A	± 500 W	± 500 W	± 0.5 %
ANN	V_{DC}	V_b	P_{PV}	V_{abc}	I_{abc}	P_{Load}	P_g	SOC
	900 Volts	600 Volts	1000 KWatt	380 Volts	2000 A	1200 KWatt	900 KWatt	80 %
	± 10 V	± 10 V	± 500 W	± 2 V	± 2 A	± 500 W	± 500 W	± 0.5 %

Moreover, the results of the proposed model in this thesis were compared with those presented by recent scientific articles and studies. Table 5 shows a brief comparison of our proposed model with those provided by recent published studies.

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Table 5: A comparison summary of our suggested model with other presented by modern published studies.

Reference	Title	Implementation	Limitations
In 2019, Easley, M.; Fard, A.Y.; Fateh, F.; Shadmand, M.B.; Abu-Rub, H., et. al., [5]; IEEE: Baltimore, MD, USA, 2019; pp. 3703–3709.	Auto-Tuned Model Parameters in Predictive Control of Power Electronics Converters	Modifications of finite set model predictive control are made for various applications, demonstrating how recurrent problems of finite set MPC can be solved. Issues of ambiguous cost function design and, for some applications, impractical computational burden are addressed. A variation of the finite-set MPC is proposed which removes ambiguity in the design phase of the finite-set MPC. Using hierarchical model predictive control, Solutions that enable real-time model alignment, fault-tolerant operation, and situational awareness of the transformer are presented. These improvements in predictive control can ensure that tomorrow's grid smart inverters are fast, aware and reliable.	The tracking performance required for each target is determined during design. Assuming multiple objectives, the designer must rank each objective and apply its associated cost tolerance (or acceptable error) to the objectives. Also complicated scheme with large computatios & increased temperature.
In 2021, Khalilzadeh, M.; Vaez-Zadeh, S.; Eslahi, M.S., et. al., [6], IEEE J. Emerg. Sel. Top. Power Electron. 2021, 9, 327–334.	Parameter-Free Predictive Control of IPM Motor Drives with Direct Selection of Optimum Inverter Voltage Vectors.	The time derivatives of the armature current (slopes) are expressed as functions of the phase angles of the inverter's fundamental voltage vectors. The slopes are then predicted independently of the motor parameters and are used in selecting the optimal inverter voltage vectors. In addition, a method is used to avoid time-consuming evaluations of the cost function to determine the optimal inverter voltage vector. Through this method, reference current slopes are used to select the optimal direct voltage vector. As a result, the control performance under parametric uncertainties is improved and the control code execution time is shortened compared with the traditional predictive method. The effectiveness of the proposed method and its superiority over the conventional method and the recently introduced predictive current control method are confirmed by simulation and experimental results.	Complicated Structure with high cost. Also huge number of computations in order to select the optimum inverter voltage vectors
Our Suggested Model	DESIGN OF SMART INVERTER FOR DISTRIBUTED ENERGY RESOURCES BASED ON ARTIFICIAL INTELLIGENT TECHNIQUES	Through the presented study, an intelligent control method was proposed to eliminate the problems of the three-phase inverter and improve the power signal using ANN technology. Moreover, we extend the proposed method to better working conditions through a new artificial neural network strategy. New predictable evaluation accuracy results of more than 25% greater than traditional control methods have been **achieved while improving the battery's state-of-charge ratio**	It suffers from Minor grunt, has moderate computational effort to train the ANN, and moderate cost.

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5. CONCLUSIONS

In this thesis, the effects of implementing smart ANN controller controllers on the three phase inerter based on PV cells system have been discussed and investigated using hybrid perturb and observe (P&O) with PQ/ANN controllers. Since the ideal voltage at which the loads receive the most power with the fewest losses is known as the maximum power point tracking (MPPT). Three photo voltaic (PV) penal cells have been utilized as a constant DC power sources to provide partially shaded direct current to the system. The designed PV cells model has been simulated and examined with three types of boost controllers. The simulation results show that the hybrid combination of the P&O-PQ/ANN controller provides the best maximum power point tracking (MPPT) among the two other controllers. The proposed model produces grid load power of 800 KW which is better by 26% times than both the PID technique and the P&O controller each individual with more stable SOC ratio.

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