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Electrical and Computer Engineering

DESIGN AND OPTIMIZATION OF A STATE-OF THE-ART SOLAR PV SYSTEM RELYING ON MAXIMUM POWER POINT TRACKING OF SOLAR CHARGE CONTROLLER USING ARTIFICIAL NEURAL NETWORKS

Raghad AL-ANI

Master's Thesis

Supervisor

Asst. Prof. Dr. Abdullahi IBRAHIM

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The thesis titled DESIGN AND OPTIMIZATION OF A STATE-OF THE-ART SOLAR PV SYSTEM RELYING ON MAXIMUM POWER POINT TRACKING OF SOLAR CHARGE CONTROLLER USING ARTIFICIAL NEURAL NETWORKS prepared by RAGHAD AL-ANI and submitted on 25/04/2023 has been accepted unanimously for the degree of Master 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.

Submission date of the thesis to Institute of Graduate Studies:____/___/____

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.

Raghad AL-ANI

Signature

DEDICATION

This study is wholeheartedly dedicated to my family, who have been our source of inspiration and gave us strength when we thought of giving up, who continually provide their moral, spiritual, emotional, and financial support. To our brothers, sisters, friends and classmates who shared me words of advice and encouragement to finish this study. And lastly, I dedicated this work to the Almighty God

.

ABSTRACT

DESIGN AND OPTIMIZATION OF A STATE-OF-THE-ART SOLAR PV SYSTEM RELYING ON MAXIMIZING POWER POINT TRACKING OF SOLAR CHARGE CONTROLLER USING ARTIFICIAL NEURAL NETWORKS

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The total effectiveness of the PV system is significantly impacted by the use of an effective MPPT (Maximum Power Point Tracking) algorithm. These algorithms are utilized as tracking controllers to get the most power possible out of PV modules based on the array temperature, solar radiation, shading circumstances, and PV cell ageing. (P&O) Perturb and observe and (InC) incremental conductance are the most used approaches. These time-tested methods are inexpensive, easy to use, and of modest efficiency. MPPT techniques using artificial intelligence for better steady-state and transient performance include fuzzy logic and artificial neural network (ANN) controllers. A proposed artificial neural network-based model of a solar power tracking system is what this thesis aims to create. Through this study, a single PV system using a Buck DC-DC Converter is tracked for maximum power under various irradiation situations employing the P&O and ANN approaches. To be able to analyse the PV array's model, determine MPP, and show the results, this study employs MATLAB-Simulink. Buck converter is the type which is used to study the converter DC/DC performance. The findings show that the ANN model can track changes in MPP far more effectively than the approach of Perturb and Observe. The system using ANN appears to deliver higher amount of power than the model using P&O since the maximum power monitored by ANN is 1990 Watts while the maximum power monitored by P&O is still 1930

Watts. Voltage and current ripples are greatly reduced by the ANN model compared to the P&O model. Therefore, ANN responds more quickly than P&O. Additionally, the use of Buck converter, offers us a better voltage, power, and thus, efficiency. The authors propose further research on novel strategies that can be efficient and useful, where MPPT methods additionally take into consideration external repercussions without concern for the cost and complexity of sensing.

Keywords: PV System, Perturb and Observe, Artificial Neural Network, DC/DC Converters, Maximum Power Point.

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ABBREVIATIONS

PV	:	Photovoltaic
AC	:	Alternate Current
DC	:	Direct Current
MPPT	:	Maximum Power Point Tracking
SCC	:	Solar Charge Controller
ANN	:	Artificial Neural Network
P&O	:	Perturb and Observe
InC	:	Incremental Conductance

1. INTRODUCTION

1.1 OVEREVIEW

The events that are currently affecting Earth are concerning since during the past 20 years, the globe has seen its highest CO2 concentration and highest recorded temperatures. According to data, the hottest years on record for the planets were from 2010 to 2019, and 2019 was one of the three warmest years ever noted. As a result of climate change, violent weather events happen much more frequently, which also affects human survival on a global scale. But it's important to remember that there is a two-way connection between population growth and climate change because the latter affects the former by encouraging activities that result in higher greenhouse gas emissions. One of the goals of EU climate policy is to increase the usage of renewable energy. Additional measures are required to ensure the stability of the energy production because renewable energy sources now make up a larger portion of the energy mix.

Solar, wind, water, and biomass are examples of renewable energy sources. These resources have the capacity to regenerate themselves naturally; therefore they can never run out. Renewable resources were initially employed to produce heat, light, and electricity. Fossil fuels were used for industry, housing, and transportation as a result of the considerable increase in energy usage in the twentieth and twenty-first centuries. Due to the negative environmental effects of non-renewable energy resources, worries about the greenhouse gases released during combustion process of dirty fuel, and the ensuing shortage of fossil energy, there is a growing interest in using more renewable resources to generate power [1]. One form of renewable energy source is solar energy which has experienced extensive-scale development and complete applications because of limits on energy transmission. Since it emits fewer greenhouse gases, enhances air quality, and can be produced again during our lifetimes, solar energy is often preferable to fossil fuels like coal and oil. Global electricity consumption has increased as a result of the state of the planet. So, scientists have focused on developing solar energy systems that have cheap investment costs, great levels of efficiency, and little impact on the environment [2].

1.2 SOLAR CELL

Solar energy is converted into DC using PV cells, which fluctuate in response to the brightness of the sun. Films of semiconductor materials are used to create photovoltaic (PV) cells, where the valence electron is closely linked to the nucleus, however, it acts as a conductor when exposed to a little amount of energy. Inverters are needed to convert a given target voltage to Alternate Current (AC) for practical use [3].

1.2.1 Photovoltaic Effect

Energy originates from the sun (Solar), is converted into electricity via photovoltaic cells. When light enters a PV cell, it causes some electrons (atomic particles which have a negative charge) to have enough energy to spontaneously ignite. This process is known as the photovoltaic effect. These electrons are affected by potential barrier which is built-in in the cell, which creates a voltage (referred to as photovoltage) that can be utilized for generating a current through a circuit. The effect of photovoltaic is shown in (Figure 1.1). A semiconductor-fabricated p-n semiconductor junction serves as a PV cell (usually silicon). Photons are the constituents of solar radiation. The photon's energy must exceed the material's gap in order to produce a current [4].

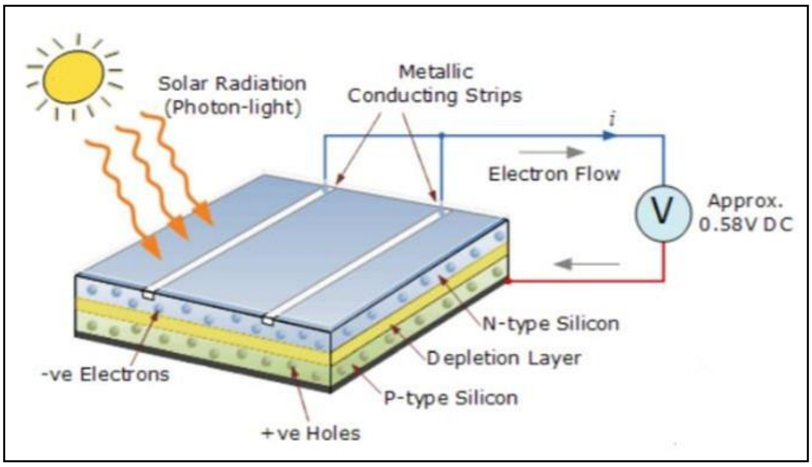

Figure 1.1: Photovoltaic Effect

1.2.2 PV Cell Modelling

Solar cell effectiveness is influenced by the temperature, radiation amount, and the basic properties of the cell material. Then, a real load must be converted into an analogous circuit in order to estimate the measurement is somewhat approximate. The analogous electrical circuit of a solar cell is depicted in (Figure 1.2). It is very important here to develop the simulation model of the photovoltaic cell in order that the maximum power point) MPP) of the solar panel can be allowed the maximal power point of a solar panel to operate at its highest photoelectric process performance. According to this model, the amount of light and the surrounding temperature will have an impact on the solar panels' production capacity. It can more intelligently consider how the environment may impact its capacity to produce [5].

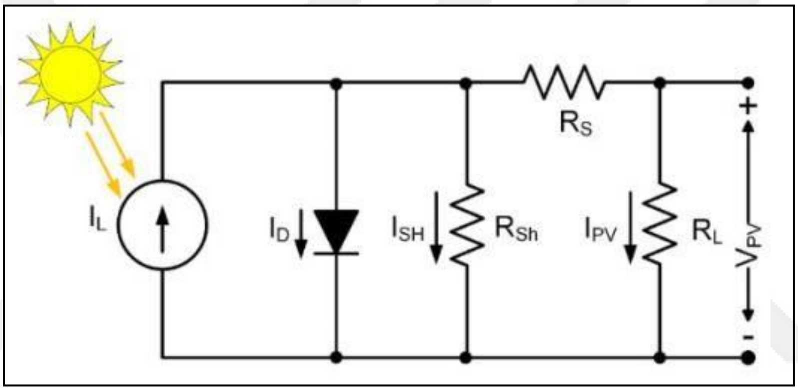

Figure 1.2 : Equivalent Electric Circuit Model of A Solar Cell**.**

The photovoltaics I-V and P-V curves are of great importance because, like Maximum Power Point Tracking (MPPT), their analysis is utilized to evaluate various methodologies and algorithms. The typical I-V & P-V curve will be illustrated as shown in (Figure 1.3) [6].

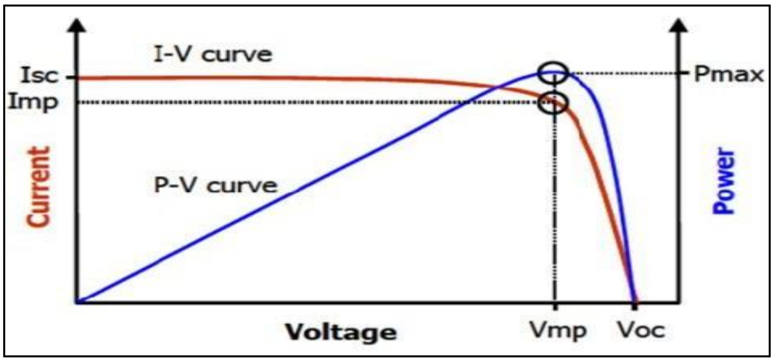

Figure 1.3: I-V and P-V Curves of Solar Cell.

I-V relationship of the PV cell exhibits a non-linear characteristic, as can be shown in (Figure 1.3). Equation (1.1) shows the maximum power expression.

$$P_{max} = I_{max} * V_{max} \tag{1.1}$$

Temperature (T), often known as ambient temperature, is the term used to describe the "normal" air temperature found outside. The highest operation temperature of a PV array in PV system can be described using this term. The performance of the panel might be impacted by excessive heat, just like it can with any electronic component. As a result, warmer or higher temperatures always result in a decrease in the system's power production; this loss can be measured using the term "temperature coefficient," which is determined by the cell producer and differs in each model. Illustrations of the way the power-voltage curve varies in relation to temperature are shown in (Figure 1.4).

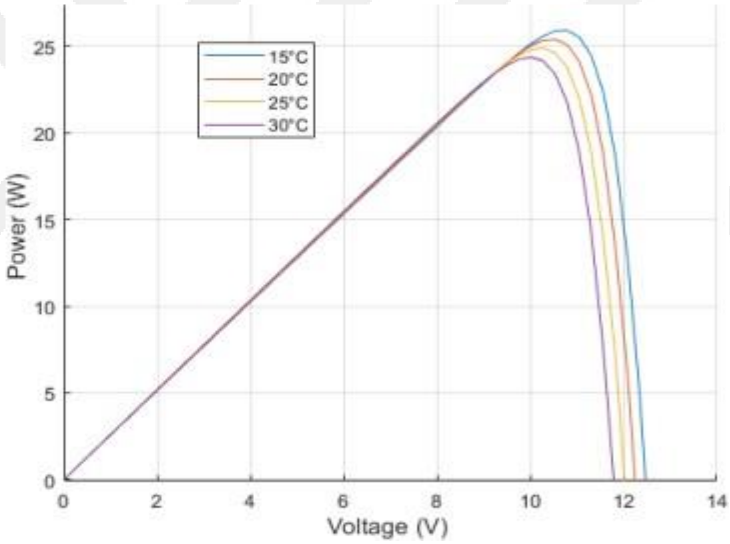

Figure 1.4: Temperature Effect on Solar PV Module at Constant Radiation (200 W/m^2).

Solar radiance is a measurement of the quantity of solar irradiance reaching a particular surface, which is expressed in W/m2. In contrast, solar irradiance (G), which is expressed in Wh/m2/day, describes the quantity of solar energy that strikes a surface over a specific time period [3].

I-V characteristics for various irradiances at constant temperature are shown in (Figure 1.5a). Sun voltage and current vary due to variations in solar irradiation. The production capacity of solar cells is determined by the light intensity, as shown in (Figure 1.5b). The only energy point that can be maintained while maintaining the same solar cell temperature is the same light intensity.

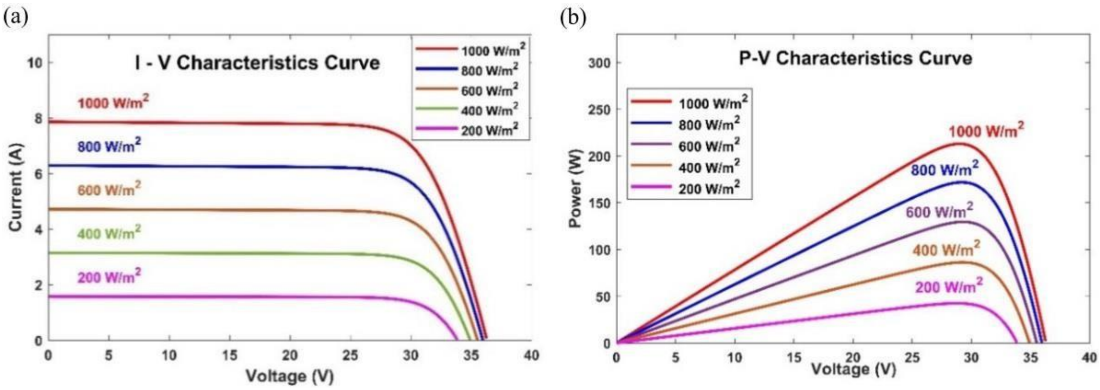

Figure 1.5: Irradiance Effect on Solar PV Module at Constant Temperature (25 ºC).

1.2.3 Types of PV Panels

PV is used in microgrids in addition to standalone systems. PV panels can be classified according to their effectiveness and installation size, or how much area they require. There are numerous varieties of PV panels on the market, including:

a. Monocrystalline Panels: This kind's cells are oriented in such a way that they operate most effectively and efficiently when the sun shines directly on them. As a result, when the cells are exposed to the sun at the correct angle.
b. Polycrystalline Panels: Due to the fact that some of the crystals are not exactly aligned with one another, these panels are less efficient than monocrystalline panels. Nevertheless, this misalignment might be useful due to the effective performance of the cell even when sunlight has various angles of arrival.
c. Hybrid Panels: Particularly in low light situations, the additional amorphous layer can capture more energy from the incident sunlight than the monocrystalline cells can. They are the most effective and take up the least amount of room. But the cost of these is higher than that of monocrystalline and polycrystalline panels.

1.3 PROBLEM STATEMENT

PV has some substantial disadvantages, such as an expensive initial setup expense and poor energy output; only 12% to 25% of solar energy is converted to electricity [7]. The PV system's nonlinear behaviour makes it harder to control the flow of power. Additionally, the type of cells utilized, the DC/ (AC or DC) converter technologies, the MPPT technique, and the system's (dust, artificial shadow) impact on the system all affect how efficiently energy is converted [8].

MPPT technique is necessary as a photovoltaic array could bring the most power to the load. Converters controlled by an MPPT algorithm continuously measure and determine the PV array's instantaneous maximum power. The maximum power varies relying on the operation point because of the non-linearity of the voltage-current and power-current curves of solar arrays. The MPPT's role is to apply the correct voltage to obtain the greatest current from the array [9]. These methods are tracking mechanisms being used to maximise the PV panel power relying on the temperature, irradiance, shading circumstances, and degradation of PV cell [10].

The kind of MPPT algorithm used greatly affects how efficient the solar system becomes. There isn't a flawless algorithm. The main problem with the traditional algorithms is the tracking while the climatic conditions are continuously changing [11]. There have been many MPPT controllers described and utilized in the literature up to this point. These controllers must meet a number of generic criteria, including being simple, affordable, having output power fluctuation to a minimum, with being able to follow changes in operating conditions fast. The most used techniques are perturb and observe (P&O) and incremental conductance (InC). These traditional techniques have a low cost, simple implementation, and modest performance. Artificial neural network (ANN) and fuzzy logic (FL) controllers have been recommended as MPPT approaches which use artificial intelligence for improved transient and steady-state performance. However, the controller of ANN has shown great result under changing irradiance, particularly in regards to effectiveness and time of response [12].

1.4 RESEARCH QUESTIONS

After reviewing the study's background and problem statement, the following questions are raised and must be answered:

a. What is the impact of MPPT on PV cell Efficiency?
b. What are the different types of algorithms used in MPPT?
c. What is the added value of using MPPT based ANN in designing and optimization of PV solar cells?
d. Which is the most popular ANN architectural type used to determine a PV system's MPPT?

1.5 RESEARCH OBJECTIVES

The primary goal of the thesis is to track the area with the highest power parameter in order to maximize gain. In order to acquire the best results, artificial neural networks trained on the most crucial aspects of solar rays will be used as the main tool for prediction procedures.

According to the research inquiries, this research seeks to:

a. Develop a proposed model of Solar Power Tracking System relied on controlled Artificial Neural Network.
b. Develop an Artificial Neural Network trained well on analyzes solar energy rays and extract features to guide PV solar array system to the most gain region.
c. Develop a solar charge controller design with its circuit components.

1.6 METHODOLOGY

Identification the part of the sun's spectrum with the best parameters, or the region where the best parameters may be absorbed to produce power is the study's main goal. By creating the Artificial Neural Network that actually has been trained on the most parameters and their values with ranges, machine learning may be used to analyse and compare regions to find the best one. Therefore, a research must be conducted to track the most crucial variables and their relationships, which can also be done using a machine learning approach.

So, the proposed designed solar power tracking system using machine learning (Artificial Neural Network) has mainly three steps as illustrated in (Figure 1.6).

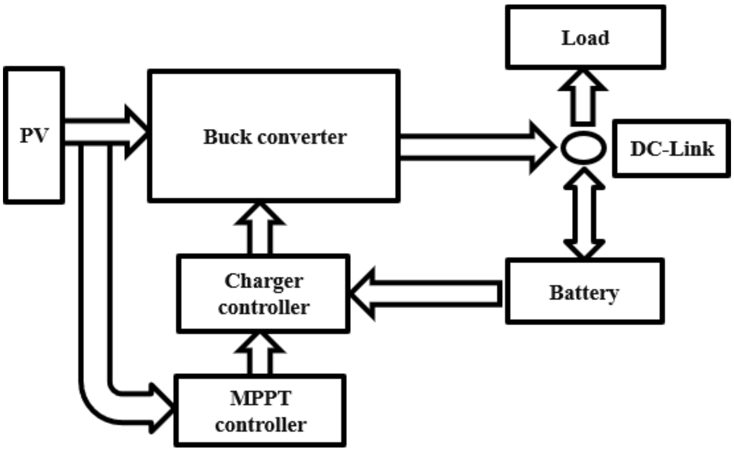

Figure 1.6: Proposed Designed Solar Power Tracking System.

a. Survey and Data Collection: The first phase involves gathering information about the values, ranges, and relationships between the parameters. The primary characteristics that need to be recorded in the data are those that have a significant impact on how much electricity a PV solar array generates, such as temperature, light intensity, irradiance, etc.
b. Training Data: A trained model (Artificial Neural Network) able to analyze, compare, pick, and send commands to track was successfully created through the extraction of features and training on the MATLAB software. Noting that there is a stage in between called try and catch that is intended to reduce errors and increase the accuracy of the results.
c. Testing the model in real life.

1.7 THESIS STRUCTURE

During this study, a proposed model of Solar Power Tracking System relied on controlled Artificial Neural Network is investigated. The study consists of five chapters as following:

i. Chapter One

This chapter starts with an overview that explains the need to switch to renewable energy, particularly solar energy. It also gives a general highlight on the PV cell and its characteristics. The problem statement discussed in this study is highlighted. Finally, the objective and a general overview about the methodology of this work were explained.

ii. Chapter Two

This chapter documents the literature review of previous studies related to the PV cell state-of-art, MPPT algorithms, Neural Networks, and the MPPT based on Neural Networks.

iii. Chapter Three

In this chapter, we explained the study's methodology and documented the various material and methods used through this study. The proposed model, controlled artificial neural network, and the solar charge controller design and hardware is deeply explained.

iv. Chapter Four

This chapter prevailed the results of testing the proposed model and showing these results in a proper representation. Then, it provided a complete analysis of them.

v.Chapter Five

This chapter documents conclusion for the whole study.

2. LITERATURE REVIEW

Utilization of photovoltaic panels to produce green electricity has increased. This technology is developing quickly, costs for PV modules are falling, and PV panels are becoming more effective. Significant investments are being made by national economies in grid-connected and off-grid PV networks. In contrast to conventional energy generation methods, PV power is unstable and depends on solar irradiation and other weather variables, including precipitation, temperature, wind direction, humidity and cloud cover. Power networks have had substantial issues as a result of the adoption of grid-connected solar PV facilities on a large scale, including a shortage in device adaptability, performance, and energy distribution. For PV grids to have a consistent electricity supply, it is essential to predict the production of solar energy. Researchers, however, have investigated strategies to boost PV performance and enhance their effectiveness due to their low efficiency. It is possible to optimize the production of maximum energy from PV cells thanks to Maximum Power Point Tracking (MPPT) inverters. Many smart algorithms perform effectively, but few are willing to use artificial neural networks (ANN). In these algorithms there is some benefit which must be mentioned that these algorithms can track the Maximum Power Point accurately and quickly. The hidden layer algorithm and the neural network's training quality both affect how effective the controller is. This chapter examined the ideas of solar charge controller, MPPT, ANN and improving PV cell performance. A study of many papers, reports, and other publications from the past 20 years that have used ANN for MPPT control is also provided.

2.1 SOLAR CHARGE CONTROLLER (SCC)

A photovoltaic solar power system employs an off-grid system and is an independent power plant. The off-grid system is a generator made up of an SPV, a battery, an inverter, and an AC load that runs on its own and isn't connected to any other plants. A battery is a part of an off-grid system that serves as a crucial storage container for SPV-generated power. SCC, a battery safety feature that prohibits overcharging and over discharging, can increase the durability of batteries or prevent harm from occurring [13].

The solar charge controller, also known as the SCC, is a device that provides the control of current voltage sent to the battery before it is sent to the load. The entering voltage that is fed into the battery can be controlled by solar charge controllers to prevent overvoltage or overcharge as well as over-discharge to the load, which leads to a battery that is quickly damaged. SCC has a safety feature that could shield users from danger, and it is also fairly priced to help pay for treatment [14].

Due to non-linear solar PV characteristics and atmospheric conditions, solar PV efficiency is significantly decreased. As a result, depending on the amount of irradiation and the weather, the solar PV system's maximum power production changes. In order to get the highest power, many maximum power tracking strategies have been comprehensively described by prior scholars. Additionally, necessary for optimising the flow of electricity from a solar PV system to the battery is a battery charger with a charge controller. The primary purpose of a battery charger with charge controller is to have the operating system on the MPP regardless of changes in irradiance, which helps keep track of the maximum power as well as shortens the time required to charge the batteries to support the PV arrays. Additionally, it regulates the overcharging and undercharging of the battery to lengthen the battery's life. The authors of this paper concentrated on developing an appropriate charge controller by taking into account the key benefits of charge controllers in order to successfully increase battery efficiency and life. Additionally, by contrasting the charge controllers put out by the many researchers in the literature up to this point, a comparative research has been presented. The efficiency of charging batteries and PV array use are managed by a PV charge controller's algorithm which improves the system's capacity to handle electrical load needs [15].

Planning a power plant must comply with a number of requirements, including that the area receive enough sunshine and that there are no large trees in the area. The following system topologies are typical of solar power plants:

a. An unconnected or autonomous power plant system, often known as an Off- Grid or stand-alone power plant.
b. A power plant or a system that is connected to others, often known as an On -Grid.
c. A power plant is a system of one or more power stations that are connected to one another and use various primary energy sources.

SCC is a device which controls the DC type current going into the battery to prevent over-charging or unstable voltage going into the battery. To maintain the battery secure and long-lasting, a solar charge controller controls the inflows and voltage. SCC plays a crucial function in determining the voltage for the battery and load voltage as well as in charging battery batteries. A portable system with a battery and SCC is created using solar cells. Through the photovoltaic effect, PV cells work to convert solar radiation to electrical energy. Batteries will be utilized in storing the electrical power produced by the solar cells. The SCC performs the role of a battery charging controller to ensure battery safety during filling. (Figure 2.1) shows the imagined system in detail [16].

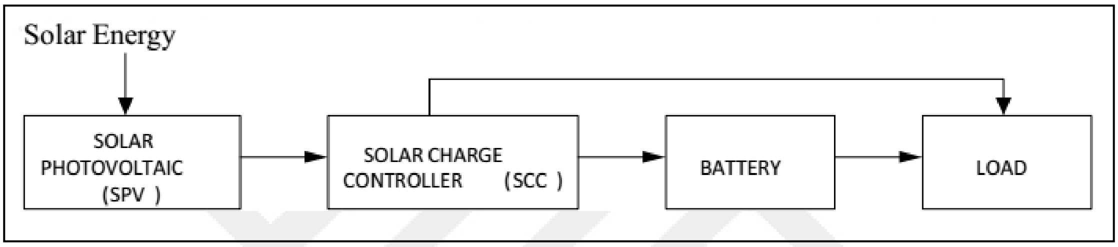

Figure 2.1: A Solar Energy System Block Diagram.

Moreover, SCC also among its functions is to monitor the current, as well as the voltage of the battery and monitoring the voltage of the photocell. SCC is made up of an input with two terminals attached to the output of a solar cell, an output with two terminals attached to a battery, and an output with two terminals connected to a load.

For the proper operation of the power performance system, some types of SCC offer monitoring [16]:

a. Switching Shunt Charge Controller (SSCC) is a subtype of Shunt Charge Controller (SCC) that use diode blocking to regulate the maximum voltage and current array of the battery's entrance. As the battery voltage reaches the predetermined point of charge termination, it should be stopped. The shunt transistor will continue to operate in this scenario to enhance the distribution of energy in the solar cell and prevent overcharge.

b. A form of SCC called a Single Stage Controller (SSC) has a higher capacity when coupled with switching shunt controllers. This kind prevents the current returning from the battery to the solar cell by using a relay or transistor to cut off the flow of electricity when the battery is charging.

c. Diversion Controller (DC): Using this kind of controller, the battery's voltage can be used to adjust how many current flows into it. When the current is greater, the load resistor will turn on, and as the battery voltage is lower, the current within the cell will flow.
d. Pulse Width Modulation (PWM): It is a method of modulation that controls the pulse width of the output. Microcontrollers use the waves generated by the wave generator to regulate the internal clock's pulse source. This charge controller uses PWM via a microcontroller to set the resulting pulse, which allows it to adjust to the status of a rechargeable battery. The efficient way to accomplish constant voltage charge of a battery is to switch the controlling power source of the solar system. The SPV's current regulation decreases in PMW, which has an effect on battery health and energy requirements. The charge control utilizes the Arduino to control the voltage of the battery.
e. A Maximum Power Point Tracker (MPPT) electrical system controls a photovoltaic cell, allowing it to produce the maximum amount of power possible. The MPPT system, which is totally electronic, modifies the module's electrical operating point to enable maximum power transmission. The extra power from the cell was then used to boost the battery charging current. This kind of MPPT is very good and can charge batteries produced by solar cells with the most power possible. With this kind, the maximum amount of electricity produced by solar panels may be captured and stored. MPPT has benefits over other solar cell types that are limited to voltage adjustments no higher than the battery voltage. This type also has the advantage of being susceptible to changes in working cell temperature brought on by changes in battery voltage.

The most popular PV charge controller types are shunt, series, PWM and MPPT controllers. The series controller, which is mounted in series between the Photovoltaic system and the battery, uses a particular sort of control component. This charge controller type is broadly utilized in simple PV systems, while it also could be utilised for larger systems, due to the current limits of shunt controllers. The shunt charge controller managed the battery charging from the PV array by making the array within the charge controller a short-circuit array. In order to avoid batteries from being overcharged or deeply depleted, both of which can harm the battery, these charge controllers are generally used to control voltage (or) current [17].

Charge controllers typically only need minor servicing. Trickle charge panels and other battery regulators manage the current flow. There are several advantages to using charge controllers to prevent over-voltage, which decreases battery performance and lifetime and prevents deeper battery charging. Constant voltage current are the greatest pictures of single stage and multistage levels in this context. Charge controllers are grouped as a series based on these levels [18].

2.2 MAXIMUM POWER POINT TRACKING (MPPT) TECHNIQUES

Reliable forecasting models boost device dependability, decrease the cost of further maintenance operations, and limit the impact of solar PV efficiency. Only 30–40% of the total incidental sun irradiation can typically be transformed into electrical power by a solar cell. MPPT method is utilized to raise a certain solar panel's effectiveness and it is employed to get the most power possible out of PV under particular circumstances. The peak power of any PV module is affected by variables like solar radiation, the surrounding temperature, and cell temperature. A PV module typically generates its highest power voltage when the cell temperature is 25 °C. However, it may decrease or increase relied on the outside temperature. The maximum power point voltage, or MPPT, is determined by checking the production of a certain PV panel and matching it to the battery voltage. A MPPT approach's objective is to use the correct resistance after measuring a PV module's output in order to provide the most power possible. Because PV cells perform more efficient in colder temperatures, MPPT is most efficient in cooler conditions. As greater current can be drawn from the battery under low charge circumstances, it is also particularly effective when the battery is completely depleted. Combining MPPT devices with power electronics to form an electric power converter system allows for the creation of solar inverter, which transform the power from DC to AC. Several methods, including the "perturb and observe" (hill climbing approach), the "incremental conductance approach," " fuzzy logic control," "constant voltage," "current sweep," and "neural network," are employed to detect the peak power point [19].

The MPP in solar renewable energy systems has been obtained using a variety of regulation and optimization techniques, as stated. This is seen in (Figure 2.2), where each technique has made use of part of the observed input parameters [20].

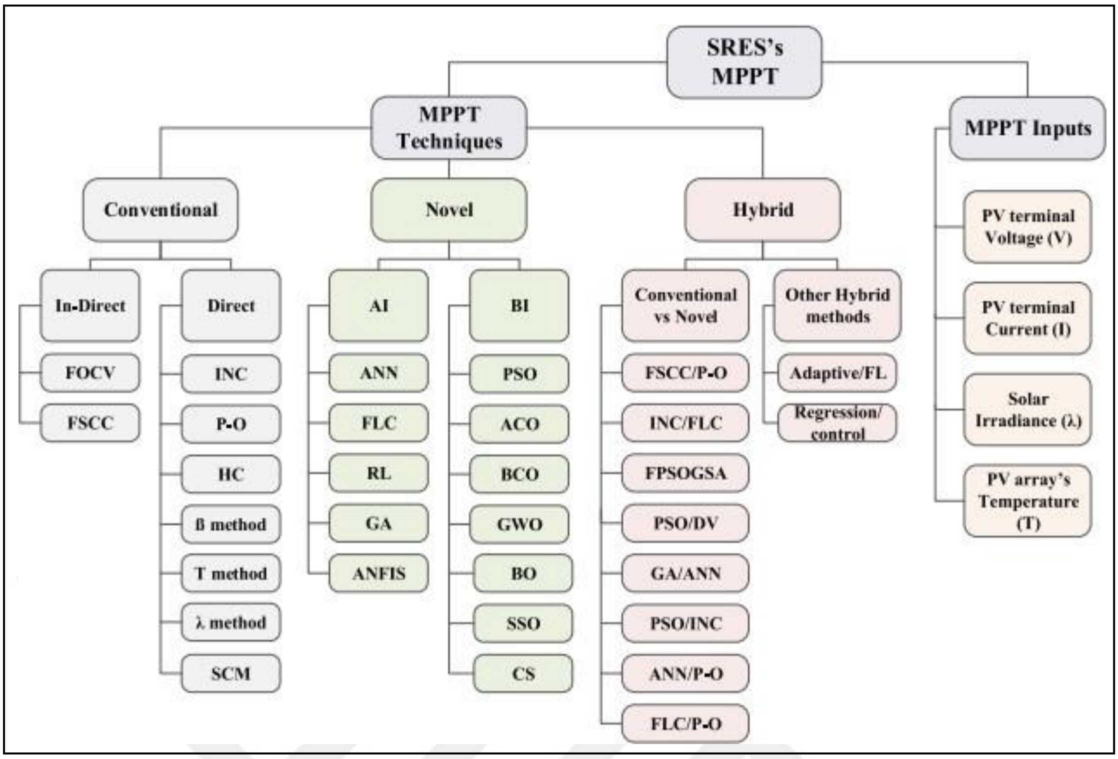

Figure 2.2: A Flowchart Showing the MPPT Approaches Currently in Use and The MPPT Input Parameters.

a. Perturb and observe (hill climbing method)

Due of its lower time complexity, perturb and observe is a simple MPPT method. The easiest and most direct method to use is this one. Because of its step-by-step approach, it is sometimes referred to as the "hill climbing method." Under covert circumstances, it does not produce satisfactory outcomes. This technique alters the output power by varying the supply voltage. The duty cycle is further enhanced if raising the provided voltage results in greater power. Now, duty cycle is reduced if increasing the provided voltage results in a drop in power. If reducing supply voltage is the cause of an increase in power, then reducing duty cycle will follow. Until the ideal point is reached, this process is continued. As a reference point, the voltage at the MPP is acknowledged. This approach has a few identified problems, including poor tracking and persistent oscillation about the MPP that results in a delayed time response. It cannot operate under the current noise. Additionally, it does not determine whether the change in power is the result of a new duty cycle or irradiation [21]. However, because the program keeps perturbing iteratively even after reaching MPP, this approach may produce oscillations in power output. Defining an error limit to stop the recursion can be used to fix this. Due to its simplicity and reliance on the increase and decrease of the P-

V curve in relation to the maximum power point, it is often referred to as the "hill climbing approach" [22].

b. Incremental conductance

The controller uses the incremental conductance method to determine small variations in voltage and current in this method. Although it requires more calculations, the perturb and observe strategy is more effective at tracking changes. Contrasting PV array conductance (dI / dV) with incremental conductance (I/V) yields the maximum power point. The voltage at these two ratios is known as the output voltage. The voltage is held constant until the radiation levels change, at which the procedure is done again. Since voltage and current are measured concurrently in this case, a change in irradiation has no effect on the accuracy. However, this strategy is more intricate than the perturb and observe method. Additionally, it makes use of the power curve's slope information to determine the tracking direction. The reference voltage is raised to track MPP if the increase in conductance ratio is greater than the negative conductance ratio. To track MPP, the reference voltage is lowered if the ratio of conductance increase to negative conductance is lower [23].

c. Current sweep

With the aid of a current sweep waveform which is adjusted at predetermined intervals of time, this technique aids in acquiring I-V parameters. From the curve at the same time intervals, MPP is determined [19].

d. Constant voltage

Constant voltage and current techniques are the quickest and easiest ways to accomplish MPP. Both methods presuppose a linear relationship among the module short-circuit current or (open-circuit voltage) and the module current (or voltage) related to the maximum power. Because both approaches anticipate constant climatic conditions, the actual MPP is not frequently attained. Online tracking techniques are used in modern applications to find short-circuit currents and open circuit voltages. In the constant voltage technique, the PV cell operation point of is kept around to the maximum power point. The PV cell's voltage is contrasted with a reference value that has been specified for optimum performance [24].

e. Fuzzy Logic Control

A subfield known as fuzzy logic exists within the fuzzy mathematics domain (FL). In their fuzzy set theory, the terminology was first used. The phrase "logic of infinite values" was used to describe it in the 1920s. The matching values in FL, a type of multivariable logic, there is a possibility that the number will have a value between “zero” and “one”. It concerns with the ideas of "partial truth" or "half-truth,".Note that the real value can vary from wholly true to wholly untrue. FL is founded on the idea that people often make judgement calls without having access to accurate data. The term "fuzzy" refers to how fuzzy models express "vagueness" or unreliable information. This kind of model is capable of identifying and employing data and information with certainty. It's been applied to control theory and artificial intelligence, among other things [25]. Microcontrollers are also utilized to implement MPPT using fuzzy logic. The requirement for precise models is not a limitation of fuzzy logic controllers. In addition to having a quick rate of convergence, they have the special advantage of managing nonlinearity and faulty inputs. Fuzzy logic serves as the foundation for the fuzzy control system. In that context, it studies analogue input values and investigates logical variables with various values between zero and 1.

2.3 ARTIFICIAL NEURAL NETWORK (ANN)

The following section will discuss the ANN system, ANN Architecture and the neural network design steps:

a. ANN System

A data processing system based on artificial neural networks, or ANNs, is derived from biological neurons. In 1943, they used electrical circuits to mimic a straightforward neuron (see Figure 2.3), but the available technology was constrained. ANN has advanced considerably since then. It excels at extracting meaning from complicated data. In data that is too complicated to be categorized using either human or machine methods, it can also find patterns and trends. The data that has been given can be analyzed by a trained ANN, which can then project outcomes and offer solutions to new problems. ANN approaches problems differently than traditional forecasting algorithms. Similar to human brains, they can handle ambiguous input and adjust to circumstances for which there are no obvious algorithmic solutions. They are employed in many systems that deal with irrelevant data, including financial applications, robotics, signal processing and pattern matching. They can succeed in some areas where conventional computers frequently struggle thanks to this advantage.

ANN are also regarded as practical models that can be used to solve a number of challenging issues. ANN are essential for solving complex system control and prediction, classification challenges, and regression [25].

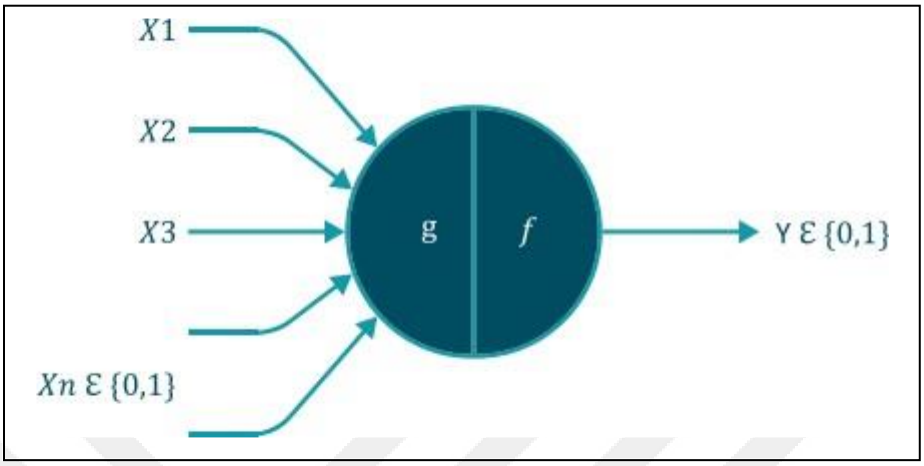

Figure 2.3: Artificial Neuron Model.

b. Architecture of ANN

For the neuron arrangement that may be organized into layer structures, the sort of connections, structures, or patterns that an ANN has are referred to as its architecture. These layers together make up an ANN. For the fundamental models, three layers can be distinguished for the basic models: the input layer, the hidden layer or layers, and finally, the output layer. The input layer is where data are received, and these can be sensors that pick up signals from the environment. The output layer can be an effector, is the network's reaction to all synaptic activities. The hidden layer is in charge of carrying out the processes (calculations, corrections) representing the environment to be modelled. Due to the way they are built, a distinction can be made between single layer networks (SLNN), this network usually consists of only one layer of neurons, and another type consisting of several layers of neural networks called multilayer networks (MLNN). MLNN can be classified according to the flow of data through it to (feed-forward) where the data goes in one direction and (RNN) which represents recurrent networks, here the data goes in any direction without specifying so that it can return from output layer towards input layer. The ANN weights computation is not an easy operation. In most cases, there is only space for trial and error. To calculate the total number of weights in a single layer feed forward multilayer ANN, the following definition can be used:

Input x size of the hidden layer + size of the hidden layer x size of the output layer.

There are many calculations depending on the architecture, and it undoubtedly requires us to check them before making any implementation [25].

A layer is created by several neurons. A network is created by the connections between these layers. The input layer is the one that is physically linked to the inputs. The output layer is the one that is linked to the output. The term "hidden layers" refers to layers that are invisible. The initial network architecture to be created is called Feed-forward, and according to this description, each layer's neurons can only link to those in the layer below them. The Feed-forward with shortcut connections, on the other hand, is a network that enables the neuron to connect with others at various layers. The Feed-forward and Feed-forward network with shortcut connections networks are depicted, accordingly, in (Figures 2.4 and 2.5) [26].

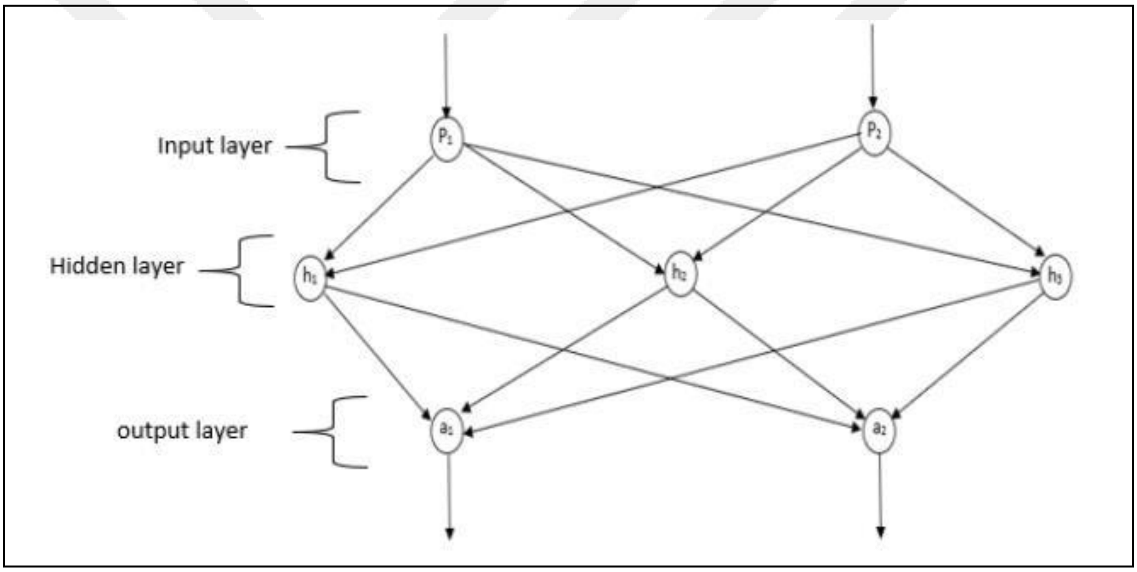

Figure 2.4: Feedforward Network.

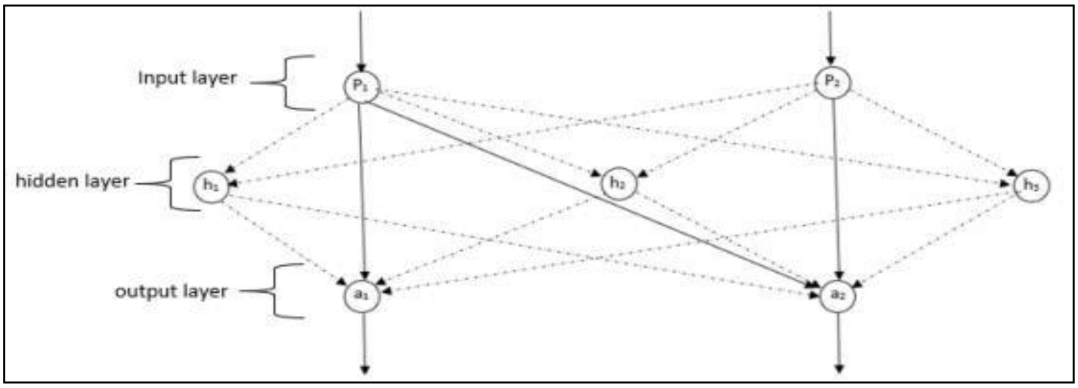

Figure 2.5: Feedforward Network with Shortcut Connections.

c. Neural Network Design Steps

The effective Neural Network outcomes produced by the appropriate training. The common procedures for creating neural networks are listed below [27]:

a. Collecting Data

Collecting data is the initial stage in developing an ANN (inputs, outputs). Increasing the amount of data helps NN function better. Numerous sun irradiances, temperatures, and matching duty cycle ratios are measured in our scenario. By changing the PV array's inputs for irradiance and temperature and measuring duty ratios, samples are obtained. When using supervised learning, tagged data, or a set of already-known data, was utilized to choose a learning algorithm [26].

b. Network Structure Selecting

The network's configuration and structure have an impact on the outcomes. The selection of a NN structure entails establishing all of the network's characteristics, which are the network's kind, layer number, neurons per layer, and activation function. Additionally, because it is differentiable, Log-Sigmoid Transfer Function is frequently employed in back-propagation networks [26].

c. Network Training

The gathered data are available for training after the NN design has been established. The weights are updated and adjusted by the training algorithms utilizing the training function. Training algorithms of neural network were categorized in five group as Gradient Descent, Resilient Backpropagation, Conjugate Gradient, Quasi-Newton, and Levenberg-Marquardt [28]. The algorithm that has a small MSE, or one where the predicted duty cycle converges to the actual duty cycle of MPP, is the one that corresponds.

d. Network Testing

The final step before utilizing a network is testing it; during this phase, weights remain constant (network topology does not change), and network performance is just measured. The network must be retrained if the findings are wrong or the performance is bad. The performance of NN can be adjusted by increasing the sample number, modifying the training procedure, and increasing neuron number [29]. It is necessary to verify the veracity of outliers, or data points where the fit is noticeably worse than the majority of the data, in order to extrapolate the network by gathering more data that are similar to them. Otherwise, they will be removed.

2.4 STATE OF THE ART OF ANN AND MPPT

Neural network, which in essence links various parameters to certain data points, is replicated in ANN. ANN models can incorporate different parameters without the use of mathematical equations or sophisticated mathematical bases. As a result, ANN requires less theoretical work than conventional ways to associate several parameters with enormous amounts of unknowable data points [30]. Supervised learning, often known as training, is used to train ANN using imported data. Several types of neurons make up the ANN. such as the brain. These neurons are linked together by a quantity named weight. In order to forecast the exact outcomes, the results are altered during the training phase, and weight quantities remain constant up until the mistake surpasses the allowable value [31]. (Figure 2.6) depicts the two-layer ANN model's fundamental structure. The inputs may be fed into the neural network at various time, according to the right side of the neural network. Whole input-output parameter sets of data are divided into two groups, with the group with the greater proportion of data point serving as the neural network's training data set. On the other hand, the validation data set is the second group made up of the other data points that is utilized to prove the trained neural network [32]. The training data points and input-output parameters of the neural network are imported. The network receives training until it commits a lawful mistake. The qualifying network is next tested by integrating the validating data set of input parameters and projecting the associated output parameter values after an acceptable error has been created.

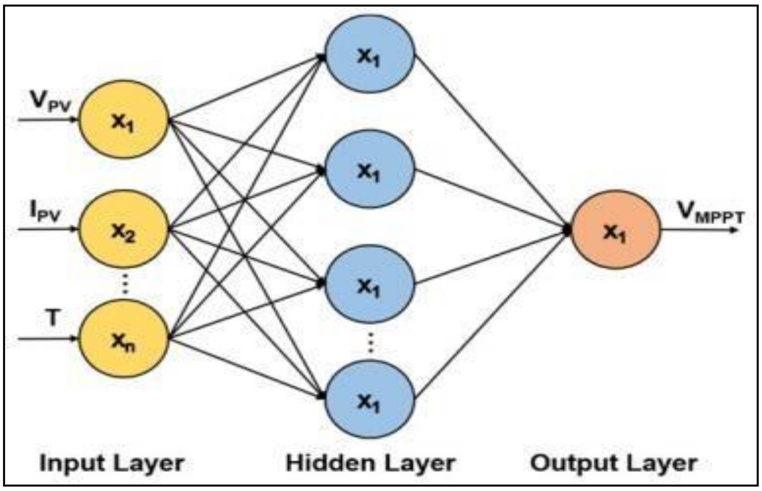

Figure 2.6: The Fundamental Design of The Two-Layer ANN Employed in MPPT.

This expected value of the output variable for the validating data set is linked to the exact values that match those anticipated values. If the gap among the actual and the forecasted results is less than the allowed maximum, the trained neural network may be the best forecast neural network. The neural network predicts the necessary training procedure and training intervals along with the pertinent input values and output parameters. If the error value is less than the permitted one, the qualified neural network and training algorithm will be selected together as the optimised neural network and training algorithm. The neural network uses the same training process for bigger error levels, but various training algorithms must be utilised before a permitted error is realised. Results predicted utilizing validation data from the most effective neural network confirm that trained neural networks can be used generally [33].

2.5 PROPOSED METHODS OF ANN-BASED MPPT IN THE PREVIOUS LITERATURE

For the purpose of this study, a thorough examination and evaluation of academic journals, conferences, novels, Ph.D., MD, and bachelor dissertations were carried out in order to identify the most representative publications in this topic. These studies are reviewed below.

The ANN system was designed based on the organic neural networks found in brains. In Photovoltaic system, it is employed to train and assess the I-V and P-V non-linearity relationships. The artificial neural network (ANN) continuously tries to alter the performance of the solar panel system for max output by collecting inputs such as input voltage, irradiance, current, temperature, and climatological data. For easier and more accurate converter creation, FLC architecture can be modelled using ANN. The appropriate maximum power or maximum voltage output, along with sun irradiation, temperature, and the voltage or current of the solar power system, are fed into the simulation or hardware configuration to create the dataset. To teach the proposed ANN how to function, these data are turned into training data and supplied to the system. After training, test datasets are utilised to evaluate how well the built-in ANN performed. Errors are then fed back into the ANN for further correction [34].

In another article, one of the crucial methods for getting the most power out of a Pv system is discussed. Artificial neural networks and DC-to-DC converters were used in its development. Using maximum power point tracking, the solar module's maximum power is transferred to the load. This novel ANN method effectively exhibits the essential capacity to maximise power. In this work, a novel MPPT method utilizing artificial neural networks for the maximum point of power has been developed. Radiation from the sun varies widely. The precise power extraction of MPP, which determines whether the system will function steadily, may be found. To improve power generation and solar power management from solar cell systems, an artificial neural network can forecast solar level of radiation and battery temperature based on various operational settings in different climate conditions. When using an ANN-based MPPT manager, the output voltage is smoother and has lesser oscillations. The Controller is quicker and more durable. In this study, a planned ANN based MPPT technique that consists of ANN or three-point evaluation technique. First, ANN is used to guide reference process points that close to MPP speedily. Then three-point contrast is used to track the exact MPP. The ANN decreases the tracking time of three-point comparison. Also, a three-point comparison tracks the exact MPP. The algorithm implement in MATLAB software confirmed the Efficiency of the algorithm. For the purpose to track the maximum PowerPoint of solar cells, an artificial neural network is utilized. The low photovoltaic power is boosted to a higher level by the DC-DC boost converter and bridge inverter used to convert DC voltage to AC. Using a neural network arrangement, the distortions in the circuit caused by various components can be identified. After inversion, the AC voltage can be increased or transferred to the grid for usage in homes [35].

Some researchers presented the MPPT algorithm for contemporary homes with electric vehicles, which is based on artificial neural networks. All the PV system parameters and MPPT component were developed in order to reach the peak of the charging performance of the EV battery and the largest maximum power point tracking efficiency. The layers and activation functions of the neural network's final architecture were detailed. The suggested model's key benefit is the ease with which input data for neural networks like voltage, current, or temperature may be obtained. There is no need for the solar irradiance sensors. PV panel electrical current, voltage, and temperature may all be easily measured with inexpensive sensors. This method requires I-V curves of a particular PV panel under various solar irradiance values. The needed I-V curves of that PV panel can be generated in MATLAB Simulink, the solar irradiance and temperature are only required parameters. The neural network's performance was tested in computer simulation based on satellite derived solar irradiance data. The presented neural network MPPT model can quickly respond to sudden changing of solar irradiance values. The response time depends mainly on speed of input data acquisition since the neural network model contains only 150 weight connections. Partial shading conditions of the PV systems were not the object of this research. Additional sensors, measuring the shielded area of a PV system, could provide important information for neural network in order to deal with partial PV panels Shading conditions. These conditions will be a part of the authors' future research [36].

Another article illustrates a solar monitor tool used in photovoltaic systems to guard against deep expulsion and overcharging of batteries. In addition to serving the protective function, the Controller also makes sure MPPT monitoring is carried out, enables the solar generator to produce the most power possible under varying weather circumstances, and conducts routine analysis or comparisons. control using "ANN"-based intelligent controls that interfere with or analyse ("P&O"). Simulations run in MATLAB and SIMULINK can highlight the benefits and drawbacks of each piece of information [37].

In a different study, the researchers worked on updating and renewing the ANN algorithm to manage MPPT in any photovoltaic systems through two methods: multithreading and bettering the synaptic weights data format. It was discovered that while the synaptic weights benefit tremendously from a one-dimensional matrix, the multithreaded programme does not. In fact, it was found from the measurements that the thread initiation durations were more crucial than the benefit of parallelizing the process. The algorithm's good match was verified by comparing the photovoltaic panels data with large amount of samples of temperature and irradiance which resulted from simulation. The findings of the MATLAB programme and the simulation were in agreement, and the code was adjusted for Launchpad Stellar device. The execution speed was measured with frequency of clock set to 80 MHz and was found to be 60 microseconds [38].

Throughout another study, the peak power of the photovoltaic array is tracked utilizing a neural network-based control. Temperature and solar irradiation level serve as the neural networks' inputs. The ANN's output is the PV's ideal current. Additionally, a predictive controller is utilized to maximize the boost converter's performance. The simulation outcomes demonstrated that the proposed strategy would work as intended. This method is better for power extraction than the earlier control schemes [9].

Another study suggested an MPPT system based on artificial neural networks for a solar-independent DC motor and SPV. The suggested MPPT technology was contrasted to INC as an application technology using a comparable approach, and a corresponding discussion took place. Get the speed of the BLDC engine under typical test settings (STC) by comparing the initial range ratios of the INC approach and evaluating how well the SPV output power can be controlled. The analysis done for this paper demonstrates that the Efficiency of ANN-based MPPT is superior to INC MPPT even in the best first cycle. To maintain these outcomes, first compute the performance of the entire system utilizing two MPPTs of the INC best cycle, and then compute the performance of the entire system using the ANN-based MPPT in terms of differential mission conditions under the STC circumstance only. The single water pump system is made up of a configuration that feeds the SPV line directly to the source inverter (VSI) and incorporates it with an electric pump, enabling it to utilize more power without the requirement for DC-DC adaption. To stop the flow of current in the other way, the diode is connected in series with the SPV line. The duty cycle and electrical interaction configuration is utilized to organize the BLDC engine's speed. Organizational presentation is processed and implemented using MATLAB/Simulink-based models [39].

MPPT using artificial neural networks when atmospheric conditions vary was investigated in another research. The point of maximum power can be quickly and precisely defined by employing an artificial neural network. The artificial neural network's superior dynamic performance in contrast to other techniques is another benefit for PV maximum power-point tracking. Additionally, a dc-dc CUK converter monitors the peak power point. Consequently, the highest power and greatest efficiency of solar energy are attained [40].

A review of research on hybrid boosts converter (HBC) and artificial neural network (ANN) based MPPT is done to improve the output power of solar plants. The evaluation of the suggested model consists of two independent steps, offline and online. While the best ANN is employed as a MPPT method in solar plants using classic converters and hybrid converters, offline training is used to train different ANN terms with regards to structure and algorithm. Additionally, a thorough analytical framework is examined for both suggested procedures. The provided model effectively regulates the output of solar plants, as demonstrated by the mathematical and simulation techniques. This method lowers the cost per generation and is suitable to currently existing solar facilities [41].

The authors of a different publication offer feed forward ANN approach with single hidden layer. The radiation, temperature, and voltage being represented as inputs and I as the output. Because ANN is poor at extrapolating attributes, they utilized data that had demonstrated fluctuations in radiation and temperature to boost the network's effectiveness. The ANN was trained using 200 test data, and the findings indicate that it performs well when computing the MPP. Better results were obtained after repeating the experiment with 500 pairs of test data. This demonstrates that our system responds more effectively the more data it has to train on. The minimal complexity allows it to be acceptable to works on microcontrollers despite the outcome is foreseeable [42].

With the help of an Xbee module and the Arduino Mega platform, another thesis creates anotherr ANN algorithm in order to control the solar energy by using MPPT. The NARX design was selected because its output is not subject to a great deal of volatility. It has 10 sigmoid transfer-functioned neurons in the buried layer. The neural toolkit in MATLAB was also used to run a simulation, also a comparison was made with P&0 algorithm in the identical circumstances. The P&O algorithm delivers somewhat more power to the battery than the ANN controller does, but there is no discernible difference between the two algorithms. The controller successfully transmits a greater percentage of power to the battery than controller of neural. It's crucial to emphasise data collected with a reasonable amount of space around the MPP, but it's likely that training the neural controller and sensor by data from the area around the MPP could lead to better results [43].

An enhanced MPPT controller for Photovoltaic system is shown in another study. To accomplish this, both the traditional P&O method and an ANN were used. The traditional P&O algorithm, Photovoltaic modules, and neural networks are all created as MATLAB modules. To achieve the highest power point, the created MPPT, however, employs the ANN to forecast the recommended voltage for the PV system (MPP). Solar radiation, air temperature, the Isc and Voc temperature coefficients of the modelled PV module are the suggested ANN's four inputs and feedback propagation set. The designed ANN yields the ideal voltage for the PV system. The findings show that the proposed MPPT controller reacts more quickly than the traditional P&O algorithm. Additionally, the new algorithm's average tracking efficiency was 95.51% as opposed to the old P&O algorithm's 85.99%. A controller with such a layout improves a PV system's conversion efficiency [44].

The solar panels (PVs) mounted on electric cars' roofs are an example of an application where uneven and rapidly changing shadowing conditions are present all the time. Another study offers a ground-breaking Maximum Power Point Tracking (MPPT) technique that can be used in any application. In order to automatically determine the global maximum power point of the PV array, a predetermined number of power measurements from the PV system are employed in an Artificial Neural Network (ANN) based technique. The method avoids the necessity for extra sensors that would have compiled data on the temperature of the Pv panels and the operating characteristics of the surrounding environment by just requiring the measurement of PV voltages and currents. The amount of time required to have the PV modules produce as much power as they can is roughly consistent and predefined. The quantity of power-voltage characteristic scansions increases both the ANN's maximal capacity and the precision of its predictions. The algorithm is cheap, doesn't need much extra hardware, and only minimally depends on changes in system settings. The success of the suggested approach has been confirmed by numerical simulations, which have also emphasised the tradeoff between the predetermined number of power-voltage characteristic scansions, ANN size, and the precision of its forecast [10].

In another paper, six MPPT techniques are analysed and discussed. The MPPT technique, which uses maximum point monitoring, is what enables the most power to be taken from a PV source. The most common MPPT instructions will be discussed and examined in this article and are as follows: FL-INC-Fuzzy ANN -SCC-OCV and finally P&O. The MPPT system is modelled in the MATLAB Simulink environment, which is used to examine or analyze the simulator results and show how effective it is [45].

An innovative hybrid MPPT approach for photovoltaic systems is proposed by another study. The proposed method for MPPT is relied on an integration of an artificial neural network (ANN) and a novel model predictive control with a kalman filter (NN-MPC-KF). In this study, the converter state vector is estimated using the Kalman filter in order to follow the maximum power point (MPP) with quickly changing meteorological conditions. The recommended control approach can keep MPP tracking even when there is a minor overshoot and quickly shifting irradiance circumstances. Finally, a simulation of the system is conducted in MATLAB/Simulink [46].

Another study offers a creative approach for maximising the power production of a photovoltaic panel utilizing an artificial neural network (ANN). The perturb and observe (P&O) technique is utilised to generate the required output, and real-world meteorological conditions are used as the input data to train the ANN controller. The system's dynamic response and steady-state performance can both be improved by the proposed model. Additionally, it correctly pinpoints the optimal operating point and forecasts the maximum power that the photovoltaic panels are capable of producing. The suggested ANN controller could increase power output by roughly 20% when compared to the conventional P&O model, according to a comparison between the two models. The system is studied and modelled using MATLAB software [47].

Another study recommends an ANN-MPPT method relied on a sizable amount of experimental training data to prevent the system from having a high training error. These data came from tests on a PV system erected at Brunel University in London, United Kingdom, over the course of a year. The output of the ANN model is the amount of power that is available from the PV system at MPP. The weather's temperature and irradiance are chosen as the inputs. A MATLAB/Simulink framework for the PV system is used to simulate Perturb and Observe (P&O) and suggested ANN-MPPT approaches in order to assess the performance. The results show that the suggested ANN method outperforms the P&O-MPPT strategy in terms of output power while correctly tracking the optimum maximum power point and eliminating the drift issue [48].

The authors of another study advise employing repeated ANN with external inputs for MPPT control of photovoltaic system. A parallel/serial architecture was constructed to have it since this type of network discovers its true output during the training phase. In MATLAB/Simulink, the simulations were performed using a single hidden layer with ten neurons and transfer function for the tangent-sigmoid, also a straightforward linear function for the output layer. The method was used with an Arduino Mega as well. The results show that, in terms of preventing energy losses, the ANN algorithm is superior when compared with P&O technique. Given that the P&O algorithm can recharge the battery in low radiation conditions, the authors advise combining the use of both approaches [49].

The authors of a different study also evolved an MPPT method using a high-order recursive ANN (RHONN) and optimised the required weights using an extended Kalman filter. Modeling the results in MATLAB was done using the Simscape toolset. When radiation is given to the system, the algorithm begins to converge speedly, then locate the MPP with error about 7% of the actual MPP. To compare performance, a discrete-time sliding mode MPPT control mechanism is created. The approach displays a great trustworthy convergence of mean error and standard deviation [50].

In this study, a novel hybrid technique for tracking the solar panel's highest power point is proposed. This method employs two loops: The first loop, called the ANN loop, is utilised to figure out and define the reference for the ideal voltage. The second loop has the Backstepping Sliding Mode (BSM) controller. By adjusting the duty cycle of the boost converter, the suggested controller is designed to follow the signal of the required voltage, which is generated by the first loop. The DC/DC converter may output its maximum power at the Photovoltaic panel and load terminals thanks to this loop. Compared to the traditional backstepping, the recommended ANN-BSM approach actually ensures 0% steady-state error. The ANN assists the system in rapidly estimating the necessary optimal voltage in addition to enabling the system to bypass useless computations and search for the greatest point of power. The sliding mode and the backstepping controller, on the other hand, are used to give strong performances against sudden changes in solar radiation. This system's asymptotic stability is also created using the Lyapunov method. In order to demonstrate the efficiency and tracking performances of the proposed ANN-BSM technique, a comparison study with the conventional approaches, P&O and incremental conductance algorithms, the ANN-Integral Sliding mode and ANN-Backstepping controllers is reviewed in the MATLAB/Simulink software [51].

For standalone PV systems, an intelligent MPPT approach to track the GMPP under various weather circumstances has been developed in this work. The P-V curve scanning process and ANN controller are integrated in the suggested approach. The results of the simulation demonstrate the capability of the proposed approach to distinguish between GMPPP and LMPPs and to guarantee a speedy convergence to the GMPP with good efficiency estimated to be 97.64 under transient modification of shading patterns. The created technique has been contrasted with PO &GS and FLE. The results show that although all three methods are capable of tracking the GMPP, the proposed technique outperforms them in terms of reaction time. Response time for the new MPPT approach is almost five times faster than for the PO&GS and three times faster than for the FLE [12].

Another paper highlights the design of the neural network controller for the single-phase induction motor (1 HP) speed control, controlled by the solar energy system. Using the incremental conductance method, the maximum power generated by the solar panel is retrieved. The single-phase inverter that powers the induction motor is fed by a SEPIC converter, which controls the voltage and current output from the solar panels. To boost the voltage produced from the solar panel, the pulses from each controller and the MPPT controller with an incremental conductance algorithm are combined and then provided to the SEPIC converter. The controller receives feedback in the form of the Induction Motor speed. The neural network controller simulation has been completed. The findings of the simulation reveal that the neural network controller performs better for induction motor speed control [52].

A strategy has been created for making the most of solar energy, and a Simulink model has been created following training. The maximum power is predicted using cutting-edge artificial neural network technology while taking into account the variance in input levels of sun irradiation and temperature. Using the suggested algorithm, the solar panel's greatest power point is tracked in 2 ms. The network monitors around 39.62 Watt as the maximum power at various irradiance and temperature of 300C after the algorithm has been applied to a 40-Watt PV panel. There are no disturbances and just minor oscillations, and tracking time is shorter than with traditional approaches [53].

In a different study, a new design of a standalone photovoltaic system which is supplying the required power to a direct current water pump that have difficulty to supply by the utility electricity. The system is controlled by an artificial neural networks (ANN) algorithm with function softening by PI controller that to guarantee the maximum power point tracking (MPPT) working conditions. A parallel connected PV array is designed to supply the required power to the water pump. The proposed design considers Permanent

Magnet DC motor (PMDC) of 48 Volts, and 500 Watts as a water pump's motor, the direct current (DC) pump is adopted to avoid the complexity of the alternating current AC pumping system which includes inverter, power filter, and insulated step up transformer, so the presented design avoids the mentioned AC system components. A feed forward ANN algorithm is adopted in this study to produce the reference voltage for the MPPT functioning of the PV system; Proportional Integral (PI) controller is inserted

to soften the MPPT controller performance [54].

In a different study, two MPPT control algorithms with ANN are proposed; the first employs fix-step, and the second, variable-step. This is shown by the simulations utilizing the variable-step method. Positive outcomes are resulted even in the face of variable air conditions, and faster response times are accomplished, as opposed to the fix-step method, which generated results very comparable to those attained using P&O [55].

A hyper twisting sliding mode using ANN algorithm was also developed for monitoring MPP in a different study. They point out that a nonlinear controller is necessary to obtain MPP since photovoltaic cell in varying temperature and radiation acts as a nonlinear system. The I-V curves from the panel were utilised as training data for an ANN with three hidden layers. Matlab/Simulink simulations claim to have a 97% performance rate [56].
Creating an ANN model training strategy is challenging because to the diverse operating and training settings of a solar system. The authors of a study built a MATLAB/Simulink simulation of the Particle Swarm Optimization (PSO) technique in order to determine the optimum structure and determine the ideal beginning weights for ANN models. As a result,

the mean squared error is reduced and the contradiction between processing time and the best-fitting regression of the ANN model is resolved. The results show that the PSO algorithm-based optimised feedforward ANN technique successfully predicts the greatest power point utilizing real data, with hourly average efficiencies of more than 99.67% and 99.30% on clear and cloudy days, respectively. An ANN-based MPPT controller demonstrates lower steady-state error and a quicker response to sudden variations in solar temperature and radiation than incremental conductance and perturb & observe [57].

3. METHODOLOGY

The main objective of this thesis is to maximize gain by tracking the region with the highest power parameter. Artificial neural networks will be the key tool for prediction operations in order to achieve the best outcomes. These networks have been trained on the most important characteristics of solar rays. By creating an Artificial Neural Network that is trained on the most parameters and their values with ranges, machine learning may be used to analyze and compare regions to get the best one. Therefore, a research must be conducted to track the most crucial variables and their relationships, which can also be done using a machine learning approach.

The research aims to create a proposed model of Solar Power Tracking System based on regulated Artificial Neural Network, per the research queries. Additionally, it aims to create an artificial neural network that is well-trained in analyzing solar energy radiation and extracting attributes to direct PV solar array systems to the area with the greatest potential for gain. With the help of its circuit components, it creates a solar charge controller design at the end.

Therefore, the proposed developed solar power tracking system employing machine learning (ANN) is illustrated in (Figure 3.1).

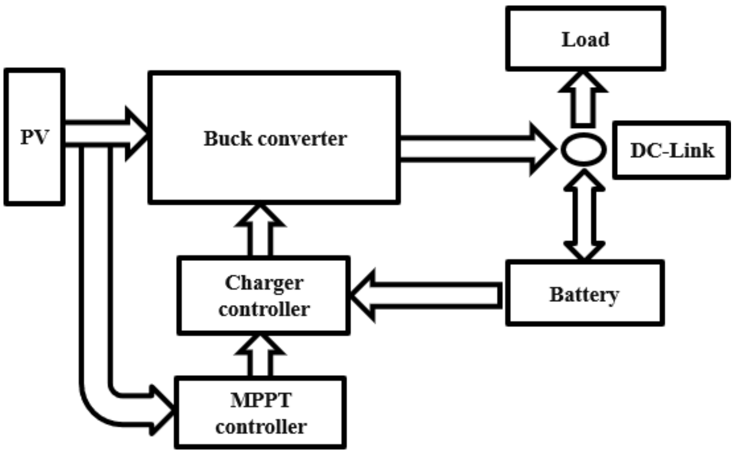

Figure 3.1: Solar Power Tracking Model.

After being trained on historical data, machine learning algorithms can be used to forecast the reference voltage with accuracy. The reference voltage is precisely estimated by the V_{ref} generating block after it has been trained on past data. It makes a prediction for $\tilde{V}_{ref}$ for a particular temperature and irradiation pair that corresponds to the panel's peak output power. The learning stage (also known as the training stage) and the running stage are prerequisites for the machine learning block to be completely functioning (also referred to as the testing stage). Building and validating a function that predicts the relationship between temperature and irradiation with the reference voltage V_{ref} using historical (training) data is the goal of the learning stage. In the running step, the model developed in the learning stage is then utilized to forecast the reference voltage value $\tilde{V}_{ref}$ using testing data that the model had not seen in the learning stage as input. (Figure 3.2) explains the learning and running stages. The root mean square error is used to identify how accurate a machine learning model is in making predictions (RMSE).

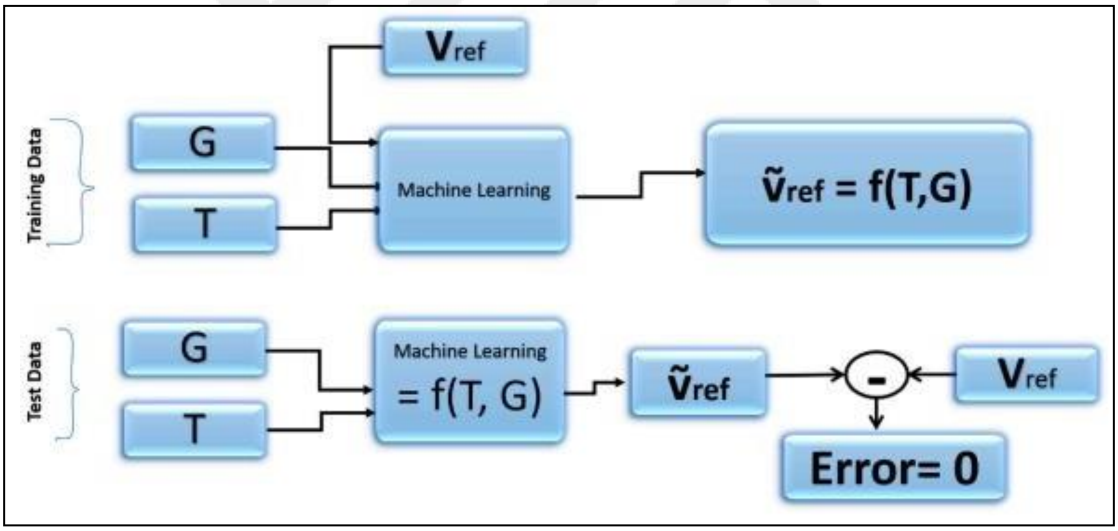

Figure 3.2: Machine Learning Algorithms' Learning and Running Phases.

ANN model design involves several systematic steps. As shown in (Figure 3.3), there are five fundamental step: (1) Surveying and data collection, (2) pre-processing data, (3) creating the network, (4) training on collected data, and (5) testing model performance.

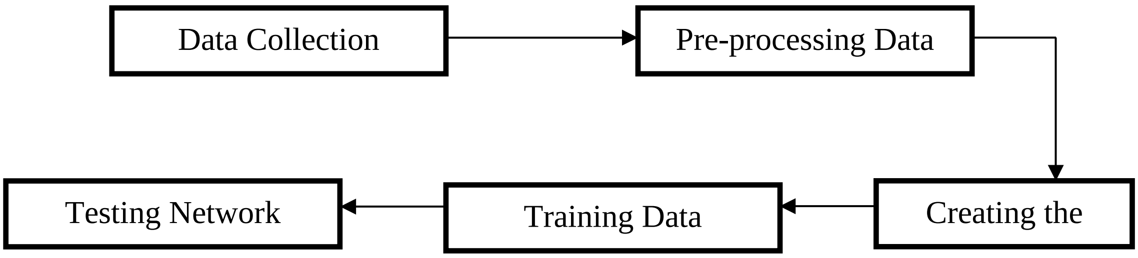

Figure 3.3: An Overview of The Basic Design Process for an Artificial Neural Network.

Programming the neural network model was conducted using MATLAB software. In addition to being a programming language, MATLAB is a numerical computation environment. It enables simple matrix manipulation, data and function charting, algorithm implementation, user interface creation, and interaction with other languages' programs. The tool of MATLAB for creating, using, the visualizing, also modelling neural network can be found in the Neural Network Toolbox. Additionally, it offers thorough support for a variety of tested network paradigms and graphical user interfaces (GUIs) that make it very easy for users to create and manage neural networks.

3.1 SURVEYING AND DATA COLLECTION

Gathering information about the values, ranges, and relationships between the parameters is the initial stage in developing an ANN (inputs, outputs). Increasing the amount of data helps NN function better. The following parameters are monitored: instantaneous panel power and solar radiation intensity (for us, these are the main measurement data); moreover, air temperature and cell temperature are measured (these are complementary measuring quantities). So that we can counteract the impacts of moving air, precipitation, and direct radiation, the sensor of detecting air temperature is housed in a protective "casing." On the upper (illuminated) side of PV panel, which is practically in the centre of the panel, is the sensor for measuring panel temperature. We also take a temperature reading on the panel's bottom (non-illuminated) side to get the whole picture. Measurements are made of both the actual and the instantaneous panel power that is optimized. The standard connection between a PV panel and an accumulator is used to measure real power.

How much solar radiation reaches the panels and the working temperature have an impact on the amount of electrical power that PV systems generate, but the connected power requirement also plays a role. You may determine the operating point for a given value of irradiance(G), temperature(T), and electrical load by drawing on the P-V characteristic curve. The working point will shift along the curve load e as a result of temperature changes and sun irradiation through the day in accordance with a general constant load linked to a PV panel. In the P-V plane, the (MPP) coordinates are (Vmax(G, T), Pmpp(G, T)); in the I-V plane, they are (Vmpp(G, T), Impp(G, T)). A thorough examination of PV curve enables one to see right away that a standard PV panel's electrical behaviour can be described in one of three modes or routines:

a. When the difference between the operation voltage and the voltage of maximum power at given temperature is less than 0.95, the P-V characteristic is nearly linear also the power is highly linked to the incident solar radiation; for constant solar irradiance, there is no temperature effect on the power output.
b. When the ratio V/Vmpp for a specific solar irradiation is greater than 1.05, the P-V characteristics of the panel degrade noticeably more rapidly and the impact of solar radiation becomes less considerable (saturation conditions), Under constant solar irradiation, the relationship between temperature and power output is linear.
c. A PV panel linked to a maximum power point tracking system (MPPT) is in the state where the load adjusts automatically to produce the maximum power when the ratio of 0.95 < V/Vmpp < 1.05 is present.

In this case, the primary characteristics that need to be recorded in the data are those that have a significant impact on how much electricity a PV solar array generates, such as temperature, light intensity and irradiance. So, large number of sun irradiances, temperatures, and matching duty cycle ratios are taken. The samples are obtained by adjusting the PV array's inputs for irradiance and temperature and measuring the duty ratios. To choose a learning method for supervised learning, tagged data, or a set of previously known data, was employed.

3.2 PRE-PROCESSING DATA

With the completion of data collection, we have completed three data pre-processing procedures are completed to improve the efficiency of training the ANNs. The three steps in this method are to address the problem of data being lost, normalise data, then randomise data. Any data being lost is filled in using the average of values from same week that are close by. Before providing the network with input data, it is usually a good idea to undertake a normalisation procedure because combining variables with big and tiny data will make the learning algorithm unsure of the perceived significance of each parameter and it may eventually push it to dismiss the smaller magnitude variable.

3.3 CREATING THE NETWORK

In this step, the designer determines the number of hidden layer, transfer function, neurons in each layer, training function, performance function and weight-bias for learning function. This study's controlled artificial neural network is demonstrated in (Figure 3.4).

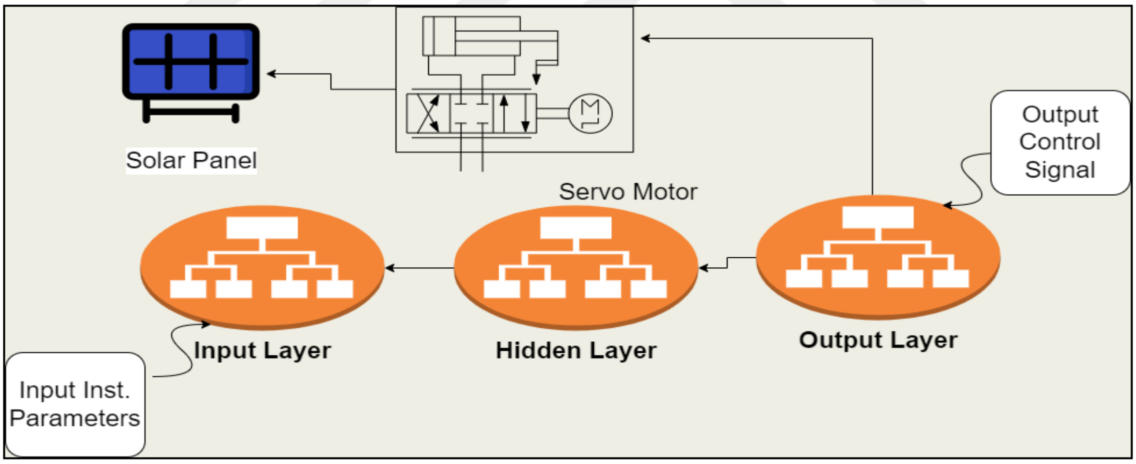

Figure 3.4: Controlled Artificial Neural Network.

The measured PV current and voltage, radiation G, or temperature T are the ANN inputs. The output is the maximum situational power a PV array can provide. To replicate the PV array output parameters that the producer has provided, determine training data using MATLAB. At the best PowerPoint, this network is used to resolve power in a photovoltaic system.

3.4 TRAINING ON COLLECTED DATA

The gathering data are provided for training after the NN design has been established. The weights are updated and adjusted by the training algorithms using the training function. The extraction of features and training on the MATLAB program resulted in a trained model (Artificial Neural Network) that can analyze, compare, choose, and transmit commands to track.

The weights of the neural network must be tuned before it can be applied to a particular task. The network is trained during the learning process, which completes this task. This algorithm alters the weight iteratively until a particular condition is confirmed. In the majority of applications, the learning procedure ends when the discrepancy between the calculated output provided by the ANN and the desired output reaches a predetermined value. The weights and biases are optimized to update the mistake.

3.5 TESTING NETWORK

The final step before utilizing a network is testing it; during this phase, weights remain constant (network topology does not change), and network performance is just measured. The network must be retrained if the findings are inaccurate or the performance is bad. The performance of NN can be altered by increasing the number of data set, modifying the procedure of training, and increasing the neurons number.

In statistical analysis, the determination coefficient, the error of root-mean square , and the error of mean bias were employed to quantify the effectiveness of developing ANN models then establish the existence of any underlying trend. The RMSE, a measurement of the variance of anticipated values around the measured values, reveals short-term effectiveness. The estimation becomes more precise as RMSE decreases. The MBE, which measures the average difference between the anticipated values and the real measured data, provides statistics on the long-term effectiveness of the models; the smaller MBE, the more accurate the long-term model projection.

The ability to test the performance of any proposed system with a comparison of the two algorithms that we will propose, ANN with the traditional observe and perturb algorithm P&O, So we will adopt the simulation in MATLAB-Simulink and as described in (Figure 3.1), the simulation results were first reviewed in order to apply P&O algorithm, and then it was training the artificial neural network on scenarios for solar irradiance(G)values also the temperature(T), then re-testing the performance in trained network at the same temperature and irradiance values with the performance of the algorithm (P&O).

We will use the method of perturb and observe to compare with the ANN algorithm in our research. Due of its lower time complexity, perturb and observe is a simple MPPT method. The easiest and most direct method to use is this one. Because of its step-by-step approach, it is sometimes referred to as the "hill climbing method." Under covert circumstances, it does not produce satisfactory outcomes. This technique alters the output power by varying the supply voltage. The duty cycle is further enhanced if raising the provided voltage results in greater power. Now, duty cycle is reduced if increasing the provided voltage results in a drop in power. If reducing supply voltage is the cause of an increase in power, then reducing duty cycle will follow. Until the ideal point is reached, this process is continued. As a reference point, the voltage at the MPP is acknowledged.

3.6 SOLAR CHARGE CONTROLLER

During the day, a PV panel's output voltage varies significantly depending on the temperature and solar radiation level. Voltage can only be produced by PV modules during the day. A storage system is therefore necessary for stand-alone module of PV system, so it be able to collect energy during the day and store it for use at night. A charge controller regulates the amount of current going into or out of a battery. The battery limits how much energy the PV array can supply to the battery once it is fully charged, preventing overcharging. Additionally, it might protect against over-voltage, which harms battery performance. Excessive discharge would occur if the battery was disconnected from the power source when it still had very little charge.

A solar charge controller's circuit should first be constructed using PCB software like Altium-Design before it can be designed.

Control of the battery charging depends on the direct connection from the solar cell to the charging controller, which depends on the battery condition in terms of charging. When it is completely charged, it is separated from the charger and when it is charged less than the voltage of the solar cell system it is charged until reaching the point concerned, either in the case of the voltage floating it is represented the completion of the charging process, and this charging control is affected by the weather conditions that is first affect the solar cell.

The charging control unit has been developed by using three stages and as follows:-

Constant voltage charging, Constant- current charging, and Floating- charging. The battery state and voltage are evaluated by charge controller. A flowchart for controlling battery charging, which we will explain as follows:-

The first stage begins to read the battery charging if it is less than 100%, we go to the stage of constant voltage or current, else if not it will go to the stage of floating the charge that represents the third stage, where D=0.During the second stage, we read the battery voltage and compare it with a constant voltage if it is less than it will enter the stage of the constant current and D = MMPT ,else if not enter the stage of charging the voltage and this is shown in (Figure 3.5).

Charge controllers typically only need minor servicing. Trickle charge panels and other battery regulators manage the current flow. There are several advantages to using charge controllers to prevent over-voltage, which decreases battery performance and lifetime and prevents deeper battery charging.

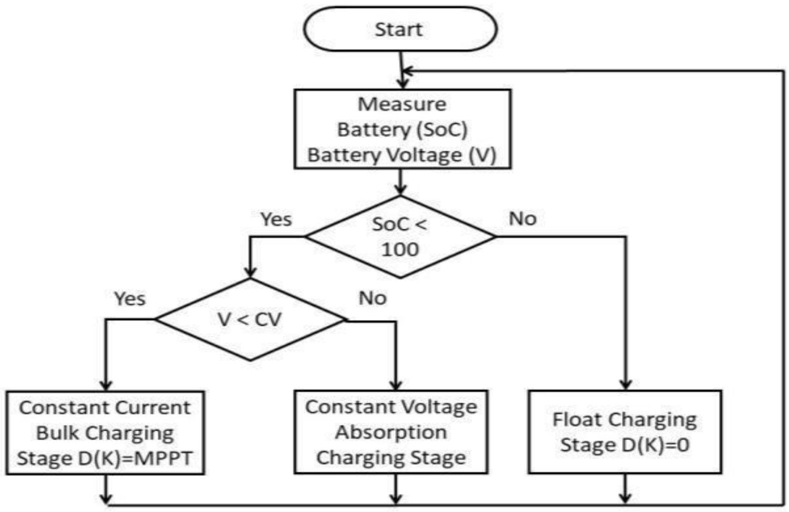

Figure 3.5: Flowchart of Charge Controller

3.7 DC-DC Converter

Depending on the system architecture, the MPPT algorithm can be used with either boost or buck converters. Buck converters are often beneficial when the battery system voltage is equal to or lower than 48 V. where, a boost converter should be used if the voltage of the battery system is greater than 48 V

The converter DC-DC transforms a source of DC input voltage into a greater or lower source of DC output voltage. The PV array voltage is greater than voltage of battery; hence buck configuration is frequently used as solar photovoltaic charge controller systems.The buck converter functions like a regulator to reduce the PV array's input voltage while keeping the power supply for battery charging. Stepping down the voltage which input and boosting the current output sent to the battery accomplish this. The buck converter circuit comprises of an output and input capacitor, diode, a large power inductor, and MOSFET. To stop the passage of current backward, the reverse blocking diode D1 is utilized.

4. RESULTS

The behaviour of diodes, which gives photovoltaic cells their exponential characteristic, serves as the foundation for all photovoltaic models. The simulation of the solar cell can be done using three modelling systems. Modelling is first made possible by instruments that can carry out any equation or algebraic relationship found in a very complicated mathematical model. Simscape TM provides an alternative by enabling direct modelling of real electrical field elements (resistors, capacitors, and semiconductors) to perform the same calculation. To simulate a system that is more complex than the ones stated above, the advanced component library, which has a block called Solar Cell, is used. The solar cell in MATLAB (R2020) is a solar current generator that takes temperature dependence and solar-induced current into account.

ANN layer is designed mainly on the collected datasets depending on the maximum positions for maximum gains in solar energy for electric energy.
The artificial neural networks (ANN) model uses calculations and mathematics to mimic the workings of the human brain. Numerous recent technological developments, including speech and image recognition, robotics, and the use of ANNs, are connected to the field of artificial intelligence research.
Integration of renewable energy sources into the electricity grid is becoming increasingly necessary. For grid-connected apps, battery charging, and other purposes, solar PV generation is crucial. Finding the most energy that can be harvested from photovoltaic panels is essential for increasing the output capacity of a solar power system. In this study, an artificial neural network is used to create the, MPPT, driver for solar PV systems. (ANN). Additionally, the effectiveness of an ANN-based MPPT controller is contrasted to traditional MPPT techniques. In particular, the fractional voltage of open circuits approach, the incremental conductance method, and the hill ascending method (perturb & observe). To analyze the findings of simulations, MATLAB/SIMULINK is used.

Due to its simplicity and simplicity in application, the P&O technique is frequently used. Additionally, A P& O method that can calculate the efficiency of MPPT (in small steps) in a simpler way than other complex techniques under the same conditions. The disadvantage of this method is that the PV array's working point vibrates around the MPP. As a result, it can lead to more energy dissipation.

Furthermore, there is a possibility that P&O's approach to MPP will fail when the sun's insolation changes quickly. Another potential drawback is that as sunshine levels drop, the PV curve flattens, making it harder for the MPPT to find the MPP. Lately, MPPT-based intelligent control systems have been created and built on intelligent control.

In order to set the duty cycle control into practice, the MPPT strategy presented here combines a neural network made up of neurons and the MPPT technique. While the neural network is concurrently learning MPP discovered by P&O, the system uses the P&O to control the DC-DC converter when solar irradiation changes gradually. Nevertheless, the neural networks controller follows the MPP quickly if the sun radiation fluctuates rapidly and modifies the DC-DC converter's duty cycle. For effective online learning, neural network typically needs independent and uniformly distributed data. However, in this case, the machine learning neural network makes use of comparable training examples.

The benefit of employing this advanced level of execution is to produce a straightforward similar circuit with significantly more complicated factors, along with the effect of device temperature, which is crucial to how this type of system behaves. By simulating once at value of sunlight of 1000W/m2 and a temperature of 25°C, the PV model is verified. The output of the PV array is where voltage and power are measured. The power, voltage, and current vs. time curves are shown here. The voltage-time connection, which alters as the resistance changes, determines the power curve.

This research conducts and presents a model analysis of PV cell, PV module, and PV array based on MATLAB-Simulink. Based on how a PV solar cell behaves as a diode, the simulation model uses fundamental circuit equations, and a thorough behavioural analysis is carried out under a variety of variables, including temperature, solar insolation, altering diode model, series and shunt resistance, etc. The study can be used to confirm the effects of various topologies and control strategies on the effectiveness of different types of solar power systems, as well as to outline the fundamentals and intricate workings of PV cells and modules. The shading effect severely reduces the PV module/performance, Array's or its P-V characteristics show several maxima. Therefore, the MATLAB/Simulink-based analysis also highlights the relevance of determining maximum power.

There is literature that provides a mathematical explanation of the current-voltage terminal parameters for PV cells. It is widely acknowledged that the power - law equation which represents a PV cell and derives from the thermodynamics of the PN junction, accurately captures the distinctive behaviour of the cell. The crystalline silicon cells may be employed using an exponential Equation (4.1).

$$I = I_{ph} - I_s\ (exp^{\frac{q.(V+IR_S)}{N.K.T}} - 1) - \frac{(V+IR_S)}{R_{sh}} \tag{4.1}$$

4.1 SIMULATION RESULTS FOR APPLYING P&O ALGORITHM

In (Figure 4.1) demonstrates the proposed photovoltaic power system's block diagram. (Figure 4.2) shows the structure of MPPT controller for (P&O) approach, and (Figure 4.3) shows the structure of the Solar Charge Controller.

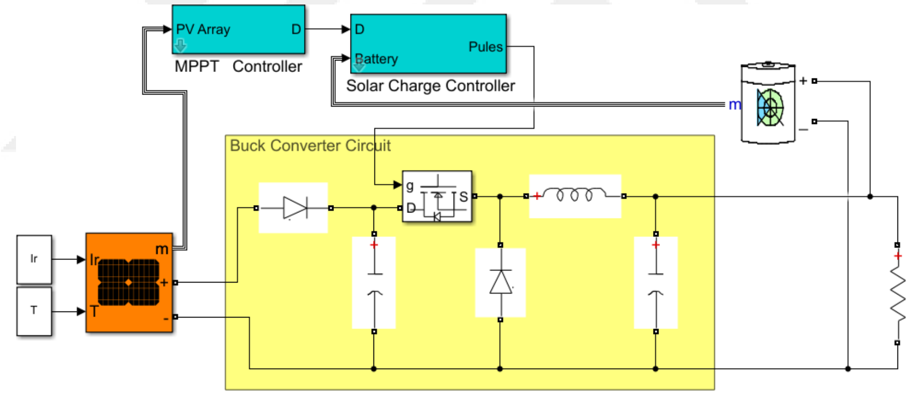

Figure 4.1: The Proposed Photovoltaic Block Diagram in MATLAB-Simulink

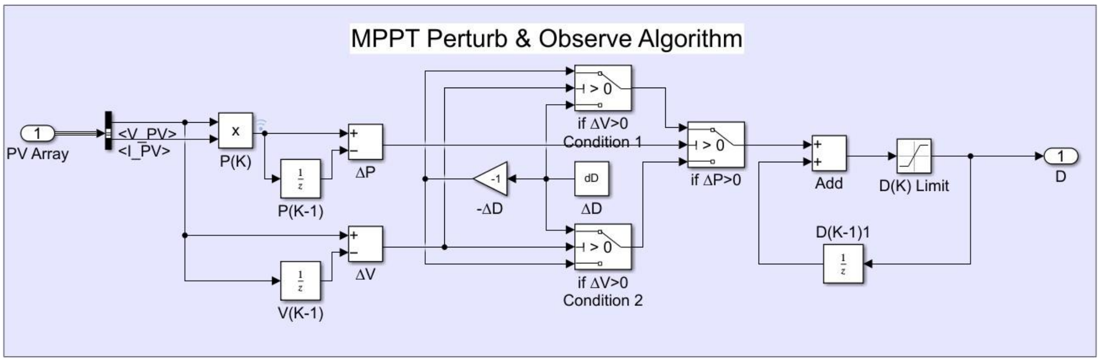

Figure 4.2: The Structure of P&O -MPPT Controller in MATLAB-Simulink

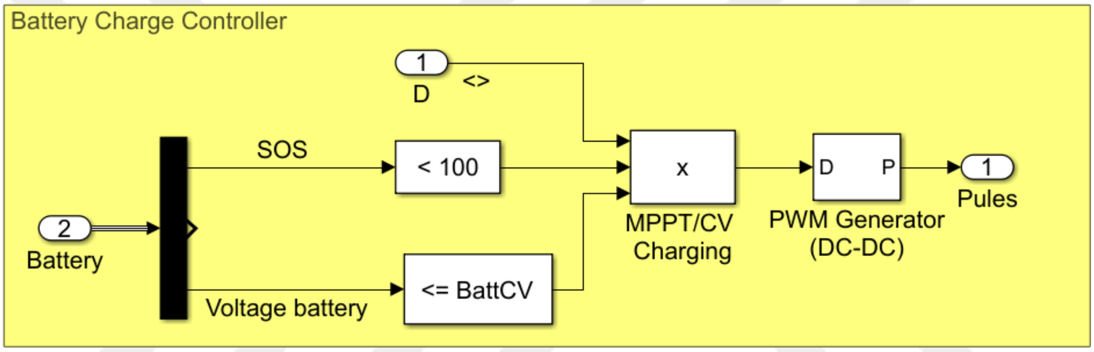

Figure 4.3: The Structure of Solar Charge Controller- in MATLAB-Simulink

The solar radiation profile was set as shown in (Figure 4.5) and the temperature profile was set as shown in (Figure 4.6)

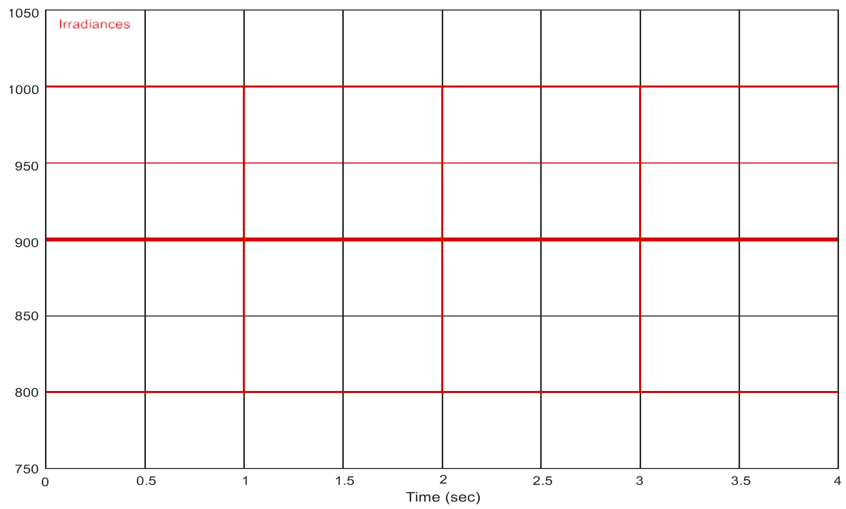

Figure 4.4: Solar Radiation Profile

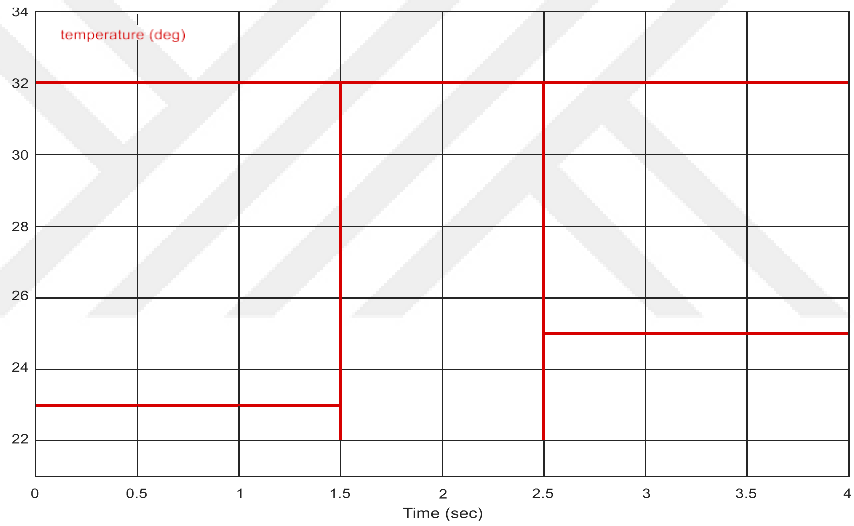

Figure 4.5: Temperature Profile

(Figure 4.7) shows the power drawn from the solar panel, (Figure 4.8) shows the power consumed by the load and (Figure 4.9) and (Figure 4.10) show the voltage and current of the battery, respectively.

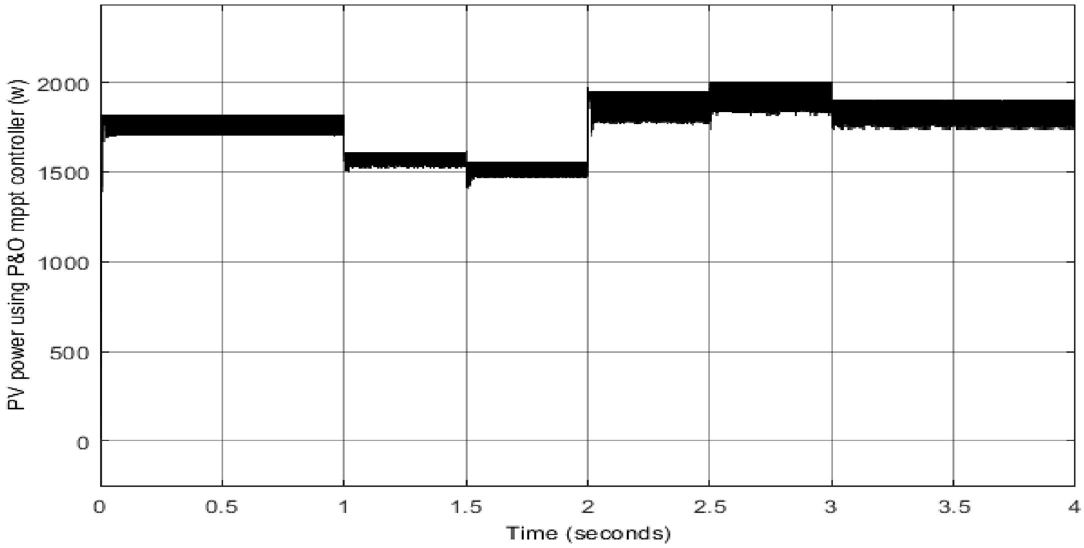

Figure 4.6: The Power Drawn From The Solar Panel When Using The P&O MPPT Controller

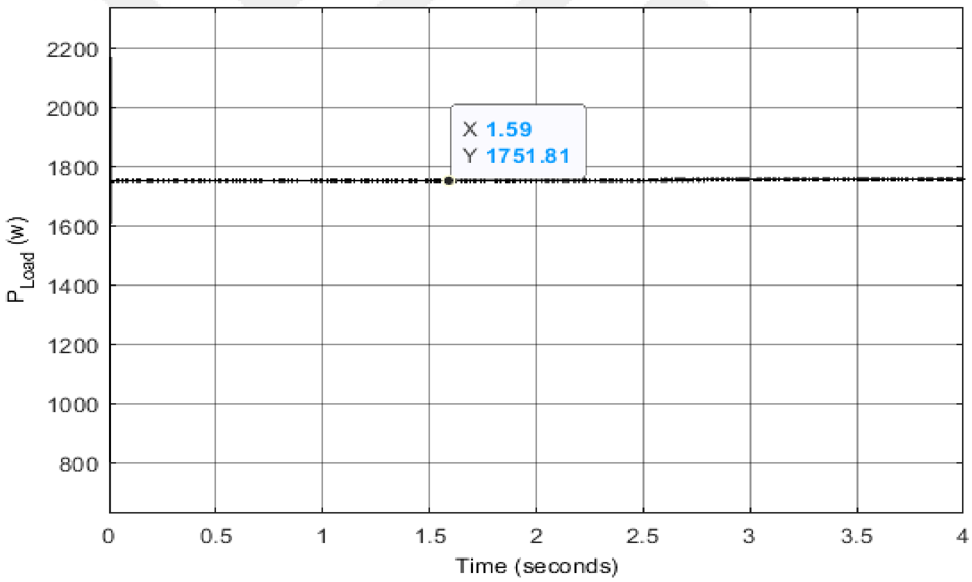

Figure 4.7: Power Consumed in The Load

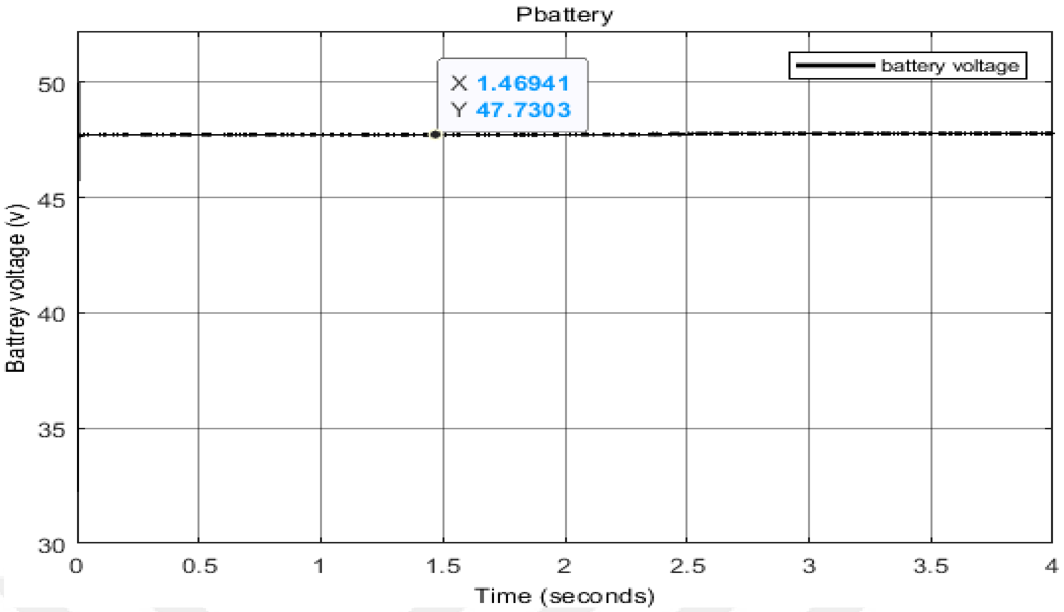

Figure 4.8: Battery Voltage

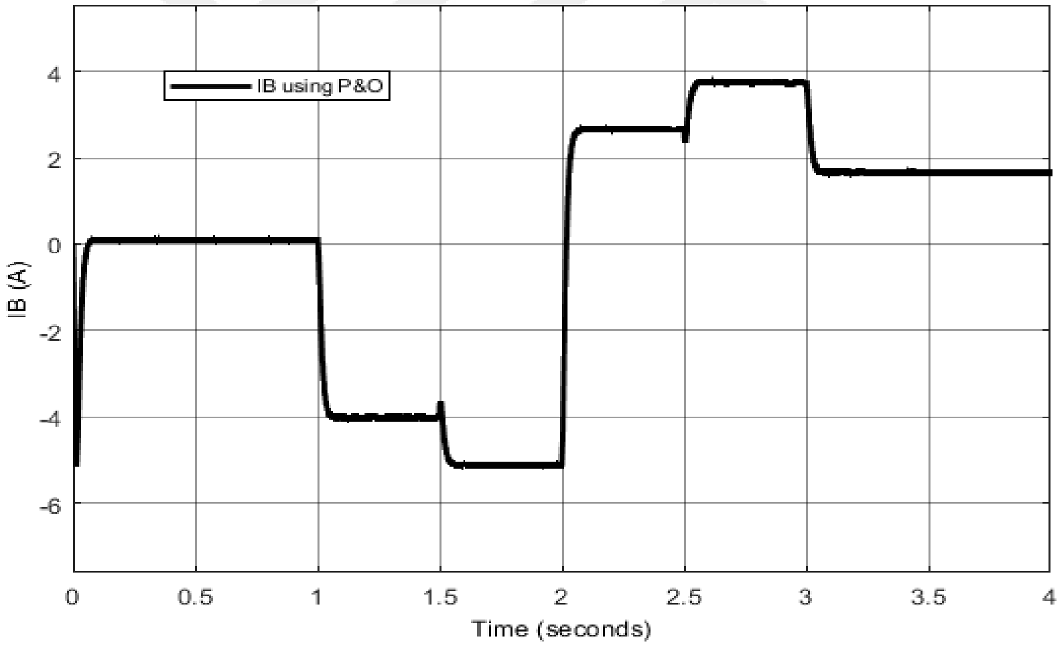

Figure 4.9: Battery Current When Using a P&O MPPT Controller

It is noted from (Figure 4.8) that the P&O algorithm achieves a good performance in tracking the maximum power point, where the photovoltaic panels have been set to give 2000w at a solar radiation of 1000w/m^2 and a temperature of 25deg. However, it is noticed that there is a vibration in the power collected from the solar panel.

It is noted from (Figure 4.9) that the value of the battery voltage is stable, while it is noted from (Figure 4.10) that the battery current during the period (2sec-4sec) is of positive values, given that the capacity for photovoltaic panel is greater than load capacity, and during the period (2sec-3sec) it is It has a negative value for the opposite case, and is almost the value is zero when PV panel capacity equal load capacity during the period (0-1sec).

4.2 SIMULATION RESULTS FOR THE APPLICATION OF ANN

(Figure 4.11) shows the block diagram of ANN MPPT controller, where the Fitnet artificial neural network is designed in two stages. The first stage includes data collection based on the results of the traditional P&O algorithm, where the solar radiation profile was set as shown in (Figure 4.12). Adjust the profile of the temperature as shown in Figure (Figure 4.13), in order to simulate the largest number of possible scenarios for the values of solar radiation and temperature.

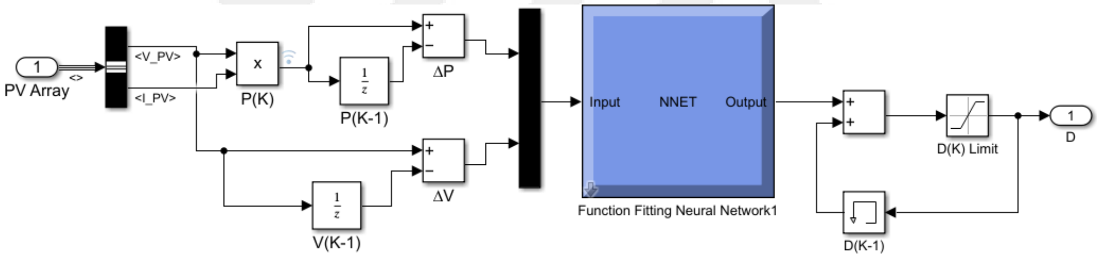

Figure 4.10: Diagram of ANN MPPT Controller

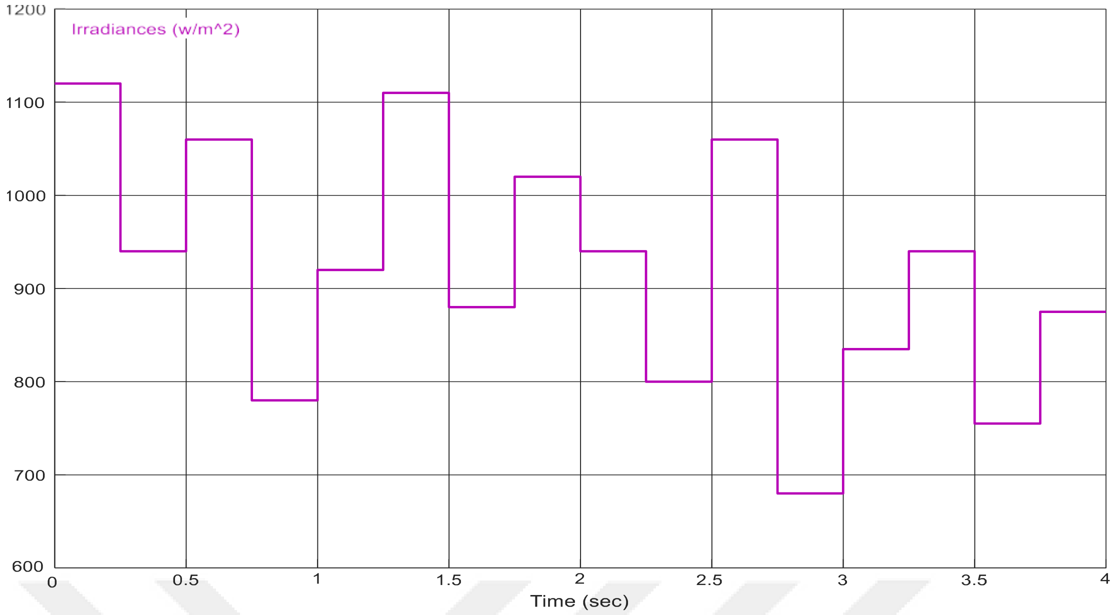

Figure 4.11: Solar Radiation Profile for Training ANN

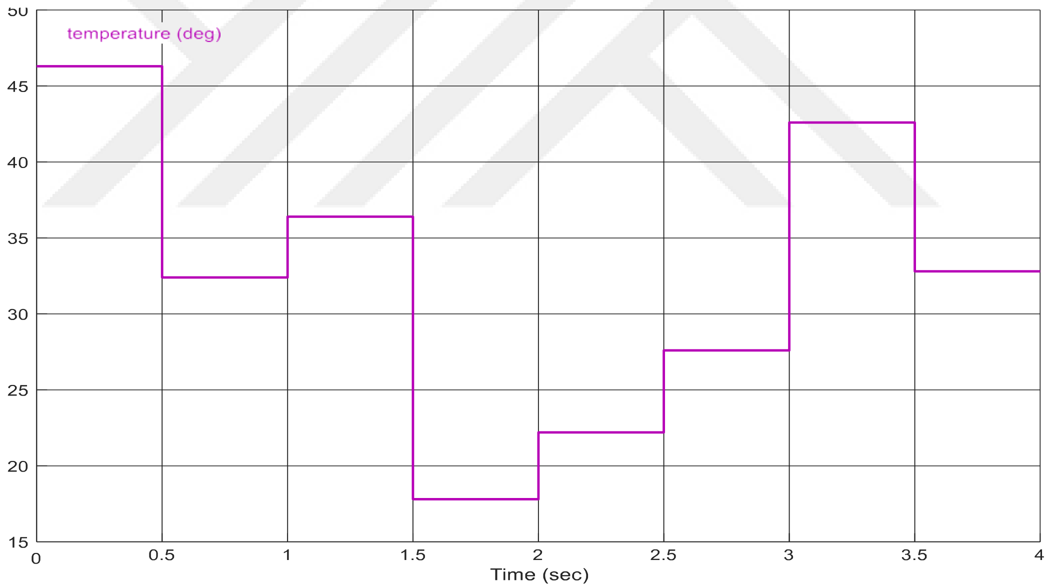

Figure 4.12: Temperature Profile for Training ANN

In the second stage, the artificial neural network architecture was chosen, as it consists of two layers as shown in (Figure 4.1), the hidden- layer with the function of sigmoid activation contains 10 neurons, also the output- layer with function of linear activation contains one neuron.

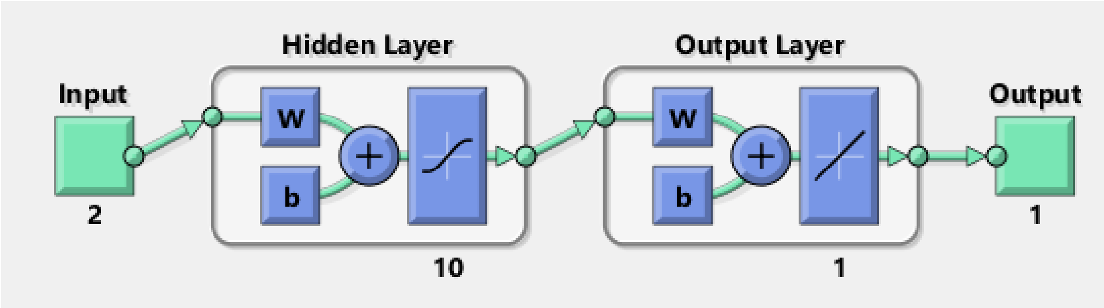

Figure 4.13: The Structure of the Proposed Neural Network

(Figure 4.14) shows the power obtained from the photovoltaic panel using the ANN network compared to the power gained by using the P&O algorithm, (Figure 4.15) shows charging & discharging current for battery.

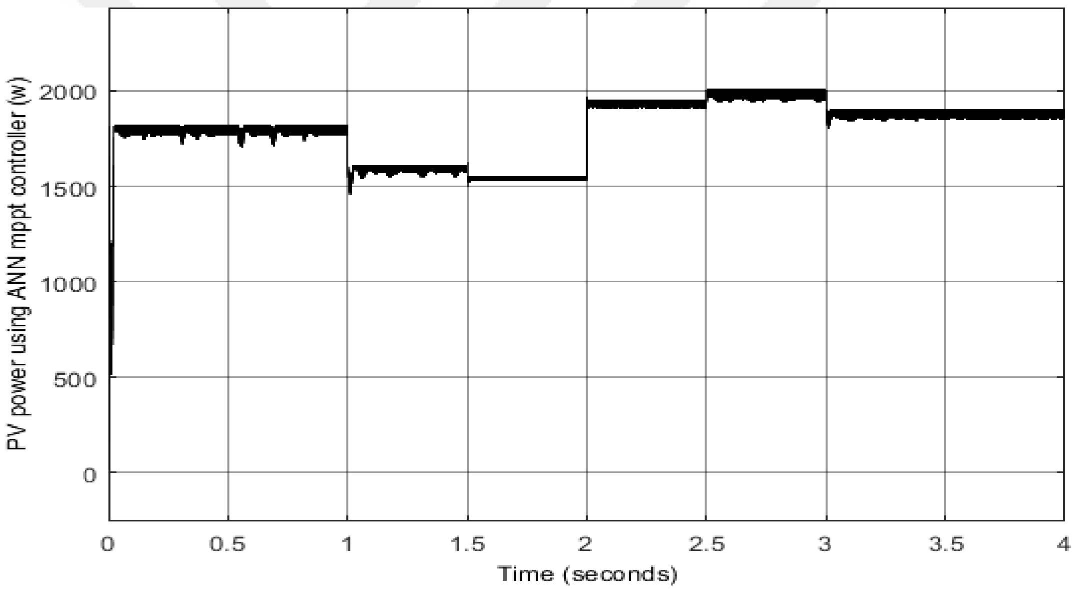

Figure 4.14: The Power Drawn From the Solar Panel When Using The ANN MPPT Controller.

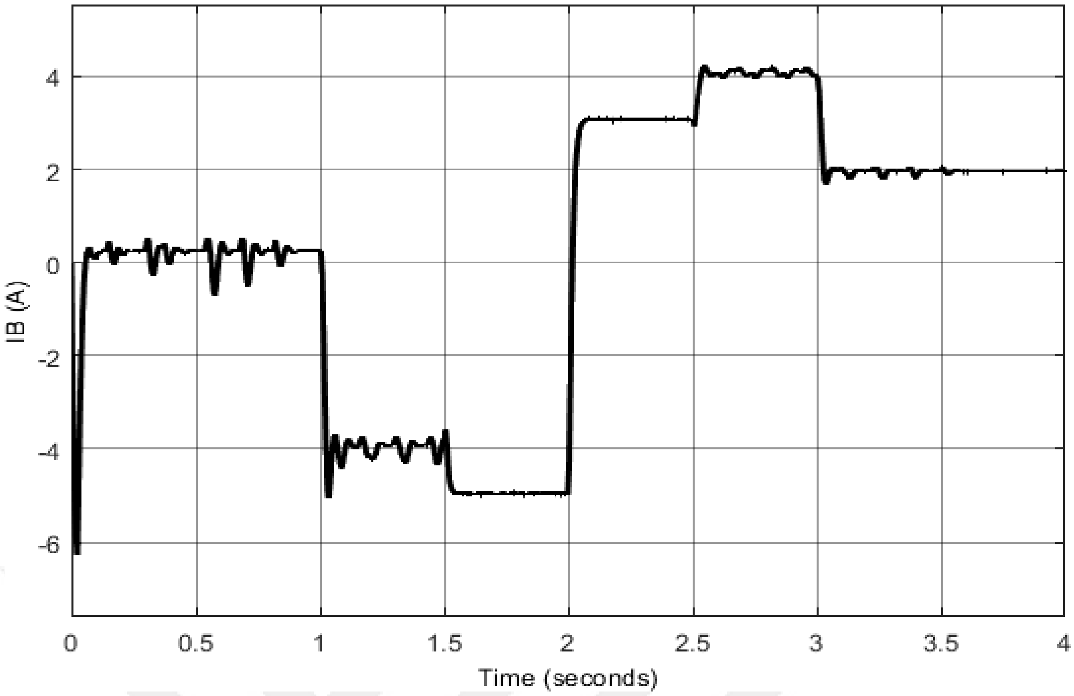

Figure 4.15: Battery Current When Using an ANN MPPT Controller

It is noted from (Figure 4.14) that the power obtained from the photovoltaic panel using the ANN network is of a greater value compared to the power obtained using the P&O algorithm, and this makes the discharge current of the battery during the period (1sec-2sec) less and the charging current during the period (2sec-4sec) larger in order to use the artificial neural network, as shown in (Figure 4.5).

4.3 COMPARISON OF ANN AND P&O RESULTS

In this research, a comparative study was conducted between each of P&O method and Fitnet ANN in term s of the performance for to pursue the MPP of PV system

The simulation results showed the superiority of the proposed neural network for different values of temperature and solar radiation, as the results were set as shown in (Table 4.1) and (Table 4.2).

Table 4.1: The Value of The Power Extracted From The Photovoltaic Panel For Different Scenarios.

Ir (w/m^2)	900	800	800	1000	1000	950
T (deg)	23	23	32	32	25	25
Power (w) using P&O	1793	1592	1536	1917	1935	1870
Power (w) using ANN	1797	1594	1547	1937	1989	1885

Table 4.2: Battery Current for Different Scenarios.

Ir (w/m^2)	900	800	800	1000	1000	50
T (deg)	23	23	32	32	25	25
IB (A) using P&O	0.16	-4.07	-5.16	2.72	3.8	1.85
IB (A) using ANN	0.2	-3.93	-4.95	3.7	4.06	1.96

5. DISCUSSION AND CONCLUSION

The maximum-power-point tracking MPPT algorithm is required for a PV array to supply the most power to the load. The main objective of the thesis is to maximise gain by tracking the region with the highest power parameter. The thesis aims to create a proposed artificial neural network-based model of a solar power tracking system. This study analyses the P&O and ANN strategies for tracking maximum power for a single PV system using a Buck DC-DC Converter under various irradiation circumstances. Under any variation in the meteorological circumstances, the neural network exactly specifies the place of maximum power. The ability of a neural network to perform more dynamically than earlier methods is another advantage of using it to monitor PV maximum power points. The basic way to change the power is to alter the duty cycle. The problem of changing the duty cycle is significantly worse when there is uneven shade.

This study uses MATLAB-Simulink to conduct and present a model analysis of a PV cell, PV module, and PV array.

The simulation model employs basic circuit equations to simulate the behaviour of PV solar cell as a diode, and a full behavioural analysis is performed under a number of conditions, including temperature, solar insolation, changing diode models, series and shunt resistance, etc. The PV module/performance is significantly decreased by the shading impact, and the array's or its P-V characteristics exhibit many peaks. As a result, the MATLAB/Simulink-based study emphasises the need of figuring out maximum power. The model that was employed was validated using simulated testing. In this simulation, the temperature is held constant while the insolation is changed in steps of 100 from 100 - 1000 W/m2. Moreover, DC/DC converter performance is studied using Buck converter.

The results show that the power obtained from the photovoltaic panel using the ANN network is about 1990 Watts ,it is a greater value compared to the power obtained using the P&O algorithm, which is about 1935 Watts , at the same temperature and irradiance, also the battery current for ANN is greater which is about (4.6 amp) where it is in P&0 about (3.8 amp) and this makes the discharge current of the battery during the period (1sec-2sec) less and the charging current during the period (2sec-4sec) larger in order to use the ANN.

the ANN model can follow changes in MPP much more effectively than the Perturb and Observe method because to its learning capabilities and prior identification to the expected

MPP in response to a certain input.. Our model's efficiency while using P&O is 96%, however its efficiency when using ANN is 99.5%.

The ANN model produces significantly lower voltage and current ripples than the P&O model. As a result, ANN reacts quicker than P&O. Additionally; the system that uses a Buck converter provides us with a larger voltage, power, and thus, higher efficiency.

This study is significant from previous literature as it provides a solar charge controller design with its circuit components for MPPT using ANN. It provides a clear comparison between two methods of MPPT which are P&O and ANN. Also, it provides an analysis of DC/DC converter on the basis of several control system factors including such efficiency, ripples, stability, and settling time. This analysis is done through measuring the performance Buck DC/DC converter, utilized in MPPT based PV system. From that is clear that ANN gives best result, so the advantages of using ANN controllers are fast response for maximum power point tracking and steady state error will be less also the reprogramming is not necessary as the learning mechanism is inherent while the disadvantages of ANN controllers are the network needs to be intensely trained and the neural network framework is sometimes sophisticated in design.

The authors of this work also suggest future investigation into innovative approaches that can be effective and practical, where MPPT methods also consider external consequences without regard for the expense and complexity of sensing. Below is a list of several likely ideas:

a. Future research may use experimental testing of the suggested MPPT to determine which hardware options are best from an investment standpoint. Investigations could focus on an important issue, which is energy losses, as well as another issue, which is the costs of building a photovoltaic cell as low as possible, and which one will be at the expense of the other.

b. The tracking of MPP would be on broad scale in the area that had rapidly changing weather and climatic conditions, measurements of radiation and temperature are required. In this situation, investigating network sensing, reduce the sensor, and the approach of data fusion, as well as vision-based algorithms, is a possible way to lower costs and complexity while potentially requiring fewer sensors and enhancing measurement accuracy.

c. Utilising feed-forward and feed-back control loops to add some more limits to MPPT techniques that are already in use.
d. Creating a dynamic model of a PV array utilising precise model identification techniques. Therefore, a solar tracker system can be used that has the ability to automatically direct the solar panels, following the movement of the sun, trying to make the solar panels perpendicular to the sun's rays, and to ensure that the maximum benefit is obtained from the sun's rays throughout the day.

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