MODELLING OF A PV ARRAY AND SHORT TIME PREDICTION OF SOLAR INSOLATION

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MODELLING OF A PV ARRAY AND SHORT TIME PREDICTION OF SOLAR INSOLATION

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ODISHA

CERTIFICATE

This is to certify that the dissertation entitled **" MODELLING OF A PV ARRAY AN SHORT TIME PREDICTION OF SOLAR INSOLATION "** being submitted by **Reema Mohanty**, **Roll No. 212EE5397**, in partial fulfillment of the requirements for the award of degree of **Master Of Technology In Electrical Engineering (INDUSTRIAL ELECTRONICS)** to the **National Institute of Technology**, **Rourkela**, is a bonafide record of work carried out by her under my guidance and supervision.

(**Prof. Bidyadhar Subudhi)**

Date: Department of Electrical Engineering

Place: **NIT Rourkela**

DECLARATION

I hereby declare that the investigation carried out in the thesis has been carried out by me. The work is original and has not been submitted earlier as a whole or in part for a degree/diploma at this or any other institution / University.

Reema Mohanty

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ABSTRACT

The thesis describes firstly PV array modeling and simulation using a two diode model. It is necessary to represent the dynamic characteristics of a PV cell through a two diode model. From the simulation studies pursued in the thesis it is envisaged that the two diode model representation of a PV array provides improved accuracy even at low solar irradiation levels. When compared with a single diode model representation, the two diode model described in the thesis gives improved representation of the PV array. In a single diode representation, the input parameters of the PV cell were approximately with seven parameters namely I_{PV}(PV cell current),I_{o1}(Saturation current of diode1),I_{o2}((Saturation current of diode2),R_p (Resistance in parallel),R_s(Resistance in series),a_1(ideality factor of diode1),a_2(ideality factor of diode2); but in this thesis the number of inputs have been reduced to four as it has been assumed that $I_{O1} = I_{O2}$ while the values of a_1 $a_2$are chosen arbitrarily from [5].The reason behind going for this model is that the input parameters have been reduced so as to reduce the computational time. The accuracy of the proposed two diode model is verified by applying it to a monocrystalline Kyocera PV cell obtained from the datasheet [4] described in Table1.Further the two diode model is useful to find the I-V and P-V curves in standard test condition since it is fast, simple and accurate as well as it leads to showcase P-V and I-V curves in large array simulation and in partial shading condition.

Subsequently, the thesis describes an algorithm to predict solar irradiation as the solar insolation is intermittent in nature. Hence this work considers development of an artificial wavelet neural network to determine solar insolation.The thesis describes the basic elements for a standardized model validation process adapted especially for PV performance models, suggests a framework to implement the process. Thus, predicting the solar intensity precisely is important for design of PV station and arrangement of large scale PV generation bases, safety and stability of grid[7] for any sort of a microgrid system.

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CHAPTER1

INTRODUCTION

1.1 Overview

1.2 Motivation

1.3 Objectives

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INTRODUCTION

1.1OVERVIEW

The most important factor that affects the accurateness of a simulation in the PV cell modeling, which basically involves the estimation of the non-linear current-voltage and P-V characteristics curves. The simplest model is the single diode model i.e. a current source in parallel to a diode and a resistance R_s[14]. It only needs three parameters which are the short-circuit current (I_{sc}), the open circuit voltage (V_{oc}) and the diode ideality factor a. This model is enhanced by the adding of one series resistance, R_p[2].Despite its simplicity, it showed various discrepancies at different temperature. Thus it was further improved when a resistance in parallel was connected to it[2].Here the Rp model was although an improved effort; but when subjected to irradiation variation it was not showing proper results.The single diode models were based on the assumption that the recombination loss in the depletion region is absent. In a real solar cell, the recombination represents a substantial loss, especially at low voltages. This cannot be adequately modeled using a single diode. Hence consideration of this loss leads to a more precise model known as the two-diode model [1] which is the motive of the work done here.

1.2 RESEARCH MOTIVATION

The necessity of a renewable energy source due to the depreciation of fossil fuel and nuclear power; hence the photovoltaic array has come into picture.Hence a fast and précised PV array was needed.PV model is one of the widely used energy source as it satisfies government's policy to sustainable green energy and generous tariff schemes.The reason behind using the specified model is to minimize the reverse effect of temperature and irradiation changes in the PV array .Also this kind of model will be helpful in irradication of the hostile effects of partial shading.

1.3 OBJECTIVES

The objectives of the thesis are follows.

- To represent the dynamics of a PV cell and a PV array using a two diode model to improve the modeling accuracy such at the model would be appropriate even for low solar irradiation levels.
- To simulate the two diode model of a PV array in MATLAB.
- To develop some efficient prediction algorithms to achieve 24 hours ahead forecasting of solar insolation

1.4 THESIS LAYOUT

CHAPTER 1 gives a brief overview of the topic, two diode model,literature review, motivation, objectives and organization of thesis.

CHAPTER 2 consists of literature review on two diode model approach,single diode model approach and comparative study of two diode model and existing[1] model approach.

CHAPTER 3 It shows the effect of incorporating large array and partial shading condition.

CHAPTER 4 gives detail idea about the suntracker with solar sensors procured by CWET Chennai.

CHAPTER 5 gives idea about artificial wavelet neural network and the methodology of the work done in order to forecast the values of global radiation.

CHAPTER2

TWO DIODE MODEL APPROACH

2.1Objective

2.2 Literature Review

2.2 Two Diode Model Approach

2.3 Results and Discussion

2.4 Chapter Summary

2.1 OBJECTIVE

- To include the recombination losses which the single diode model has not taken into consideration.
- For simplifying the complexity of the circuit while modeling as here input parameters are reduced.
- The suggested two diode model[2] gives better performance at lower irradiation level.

2.2 LITERATURE REVIEW

The equation of diode current as derived by Shockley's equation[4] is written as-

$$I = I_{PV} - I_O \exp[\left(\frac{V+IR_S}{aV_t}\right) - 1] \quad (1)$$

Where I= terminal current of the PV cell

V= terminal voltage of the PV cell

I_{pv} = current of PV Cell

I_o = reverse saturation current of diode

R_s = series resistance

R_p = resistance in parallel

V_t = thermal voltage of diode

a= diode ideality factor

2.2(a) SINGLE DIODE MODEL

The single diode models were based on the assumption that the recombination losses are negligible . Recombination layer in the depletion region is absent.In a real solar cell, the recombination loss represents a substantial loss, especially at low voltages. The single diode model consists of a current source across which a diode is connected and a resistance is also connected in series.The main drawback of the circuit is during temperature variations it deviates from the vicinity of V_{oc}.Hence again this model was improved by connecting a resistance R_p in parallel with the diode.

The Rp model is given as-:

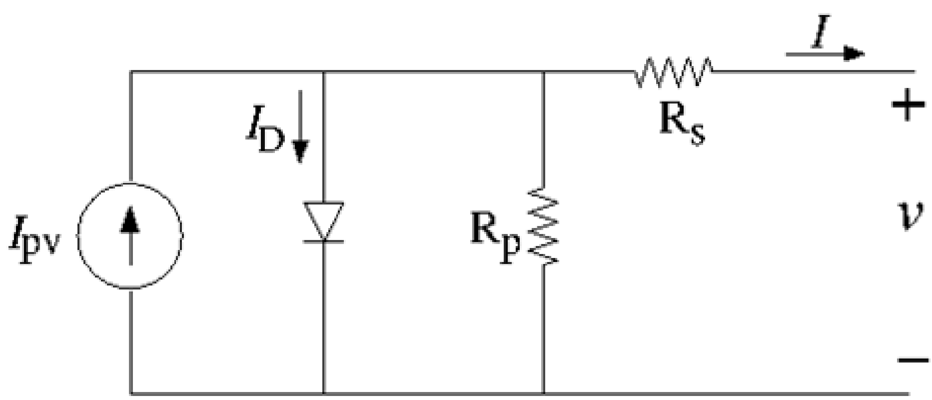

Fig 2. 1 Single diode model with resistance Rp

Where I= terminal current of the PV cell

v= terminal voltage of the PV cell

I_{pv} = current of PV Cell

I_D = Diode current

R_p = resistance in parallel

DRAWBACK OF R_p MODEL

But the problem with this Rp model is when it is subjected to lower irradiation level its performance gets low.Also here computational time is more.So in order to eradicate this problem Two diode model came into picture.Here the modeling is done by taking two diodes along with two resistors namely Rs and Rp along with current source.

Consideration of this loss leads to a more precise model known as the two-diode model [1].The addition of an extra diode increases the parameters. The main challenge now is to evaluate the values of all of the model parameters.Meanwhile the rational simulation time should be maintained. In this work we have devised a computational method that requires only a marginally longer simulation time than the popular single diode model. The input to the simulator is information available in a standard PV module datasheet. In addition, the simulator supports large array simulations that can be interfaced with MPPT algorithms and actual power electronic converters. This allows for performance evaluations when interacting with the other components of a system. After analyzing the two diode model topology we will be clear about the concept of inserting another diode. Hence the Two Diode Model is demonstrated below in figure 1(b).

2.2(b) TWO DIODE MODEL APPROACH

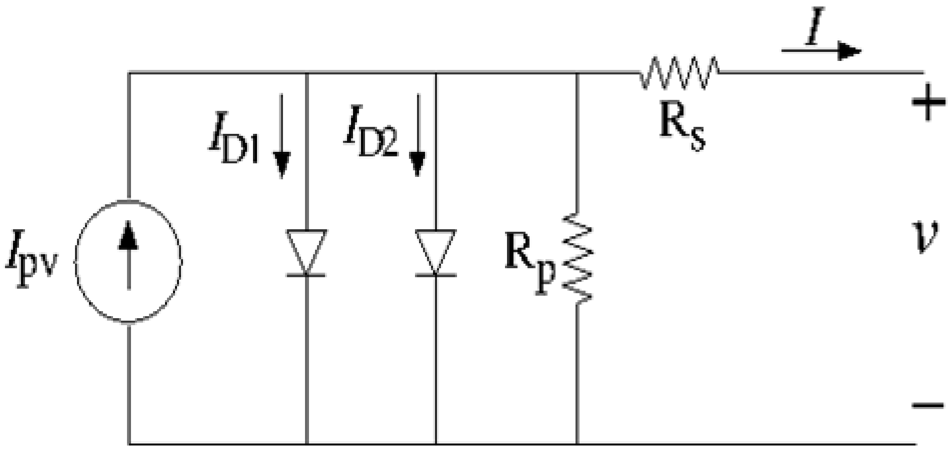

fig.2. 1 Two diode Model

Here in the Two diode model instead of taking Seven parameters namely I_{o1}, I_{o2}, I_{PV}, R_s , R_p a_1 , a_2 we have assumed that a_1 =1, a_2 = 2 , and $I_{o1} = I_{02}$ our input parameters here have been reduced to four.

Where I= terminal current of the PV cell

V= terminal voltage of the PV cell

I_{pv} = current of PV Cell

$I_{D1}=I_{D2}$ = Diode current in diode 1 and 2 respectively

R_s = series resistance

R_p = resistance in parallel

Further the expression for PV current is given by-

$$I_{PV} = (I_{PV\_STC} + K_I \Delta T)\frac{G}{G_{STC}} \qquad (2)$$

G_{STC}=1000W/m^2

I_{PV_STC} = PV current at 25°C

ΔT= change in temperature in kelvin

The reverse saturation current $I_{o1} = \left(\frac{I_{STC}+K_I\Delta T}{\exp[(V_{OC,STC}+K_V\Delta T)/aV_{t_1}}\right)$ (3)

Hence the terminal current of two diode model is given by-:

$$I = I_{PV} - I_{O1}\left[\exp\left(\frac{V+IR_S}{a1V_t}\right) - 1\right] - I_{O2}\left[\exp\left(\frac{V+IR_S}{a2V_t}\right) - 1\right] - \left(\frac{V+IR_S}{R_P}\right) \quad (4)$$

Now the two diode model is implemented by taking the datas from KyoceraKC200GT solar Array. Not only Kyocera KC200GT array but also the model can be analysed by using different modules. Such as BP Solar MSX-60 , Kyocera KG200GT Shell S36 ,Shell SP-70 ,
Shell ST40.The datasheet of Kyocera KC200GT is given below.

2.2(c) (Datasheet of Kyocera KC200GT)

Table 1 : Datasheet of Kyocera KC200GT

Parameter	Specification
Maximum Power(P_{mp})	200 W (+10% / -5 %)
Open circuit Voltage(V_{oc})	32.9 V
Short circuit Current(I_{sc})	8.21 A
Maximum Power Voltage(V_{mpp})	26.3 V
Maximum Power Current(I_{mpp})	7.61 A
Max System Voltage	600 V
Temperature coefficient of I_{sc}(K_I)	3.18mA/^{0} C
No of cells(N_s)	54
Temperature coefficient of V_{oc} (K_v)	-123mV/ ^{0}C

TABLE 2. 1 Datasheet

2.3RESULTS AND DISCUSSION

Beneath, the results of the Two Diode model of Photovoltaic Array under different Temperature and irradiation are shown.

First the current-voltage plot at standard test condition is shown.

Then the plot between power and voltage is shown.

<u>IV Curve of Two diode model at $T=25^{0}$ C and G=1000 W/m^2</u>

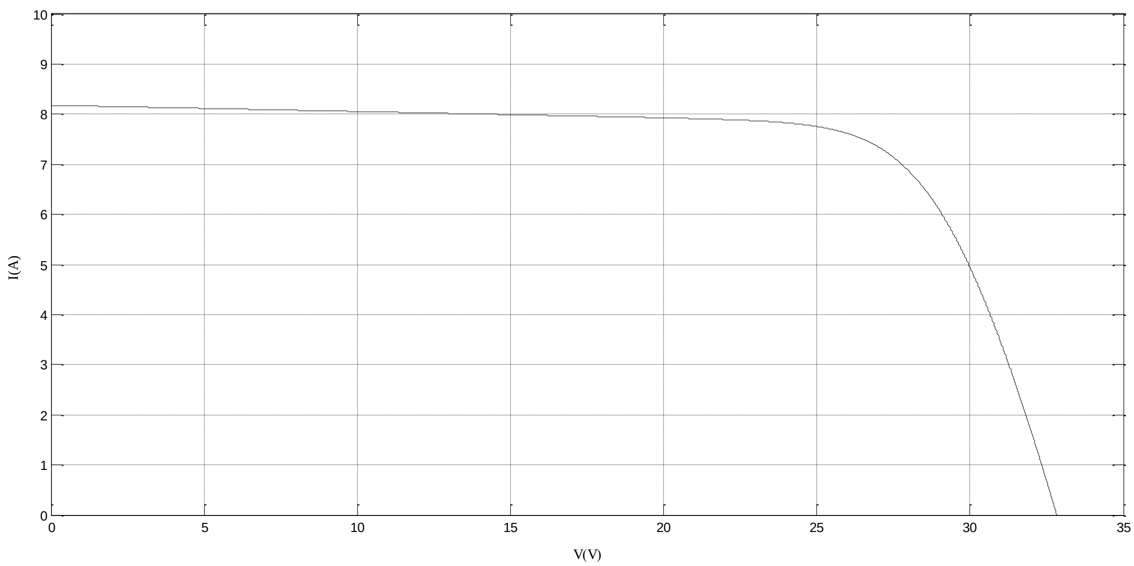

fig.2. 2 IV Curve at STC

Here the IV characteristics is taken at $T=25\ ^{o}$ C , and G=1000 W/m $^{2.}$ result shown here is accurate as it lies within the terminal voltage and current specification that is V=32.8 Volt and I =8.21 A .

PV Curve of Two diode model at T=25^0 C and G=1000 W/m^2

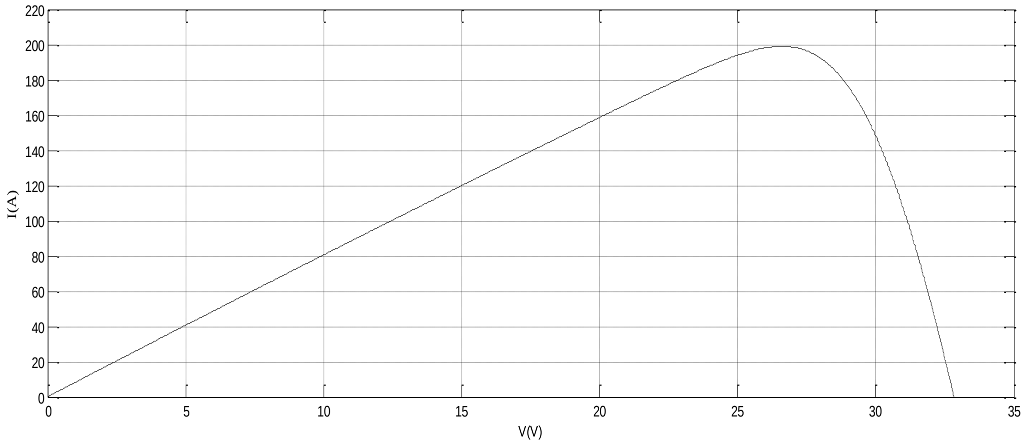

fig.2. 3 P-V Curve at STC

Similariliy here Power lies within 200W to 250 W and voltage within 32.8 V .

IV Curves at different temperature

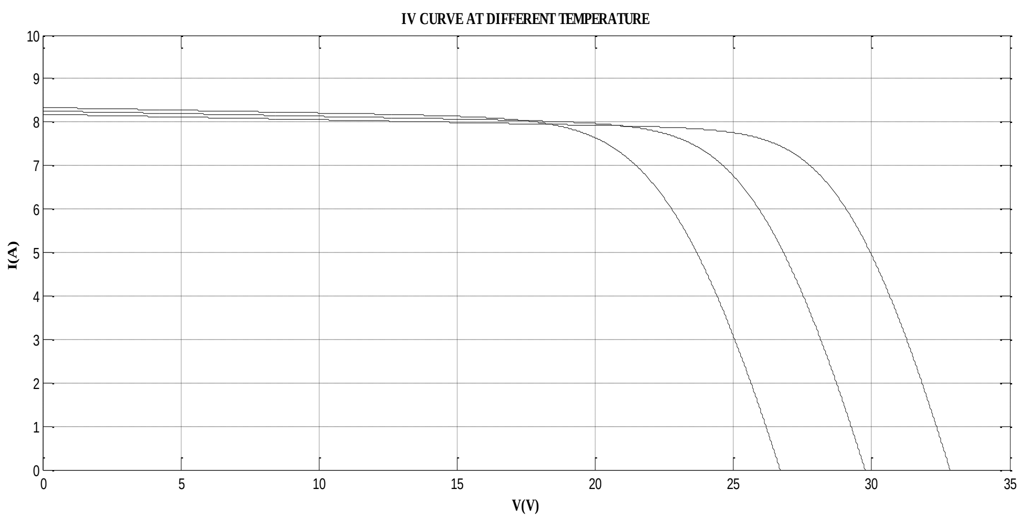

fig.2. 4 IV Curves at different temperature

This gives I-V Curves at 25^0 C,50^0 C and 75^0C respectively.

IV curves at different irradiation

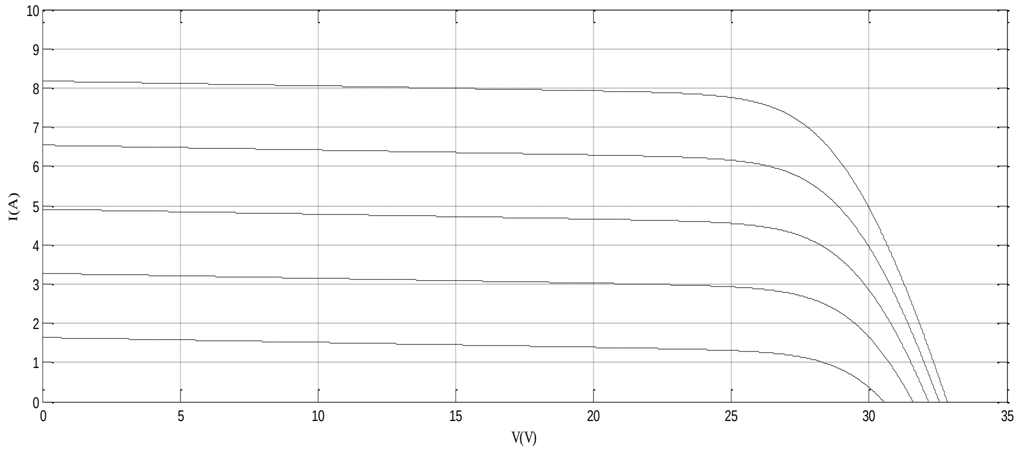

fig.2. 5 IV Curves drawn at different irradiation values

Fig. 2(f) IV Curves drawn at different irradiation value

The above curve is drawn for G= 1000, 800, 600, 200 W/m^2

2.4 Comparative data of Two Models

R_p model		Two Diode Model	
I_{sc}	8.21A	I_{sc}	8.21A
V_{oc}	32.9 V	V_{oc}	32.9 V
V_{mp}	26.3 V	V_{mp}	26.3 V
I_{mp}	7.61V	I_{mp}	7.61V
K_V	-123mV/ ^{O}C	I_{PV}	8.21 A
K_I	3.18mA/ ^{O} C	R_S	0.32Ω
N_S		R_P	160.5Ω
		I_{O1}=I_{O2}	4.218e^{-10}A

TABLE 2. 2 COMPARISION OF TWO MODELS

IV Curves of Two diode Model, R_P Model and Datasheet

Now the comparative graphical result of Two Diode Model,R_p Model[3] has been shown graphically from which it is clear that the proposed two diode model gives better result at lower irradiation.

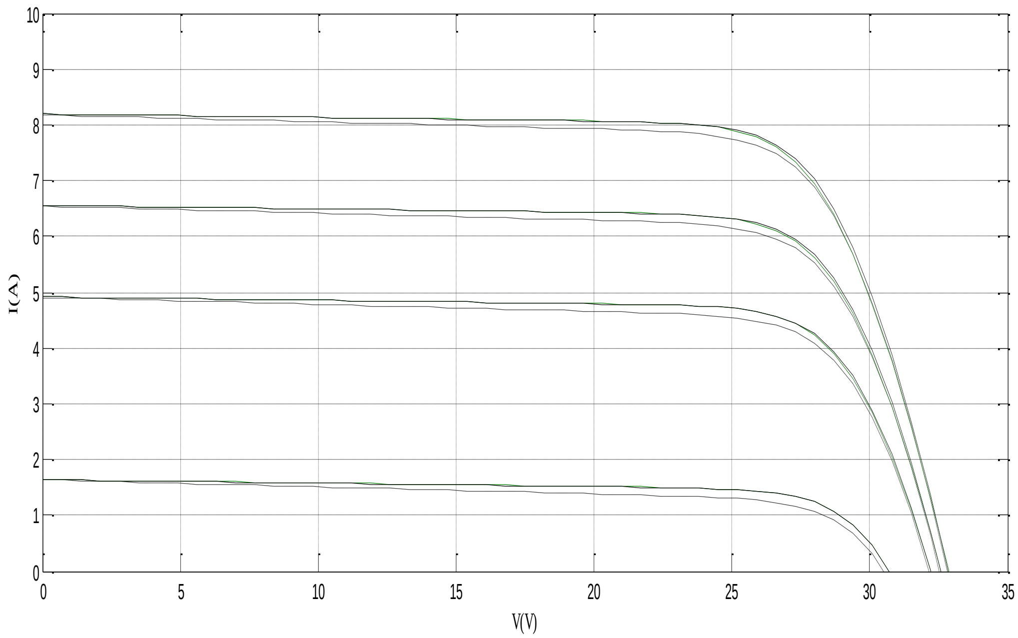

fig.2. 6 Comparative studies of Two Diode Model and Single Diode Model

IV Curves of Two Diode model and Single Diode Model at different insolation.

Here insolation varies as 1000 W/m^2, 800 W/m^2, 600 W/m^2, 200W/m^2.

2.5 CHAPTER SUMMARY

- In this work first the single diode model is shown and to overcome the drawback two diode model concept was proposed.
- Here only the simple I-V curves at STC(Standard Test Conditions) are shown.
- The two diode model proposition came from the idea of recombination loss.
- Again the comparative study between two diode model and single diode model is done where the two diode model shows better performance at lower irradiation level.

CHAPTER3

DIODE UNDER PARTIAL SHADING CONDITION

3.1 INTRODUCTION

Some past studies assume that the decrease in power production is proportional to the shaded area and reduction in solar irradiance, thus introducing the concept of shading factor. While this concept is true for a single cell, the decrease in power at the module or array level is often far from linearity with the shaded portion. Other past studies tend to be rather complicated and difficult to follow by someone with limited knowledge on electronic/solid-state physics. The objective of this study is to clarify the impact of shading on a solar panel performance in relatively simple terms that can be followed by a power engineer or PV system designer without difficulty. In a solar photovoltaic module which is series connected, the performance is harmfully affected if all of its cells are not equally illuminated. All the cells in a series array are made to carry the same current even though some cells under gloom produce less photon current. The cells which are under gloom may get reverse biased, acting as loads , draining power from fully illuminated cells . If the system has not been properly protected, hot-spot problem can take place and in several cases, the system can be irreversibly damaged. In the new trend of integrated PV arrays, it is difficult to avoid partial shading of array due to adjoining buildings right through the day in all the seasons. This is the thing which makes the study of partial shading of modules an important issue.

3.2 OBJECTIVE

- To simulate the diode model in a large dimension here 50×10 array is selected and the results are validated with thedatasheet results.
- Similarily in order to observe the performance under partial shading condition the two diode model is simulated.
- To observe IV and PV curves under partial shading condition.

3.3 SIMULATION OF LARGER PV ARRAY

After finding out the IV curves and PV curves of two diode model, we proceed to find out the IV curves of larger array. Previously only one array was simulated for simplicity; but as the demand increases the voltage and power supply should increase. Hence larger array is simulated.

In a typical installation of a large PV power generation system, the modules are configured in a series parallel structure i.e. Nss×Npp modules[2].

To handle such cases, the output current equation given in (i) has to be modified as follows-

$$I = I_{PV}N_{pp} - I_{O1}N_{PP}\left[\exp\left(\frac{V+IR_S\left(\frac{N_{SS}}{N_{PP}}\right)}{a_1V_tN_{SS}}\right) - 1\right] - I_{O2}\left[\exp\left(\frac{V+IR_S\left(\frac{N_{SS}}{N_{PP}}\right)}{a_2V_tN_{SS}}\right) - 1\right] - \left(\frac{V+IR_S\left(\frac{N_{SS}}{N_{PP}}\right)}{R_P\left(\frac{N_{SS}}{N_{PP}}\right)}\right)$$

………………………………….. (5)

Where I = terminal current of the PV cell

I_{pv} = current of PV Cell

$I_{O1} = I_{o2}$ = reverse saturation current of diode

R_s = resistance in series

R_p = resistance in parallel

V_t = thermal voltage of diode

$a_1 = a_2$ = diode ideality factor

N_{pp} = Diodes in parallel

N_{ss} = Diodes in series

Simulation of 50 ×10 Array of Two Diode Model in different irradiation

This gives IV Curves at different temperature levels i.e 25^0 C, 50^0 C and 75^0 C where the voltage value goes to 1600 volts and current upto 80A.

IV Curveof50 ×10 Array of Two Diode Model in different irradiation

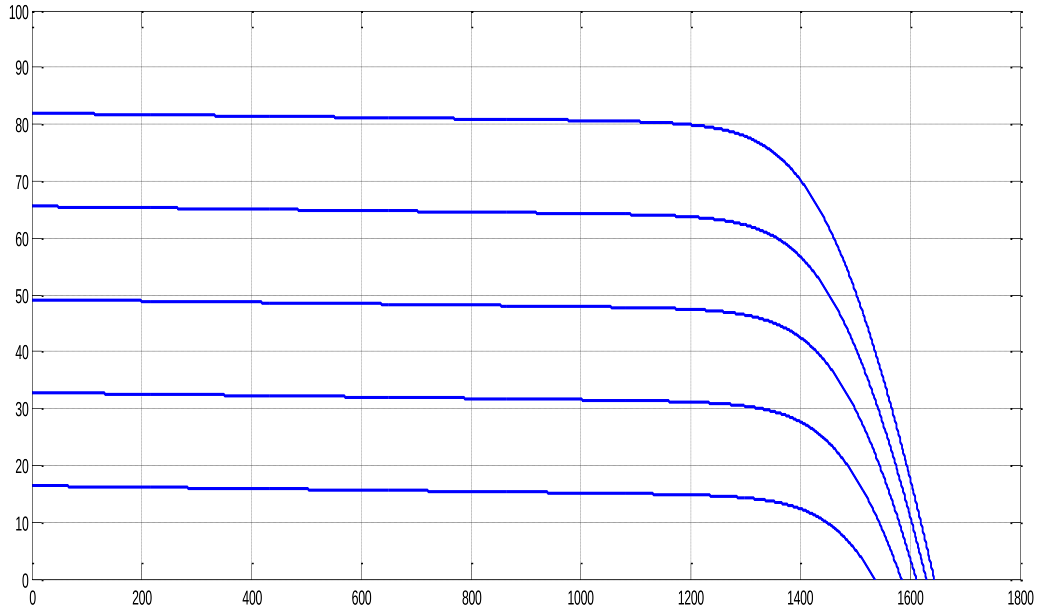

Fig. 3. 1 Current – voltage characteristics curve at irradiation level of 1000,800,600,400 and 200 W/m2

Simulation of 50×10 Array of Two Diode Model in different temperature

In this previous simulation the IV curve is drawn between different values of irradiation i.e G=1000,800, 600,200 W/m^2 which shows that at lower value of irradiation the IV curve shows good results.

IV Curve of50 ×10 Array of Two Diode Model in different temperature

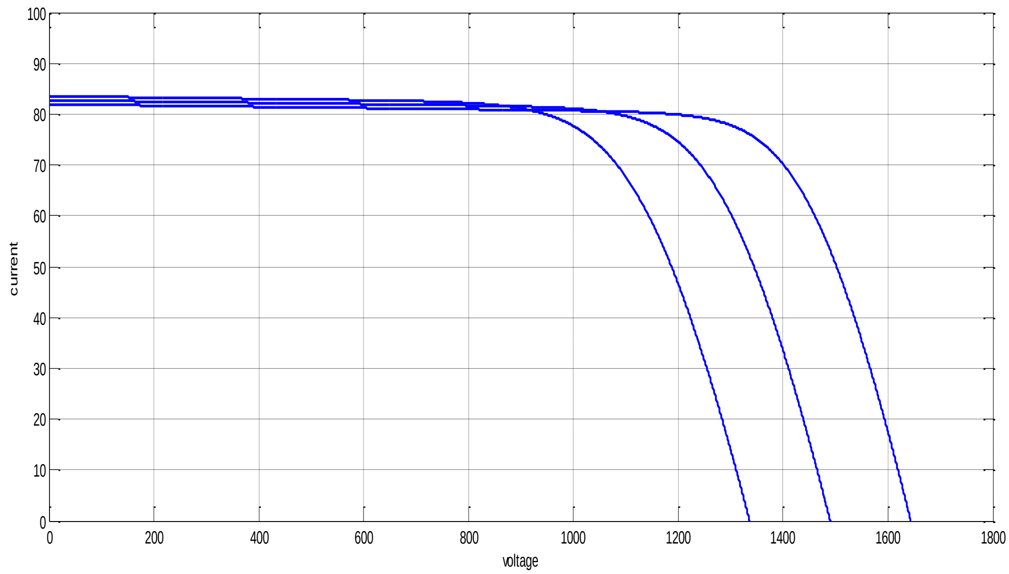

Fig. 3. 2 Current-Voltage characteristics of 50 ×10 array

3.3 PARTIAL SHADING CONDITION

The figure below mentions a model of the connection of diode which are subjected to partial shading condition.In the partial condition the main role is is done by the diodes connected in reverse direction.These are the bypass diodes which plays the major role.Modules that always refer to a typical Solar PV panel consisting of a group of 30 cells connected in series. An antiparallel diode shunting 30/15 cells connected/ignored along with it. Modules that are receiving the same irradiance connected in series form a “substring.” Several substrings that are receiving different irradiance but connected in series form a “string.”Identical strings that are connected in parallel form an “assembly.”(v)Assemblies that are connected in parallel form an “array.” Common use of bypass diodes in antiparallel with the series-connected solar PV panel(SPV) modules can partially mitigate the power reduction due to partial shadow.A 50×10 Array under partial shading condition has been discussed in the figure below.

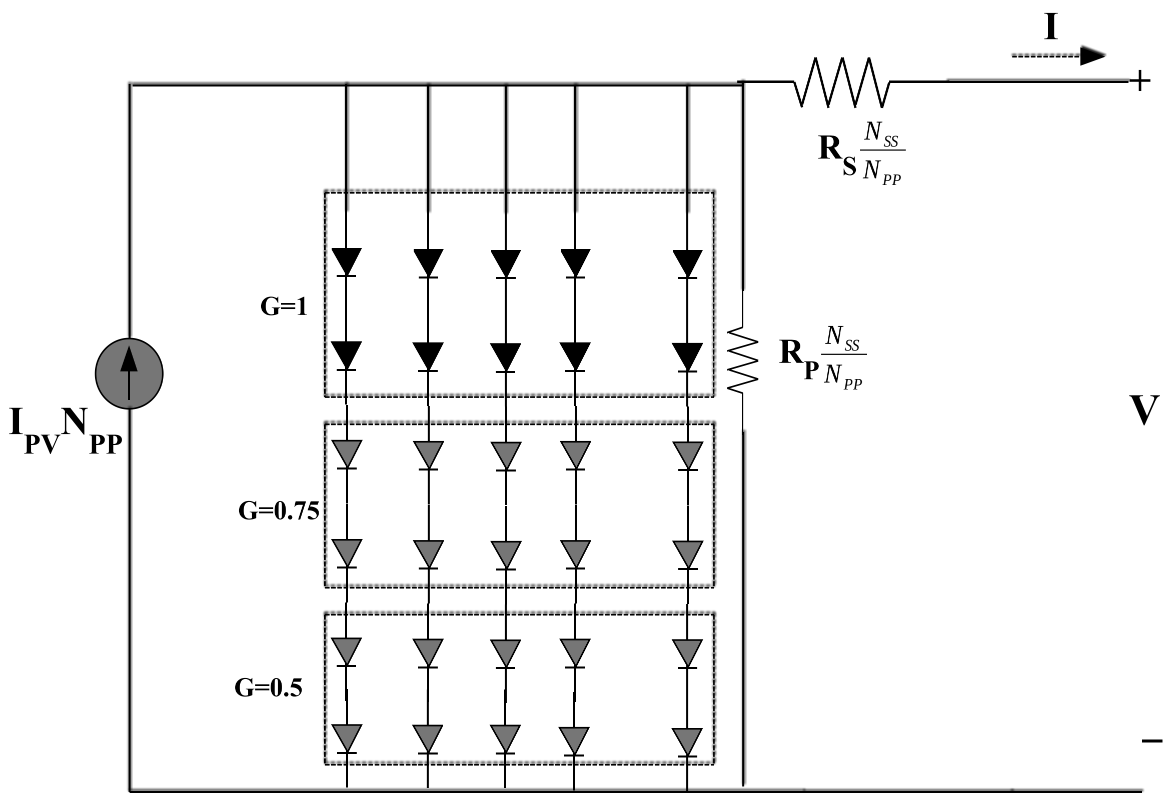

Fig. 3. 3 Current-Voltage characteristics of 50 ×10 array

Here the PV Array of configuration in the order of $N_{SS} \times N_{PP}$ is taken where $N_{SS}=50$ and $N_{PP}=10$.

Fig.3 (c) shows an application of the simulator for a typical partial shading condition[2]. In this example, three shading patterns, i.e. G = 1, G = 0.75 and G = 0.5 are applied to the group of modules and further the resulting I-V and P-V curves for the above shading patterns is also shown.The results are shown in figure 2(c) and 2(d) respectively.

IV CURVE AT PARTIAL SHADING CONDITION AT STC

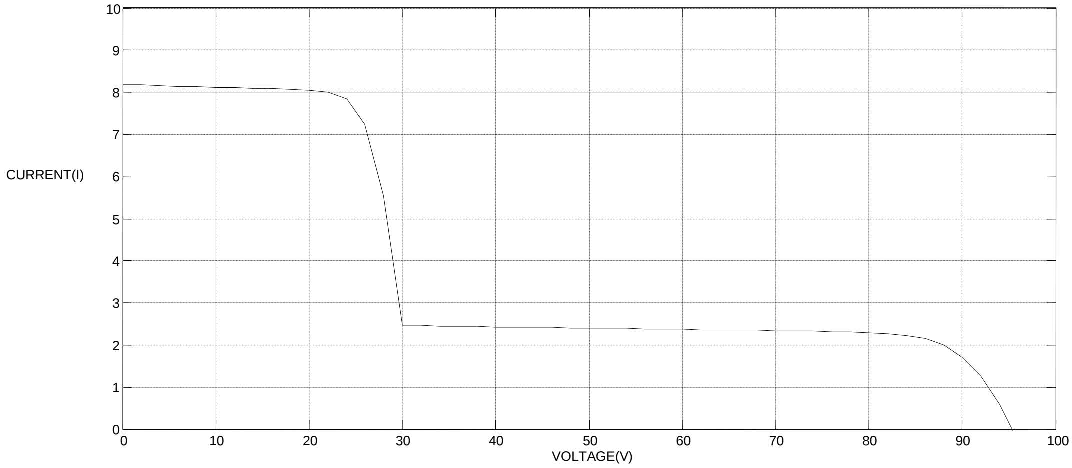

Fig. 3. 4 IV Curve of 3×1 Array

PV CURVE AT PARTIAL SHADING CONDITION AT STC

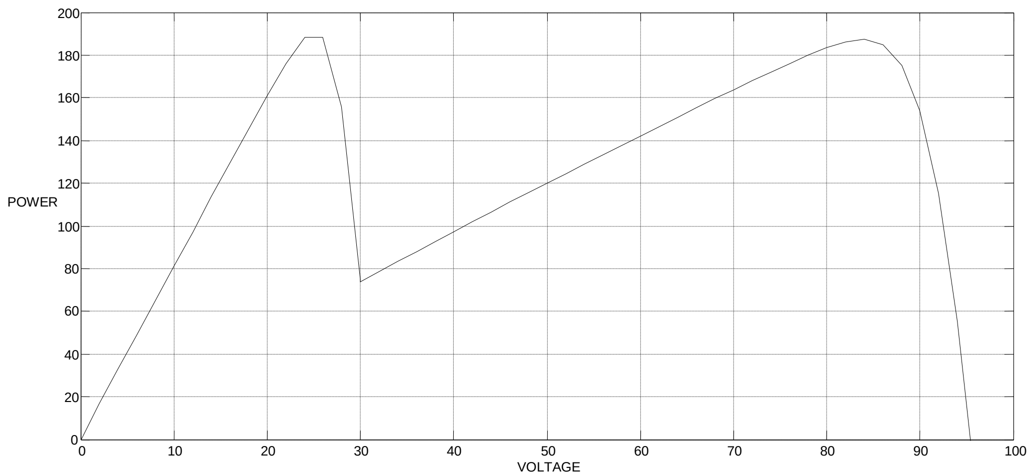

Fig. 3. 5 PV Curve of 3×1 Array 1

3.4 CHAPTER SUMMARY

In this paper, proposition of two diode model is done. To decrease the computational time, the input parameters are made to four and the values of Rp and Rs are estimated by an efficient iteration method. Furthermore the inputs to the simulator[2] are information available on standard PV module datasheets.The simulator supports large array simulations that can be used along with actual power electronic converters. The accurateness of the simulator is verified with five PV modules of different types (multi-crystalline, monocrystalline and thin-film) from various manufacturers. It is observed that the two-diode model is superior to the Rp and Rs models. Furthermore, it achieves good results good results in partial shading condition.The purpose here is to show that the proposed model works better in partial shading condition and the results achieved shows that the two diode model gives optimum results without comprising the threshold value of terminal voltage and current.

CHAPTER4

STUDYOF THE COMPONENTS

4.1 INTRODUCTION

4.2 OBJECTIVE

4.3 BRIEF SUMMARY OF THE COMPONENTS

4.3 (a) WIND SPEED AND DIRECTION SENSOR

4.3(b)SUNTRACKER WITH SOLAR SENSORS

4.3(c)PYRANOMETER

4.3(d) PYRHELIOMETER

4.3(e)DATA LOGGER AND MODEM

4.3(f) TEMPERATURE AND HUMIDITY SENSOR

4.3(g) SENSOR TO MEASURE ATMOSPHERIC PRESSURE

4.4 CHAPTER SUMMARY

4.1 INTRODUCTION

Solar power has got the features of intermittent, random and fluctuation etc. These components would directly affect the output power feature of a PV station, and makes the change rate of PV power output very high. Thus, predicting the solar intensity accurately is very important for designing of a PV station and arrangement of high scale PV generation bases, stability of grid and safety. Along with many other parameters, the overall efficiency of PV module depends on cell temperature, which, in turn, relies on various environmental factors. Environmental conditions such as solar irradiance, wind speed, and wind direction and most importantly, the temperature around the cell affects cell's performance. Although weather prediction and meteorology is a very complex and imprecise science, recent research activities with artificial neural network (ANN) have shown that it has powerful pattern classification and pattern recognition capabilities which can be used as a tool to get a reasonable accurate prediction of weather patterns. This paper presents an application of Artificial Neural Network (ANN) to estimate the Global irradiation of Rourkela,city of Odisha. The trend of temperature all over the Rourkela has been studied over last three months by the help of the setup installed by CWET Chennai. Here the major instrument for estimatimation of global irradiation is the pyranometer.With the help of pyranometer direct irradiation and global irradiation measurement is done.An Artificial Neural Network model based on Multilayer Perceptron concept has been developed and trained using back propagation learning algorithm for prediction. The model was tested and trained using two months data of global irradiation given by the official website of CWET. The accuracy of the model was calculated on basis of Mean Square Error.

Before going to describe how the short time prediction of solar irradiation is done,we need to know certain aspect of the tool we are using in measurement of the irradiation.The pyranometer installed in the setup is the basic tool which helps us to provide information about the insolation or irradiation value.

Here is the pictorial diagram of the suntracker with sensors installed on the rooftop of the Electrical department,NIT Rourkela.

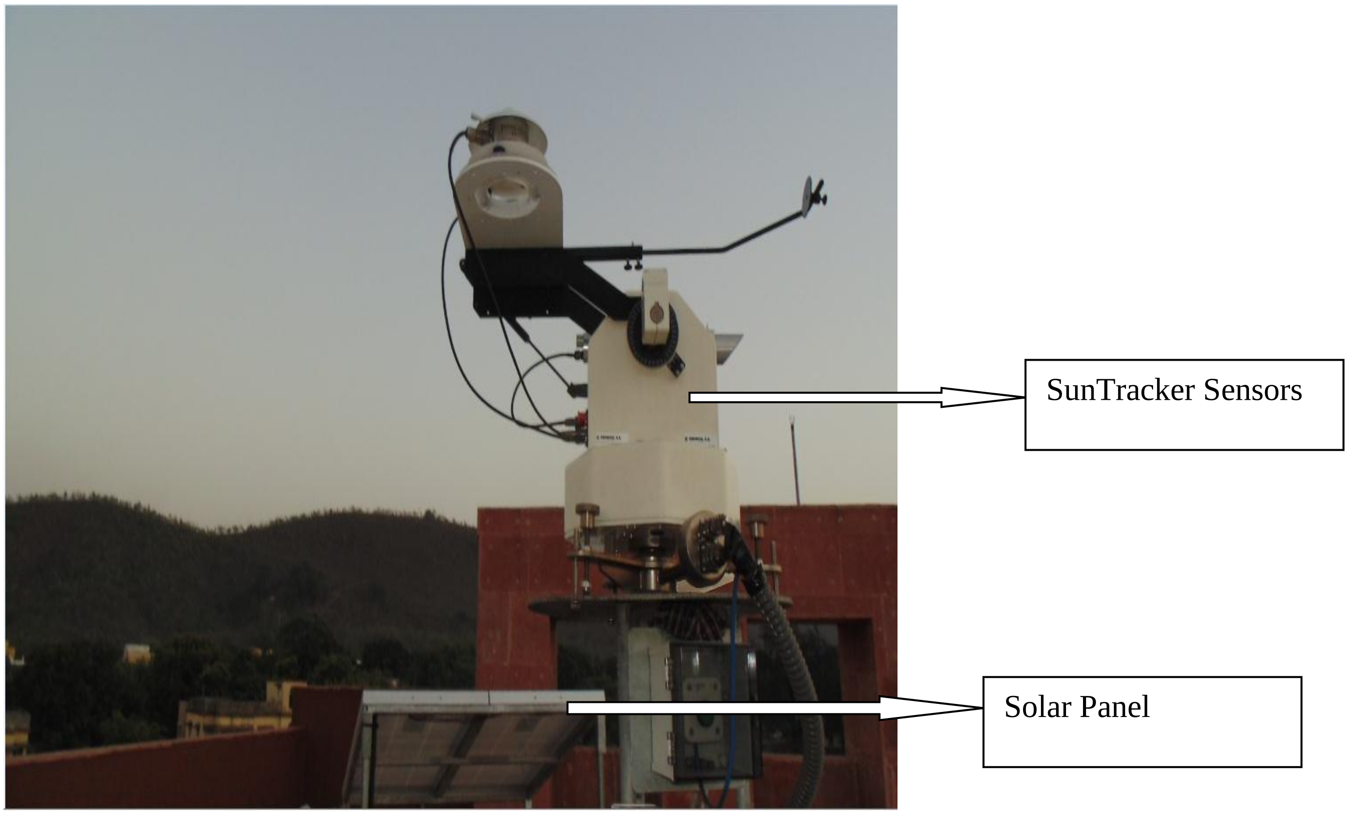

Fig.4. 1 Solar Radiation Tracking System

4.2 OBJECTIVES

- In order to study the components in thorough manner the components of the set up are studied.

- To get the idea about the components which help us to know how the irradiation is tracked.

4.3DESCRIPTION OF THE COMPONENTS

The suntracker with sensors not only comprises the sensors , pyranometers; but also it consists of ultrasonic wind sensor, rain gauge, pressure sensor, GPS, data logger, GPRS antenna, etc.

1.WIND SPEED AND DIRECTION SENSOR

Two axis ultrasonic wind sensor.

Range:- 0-70 m/s

Wind Direction:-0 -360^0

Resolution :Wind Speed : 0.1 m/s

Accuracy : Wind Speed:0.1 m/s

Wind Direction:1^o

Fig.4. 2 wind sensor 1

2.SUNTRACKER WITH SOLAR SENSORS

Fig.4. 3 Suntracker and solar sensor

DESCRIPTION

The SunTracker is of a bi axis fully mechanical solar tracker to line up solar radiation instruments with the normal incidence of the sun, from any location on the earth's surface.It includes a bi axis mechanical device with two stepping motors,managed by an electronic module combined with two stepping motors, controlled by an electronic module combined with our data with the datalogger , Model METEODATA. The Sun Tracker-3000 allows to build up one or two pyrheliometers for the capacity of the direct solar radiation, as well as one or two pyranometers having an voluntary support and shading assembly, for the measurement of both global and diffuse radiation.

FEATURES

- The function of sun tracker is done with the help of METEODATA logger.The SunTracker with the METEODATA logger allow to profit all the unique advantages offered by our versatile unit, as indicated below. Unattended and automatic operation.

- Remote control of the solar tracker by means of the same communication network used with the data logger (GSM/GPRS, 3G, satellite, Wi-Fi, Wi Max, etc.).

- SMS fear messages are transmitted automatically in case of low battery or vandalism. (GSM/GPRS optional modem is required for the logger).

- Immediate calculation of the sum elevation and azimuth with absolute positioning each second. Clock synchronization via Internet time base or by an optional GPS receiver integrated with the data logger.

TYPICAL CONFIGURATION

The monitored solar radiation sensors and local running algorithms at the data logger are :-

1. Global, Diffuse and Direct solar radiation sensors readings.
2. Accurate GPS fixes.
3. Astronomical sun tracking algorithm.
4. Digital Signal Processing Functions.

PYRANOMETER

Pyranometer is the equipment which primarily along with the solar sun tracker system helps to record the data of direct radiation and global radiation.

- The pyranometer designed by Geonica S.A is a solar radiation sensor that meets and exceeds the ISO-9060 Standard performance mandate for a First Class pyranometer, specific to solar energy test applications.
- The pyranometer here is supplied standard with a laboratory characterized directional response report, built-in case temperature sensor, and low power resistive heater for dew/frost prevention. Ideally suited for solar renewable systems performance and solar energy resource validation, the instrument used is the first (COTS) i.e. Commercial Off-The-Self pyranometer of its kind meeting the ISO-9060. First Class performance mandate for solar energy test

Fig.4. 4 Pyranometer

The other sensors of the setup are temperature and humidity sensor, rain gauge, Barometer etc. The pictorial diagram of these two instruments are given below.

PYRHELIOMETER

Fig.4. 5 Pyrheliometer

Features:-

- The apparatus pyrheliometer helps to measure direct solar radiation.
- The model given by Geonica is a research grade standard incidence direct solar irradiance sensor.
- It is suitable for mounting and tracking operation, the GEO-DR01 is intended for short-wave direct solar irradiance measurement of the sun.

DATA LOGGER AND MODEM

Fig.4. 6 Data logger

- Data logger is used for receiving storing and transmitting data to CWET(Centre for wind energy Technology) Chennai.
- The display is Alphanumeric display (LCD) 4x20 characters, with integrated 18 key membrane keypad.
- It has got an internal memory for storage of data and a GPRS antenna for communication.

TEMPERATURE AND HUMIDITY SENSOR

Fig.4. 7 Temperature sensor

- As the name suggests the sensor give the precise data of the temperature and relative humidity of Rourkela .
- It is made up of naturally ventilated multiplate radiation shield (and sensor support) to be used with relative humidity and air temperature probes

SENSOR TO MEASURE BAROMETRIC PRESSURE

Fig.4. 8 Pressure Sensor

Barometric pressure sensor.

- **Range:** 500 - 1100 hPa.
- **Accuracy:** ± 0.2 hPa at 25ºC .

4.4 CHAPTER SUMMARY

In this chapter we got a descriptive idea about the products of the set up procured by CWET Chennai.The features of the main components ,that are the pyranometer,pyrehliometer wasStudied and we got the idea of how the global and direct radiation is trapped.Also it helped us to gain knowledge on how the whole process is carried out ,that is the detection of solar irradiation and sending the information through GPS communication.

CHAPTER5

INTRODUCTION TO ARTIFICIAL WAVELET NEURAL NETWORK

5.1 INTRODUCTION ANN

5.2 OBJECTIVE

5.3 NEURAL NETWORK TOPOLOGY

5.4 BREIF SUMMARY ON AWNN

5.4(a) WAVELET TECHNIQUE

5.4(b) LEARNING ALGORITHM

5.4(c) CHAPTER SUMMARY

5.1 INTRODUCTION TO ANN

Many attempts have been made to model performance parameters of forecasting process using ANN.To obtain an improved ANN model, generally ANN architectures, learning/training algorithms and nos. of hidden neurons are varied, but the variation so far has been made in a random manner. So here a full factorial design has been implemented to achieve the optimal of above for modelling.

5.2 OBJECTIVE

- Since the previous methods of forecasting were statistical or regression based analysis, so a definite method has to be made in order to predict the irradiation. Hence we are going for this kind of forecasting technique.
- To make the prediction of solar insoltaion accurate the artificial wavelet neural network is implemented here.

5.3NEURAL NETWORK TOPOLOGY

ANN refers to the computing systems whose fundamental concept is taken from analogy of biological neural networks. Many day to day tasks involving intelligence or pattern recognition are extremely difficult to automate, but appear to be performed very easily by animals. The neural network of an animal is part of its nervous system, containing a network of specialized cells called neurons (nerve cells). Neurons are massively interconnected, where an interconnection is between the axon of one neuron and dendrite of another neuron.This connection is referred to as synapse. Signals propagate from the dendrites, through the cell body to the axon; from where the signals are propagate to all connected dendrites. A signal is transmitted to the axon of a neuron only when the cell 'fires'. A neuron can either inhibit or excite a signal according to requirement. Each artificial neuron receives signals from the environment, or other artificial neurons, gather these signals, and when fired transmits a signal to all connected artificial neurons. Input signals are inhibited or excited through negative and positive numerical weights associated with each connection to the artificial neuron. The firing of an artificial neuron and the strength of the exciting signal are controlled via. a function referred to as the activation function. The summation function of artificial neuron collects all incoming signals, and computes a net input signal as the function of the respective weights and biases. The net input signal serves as input to the transfer function which calculates the output signal of artificial neuron. Figure 4.1 (a) and (b) shows the analogy between biological and artificial neurons and the analogy has been shown in parametric terms in Table 4.1.However ANN s are far too simple to serve as realistic brain models on the cell levels, but they might serve as very good models for the essential information processing tasks that organism perform. Now in figure 4(b) the connection of the artificial neural network is given which is compared with the neuron anatomy of living beings.

5.3 BRIEF SUMMARY ON AWNN

5.3(a) WAVELET TECHNIQUE

The first step towards forecasting solar radiation values is to go for normalization process.The data has been normalized using normal distribution method.The data lies in the range of -1 to1.Then comes the decomposition method; where the wavelet is decomposed using daubechies method.

GLOBAL RADIATION

The data collected in order to be normalized is the global radiation value as given by CWET Chennai[12].A typical graphical representation of the global radiation as given by CWET is given below.

In practice many types of wavelet transform has been applied.Such asHaar,Daubechies, The Dual-Tree Complex Wavelet Transform etc. Among all these transforms Daubecheis gives the Least mean square error. Hence it is chosen for decomposing the normalized data. In order to find out fine discrete samples from the implicit mother wavelet function based on the recurrence relation. The advantage of Daubechies is the flexibility as its order can be controlled to suit specific requirement. Again among the different analysis db4 is taken into account as it best suits the specific requirements. In the DWT while decomposing a signal maximum N-1 detail level and1 approximate or smooth level can be found out.Here the signal is decomposed maximum upto third level as db4 method is implemented.

A pyramid diagram has been given below in the fig4(c) which shows the decomposition process upto level 2.It is clear that decomposition is the process of passing the signal through series of low pass filter and high pass filter .The low pass filter gives the smooth coefficient whereas the high pass filter gives the detail coeffient[11].

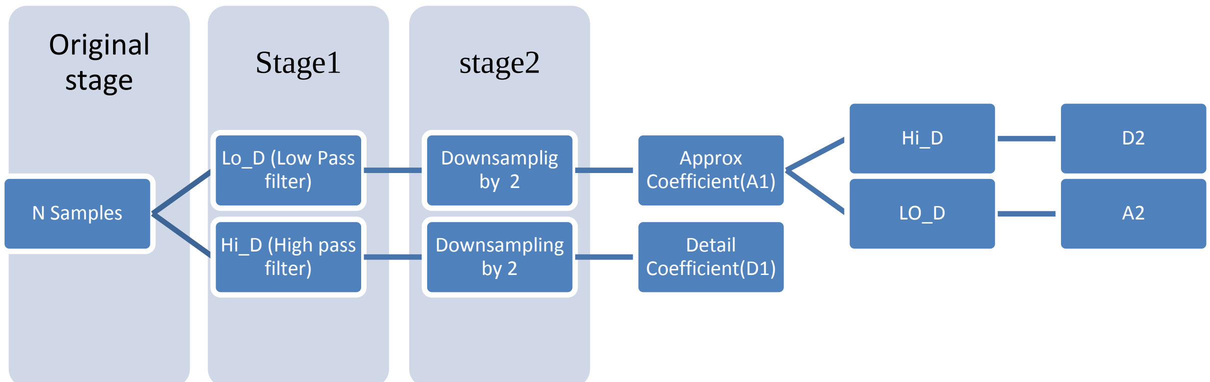

Fig.5. 1 decomposition in dwt

Here in order to get smooth and detail signal the wavelet is passed through wavelet and scaling filters. This method is repeated unless and until the desired scaling level reaches.Where, X represent input data samples,D1 and A1 are detail &smooth coefficients at 1^{st} level of decomposition,D2 and A2 are details &smooth coefficients at 2^{nd} level ,etc.

In distinct domain, if there is some factual valued finite series which can be defined as $X = [X_1, X_2, \ldots X_N]^T$,where $N(=2^j)$ shows the span of the series, then the DWT of X is as follows:-

$$W = \mathcal{O}X \tag{6}$$

Where $\mathcal{O}X = \begin{bmatrix} \mathcal{O}_1 \\ \mathcal{O}_2 \\ \mathcal{O}_3 \\ \vdots \\ \mathcal{O}_N \end{bmatrix} X$, $W = \begin{bmatrix} W_1 \\ W_2 \\ W_3 \\ \vdots \\ W_N \end{bmatrix}$

W is defined as a column vector of length N whose nth element is the nth DWT coefficient$W_n$and $\mathcal{O}$is $N \times N$ real-valued matrix defining the DWT and fulfilling orthonormal condition

$\mathcal{O}^T\mathcal{O} = \mathrm{I_N}$.Vector Xcan also be expressed as an addition of$\mathrm{j} + 1$ vectors of length N as

$$\mathrm{X} = \mathcal{O}^T\mathrm{W} = \sum_{\mathrm{j}=1}^{\mathrm{J}} \mathcal{O}_j^T\,\mathrm{W_j} + \mathrm{v_J^T V_J} = \sum_{\mathrm{j}=1}^{\mathrm{J}} \mathrm{D_j} + \mathrm{S_J} \qquad (7)$$

where the jth factor signal is given by$D_j$and the last vector isreferred as approx signal$\mathrm{S_J}$which leads to the MRA analysis.

5.3(b)LEARNING ALGORITHM

As we know that there are two types of network satisfying the ANN topology i.e 1) Feed Forward Network 2) Recurrent Network. The multilayer Neural Network applied here refers to feedforward network. A single neuron is not enough to solve real life problems (any linear or nonlinear computation) efficiently, and networks with more number of neurons arranged in particularsequences are frequently required. This particular ways /sequences of arrangement of neurons are coined as neural architecture. The sequences of arrangements of neurons determine how computations will proceed and also responsible for the effectiveness of the model. MLP utilizes a supervised learning technique called back propagation for training the network.

The feature that makes a multilayer perceptron diverse is that each neuron uses a nonlinear activation function in which the frequency of action potential, or firing, of biological neurons in the brain. This function is modeled in several ways. Here sigmoidal function is used as the activation function. Sigmoidal function is described as follows.

A sigmoidal function being 'S' in shape is described as- S (t)= $\frac{1}{1+\mathrm{e}^{-\mathrm{t}}}$ .In the figure below a multi Layer perceptron topology is shown.

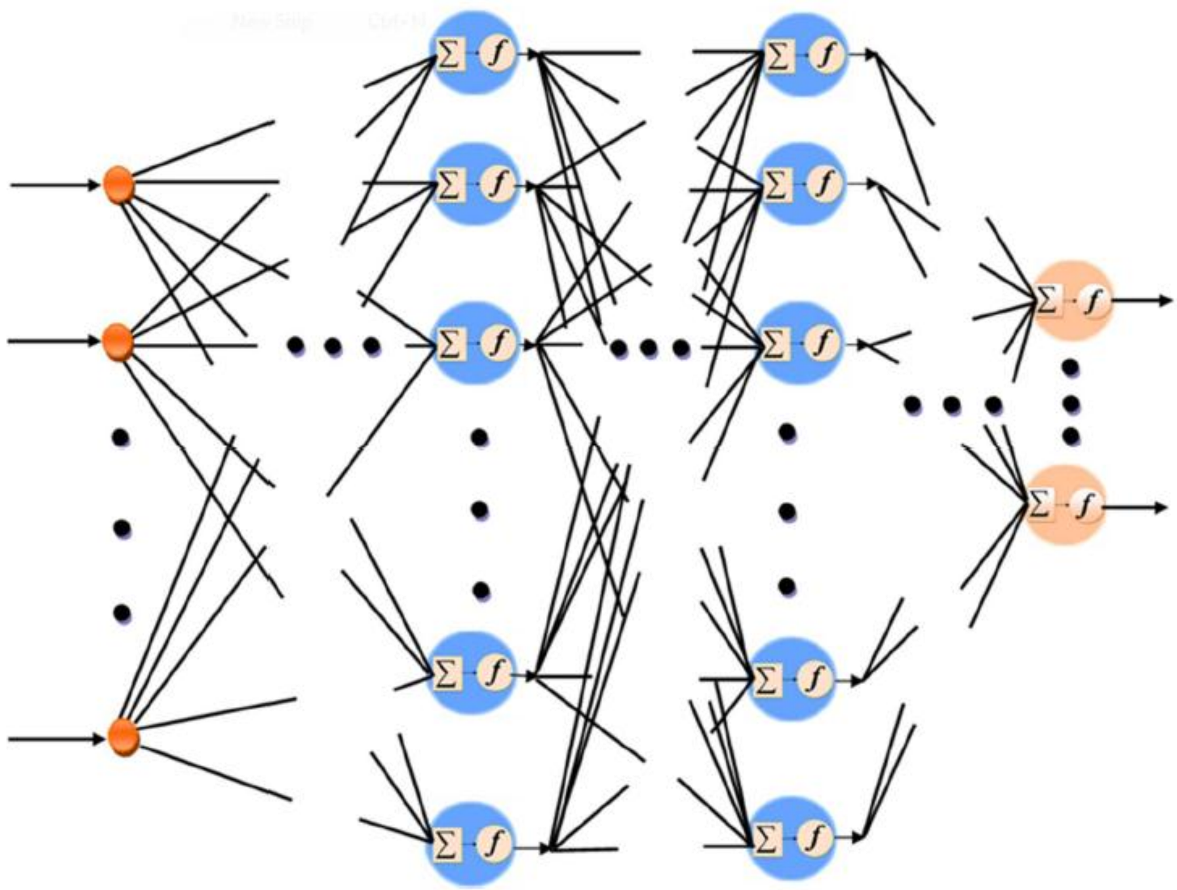

Fig.5. 2 Multilayer Perceptron

Here the Artifial wavlet neural network includes a definite procedure .Weights Y, V are initialized between the input node to hidden and hidden to output neurons respectively.

Step 1. The hourly wind speed data consisting of 450 samples has been decomposed to the 3rd level using ‘db4’.

Step 2. Input pattern fed to the Wavelet Neural Network. The components of individual pattern give the values of continuous lag hours of available decomposed signal.

Step 3. A Daubechies is chosen as mother wavelet in wavelet layer(hidden layer).

There are many wavelets in Daubechies family. Hence according to the MSE error given here db4 method has been choosen.

Step 4.In case of mapping the input output,it is required to have a direct connection from input layer to output layer. If we need to connect the linear input-output coherence, it is customary to have added straight connection from the input layer to the output layer and there is is no point in using wavelets for reconstructing linear term. The output of AWNN, representing the hour-ahead prediction of the decomposed signal, can be computed .

$$\mathrm{Y} = \sum_{j=1}^{m} w_j z_j + \sum_{i=1}^{n} v_i u_i + g \quad (8)$$

Step 5. In this step network is trained. The training algorithm [17] used here is the back propagation algorithm. This algorithm is used in order to train the wavelet neural network. Where training is purely base on minimizing the cost function also call mean square error(E) is shown as

$$E = \frac{1}{2p}\sum_{k=1}^{p}[e(k)]^2 \quad (12)$$

And

$$e(k) = y^d(k) - y(k) \quad (9)$$

Where $y(k)$ is the output of thed $y^d(k)$ is the output desired for a given kth input pattern. The updation of the liberated parameter is specified as

$$\Gamma(k+1) = \Gamma(k) + \eta\Delta\Gamma(k) + \alpha\Delta\Gamma(k-1) \quad (10)$$

Where Γ is a random unknown free variable, η & α represents learning and momentum parameters, respectively.

All free parameters are updated by

$$\Delta w_j = ez_j,\ j \in m \quad (15)$$

$$\Delta v_i = eu_i, i \in n \quad (16)$$

$$\Delta g = e \quad (17)$$

$$\Delta a_{ij} = \frac{ew_j z_j}{a_{ij}}[\frac{u_i - b_{ij}}{a_{ij}}]^2 \times [3 - [\frac{u_i - b_{ij}}{a_{ij}}]^2]e^{-0.5[(u_i - b_{ij})/a_{ij}]^2}$$

$$\Delta b_{ij} = \frac{ew_j z_j}{a_{ij}} [\frac{u_i - b_{ij}}{a_{ij}}] \times [3 - [\frac{u_i - b_{ij}}{a_{ij}}]^2] e^{-0.5[(u_i - b_{ij})/a_{ij}]^2} \qquad (19)$$

Step 5:After training the signal was tested and finally the signal is reconstructed using original and new predicted approximation & detail coefficients. The reconstructed signal contains the original samples plus 24 hours predicted wind speed data.

5.4 RESULTS AND DISCUSSIONS

First of all before going to perform the decomposition on e should know which type of mother wavelet be taken in order to perform the AWNN .Therefore some comparisons in the value of MSE is found out in order to decide the best suitable mother wavelet.

Table 4(a) MSE values of different types of Wavelet technique

Type of Wavelet	Value of MSE
db1	0.0193
db2(Haar)	0.0025
db4	0.0018

Table 5. 1 Types of DWT Method

It is clear from the above table that choosing db4 will be appropriate choice.Hence the mother wavelet is db4 here.

Now the results of decomposed value in db4 method is given as follows

LEVEL 1 DECOMPOSITION

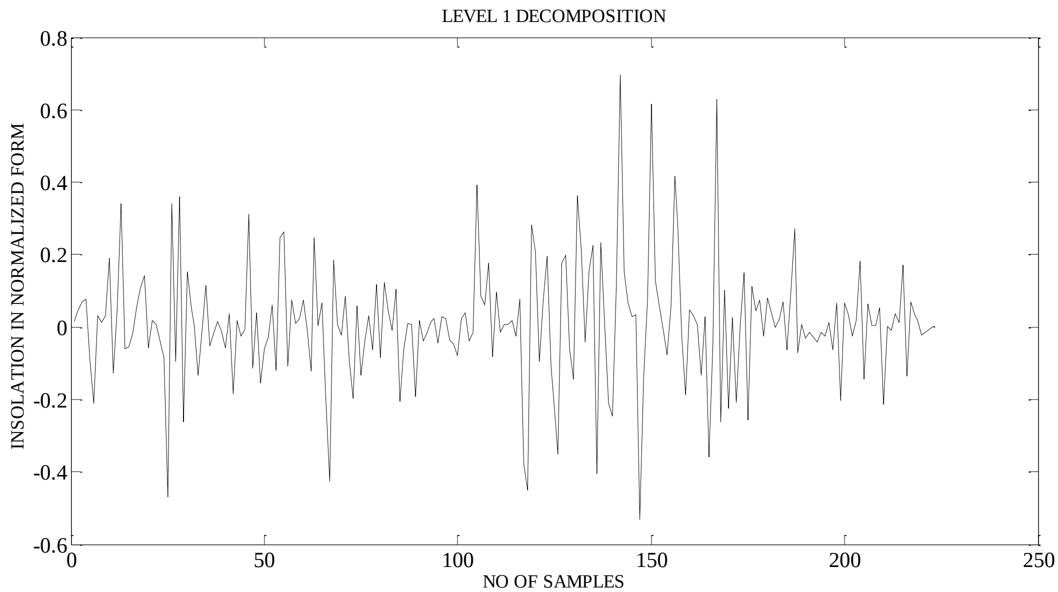

Fig.5. 3 Level1 decompostion 1

<u>LEVEL2 DECOMPOSITION</u>

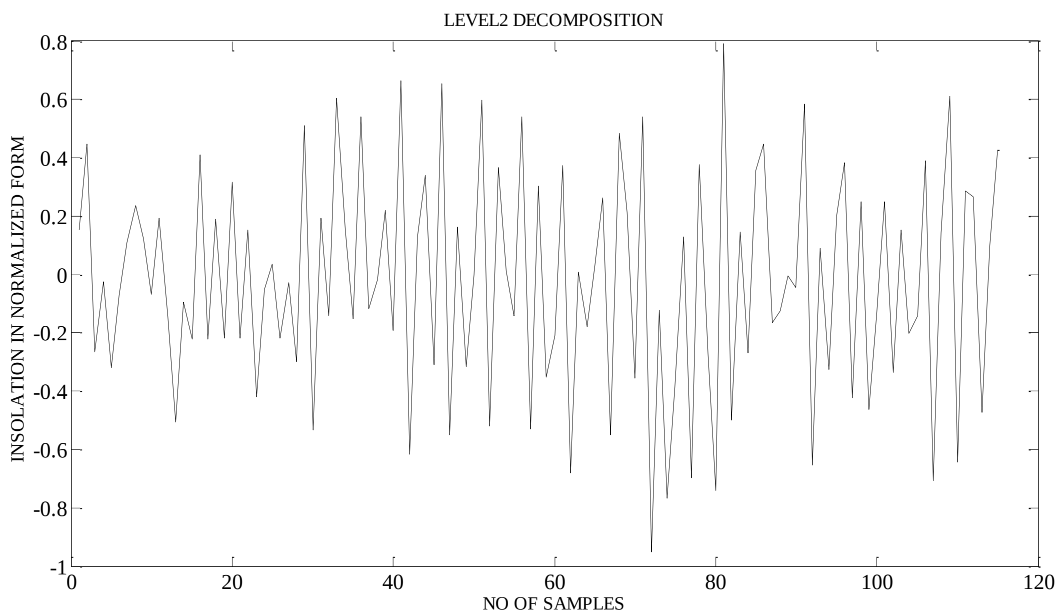

Fig.5. 4 Level2 decompostion

LEVEL3 DECOMPOSITION

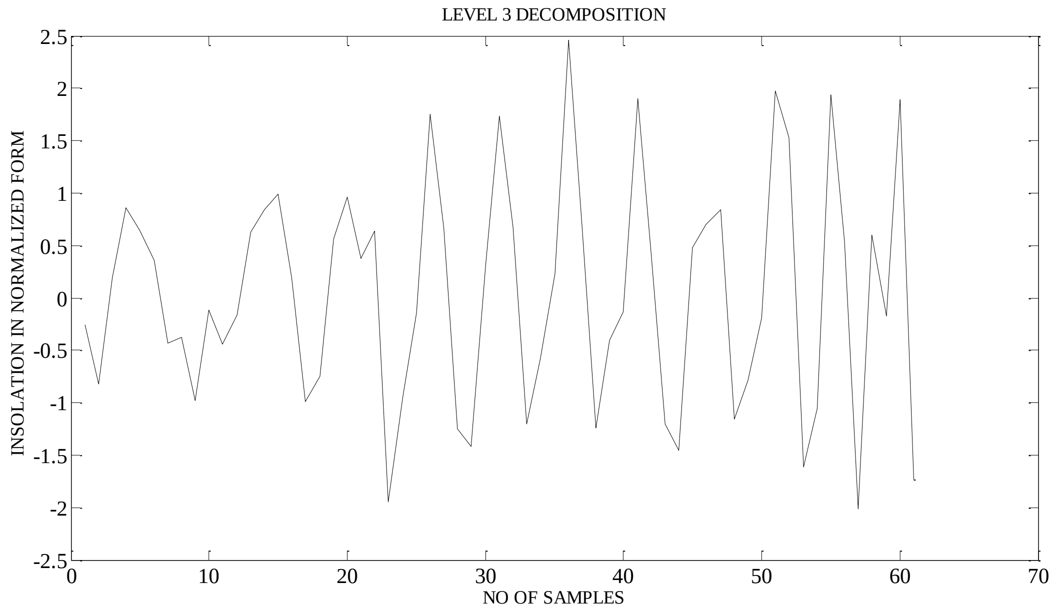

Fig.5. 5 Level3 decompostion

Now after training the individual MSE of different level is given by

MSE OF LEVEL1(D1)

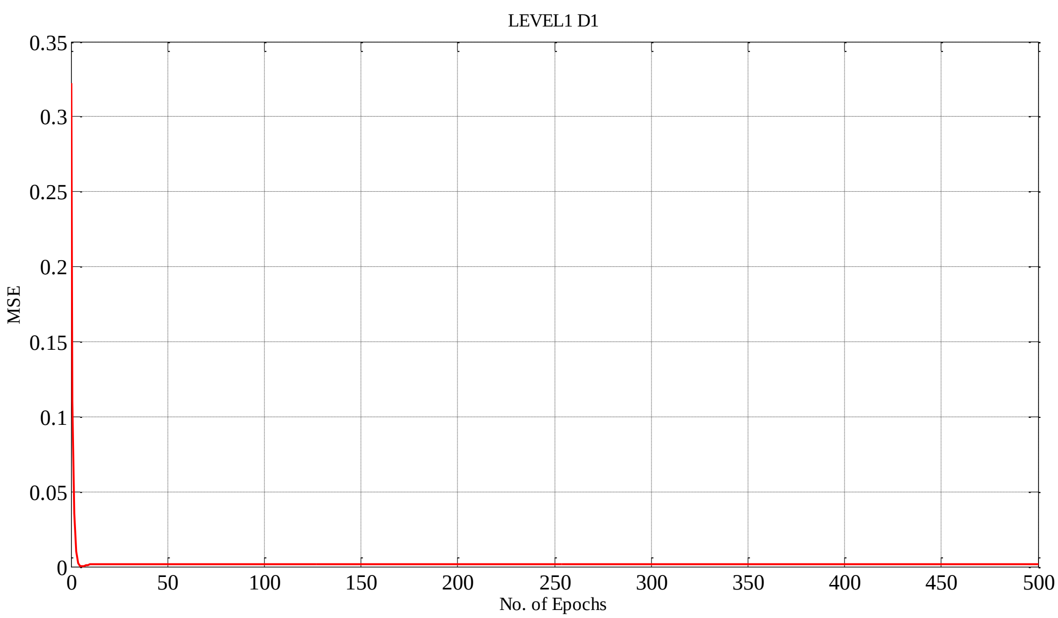

Fig.5. 6 MSE plot for level1

In the MSE plot of figure 4(h) the mean square error lies in the range of 0 to 0.0015.

MSE OF LEVEL2(D2)

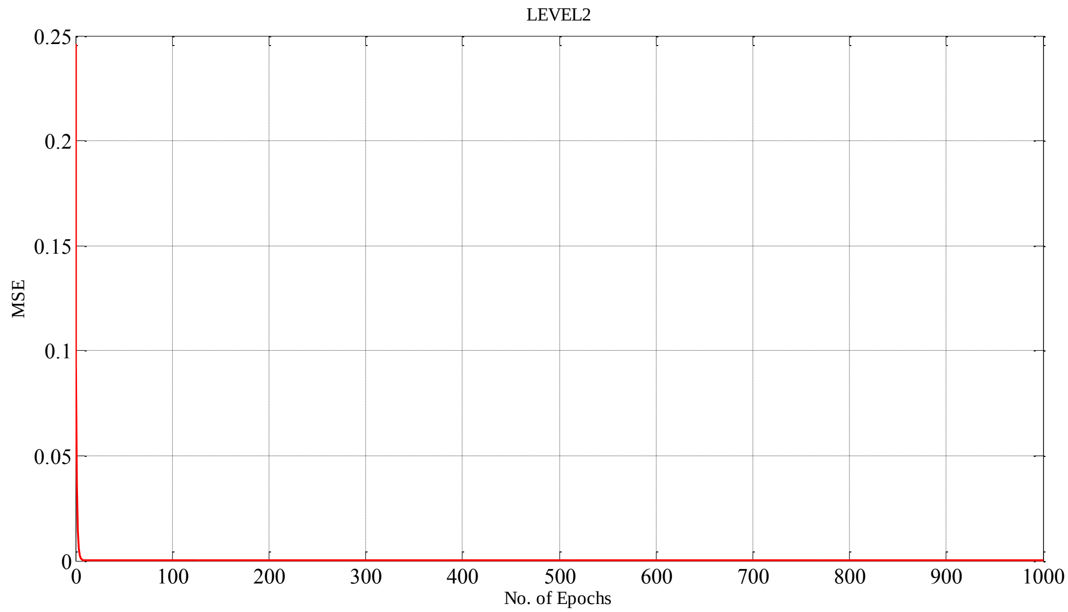

Fig.5. 7 MSE plot for level 1

In the MSE plot of figure 4(h) the mean square error lies in the range of 0 to 0.001.

MSE OF LEVEL3 (D3)

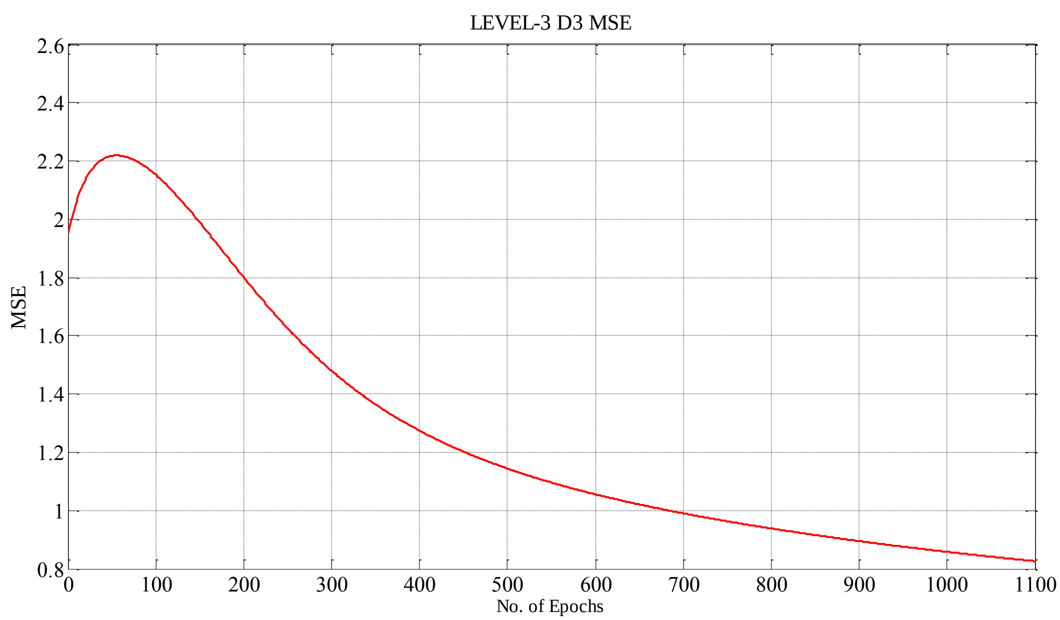

Fig.5. 8 MSE plot for level 3

The figure below show a example window of global radiation forecast using MRA based AWNN. The performance evaluation using MRA based AWNN method is illustrated in figure 4(k).The forecast model here provides information for 24 –hour-ahead prediction over the entire period.

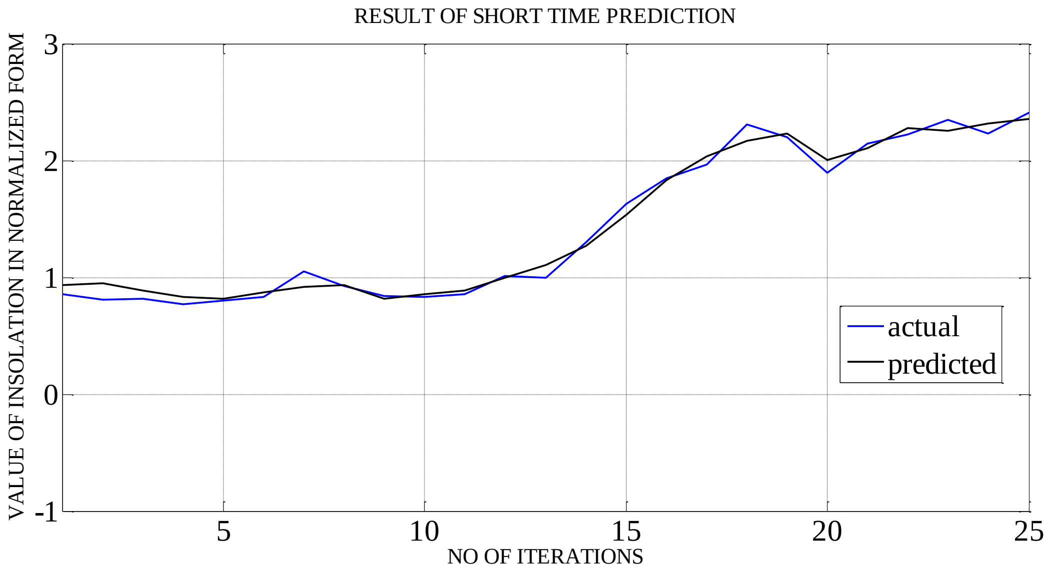

Fig.5. 9 Data predicted for 24-look-ahead -hour

5.5 CHAPTER SUMMARY

The adopted neural network gives short term prediction of daily global radiation. Based on the simplified PV model [9] using forecasted data is estimated and it shows fine results. The data which has been predicted is viable for planning and operation of PV. Various structure of wavelet-neural network could lead to big margin of distinction between predicted results. Here MRA based technique is used in order to predict the global radiation value Choosing proper wavelet improves the prediction process.In the thesis, a two-stage method has been developed in order to know global radiation upto 24 look-ahead hours. The result of short time prediction strategy proves the effectiveness of purposed approach.

CONCLUSIONS AND FUTURE WORK

- The two diode model approach described here gives the same result as the single diode without neglecting the recombination losses.
- Here in lower irradiation value the performance of two diode model is better than existing single diode model.The value of open circuit voltage (V_{OC}) lies in the range of 32 to 33 volt.
- Also the proposed model achieves good results in partial shading condition.
- Although the solar insolation is intermittent ,its prediction is done in AWNN method.
- Here the forecasting is done for 24-hr-ahead which gives mean absolute error within range of 2.8 to 2.9 percent.The data obtained will be helpful to decide the installation of PV Station in the next five years.

SUGGESTIONS FOR FUTURE SCOPE

In future the two diode model can be connected to power electronic converters along with a controller algorithm in order to provide energy to the grid.

Various structures of wavelet –neural network would lead to huge amount of difference in between predicted results. Considering proper network can improve the accuracy of forecasting. Here we have implemented AWNN in with 10-2-1 pattern. In future more patterns with different kind of AWNN technique will lead to precisely forecast the future value.

The change of lighting has deep impact on temperature, cloud thickness, season etc.Also the average power and average energy effect will be taken into account while prediction of the solar insolation value.

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