COMPARISON OF P&O AND ANN BASED MPPT ALGORITHMS FOR A STANDALONE PV SYSTEM UNDER CHANGING IRRADIATION CONDITIONS

A PROJECT REPORT

SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF

BACHELOR OF TECHNOLOGY IN ELECTRICAL AND ELECTRONICS ENGINEERING

Submitted by:

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and ANN based MPPT Algorithms for a Standalone PV System under Changing

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CERTIFICATE

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based MPPT Algorithms for a Standalone PV System under Changing Irradiation

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ABSTRACT

The concerns for environment due to the ever-increasing use of fossil fuels and rapid depletion of this resource have led to the development of alternative source of energy such as solar energy. Renewable sources such as the Photovoltaic Systems (PV) are being used in order to focus on greener sources of power generation. It is widely preferred due to sun's abundant availability and causes very less pollution, thus contributing in environment preservation. Today it has become a matter of concern on how to reduce cost and improve efficiency in order to harness and use these natural resources in a much better way possible. Hence the idea of Maximum Power Point Tracking System (MPPT) has emerged, which is basically used to provide a maximized power output.

This project focuses to study the performance of P&O and ANN based MPPT algorithms with boost converter which supplies constant output to the load, used in a PV Standalone system under changing irradiation conditions. Perturb and Observe (P&O) technique and Artificial Neural Network algorithm is used to generate duty cycle of converter. The simulation study is performed using MATLAB/Simulink for the PV system.

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LIST OF ABBREVIATIONS

- 1. **MJ** MEGAJOULE
- 2. PV PHOTO VOLTAIC
- 3. MPPT MAXIMUM POWER POINT TRACKING
- 4. **P & O** PERTURB AND OBSERVE
- 5. **INC** INCREMENTAL CONDUCTANCE
- 6. **NN** NEURAL NETWORK
- 7. **DC D**IRECT CURRENT
- 8. AC ALTERNATING CURRENT
- 9. **MPP** MAXIMUM POWER POINT
- 10. **MV** MICROVOLT
- 11. **PVF** POLYVINYL FLUORIDE
- 12. SMPS SWITCHED MODE POWER SUPPLY
- 13. **STC** STANDARD TEST CONDITIONS
- 14. **IGBT** INSULATED GATE BIPOLAR TRANSISTOR
- 15. **MSE** MEAN SQUARE ERROR
- 16. **EMI** ELECTROMAGNETIC INTERFERENCE

CHAPTER-1

RENEWABLE ENERGY

1.1 WHAT IS RENEWABLE ENERGY?

Renewable sources of energy refer to the energy sources which do not get replenished with time. These sources of energy are present in abundant amount and they keep renewing themselves naturally. The energy from the sun and the energy of the moving wind are some of the examples of renewable energy. They are environment friendly and do not cause any kind of pollution.

1.2 TYPES OF RENEWABLE ENERGY

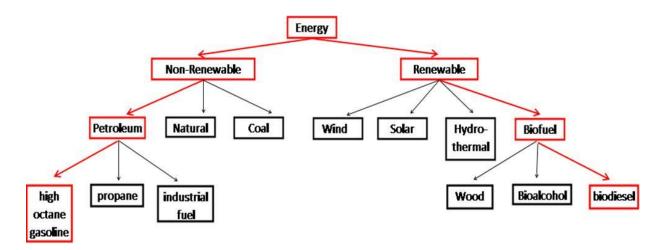


Fig 1.1: Flowchart on types of energy resources

1.2.1 WIND ENERGY

When sunlight falls on the earth's surface, there is a variation of temperature due to irregular surface and the amount of light reaching a particular area. Due to these variations in temperature the movements of atmosphere are driven. Wind energy can be used for small scale activities like to pump water or on a larger scale to generate electricity[1].

1.2.2 SOLAR ENERGY

Solar energy refers to the energy that is obtained by the sunlight. Sun is the main source of energy. The rays of the sun contain energy in the form of photons. When these

photons strike on a semiconductor's surface there is dislocation of electron and it jumps to a higher state releasing energy equivalent to one photon.

1.2.3 HYDRO-THERMAL ENERGY

In hydro-thermal energy, the variation in the temperatures of different layers of water due to different amount of sunlight reaching to them is used to change the temperature inside a building that is to cool it or heat it using the available techniques.

1.2.4 BIOFUEL

Biomass energy refers to the energy that is stored through the process of photosynthesis. It can be converted directly into liquid fuels – biofuels. Biofuel is a type of fuel produced by contemporary biological processes. It is used for transportation.

1.2.4.1 Wood

Everything from wood and sawdust to garbage, agricultural waste, manure is used to produce solid biofuels. It has energy density of around 16 - 21 MJ/kilogram.

1.2.4.2 Bio-Alcohol

It is a first-generation biofuel which is produced from starches from wheat, corn, sugar cane, molasses, potatoes, other fruits. It has energy density of about 30 MJ/kilogram.

1.2.4.3 Biodiesel

Biodiesel is produced from Oils and fats including animal fats, vegetable oils, nut oils, hemp, and algae. It has energy density of about 37.8 MJ/kilogram.

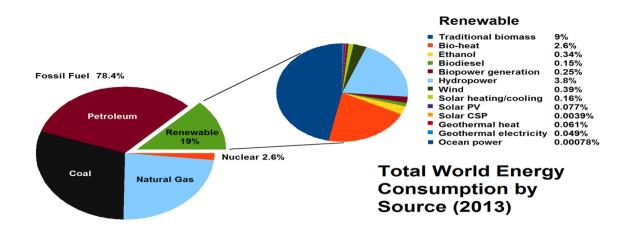


Fig 1.2: Consumption of world energy by source

1.3 INTRODUCTION TO SOLAR ENERGY

The growing concern for environmental preservation due to the harmful effects of fossil fuel usage and a drastic decline in the reserves of this popular source of energy, has led to an increasing interest and shift in the development of alternative renewable sources of energy One of these sources gaining increasing attention is Solar energy. This energy is harnessed using the principle of photovoltaic effect through a Solar Photovoltaic system. Solar PV system is considered as an eco-friendly and clean energy source. PV systems are used practically in two types of configurations- standalone and grid connected. Standalone PV generation systems are considered as an attractive source of electricity especially in remote areas, where a conventional power plant is difficult to use.

The PV system produces varying energy which depends on environmental conditions. Two main environmental factors affecting its performance are: -solar irradiance and temperature. Due to this dependency, a direct connection between panels to the load is not feasible. To reduce the effects caused by changing environmental conditions and improve power generated by the PV system, Maximum Power Point Tracking (MPPT) technique is used. It tracks the maximum power obtained from the panel to improve power generation. MPPT controllers have certain basic features such as simple design, low cost, good performance characteristics with minimum output power fluctuation, and the ability to track efficiently and quickly under changing operating conditions. There are many MPPT techniques available to extract maximum power from the PV system, namely, Perturb and Observe (P&O) method, Incremental Conductance (INC), hill climbing method, Neural Networks, Fuzzy Logic Controller, and Genetic Algorithms and so on.

Currently the most widely used algorithms for MPPT are Perturb and Observe (P&O) and incremental conductance which are attractive due to their low cost and simple design. In the P&O method the power of PV system is measured before and after a perturbation, based on that result the next perturbation size is decided by the controller. However, it lacks an appropriate level of tracking performance. Therefore for better accuracy complex methods are used such as fuzzy logic and multi-layer perceptron neural networks. However, it has been observed that PV systems have various factors affecting its performance. Two major areas of concern are the low conversion efficiency

obtained in presence of low irradiation levels of up-to 12 % and the fluctuation in amount of electric power produced during changing weather conditions by an array of PV cells. Therefore, there are still on-going research projects focusing on methods to increase efficiency of PV arrays. PV cell output is in the form of an unregulated DC output that has to be increased/stepped up to an appropriate high level, for practical purposes. Generally for most applications, a transformer with increased output/input voltage gain is preferred, depending on the requirement. However there are has been a change in this trend, for number of application transformer-less power electronic energy converter system has replaced the existing system by offering significant advantages like low cost and small converter size. The DC to DC or popularly used boost converter is one such basic component that is connected between the load and the PV module[2].



Fig 1.3: PV array installed

1.4 System Description using block diagrams

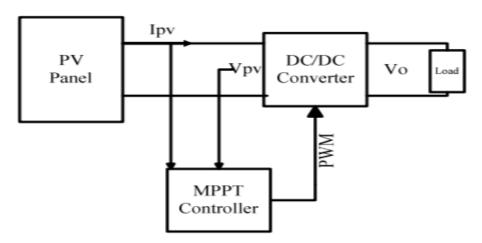


Fig 1.4: General overview of simulation model

Fig 1.4 an overview of our system with its major components is shown as a block diagram.

- a) Solar panel
- b) MPPT
- c) DC –DC Converter

Each of the major components shown in the block diagram have been briefly described below.

1.5 THE PV CELL

A solar cell is an electronic device based on the principle of photovoltaic effect, which converts light energy directly into electric energy. It directly depends on the amount of light hitting the cells, more the light that is incident on the cell, and the more electricity it produces. In order to maximize the energy output from solar panels installed on a spacecraft, they are designed in such a way that panels constantly face the sun while the rest of the spacecraft body might move around and face some other direction.

As we all know the energy from the sun is renewable (not a finite source) and it is completely pollution-free source of electricity. Instead of burning fossil fuels dug up from the ground in big power plants which is a finite source of energy, solar panels convert sunlight directly into electricity, with no harmful emissions. Solar panel is a combination of many single solar cells. It has longer average life as it contains no moving parts.



Fig 1.5: PV Cell

- Solar cell is also commonly known as Photovoltaic (PV) Cell.
- It is a static device, has no moving part.
- "Photo" in photovoltaic stands for light while "voltaic" means producing electricity.
- It is a solid state electronic device made of semiconductor materials like silicon.
- Solar cell converts energy of light directly into direct Current (DC).
- Solar cell do not use heat energy emitted from light to produce electrical energy.
- In 1839 the photovoltaic effect was discovered, in 1883 the first thin film solar cells were fabricated and the first practical photovoltaic cell was developed in 1954.
- Efficiency of solar cell depends on many factors like shading on cells, irradiance, temperature ,dust etc.
- In 2014 the highest efficiency of 44.7% was achieved by using the multiple junction cells.

1.5.1 BASIC THEORY OF SOLAR CELL

Solar cell is the basic unit of a solar panel ,generally made up of one or more layers of semiconductor wafers like silicon. When these cells are struck by light photons present in sunlight, they result in the generation of electricity due to the "photovoltaic effect". Electric currents flows from one end of the cell to another[3].

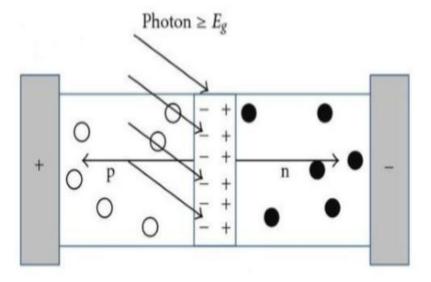


Fig 1.6: Working mechanism of PV Cell

1.5.2 SOLAR CELL TECHNOLOGIES

Solar cell is manufactured using different materials. The two major technologies employed are wafer-based silicon and thin-film silicon technology.

- Crystalline silicon solar cell is more efficient than thin-film solar cell but that is
 more expensive to produce. They are most commonly used in large to medium
 electric applications like grid connected PV power generation.
- Mono-crystalline solar cell is manufactured by pure semi-conducting materials
 so it has highest efficiency (above 17% in industrial production and 24% in
 research laboratories). Poly-crystalline solar cell is made from more than a
 single crystal of silicon and is therefore slightly less efficient than monocrystalline but costs less.
- In thin-film solar cell, very thin layers of semiconducting materials are used.
 Even though their efficiency is less, they can be mass produced at a cheaper rate cost .This technology is used in calculators, watches and toys etc.

There are many other PV technologies which use a combination of the above technologies like Organic cells, Hybrid PV cells etc.

1.6 PHOTOVOLTAIC SYSTEM

Photovoltaic systems comprise of photovoltaic cells that convert solar radiation directly into electricity. They are made up of semiconductor material such as silicon. A typical single PV cell usually produces less than 2 W at approximately 0.5 V DC. So, to get desired level of power and voltage rating, it is necessary to connect number of PV cells in series-parallel configuration.

Dozens of these PV cells are packaged together and called solar modules, which are again packaged into a single unit to form solar panels that are straddling on a rooftop, arranged to maximize their hours of exposure to direct sunlight. The electricity generated by all those solar cells is direct current (DC), it is for this reason that this current is then sent to an inverter that transforms it into the equivalent alternating current (AC).

AC obtained is then ready to be used by the appliances at home or even for the local utility electricity distribution grid.

Some of the advantages of solar panels are:

- -They are the most readily available due to sun's abundant availability.
- -In terms of maintenance, they require very less maintenance.
- -They operate best on bright days with the sun shone incident to the panels under ambient temperature conditions.

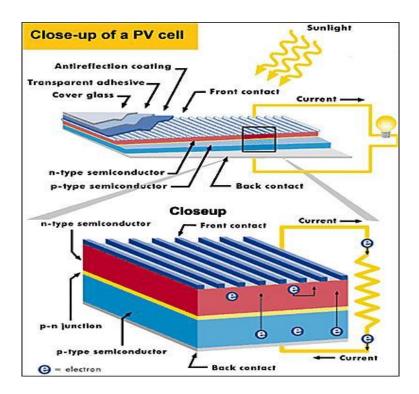


Fig 1.7: Close up internal structure of a PV cell

<u>CHAPTER – 2</u>

LITERATURE REVIEW

'A Comparative study of different MPPT techniques using different dc-dc converters in a standalone PV system' by Bikram Sah and GVE Kumar [1] was one of the first papers considered, that formed the base of our project. In this paper two dc-dc converters-: buck-boost and cuk were compared both employing two MPPT techniques-: Perturb and Observe and Incremental Conductance, each. A stand-alone system was considered with a load resistance of 7.5 ohms. We decided to do a similar comparison of both DC-DC converters and MPPT algorithms for a stand-alone PV system, but in two steps instead of one. Also, we considered our load to be resistive as well with a value of 30 ohms.

For the first leg of our project, we decided two compare two DC-DC converters both employing one MPPT technique. P&O being the simplest, one of the most basic and popular MPPT algorithms, was thus chosen so as to focus more on the design and comparison of the two converters. Another work of research that helped decide our next step, i.e. the selection of two DC-DC converters to compare, was 'Comparative Study of-Various DC-DC ConvertersUsed in AI-Based Solar fed PMBLDC Motor Drive' by Gaurav Gupta and Prena Gaur [2]. in this paper, five types of DC-DC converters-: boost, Cuk, Flyback, sepic, buck-boost, were compared. Of them boost being the simplest with one pair of inductor-capacitor and having a high efficiency, was selected for those reasons. For the second one, we decided to pick another popular, yet a bit more complex converter (with two pairs of inductor and capacitor) which is the Cuk converter.

The second leg of our project is about comparison of two different MPPT algorithms. We have used the results of the first leg employing P&O MPPT algorithm as it is, to be compared with another algorithm. We have used Boost DC-DC converter only for both of these algorithms, while comparing them, as it gave a higher efficiency in the first stage. In the first paper, i.e. 'A Comparative study of different MPPT techniques using different dc-dc converters in a standalone PV system' by Bikram Sah and GVE Kumar [1], the two algorithms compared are P&O and Incremental conductance, both of which are one of the simplest MPPT techniques but are not very reliable even if they give a high efficiency, they do not track with enough effectiveness in a practical system. Therefore, we decided to pick a more complex and promising MPPT technique. Taking

the paper, 'Comparison of ANN and ANFIS based MPPT controller for grid connected PV Systems' by Ankita arora and Prerna Gaur[3], into consideration we went ahead with Artificial Neural Network based MPPT algorithm. 'A New Neural Networks MPPT controller for PVSystems' by Sabir Mesalti [4] formed the basis of this study. This paper takes training data from the system implementing P&O technique and using it to train our neural network and then analyzing the output. For our project as well, training data for neural network has been taken from the data obtained from the system implementing P&O technique.

For training purpose, several combinations of parameters can be considered, for instance, voltage, current, power, irradiance, temperature, duty cycle etc. The paper, 'Comparison of ANN and ANFIS based MPPT controller for grid connected PV Systems' by Ankita arora and Prerna Gaur[3], uses voltage and current as inputs to the ANN.'A New Neural Networks MPPT controller for PV Systems' by Sabir Mesalti and Harrag A.G, Loukriz [4] uses output power and voltage as the inputs to ANN and normalized increasing or decreasing duty cycle as its output. Another research paper that was considered, 'An Artificial Neural Network based MaximumPower Point Tracking Method for Photovoltaic System' by Munish Manas and Ananya Kumarib [5] uses irradiation and temperature as input to the ANN.

After considering several of the combinations, we finally chose Voltage and current as input and duty ratio as output to the ANN based MPPT controller, as it gave satisfactory result.

- [1]Sah Bikram, GVE Kumar" A comparative study of different MPPT techniques using different dc-dc converters in a standalone PV system",IEEE Region 10 Conference,2016[18]
- [2] G.Gupta, P.Gaur,"Comparative Study of-Various DC-DC Converters Used in Al-Based Solar fed PMBLDC Motor Drive", IEEE INDICON 2015 1570176293[19]
- [3] A. Arora, P. Gaur, "Comparison of ANN and ANFIS based MPPT Controller for grid connected PV systems", 2015 Annual IEEE India Conference (INDICON), pp. 1-6, 2015.[20]
- [4] Messalti S, Harrag A.G, Loukriz A.E, "A new neural networks mppt controller for PV Systems," Renewable Energy Congress (IREC), 2015 6th International, Sousse, Tunisia, 2015, pp. 1-6.[21]

[5] Munish Manas\ Ananya Kumarib , Sanjeev Das ,"An Artificial Neural Network based Maximum Power Point Tracking Method for Photovoltaic System", IEEE International Conference on Recent Advances and Innovations in Engineering (ICRAIE-2016), December 23-25, 2016, Jaipur, India[22]

CHAPTER-3

FULL SYSTEM OVERVIEW

3.1 PHOTOVOLTAIC PANELS

The whole process by which a photovoltaic cell works is fairly complex. To put it quite simply the mechanism is as such; the light excites electrons to move from one layer to another through semi-conductive silicon materials. This produces an electric current. This phenomenon is known as photo electric effect. Solar cells also called photovoltaic cells are made from thin slices of crystalline silicon, gallium arsenide, or other semiconductor materials which are capable of converting solar radiation directly into electricity.

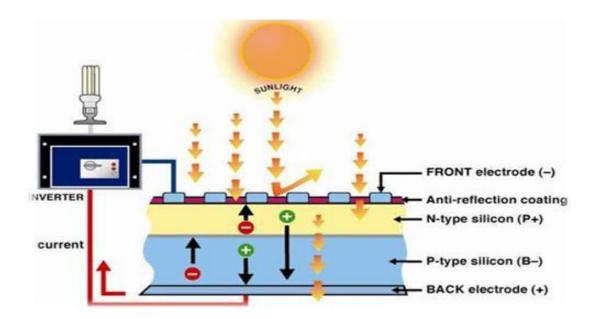


Fig 3.1: Mechanism of a PV Panel

Whenever a light photon strikes the surface of the "n type semiconductor material", the energy is absorbed by the atoms present, ultimately removing the electron and producing a free electron and hole capable of crossing the depletion zone. This area around the p-n junction where the electrons from the "n type" silicon diffuses into the holes of the "p type" semiconductor material is called the depletion zone. This depletion zone is responsible for generating the electric current. If a wire is connected between the two electrodes -from the cathode (n-type) to the anode (p-type) electrons an electric

current will flow through the wire. Electron being a negatively charged ion moves towards the p-type semiconductor material, while the hole move towards negative charged "n-type" material resulting in the flow of electric current through the external load. Recombination occurs as electron combines with the holes in the p type layer to establish electrical neutrality.

The cost for photovoltaic electricity (amount per kilowatt-hour) is reduced by connecting individual cells into modules. The simplest solar cells can provide small amounts of power suitable for watches and calculators. Complex modules can be used to provide bigger units like residential houses and electric grids.

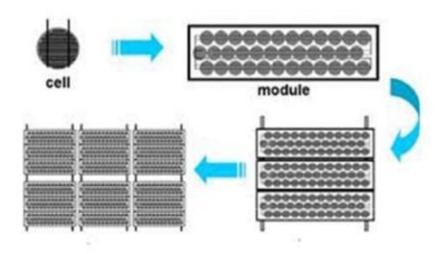


Fig 3.2: The formation of a PV system from cell to array.

3.2 PHOTOVOLTAIC CELL MODEL

The characteristics of a PV cell can be further explained using an equivalent circuit shown in the Fig 3.3. The PV model consists of a current source, a diode and a series resistance.

The effect of parallel resistance represents the leakage resistance of the cell which is very small in a single module. The current produced by photons is represented by a single current source. The output is obtained under constant temperature irradiation Conditions[4].

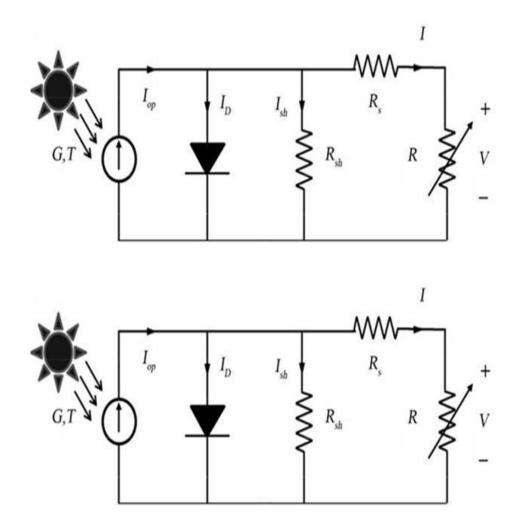


Fig 3.3: Equivalent circuit of PV cell

Current-voltage (I-V) curves are obtained by exposing the cell to a constant irradiation and temperature conditions, while varying the resistance of the load, and measuring the current produced. When an I-V curve is drawn it normally passes through two points.

Short-circuit current (Isc): This is the current produced when the positive and negative terminals of the cell are short-circuited (i.e., when the solar cell is short circuited), and the voltage between the terminals is zero, which corresponds to zero load resistance.

Open-circuit voltage (Voc): This is the voltage across the positive and negative terminals under open-circuit conditions, when the current is zero, which corresponds to infinite load resistance.

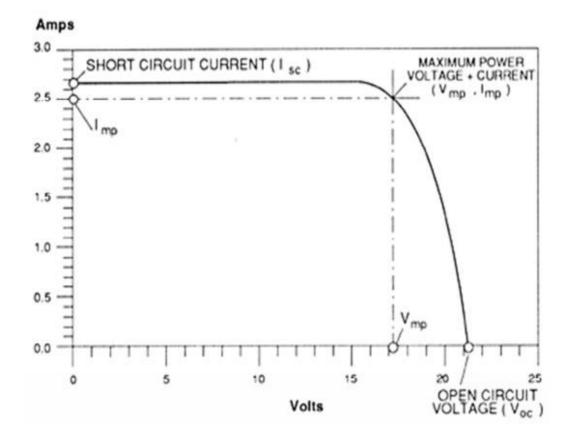


Fig 3.4: The I-V graphs showing the characteristic of a PV cell

3.3 MAXIMUM POWER POINT TRACKING

In each Power-Voltage or current-voltage curve of a solar panel, a peak operating point is obtained where the solar panel delivers the maximum possible power to the load. This distinct point is called the maximum power point (MPP) of a solar panel.

The photovoltaic nature of the solar panels makes these (Power-Voltage or current-voltage) curves depend on temperature and irradiance (the flux of radiant energy per unit area) levels.

In other words, depending on the amount of sunlight per unit area of the panels the curve will vary hence the peak point or MPP will vary accordingly.

Therefore, it can be deduced that the operating current and voltage which maximize power output will change with environmental conditions.

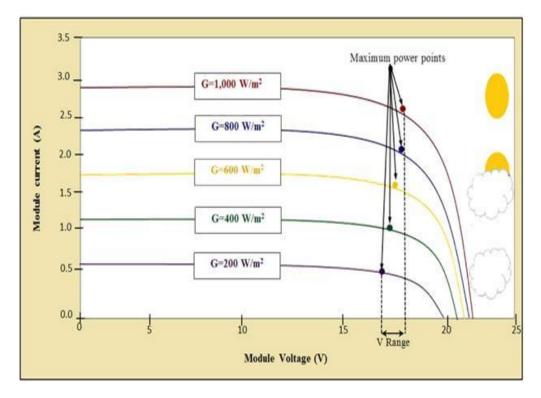


Fig 3.5: Shows the variation of maximum Power Point (MPP) at different sunlight conditions

From the Fig 3.5 it can be seen that the MPP depends on certain conditions such as the irradiance level for instance which is denoted here by the symbol 'G'. At different values of G, from the graph it can be seen that there is a corresponding shift in the values of MPP.

Therefore, an MPPT algorithm has to be used which constantly tracks the MPP at every instance to provide the maximum power, leading to greater efficiency in the system. In various applications, the load demand can be greater than the power delivered by the PV system. Hence, many different approaches are incorporated ranging from simple relationships among parameters to complex time based analysis in order to maximize power generation from PV systems.

Temperature plays another major role in determining solar cell efficiency. With the increase in temperature, the photon generation rate increases, causing the band gap to reduce due to an increase in reverse saturation current. Hence this process results in a marginal change in current but a significant difference in the voltage .With every one degree rise in temperature, the cell voltage reduces by a step of 2.2V[5].

Therefore temperature and solar cell performance share a negative relationship. Solar cells show their best performance on cold and bright sunny days instead of hot and bright sunny days. Nowadays, solar panels are manufactured using non-silicon materials which are temperature insensitive. Thus, they are used under constant or close to room temperature conditions.

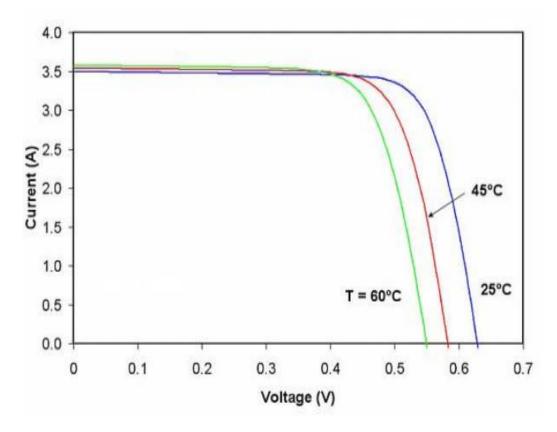


Fig 3.6: Shows the variation of MPP at different temperature conditions

3.4 MPPT Methods

There are a number of MPPT algorithms commonly used for maximum power point tracking. Of them, seven are listed here. These methods include:

- 1. Constant Voltage method
- 2. Open Circuit Voltage method
- 3. Short Circuit Current method
- **4.** Perturb and Observe method
- 5. Incremental Conductance method
- **6.** Temperature method

7. Temperature Parametric method

Out of these, three methods mentioned above have been discussed below in detail.

3.4.1 CONSTANT VOLTAGE METHOD

One of the simplest methods of those mentioned above is the constant voltage method. However it is quite inefficient in comparison to others. This method basically represents the system using single voltage. In many cases this value of voltage is set by a resistor externally connected to a pin of the current source of the control IC.

For the varying irradiance conditions, the method collects around 80 per cent of the maximum power that is available. The accurate measure performance is determined by the average level of irradiance. As we know that the maximum power point of a solar photo-voltaic module does not necessarily lie between 70-80 per cent of Voc, hence the tracking efficiency is low in these cases.

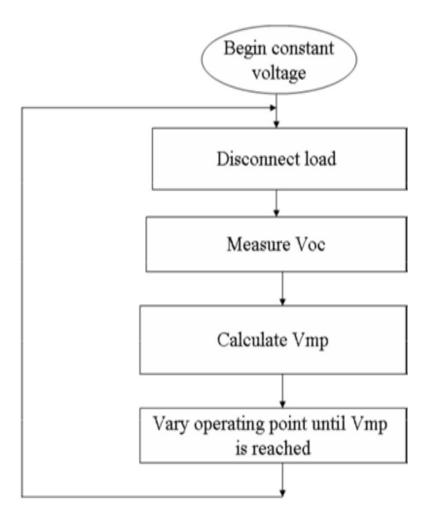


Fig 3.7: Flowchart of constant voltage method [6]

3.4.2 PERTURB AND OBSERVE METHOD

This method forms the foundation of the complex MPPT techniques in many ways. It is simplest of the practical techniques that is used for maximum power point tracking and has higher efficiency than the previous method, thus making it one of the most popular tracking techniques. In this method the controller perturbs the system by changing the voltage by a small amount and then observes its affects in form of the variations caused in power due to the perturbation. If the power has increased after the voltage change, then the system is further varied in the original direction that caused the power to increase. Thus the voltage is increased until the power stops increasing. To do that the output power has to be monitored continuously. This is called the Perturb and Observe Method. If the increase in voltage has decreased the power, then the system is changed in the reverse direction, i.e. the voltage is decreased until the power stops increasing. Thus, the basic goal is to realise the maximum power point by comparing it with its left and right values.

The system is continuously disturbed in order to account for the changing irradiation, temperature and other conditions that affect the actual PV model. This causes oscillations of the output power around the maximum power point. The output power characteristic of the PV module is a function of the voltage, hence more popularly called the P-V curve. The P-V characteristic can be safely assumed to be unique for every combination of irradiation and temperature. Other than that, during implementation of the P&O technique, it is assumed that our model is operating at a point away from the MPP.

Now, in terms of the algorithm, first the operating voltage of PV panel is varied by a small amount and the resulting power P is observed. If the change in P is found to be positive, then naturally it is supposed that the current operating point is closer to the maximum power point and hence more variation is made in that direction. If the change in power is found to be negative, then the operating point is assumed to move further away from the maximum power point and so the direction of perturbation has to be reversed to achieve the maximum power point.

Advantages of using the P&O method:

- The simplicity of its algorithm
- Ease of implementation

- Comparatively lesser implementation cost
- More accurate than most other method

Limitations to using this method:

- Unable to determine the exact point when MPP has been reached as under steady state condition the output power oscillates around the maximum power point.
- Slow speed of operation of this method especially if the operating point is far away from the desired point.
- In many cases when there is a shadow on the panel then the power-voltage characteristic of the PV module will have several peaks and the P&O will not be able to make satisfactory distinction amongst them and find the real peak.

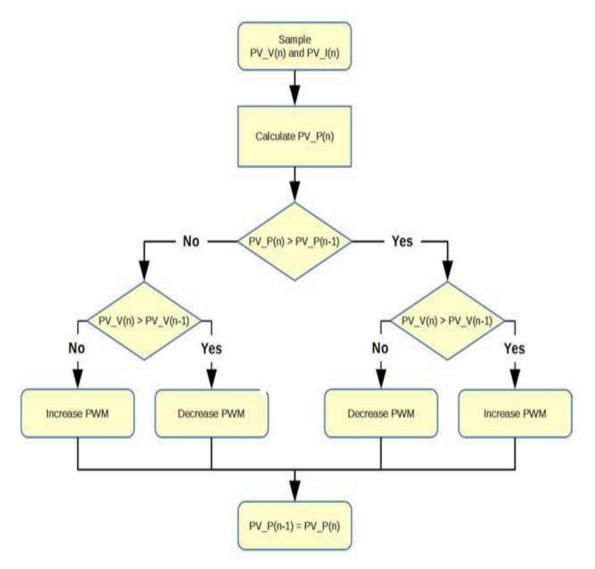


Fig 3.8: Shows the flowchart of P & O [7]

3.4.3 INCREMENTAL CONDUCTANCE METHOD

Based on the observation made using the P-V characteristic curve, the Incremental Conductance method was planned in 1993. This algorithm was formulated to overcome some of the drawbacks found in the P&O algorithm. The maximum power point was tracked using the relation between the variation in current with respect to the variation in voltage and the negative ration of current to voltage, i.e. dI/dV and -I/V.

The basic principle governing the incremental conductance method is that, the slope of the P-V curve of the photovoltaic module is zero at the maximum power point, positive on the left of the maximum point and negative on its right. This can be given by,

$$\frac{dP}{dV} = \frac{d(V.I)}{dV} = \frac{IdV}{dV} + \frac{VdI}{dV} = I + \frac{VdI}{dV}$$

Maximum power point is reached when dP/dV=0 and

$$\frac{dI}{dV} = -\frac{I}{V}$$

$$\frac{dP}{dV} > 0 \text{ then Vp} < Vmpp$$

$$\frac{dP}{dV} = 0 \text{ then Vp} = Vmpp$$

$$\frac{dP}{dV} < 0 \text{ then Vp} > Vmpp$$

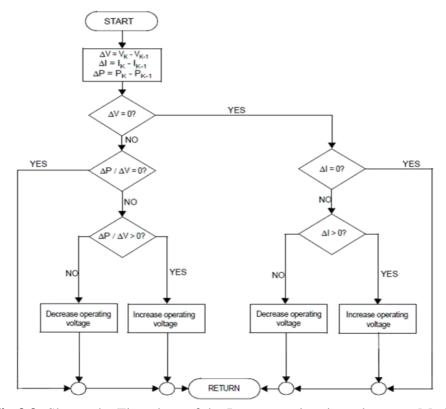


Fig 3.9: Shows the Flowchart of the Incremental and conductance Method [8]

So, if the maximum power point is to the right of the operating point, i.e. dI/dV< -I/V then the operating voltage of the PV panel must be decreased to reach the MPP. Incremental Conductance method gives efficiency higher than that of the P&O method. It reduces power loss by minimizing the oscillations considerably and hence the system cost is reduced. It also gives a better performance in terms of stability when these techniques are implemented using a microcontroller.

Benefits:

- Successfully detect changes in the irradiation and other conditions and hence shift its maximum power point by proper adjustments in the duty cycle.
- It gives a good tracking efficiency.
- -This method minimizes oscillations around the MPP considerably.
- Lowers power los
- Lowers system cost

Drawbacks:

This method is slower, i.e. it has a larger computational time due to slow down of the sampling frequency by the additional complexity of the algorithm when compared to Perturb and Observe method.

<u>CHAPTER – 4</u>

DC-DC CONVERTERS

4.1 INTRODUCTION

A DC-DC converter is an electronic circuit that converts a DC voltage from one level to another. It either steps up the voltage or step it down. Hence it is also popularly known as the DC counterpart of the voltage transformers. A DC-DC converter is also known as a chopper. Controlled switch-mode DC power supplies and DC motor drives are some of the applications of DC-DC Converters.

Other than changing the source voltage level, the other application of a DC-DC Converter is to voltage regulation. Usually the line voltage is an unregulated AC voltage, which is rectified to a DC value. Hence, now the voltage fluctuates due to the changes in the line voltage magnitude. Switch-mode choppers are used to change the unregulated DC input into a monitored DC output at a regulated voltage level.

The DC-DC converter is the heart of the hardware system of the MPPT controller. It uses a switch-mode DC-DC converter. MPPT needs the converter to regulate the input voltage at the maximum power point and provides load matching for transferring maximum power [9]. In this chapter we have discussed about the different topologies of DC-DC converters. We have explained Boost and Cuk converters [10].

4.2 Boost Dc-Dc Converter

A boost converter is a step-up DC-DC power converter that steps up voltage while stepping down current from supply to the load. It is a switched-mode power supply (SMPS) DC-DC converter with two or more semiconductor elements-diode and transistor and more than one energy storage element- an inductor, capacitor, or a combination of the two.

To take care of the voltage ripples, filters are used that comprise of capacitors in combination with inductors. They are usually added to the load side as well as supply side.

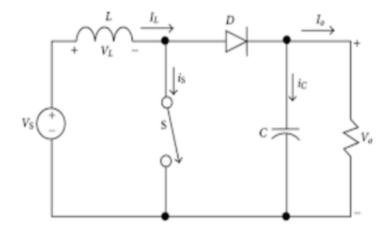


Fig 4.1: Basic diagram of DC-DC Boost converter

The fig above shows a step-up boost DC-DC converter, which increases the output voltage thus performing the function of a transformer. It has a dc voltage as input source 'Vs', inductor 'L' or the boost inductor, capacitor 'C' acting as the filter, diode D and power semiconducting device as switch 'S'. The switch is usually an IGBT or a power mosfet. The power is delivered to the load at a higher voltage than the input supplied. The control function is performed by the switching element which is the IGBT or the power mosfet which works according to the variation provided to the duty cycle of the switch. A boost converter operates in two modes- charging mode, discharging mode. The charging mode of operation is when the switch is closed, while the discharging mode is when the switch is open.

The duty cycle can be obtained as

$$Vo = \frac{Vin}{1-D} \tag{4.2.1}$$

4.2.1 DESIGN CONSIDERATION OF INDUCTOR AND CAPACITOR

The performance of the DC-DC converter is heavily dependent on the selection of inductor and capacitor values which are basically based on the output current and voltage required by load of the converter. The values of these elements are calculated by using the following formulae [11]

$$L = \frac{D(1-D)^2 R}{2f} \tag{4.2.1.1}$$

This formula gives the value of the inductor L while D is the duty ratio, F is frequency in Hertz, and R is resistance in Ohm.

The switching frequency, duty ratio and the load resistance are selected before-hand by considering the size of the inductor and capacitors that will be required for a particular value. Thus, after taking sufficient care, the duty ratio D=0.69 and, load resistance R=40 Ohm and switching frequency f=5 KHz are chosen. It is advisable to operate the converter as close to the maximum duty cycle as possible while the time period should be quite long to reduce the switching losses. The Capacitor 'C' value is found out using the following formulae-

$$C = \frac{D}{R(\frac{\Delta Vo}{Vo})f} \tag{4.2.1.2}$$

Where Vo is the output voltage and Δ Vo change in the output voltage. Also, Δ Vo /Vo = 0.05.

4.3 CUK DC-DC CONVERTER

The Cuk converter is a back to back connection of both the boost converter as well as the cuk converter. It is operated in both step up and step-down principle, i.e. the output voltage can be decreased or increased and it has a reversed polarity. This type of converter consists of two inductors, two capacitors, a diode and a switch as shown in Fig.

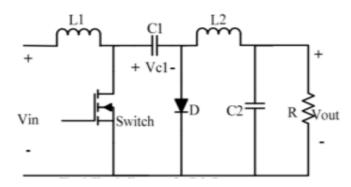


Fig 4.2: Basic diagram of DC-DC Cuk converter

When the switch is closed, the diode gets reversed bias i.e. it can be considered equivalent to an open circuit. The current flows through the inductor L2 and capacitor C2. When the switch is in opened, the diode is forward biased and can be treated as a

short circuit. The duty cycle is designed using output and input voltage values as described in the equaton.

$$Vo = -Vin(\frac{D}{1-D}) \tag{4.3.1}$$

V0: Output Voltage, Vin: Input Voltage, D: Duty Cycle

4.3.1 DESIGN CONSIDERATION OF INDUCTOR AND **CAPACITOR [12]**

Inductance
$$L1 = Vin * \frac{D}{\Delta IL * fs}$$
 (4.3.1.1)

Inductance
$$L2 = Vin * \frac{D}{\Delta IL2*fs}$$
 (4.3.1.2)

Capacitor
$$C1 = lin * \frac{D}{\Delta V_a}$$
 (4.3.1.3)

Capacitor
$$C1 = lin * \frac{D}{\Delta Vc}$$
 (4.3.1.3)
Capacitor $C2 = \frac{1-D}{L2*fs^2}$ (4.3.1.4)

4.4 SELECTION OF SWITCHING DEVICE

One of the important design consideration while selecting the switching device is the minimization of the switching losses. For boost converter, the on-state voltage drop should be kept as low as possible. In this way switching losses are considerably reduced. Other ways to go about this complex task of selecting the right switching device is by considering the element which is actually causing the power loss rather than just focusing on the device dissipating heat. The right way is to balance the device size with switching and conduction losses.

Chapter – 5

NEURAL NETWORK

5.1 INTRODUCTION TO NEURAL NETWORK

An Artificial Neural Network (ANN) is a replica of the human nervous systems which learns from its surroundings just like the brain in order to process information. This paradigm is gaining fast popularity for its high accuracy and bright future prospective. What differentiates ANN from the other information processing techniques is its unique, biological nervous system resembling, and structure. It is made up of a huge number of interconnected elements used in the processing of information, also called the neurons, which work together and are the basic elements in problem solving. ANNs, just like humans, learn from their surroundings. An ANN can be used for a variety of purposes such as pattern recognition or classification of data, each having different algorithm and configuration. The act of learning from the surroundings is analogous to the adjustments made to a set of weights called synaptic weights that link various neurons together. This is how the biological nervous system works and is true for an ANN as well [13].

5.2 HISTORICAL BACKGROUND

It is a common misconception that the duplication of biological neural network for information processing is an outcome of a very recent research. The truth is that the field of Artificial Neural network was established even before the computers, that we see today, came into picture. The first artificial neuron was developed by Warren McCulloch, a neurophysiologist and Walter Pits, a logician in 1943. The field, both flourished and survived quite a few setbacks in the decades that followed, before it became a trustworthy and potential technique for multiple purposes. However, in the recent times it has flourished like never before and has given promising results. Such major advancements can be credited to the use of computer emulations that are now cheaper than before. The advent of such a unique methodology saw quite a lot of enthusiasm at the beginning. However, it died out soon due to unacceptable results leading to frustration and doubts. During this period, the support that it got from the professionals of the time- both monetary and otherwise was minimal. The funding was

too less and the technological advancements were far lesser than what we know today. This led to only a few researchers dedicating their work to this novel field. Out of these few, most disregarded the field completely out of frustration as is evident in the book published by Minsky and Papert in 1969, which was quite easily accepted by the research community. However, despite these setbacks, some pioneers in the field were able to develop techniques and technologies and algorithms, which went beyond the limitations identified earlier during the period of low downs.

In today's time, ANN has surpassed many of the previous apprehensions people had about the field and has emerged as one of most promising advancement of recent time. Its more broader field, machine learning, is said to be the future that can change the system completely. Currently, it garners significant interest from people all over and enjoys a funding that was never seen before [14].

5.3 WHY USE NEURAL NETWORKS?

Neural networks have an impeccable ability to harness meaningful observations from a large chunk of data that are quite complicated and imprecise in itself. They can give exceptional results while extracting patterns and are able to identify trends that are quite complicated for other computer techniques, and almost impossible for humans to notice. A neural network is first trained using a similar data set and is then used or tested on a different set of data given to analyse. A neural network model can answer new sets of questions other than the kind answered in the training data set and can provide new projections.

Other advantages include-

- 1. Adaptive learning: It implies learning to do tasks from the data set provided for training.
- 2. Fault Tolerance via Redundant Information Coding: Fault could be a semidestruction of the neural network that ultimately degrades network performance. However, retraining of data can provide fault tolerance to an extent.
- 3. Real Time Operation: The computations needed in ANN can be done in real time, but require special hardware that needs to be designed specifically for the purpose.
- 4. Self-Organization: ANN forms its own structure or representation that suits itself while processing information received from the training data set.

5.4 <u>NEURAL NETWORKS VERSUS CONVENTIONAL</u> <u>COMPUTERS</u>

Neural networks work in a completely different manner while solving a problem. On one hand conventional computers need to be fed everything- data, a set of instructions or the algorithm, a method of information representation. It needs to be provided with an ordered set of steps; else the computer cannot go about the problem. It poses as a significant restriction in today's world where we have machine learning and ANN that can learn on its own and require minimum efforts on the user side. Neural networks are just an artificial counterpart of the human brain. The multitudes of inter-connected neurons work simultaneously and process information and solve a problem just like in human brain. They need not be programmed specifically but they just need to be provided with the right data set, in order to learn on their own. The data and sorting out of the input parameters need to be carefully done. It however suffers with one disadvantage that makes the user unaware about what exactly is happening in the background and which specific point or step is causing the ineffective result of the model.On the other hand, the user or the programmer working on a conventional computer might be able to easily identify the source and cause of error in the program and can modify the steps accordingly. This is known as the cognitive approach, making the machines completely predictable. The steps written by the programmer are in high level language and are converted to machine language for the computer to process.

However, despite the differences, both type of techniques can be used as each other's complement. There are times where a cognitive approach would be beneficial, and times where we want our machine to work on its own with the help of neural network. Hence it is best for a machine to use a combination of the two, for instance, a conventional computer can be used to observe the ANN.

5.5 <u>Artificial Neural Networks</u>

Human Brain is a very powerful tool and can perform very difficult task with ease. Artificial neural networks are based on the fact that the human brain can be recreated artificially. Though at this stage the exact human brain cannot be mimicked, there is a certain limit to what can be achieved artificially with the available technology. A

simplified version of artificial neurons can be created and an artificial neural network can be obtained through interconnection of the neurons. These ANNs can be implemented to mimic the brain in various ways.

Artificial Neural Network works in an excellent manner when it comes to recognizing simple patterns or solving the problems that are complex. They are used in artificial intelligence research as they have excellent training skills.

ANNs are trained with the help of datasets that contain a large amount of data. For instance, the neural network is trained with the data that contains pictures of different animals. The data is marked to differentiate between mammals and other animals. So once the network has been trained it can identify and categorize the input given to it, even if the data input given is outside the dataset with which the neural network was trained initially. That means that we do not need to explicitly define the characteristics of a mammal for its identification, the network learns through the training to differentiate.

5.5.1 THE ARTIFICIAL NEURON

The implementation of a single artificial neuron can be done in many different ways. The general mathematic definition is as showed in equation 5.5.1.1. [15]

$$y(n) = k(\sum_{j=0}^{p} w_j n_j)$$
 (5.5.1.1)

n = neuron with p input dendrites (x0,...,xp);

y(n) = output axon;

(w0.....wp) = weights determining how much the input should be weighted;

k = an activation function;

Activation function weights are based on the sum of input and the power of the output from the neuron.

0< k< 1, If the artificial neuron mimics a real neuron;

Artificial neurons are not implemented in this manner due to different reasons. It is better to have activation function that is smooth.

The activation function range can be:

- (i) Between 0 and 1;
- (ii) Between -1 and 1, depending on which activation function is used.

Most of the activation functions follow the limitations given above, there are some exceptions like the identity function, does not have these limitations.

There are no such restrictions or limitations on inputs and the weights. They can be anything between $-\infty$ and $+\infty$, but usually the values are concentrated around zero. The artificial neuron is also illustrated in fig 5.1.

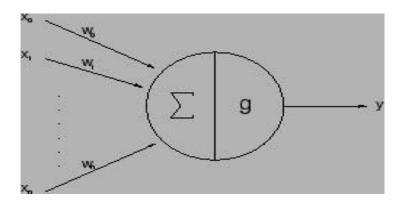


Fig 5.1: An artificial neuron

- Fig 5.1 presents an artificial neuron, the weights have not been assigned to the inputs, and the weights are implicitly given by:
- (i) The number of pulses a neuron sends out
- (ii) The strength of the pulses
- (iii) How closely connected the neurons are.

There are many activation functions that are available in neural networks but the most commonly used activation functions are: -

- (i) Threshold function given by equation 5.5.1.2
- (ii) Sigmoid function given by equation 5.5.1.3
- (iii) Hyperbolic tangent given by equation 5.5.1.4

$$g(z) = \begin{cases} 1 & \text{if } z = t > 0 \\ 0 & \text{if } x + t \le 0 \end{cases}$$
 (5.5.1.2)

$$g(x) = \frac{1}{1 + e^{-2z(z+t)}}$$
 (5.5.1.3)

$$g(x) = \tanh(s(x+t)) = \frac{\sinh(s(x+t))}{\cosh(s(x+t))} = (e^{x(x+t)} - e^{-x(x+t)})/(e^{x(x+t)} + e^{-x(x+t)})$$
(5.5.1.4)

t = value that pushes the centre of the activation function away from zero;

s = steepness parameter;

Sigmoid and hyperbolic tangent are both smooth activation function, by sooth it means that both are continuous. The graph of both the functions is almost similar with only a little difference in the range. The range of the sigmoid function varies from 0 to 1, while the range of the hyperbolic tangent function varies from –1 to 1. A sigmoid function is shown in Fig 5.2.

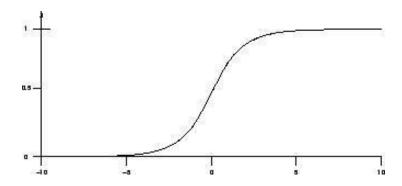


Fig 5.2: A graph of a sigmoid function with s = 0.5 and t = 0.

The amount of incoming pulses needed to activate a real neuron can be represented by parameter 't'. When the learning in a neuron network takes place, the parameter 't' and the weights are adjusted.

5.5.2 THE ARTIFICIAL NEURAL NETWORK

Multilayer feed forward ANN have been chosen to implement, it is the most common kind of ANN. There are three main categories of layers with the starting layer being an input layer and the last layer being an output layer. Between the two layers, a number of hidden layers are present in the multilayer feed forward ANN. The connection is from the initial layer to the next layer and they move in a forward direction only.

Multilayer feed forward ANNs have two different phases:

(I) Training phase also called as the learning phase

Training phase works on providing a specific output when given a specific input is given to the ANN, this is done by continuous training on a set of training data.

(II) Execution phase.

The outputs are returned depending on the value of inputs.

The way the execution of a feed forward ANN functions is the following:

The input is received by the input layer, then it passes through all the hidden layers (using equation 5.5.1.1) and finally the output is returned by the output layer. It is easy to propagate an input through the network of a feed forward ANN to obtain an output. The difficulty comes when we deal with a network in which connections are in all directions (like in the brain) and are required to compute an output.

Due to the connection in all directions in a network, loops are created, these loops can be dealt with the help of recurrent networks, recurrent networks can code time dependencies, but feed forward networks are better for problems that are not time dependent.

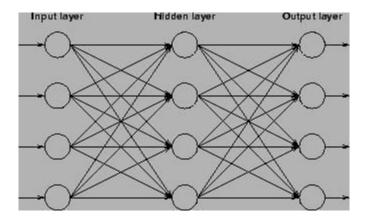


Fig 5.3: A fully connected multilayer feed forward network with one hidden layer

Fig 5.3 shows a multilayer feed forward ANN where all the neurons in each layer are connected to all the neurons in the next layer. This network is called a fully connected network and ANNs usually are fully connected, though they need not to be. When we train an ANN, there are two parameters that can be adjusted, the first one is the weight that is given to the different inputs and the second one is the *t* value in the activation functions. Such an arrangement is impractical and if only one parameter is adjusted the system would be easier to control. To cope up with this problem a bias neuron is invented. Now what the bias neuron does, it always gives the result to be 1. The bias neuron is connected only to the next layer neurons, it does not have any connection to the previous layer. Since the result of a bias neuron is always 1 the weights connected to

it are added directly to the cumulative or combined sum of the other weights (equation 5.5.1.1), similar to the t value in the activation functions.

Equation 5.5.2.1 is the modified equation for the neuron, where the weight for the bias neuron is represented as W_{n+1} ,

$$Y(x) = g(W_{n+1} \sum_{i=0} W_i x_i)$$
 (5.5.2.1)

Adding the bias neuron helps in removing the t value from the activation function, so that only the weights needs to be adjusted, when the ANN is being trained. Equation 5.5.2.2 shows the modified version of the sigmoid function.

$$g(x) = 1/(1 + e^{2sx}) (5.5.2.2)$$

The "t" value cannot be removed without adding a bias neuron, since this the sum function will give if all inputs where zero, regardless of the values of the weights. The value 't' is removed without adding bias neurons ANN libraries, the subsequent layers are counted in such libraries to get the right results. An ANN with added bias neurons is shown in fig 5.4. [16]

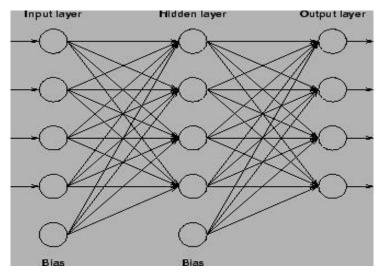


Fig 5.4: A fully connected multilayer feed forward network with one hidden layer and bias neurons.

5.6 THE BACK PROPOGATION ALGORITHM

Back propagation Algorithm: The working of the back propagation algorithm resonates with the name. In this algorithm, first the input is propagated forward through the network, after reaching the last stage the error between the obtained result and the

desired result is calculated, and lastly the error is propagated back through the network and the weights are adjusted in a manner so that the resulting error is small. The algorithm is explained only for fully connected ANNs here, but the theory is the same for sparse connected ANNs.

The training data should have minimum mean square error, and it can be achieved more efficiently in back propagation, if the training of data is done sequentially that is one input at a time instead of training the neural network with the whole data altogether. But the sequential training emphasizes the need of giving at-most caution towards the order in which the data is fed to the network for the training and also provides the escape from getting stuck in a local minimum.

The implementation of this explanation using back propagation:

First the input is propagated through the ANN to the output. After this the error e_p on a single output neuron "p" can be calculated as:

$$e_p = R_p - S_p \tag{5.6.1}$$

Where S_p is the calculated output and R_p is the desired output of neuron "p". This error value is used to calculate a " α_{p} " value, which is again used for adjusting the weights. The " α_{p} " value is calculated by:

$$\alpha_p = e_p g'(S_p) \tag{5.6.2}$$

value of α_p , we calculate the value of α_j , it is the value for preceding layers and is calculated with the help of α_p by the following equation:

$$\alpha_i = \mu g'(S_p) \sum_{p=0} \alpha_p W_{ip}$$
(5.6.3)

p = number of neurons in this is layer;

 $\mu =$ learning rate parameter;

The learning rate parameter determines how much the weight should be adjusted. The advanced gradient descent algorithms do not use learning rate for adjusting the weights, instead they make qualified guess using a set of more advanced parameters to get to the amount of weight to be adjusted.

Using these α values, the ΔW values, the weights should be adjusted by, can be calculated by:

$$\Delta W_{jp} = \alpha_{jp}(S_p) \tag{5.6.4}$$

 $\Delta W_{jp} = value \text{ used to adjust the value of } W_{pj}$;

$$W_{jp} = W_{jp} + \Delta W_{jp} \tag{5.6.5}$$

The process in equation 5.6.5 goes on until a certain stop criterion is reached. The mean square error of the training data while training with the data determines the stop criteria, when the limit of mean square error is reached, the training is stops. Both training and testing data are used in most advance criteria.[17]

Chapter- 6

PROPOSED MODELLING OF PV STANDALONE SYSTEMS

6.1 PANEL SPECIFICATIONS

The solar panel considered for the project is Vikram Solar Panel, installed in the campus premises of Delhi Technological University. Hence, the parameters considered for modelling of PV Panel on Simulink are as follows-

Peak Power P _{max} (Wp)	250
Maximum Voltage V _{mpp} (V)	30.6
Maximum Current I _{mpp} (A)	8.18
Open Circuit Voltage V _{oc} (V)	37.5
Short Circuit Current I _{sc} (A)	8.7

Table 6.1: Electrical Data

All data refers to STC [1000 W/m², 25 degrees Celsius].

DESIGNING P&O MPPT ALGORITHM ON SIMULINK

The comparison of Boost and Cuk converter was done with both of them employing P&O MPPT technique. The P&O technique was designed on Simulink with inputs, voltage and current as were obtained from the PV subsystem and duty cycle as the output to the gate of IGBT.

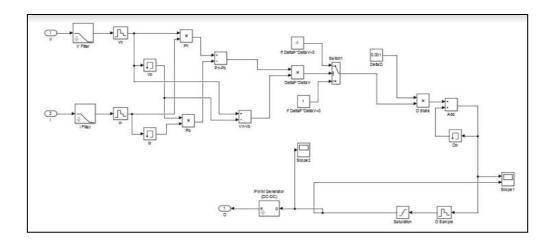
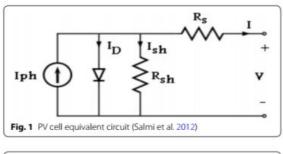


Fig 6.1: Simulink model of P&O MPPT algorithm

6.2 <u>MATHEMATICAL EQUIVALENT CIRCUIT FOR</u> PHOTOVOLTAIC ARRAY

The equivalent circuit of a PV cell is shown in Fig 6.2. The current source Iph represents the cell photocurrent. Rsh is the intrinsic shunt and Rs is the intrinsict series resistances of the cell, respectively. Usually the value of Rsh is very large and that of Rs is very small, hence they may be neglected to simplify the analysis.[23]

Practically, PV cells are grouped in larger units called PV modules and these modules are connected in series or parallel to create PV arrays which are used to generate electricity in PV generation systems. The equivalent circuit for PV array is shown.



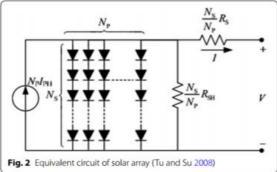


Fig 6.2: Equivalent circuit of PV Cell

The **voltage–current** characteristic equation of a solar cell is provided as:

Module photo-current Iph:

$$I_{ph} = [I_{SC} + K_i(T - 298)] * \frac{I_r}{1000}$$
 (6.2.1)

Here, Iph: photo-current (A);

Isc: short circuit current (A);

Ki: short-circuit current of cell at 25 °C and 1000 W/m2;

T: operating temperature (K); Ir: solar irradiation (W/m2).

Module reverse saturation current Irs

$$I_{rs} = \frac{I_{sc}}{\left[\exp\left(\frac{qV_{oc}}{N_{sk} n} T\right) - 1\right]}$$
 (6.2.2)

Here, q: electron charge, = $1.6 \times 10-19$ C;

Voc: open circuit voltage (V);

Ns: number of cells connected in series;

n: the ideality factor of the diode;

k: Boltzmann's constant, = $1.3805 \times 10-23$ J/K.

The module saturation current Io varies with the cell temperature, which is given by:

$$I_O = I_{rs} \left[T/Tr \right]^3 \exp \left[q * \frac{E_{go}}{nk} \left(\frac{1}{T} - \frac{1}{Tr} \right) \right]$$
 (6.2.3)

Here, Tr: nominal temperature = 298.15 K;

Eg0: band gap energy of the semiconductor, = 1.12 eV;

The current output of PV module is:

$$I = Np * Iph - Np * Io \times \left[\exp\left(\frac{\frac{V}{N_S} + I \times \frac{R_S}{N_p}}{n \times V_t}\right) - 1 \right] - I_{sh}$$
 (6.2.4)

With

$$V_t = \frac{k \times T}{q} \tag{6.2.5}$$

And

$$I_{sh} = \frac{V \times \frac{N_P}{N_S} + I \times R_S}{R_{sh}}$$
 (6.2.6)

Here:

Np: number of PV modules connected in parallel;

Rs: series resistance (Ω) ;

Rsh: shunt resistance (Ω) ;

Vt : diode thermal voltage (V).

6.3 STEP BY STEP PROCEDURE FOR MODELLING OF PHOTOVOLTAIC ARRAYS

A mathematical model of PV array including fundamental components of diode, current source, series resistor and parallel resistor is modeled with Tags in Simulink environment. Using the equations given in the section above the simulation of the solar model is done by the following steps.

Step1:Provide input parameters for modelling: Tr is reference temperature = 298.15 K; n is ideality factor = 1.2; k is Boltzmann constant = $1.3805 \times 10-23$ J/K; q is electron charge = $1.6 \times 10-19$; Isc is PV module short circuit current at 25 °C and 1000 W/m2 = 8.70 A; Voc is PV module open circuit voltage at 25 °C and 1000 W/m2 = 37.5 V; Eg0 is the band gap energy for silicon = 1.12 eV. Rs is series resistor, normally the value of this one is very small, = 0.018Ω ; Rsh is shunt resistor, the value of this is so large, = 360Ω

Step 2: Module photon-current is given in Equation (Ir0 = 1000 W/m2).

$$I_{Ph} = [I_{sc} + K_i(T - 298)] \times I_r / 1000$$
 (6.3.1)

Step 3: Reverse saturation current of the Module is given in Equation 6.2.2.

Step 4: Module saturation current Io is given in Equation 6.2.3.

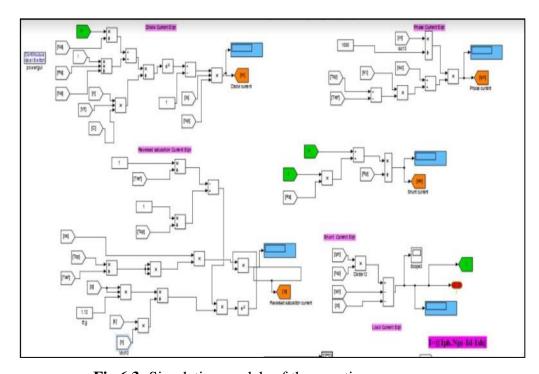


Fig 6.3: Simulation models of the equations

6.4 DESIGNING BOOST CONVERTER

The boost converter was designed using the formulas derived above. The value for inductor and capacitor was found out to be the following.

CONVERTER	INDUCTOR L (H)	CAPACITOR C (F)
Boost	8.5e-03	1.6e-03

Table 6.2: Parameter values of Boost converter

The Simulink model was generated using the above values for inductor and capacitor, employing P&O MPPT technique with the PV Panel designed previously.

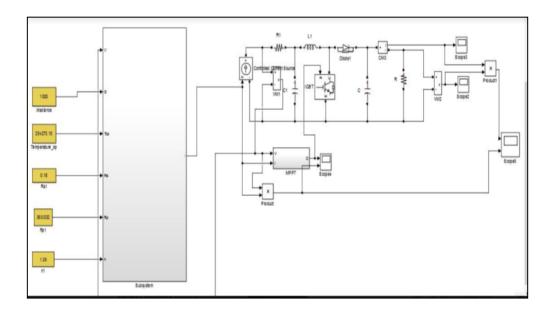


Fig 6.4: Simulink model of Boost DC/DC converter connected to PV Panel

6.5 <u>DESIGNING CUK CONVERTER</u>

The Cuk converter was designed using the formulas derived above. The value for inductor and capacitor was found out to be the following.

CONVERTER	Inductor (H)	Capacitor (F)
Cuk	L1= 2.86e-03	C1= 5.86e-05
	L2= 9.37e-03	C2= 2.501e-04

Table 6.3: Parameter values of Cuk converter

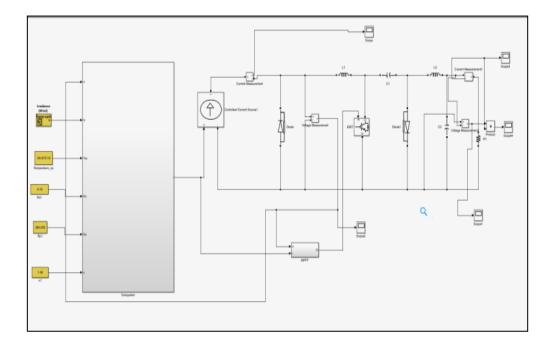


Fig 6.5: Simulink model of Cuk DC/DC converter connected to PV Panel

6.6 DESIGN OF ANN MODEL

New Artificial Neural Network (ANN) based on the data collected from the Incremental Conductance (Inc-Cond) Method.

Artificial neural network consists of three layers: input, hidden and output layers as shown in Fig 6.6.

The training of ANN can be done by PV array voltage and current, solar irradiance and temperature or any combination of these.

The learning of Neural Network is performed by updating the weights by Feed-Forward back propagation Levenberg- Marquardt algorithm with PV voltage and PV current as the input of ANN.

The hidden layer has fifteen neurons and uses tangent sigmoid activation function to produce hidden layer output, while output layer neurons are trained with linear activation function to produce output layer output.

Performance function of neural network is analysed by its mean square error (MSE) which is given by equation below:

$$E_{mse} = \sum_{k=0}^{n} = \frac{1}{12} [m(k) - o(k)]^{2}$$
 (6.6.1)

where m(k) denotes the measured output and o(k) denotes the desired output and N denotes the number of training patterns.

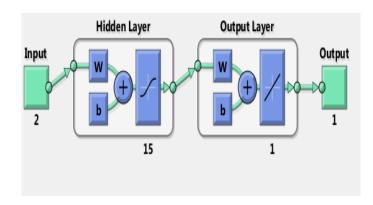


Fig 6.6: Neural Network structure

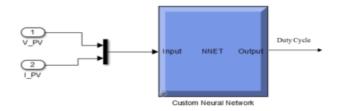


Fig 6.7: Simulink model of ANN based controller

200000 data collected from Perturb and Observe algorithm are used for training. Part of the data used for training is shown in Table below.

PV Curren	PV Voltage	Duty Cycle
0.025206	3.555428	0.398
0.085198	6.756311	0.397
0.177948	9.635283	0.396
0.300781	12.2222	0.395
0.450889	14.54424	0.394
0.625579	16.62572	0.393
0.822299	18.48883	0.392
1.038698	20.15354	0.391
1.272627	21.63786	0.39

Table 6.4: Training Data set used for ANN

The advantage of proposed algorithm is that time taken to track MPP is faster. The parameters of PV array alter with time therefore the neural network has to be trained regularly to ensure exact tracking of MPP. The input to the PV panel subsystem, i.e. Irradiation has been varied as follows.

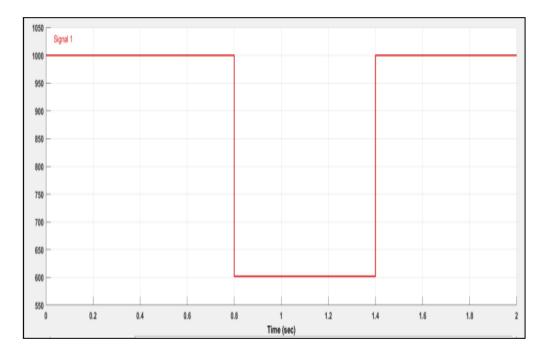


Fig 6.8: Signal builder used for changing irradiation

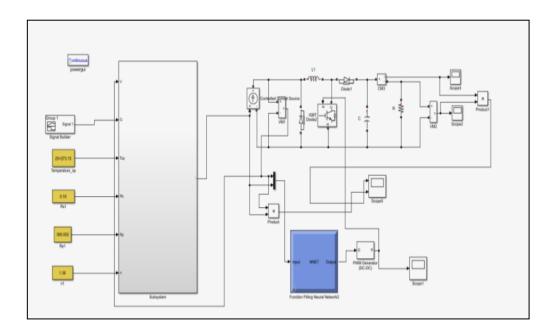


Fig 6.9: Simulink model of ANN based MPP Tracker with PV Panel

CHAPTER-7

RESULTS AND DISCUSSION

7.1 OUTPUT CHARACTERISTICS OF PV CELL

The output characteristics of PV array are non-linear affected by change in weather conditions such as changing irradiation level and temperature as shown in Fig 7.1 and therefore point of maximum output power also varies accordingly.

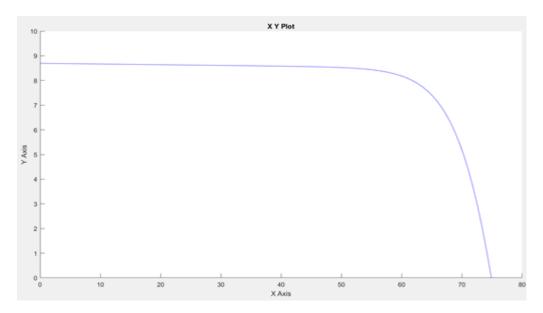


Fig 7.1: I-V characteristics of Solar Cell

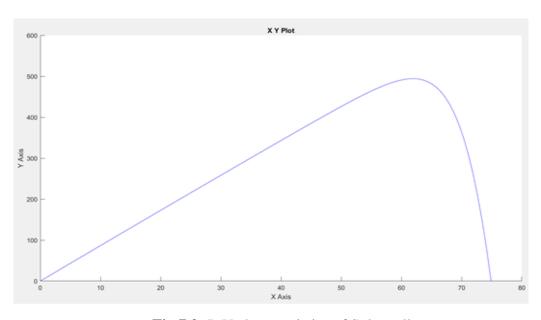


Fig 7.2: P-V characteristics of Solar cell

(I) OUTPUT VOLTAGE, CURRENT, POWER OF BOOST CONVERTER

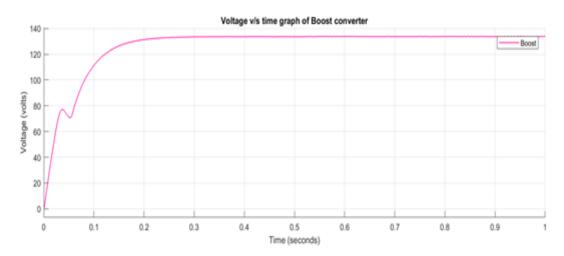


Fig 7.3: Output Voltage of Boost Converter

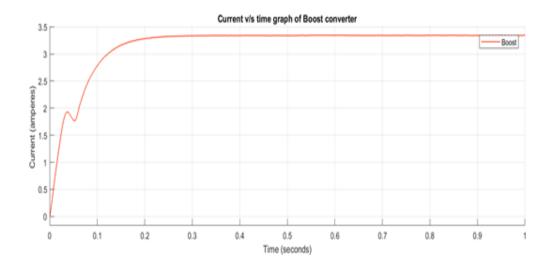


Fig 7.4: Output current of Boost converter

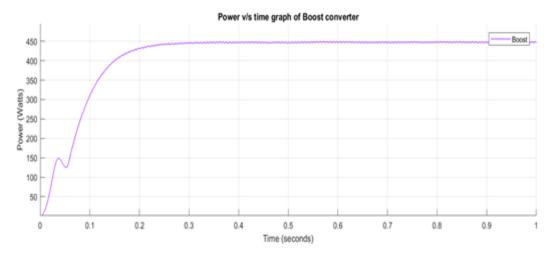


Fig 7.5: Output power of boost converter

(II) OUTPUT VOLTAGE, CURRENT, POWER OF CUK CONVERTER

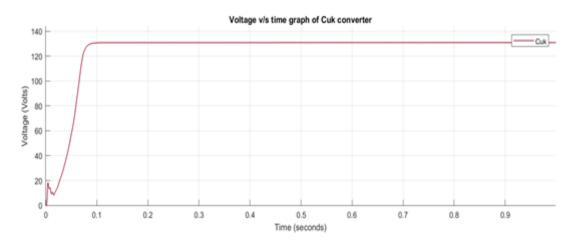


Fig 7.6: Output Voltage of Cuk converter

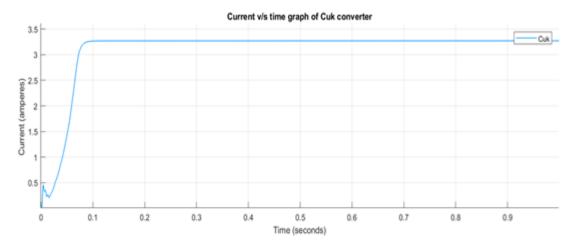


Fig 7.7: Output current of Cuk converter

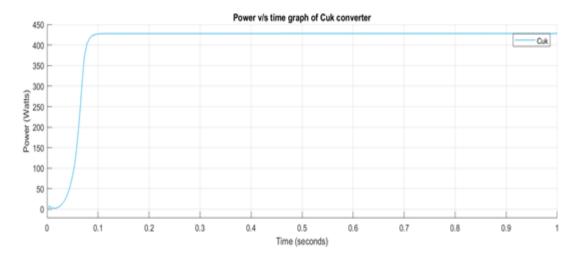


Fig 7.8: Output Power of Cuk converter

7.2 <u>COMPARISION OF RESULTS OF BOOST AND CUK</u> <u>CONVERTERS</u>

Performance comparison analysis of power and voltages as obtained by DC/DC converters on the basis of various control system parameters such as efficiency, ripples, stability, settling time[24]

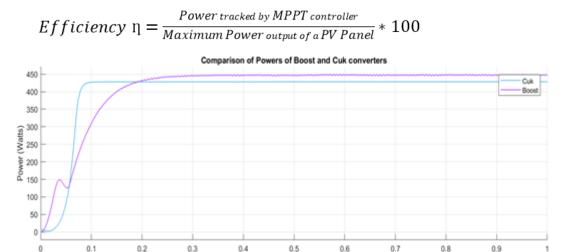


Fig 7.9: Comparison of powers of Boost and Cuk converters

CONVERTER	MAX. POWER (W)	SETTLING TIME (s)	EFFICIENCY (%)
BOOST	449.4	0.28	89.88
CUK	428.7	0.09	85.74

 Table 7.1: Power Comparison between Boost and Cuk converters

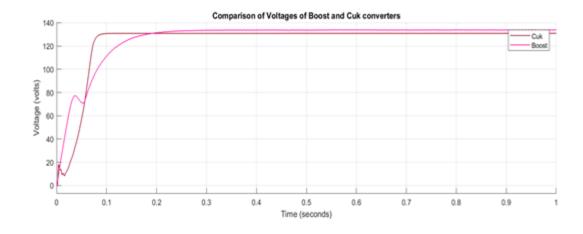


Fig 7.10: Comparison of Voltages of Boost and Cuk converters

CONVERTER	MAX. VOLTAGE (V)	RIPPLES	STABILITY
BOOST	134.1	0.29	Stable
CUK	131	0.05	Stable

Table 7.2: Voltage Comparison between Boost and Cuk converters

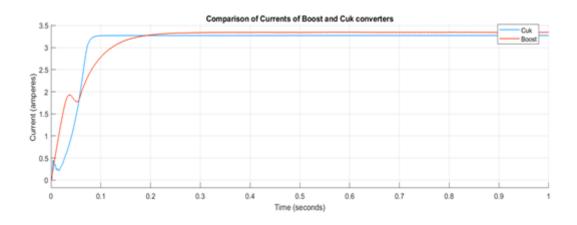


Fig 7.11: Comparison of currents of Boost and Cuk converters

CONVERTER	MAX. CURRENT (A)	RIPPLES
BOOST	3.352	0.01
CUK	3.274	0.0021

 Table 7.3: Current comparison between Boost and Cuk converters

As we can see from the output graphs as well as the table given above, the system implemented using Boost converter give us a higher voltage, power and thus, higher efficiency as well. However, the ripples are more in boost (approximately 3 times more) as compared to the system implemented with Cuk converter. This can be attributed to the inductor present in the Cuk converter circuit, which smooths out the ripples.

However, due to the low efficiency offered by PV Panels, current research work is driven towards achieving higher efficiency. This is the reason, we picked the system using Boost converter for the training data set that we require for creating our ANN model. Our boost model gives an efficiency of 89.88% where as that of the Cuk model

is 85.74%. Next, we compare the results obtained by the P&O MPPT technique and the ANN MPPT technique, both using the Boost DC/DC converter.

(I) REGRESSION CHARACTERISTICS

The regression characteristics obtained, using the data set obtained from the P&O MPPT method is as follows.

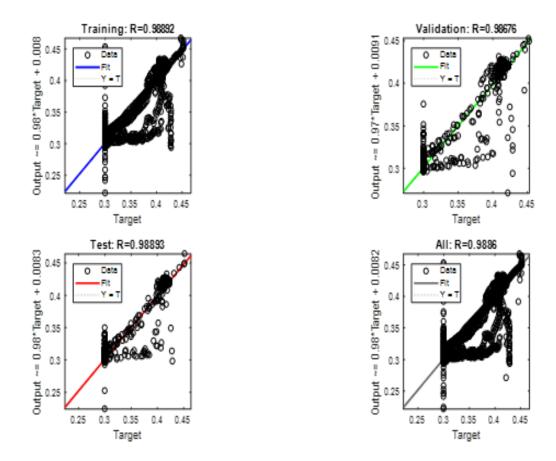


Fig 7.12: Regression Characteristics

The ideal fit has the regression coefficient R as 1. But in practical scenarios R=1 is never achieved. However, the fits that yield good enough results have R>0.95. Our training set has the value of R as 0.98892, where as that of Validation set and Testing data set is 0.98676 and 0.98893 respectively. Our overall regression coefficient comes as R=0.9886. The straight line passing through the origin is the perfect fit line, obtained in ideal scenarios. For practical purposes the outliers, shown by black circles should lie along the length of the perfect fit line, as shown in the fig above.

(II) OUTPUT VOLTAGE, CURRENT, POWER OF SYSTEM USING P&O TECHNIQUE

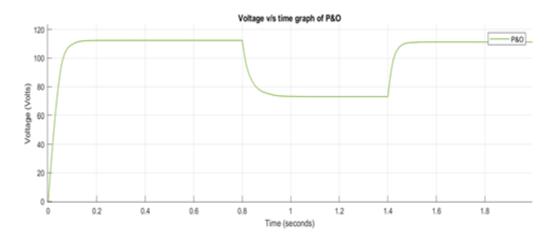


Fig 7.13: Output voltage of system using P&O technique

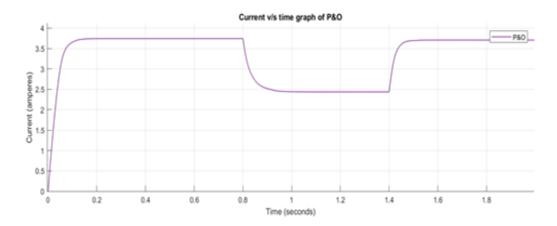


Fig 7.14: Output Current of system using P&O technique

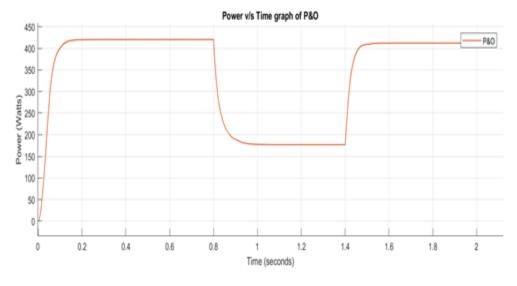


Fig 7.15: Output Power of system using P&O technique

(III) OUTPUT VOLTAGE, CURRENT, POWER OF SYSTEM USING ANN TECHNIQUE

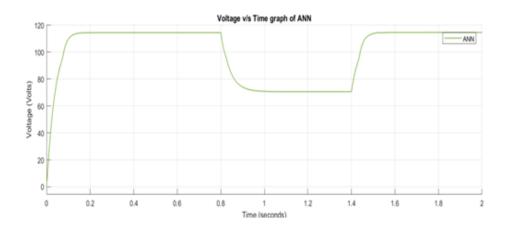


Fig 7.16: Output Voltage of system using ANN technique

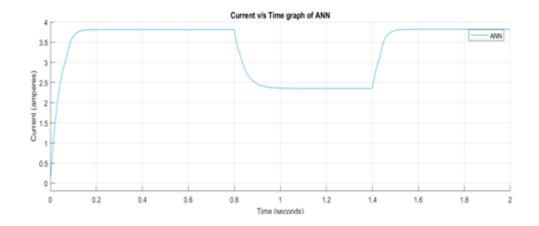


Fig 7.17: Output Current of system using ANN technique

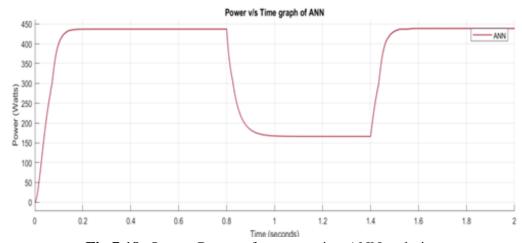


Fig 7.18: Output Power of system using ANN technique

7.3 COMPARISION OF RESULTS OF P&O AND ANN

Performance comparison analysis of power and voltages tracked by MPPT controller on the basis of various control system parameters such as efficiency, ripples, stability, settling time.

Efficiency
$$\eta = \frac{Power tracked by MPPT controller}{Maximum Power output of a PV Panel} * 100$$

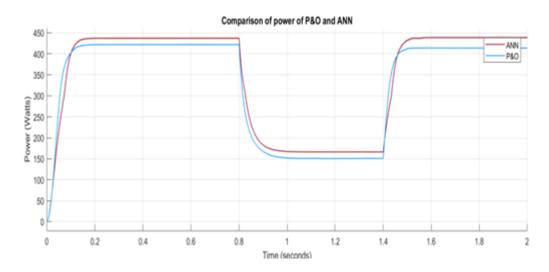


Fig 7.19: Comparison of Power of P&O and ANN

MPPT ALGORITHM	MAX. POWER (W)	EFFICIENCY (%)
P&O	421.3	84.26
ANN	439.5	87.9

Table 7.4: Power comparison between P&O and ANN

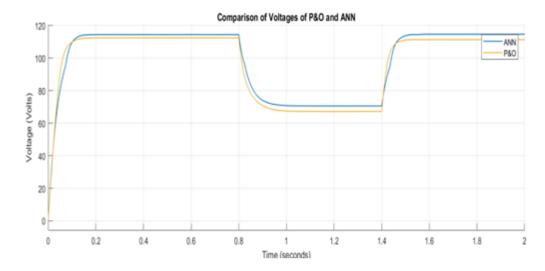


Fig 7.20: Comparison of Voltages of P&O and ANN

MPPT ALGORITHM	MAX.VOLTAGE (V)	RIPPLES	STABILITY
P&O	112.4	0.075	Stable
ANN	114.8	0.05	Stable

Table 7.5: Voltage comparison between P&O and ANN

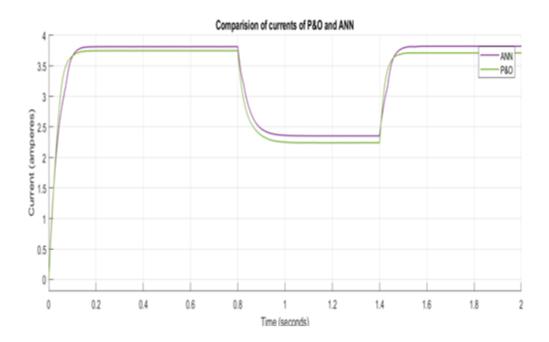


Fig 7.21: Comparison of Currents of P&O and ANN

MPPT ALGORITHM	MAX. CURRENT (A)	RIPPLES
P&O	3.747	0.004
ANN	3.828	0.0025

Table 7.6: Current comparison between P&O and ANN

Our comparison shows that the model implemented using ANN MPPT technique gives higher efficiency of 87.9% as compared to 84.26% obtained by the P&O MPPT technique. Also, ANN model gives far lesser voltage and current ripples as compared to P&O model.

On the basis of the given parameters, it can be easily concluded that ANN gives a better performance on the stand alone PV system.

CHAPTER-8

8.1 CONCLUSION

This project is based on comparing the P&O and ANN techniques used for tracking maximum power during varying irradiation conditions for a standalone PV system employing a Boost DC-DC Converter.

Under any variation in atmospheric conditions, by using neural network, point of maximum power is specified precisely. The other advantage of using the neural network in PV maximum power-point tracking is that it has better dynamic performance compared to the other methods. The primary way of varying the power is through modification of the duty cycle. The problem of varying the duty cycle is compounded in the presence of non-uniform shading.[25]

The ANN model, because of its training and prior knowledge about probable MPP in response to a particular input can track the changes in MPP much better than the Perturb and Observe method.

The Simplot curves shown above clearly depict the maximum power tracked by both P&O and ANN. The maximum power tracked by ANN is 439.5 Watts while that of P&O is 421.3 Watts, which implies that the model using ANN gives higher power than that using P&O. Our model employing P&O gives an efficiency of 87.9 % while the model employing ANN gives an efficiency of 84.26 %. The voltage and current ripples obtained in the ANN model are far lesser than that obtained in the P&O model. Thus, ANN gives smoother response than P&O. The results obtained by the project are in synch with the results obtained through theoretical approach.

8.2 PROPOSED EXTENSION OF WORK

Our project compares a very popular and trending maximum power tracking technique (Artificial Neural Network) with the simplest one (P&O), proving ANN to be better than P&O. However, in order to arrive to a better conclusion as to which technique and algorithm would give the best result for achieving maximum efficiency possible for a solar panel, we need to incorporate more techniques into our study and build a more comprehensive analysis chart.

We can further improve our analysis by studying the results of Fuzzy logic and Neuro-fuzzy techniques as well. Comparing these with the results of P&O and ANN techniques would form the next step of our research.

Also, other than the maximum power tracking techniques used, we can also modify our model. To improve our model and get outstanding results with minimum limitations we can use Quasi Z-source converter which is more reliable, cost effective and gives high immunity to EMI noise and high efficiency. At the same time, it offers the unique advantage of low rating components.

REFERENCES

- [1] http://www.altenergy.org/renewables/photovoltaic-modules.html
- [2] G.Neelakrishnan, M.Kannan, S.Selvaraju, K.Vijayraj, M.Balaji, D.Kalidass ,"Transformer Less Boost DC-DC Converter with Photovoltaic Array", IOSR Journal of Engineering (IOSRJEN) e-ISSN: 2250-3021, p-ISSN: 2278-8719 Vol. 3, Issue 10 (October. 2013), ||V4|| PP 30-37
- [3] https://solargaininc.com/how-solar-works/
- [4] J. Bikaneria, S. Prakash Joshi and A. R. Joshi. "Modeling and Simulation of PV Cell using One-Diode model". International Journal of Scientific and Research Publications, Volume 3, Issue 10, October 2013 1 ISSN 2250-3153
- [5] M. Irwanto, Y. M. Irwan, I. Safwati, W. Z. Leow, N. Gomesh, "Analysis simulation of the photovoltaic output performance", Power Engineering and Optimization Conference (PEOCO) 2014 IEEE 8th International, pp. 477-481, 2014.
- [6] http://shodhganga.inflibnet.ac.in/bitstream/10603/9992/2/11%20chapter%205.pdf
- [7] http://coder-tronics.com/tag/perturb-observe/
- [8] Masood, Bilal & Shahzad Siddique, M & Asif, Rao & Zia-ul-Haq, M. (2014). Maximum power point tracking using hybrid perturb & observe and incremental conductance techniques. 354-359. 10.1109/ICE2T.2014.7006277.
- [9] W N Husna, A & F Siraj, S & Z Ab Muin, M. (2012). Modeling of DC-DC Converter for Solar Energy System Applications. 10.1109/ISCI.2012.6222679.
- [10] Babu.N, Ramesh & Subramani, Saravanan. (2015). Performance analysis of boost & Cuk converter in MPPT based PV system. 10.1109/ICCPCT.2015.7159425.
- [11] Stallon, S.Daison & Kumar, K & Kumar, Suresh & Baby, Justin. (2013). Simulation of High Step-Up DC–DC Converter for Photovoltaic Module Application using MATLAB/SIMULINK. International Journal of Intelligent Systems and Applications. 5. 72-82. 10.5815/ijisa.2013.07.10.
- [12] Sriranjani, R & ShreeBharathi, A & Jayalalitha, S. (2013). Design of Cuk Converter Powered by PV Array. Research Journal of Applied Sciences, Engineering and Technology. 6. 793-796. 10.19026/rjaset.6.4121.
- [13] Maind, S.B. & Wankar, P. (2014). Research paper on basic of Artificial Neural Network. International Journal on Recent and Innovation Trends in Computing and Communication. 2. 96-100.
- [14] Bishop, John. (2015). History and Philosophy of Neural Networks. 22-96.

- [15] Basheer, Imad & Hajmeer, M.N.. (2001). Artificial Neural Networks: Fundamentals, Computing, Design, and Application. Journal of microbiological methods. 43. 3-31. 10.1016/S0167-7012(00)00201-3.
- [16] A Guarnieri, Ricardo & Pereira, Enio & Chou, Sin Chan & Chou, Instituto & Nacional & Espaciais, Pesquisas & José, São & Campos, Dos & Paulo, São & Brazil. (2006). Solar radiation forecast using artificial neural networks in south Brazil.
- [17] Jia, Shuran & Shi, Daosheng & Peng, Junran & Fang, Yang. (2015). Application of Back-Propagation Neural Network in Multiple Peak Photovoltaic MPPT. 231-234. 10.1109/ICIICII.2015.139.
- [18]Sah Bikram, GVE Kumar" A comparative study of different MPPT techniques using different dc-dc converters in a standalone PV system", IEEE Region 10 Conference, 2016
- [19] G.Gupta, P.Gaur,"Comparative Study of-Various DC-DC Converters Used in AI-Based Solar fed PMBLDC Motor Drive", IEEE INDICON 2015 1570176293
- [20] A. Arora, P. Gaur, "Comparison of ANN and ANFIS based MPPT Controller for grid connected PV systems", 2015 Annual IEEE India Conference (INDICON), pp. 1-6, 2015.
- [21] Messalti S, Harrag A.G, Loukriz A.E, "A new neural networks mppt controller for PV Systems," Renewable Energy Congress (IREC), 2015 6th International, Sousse, Tunisia, 2015, pp. 1-6.
- [22] Munish Manas\ Ananya Kumarib , Sanjeev Das ,"An Artificial Neural Network based Maximum Power Point Tracking Method for Photovoltaic System", IEEE International Conference on Recent Advances and Innovations in Engineering (ICRAIE-2016), December 23-25, 2016, Jaipur, India
- [23] Mathematical modeling of photovoltaic cell/module/arrays with tags in Matlab/Simulink,Nguyen, X.H. & Nguyen, M.P. Environ Syst Res (2015) 4: 24. https://doi.org/10.1186/s40068-015-0047-9
- [24] S Saravanan, N. Ramesh Babu, Performance Analysis of Boost &Cuk Converter in MPPT Based PV System, 2015, IEEE International Conference on Circuit, Power and Computing Technologies [ICCPCT], 978-1-4799-7075-9
- [25] B. Subudhi, and R. Pradhan, "A Comparative Study on Maximum Power Point Tracking Techniques for Photovoltaic Power System," IEEE Trans. Sustain. Energy., vol. 4, no. 1, pp. 89-98, Jan. 2013.