Solar Power Forecasting Using Artificial Neural Networks

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Abstract—**In recent times, large scale commercial wind and solar energy production make up a increasingly larger fraction of the total power generating capacity of the grid. Compared to traditional thermal or hydel plants, these are a consistently variable source of electric power where the operator has little control over the power input to the system. This affects both the stability as well as the economic scheduling of energy generation and poses increasingly difficult problems in grid management. Although most of the uncertainty in the grid occurs due to load behaviour of the system, it can still be a worthwhile goal to limit the energy variablility. Solar energy in particular follows predictable patterns that can be modeled easily. Solar power forecasting is therefore becoming a prominent topic in modern electrical engineering. Modern forecasting methods rely on Machine Learning which provides systems the ability to automatically improve from experience without being explicitly programmed. This allows a power system to adaptively learn the patterns in solar fluctuations. This undergraduate project investigates an ANN based model for the forecasting of solar energy by photovoltaic power plants.**

I. INTRODUCTION

A. Problems with solar power

India has decided to phase out fossil-based energy generation and adopt green energy and as a result has emerged as the second most attractive market for renewable energy equipment in the world. India has already achieved 23 GW of solar installations with another 40 GW of solar power being at different stages of bidding and installation. According to a report by Green-Peace, the country could make renewable resources the backbone of its economy by 2030, curtailing carbon emissions without compromising its economic-growth potential. However, the use of renewable energy sources such as solar comes with their own unique challenges. While these offer many environmental advantages over fossil fuels for electricity generation, the energy produced fluctuates with changing weather conditions. Photovoltaic (PV) energy generation directly depends on the amount of solar global irradiation incident on the panels which variable over both short and long term intervals. The long term part of the fluctuations are deterministic and caused by the revolution of the Earth around the sun i.e. the seasonal cycle. In addition, the short term uncertainty is due to unexpected changes due to the presence of clouds, which randomly block the Sun's rays. As a tropical country, India has high insolation, but also has a climate pattern that includes monsoon season. If it is overcast or cloud cover present during the day, then the photovoltaic cells are unable to produce electricity, or will do so inefficiently. This inherent variability poses issues with grid reliability and the expenses associated with operating the solar units and photovoltaic forecasting is a method used to address this issue.

B. How can Solar Power Forecasting help?

Energy plants have hot reserves in case of large upsurges in load demand or an unexpected drop in power generation. The application of forecasting is to reduce the need for having high number of hot standby reserves and thus reduce operation costs. Also energy plant operators and grid management systems need accurate forecasts of energy production in order to have economic scheduling of renewable and fossil fuels. Historically, almost all electricity generation decisions were made a day ahead of time. Now, many grid operators can adjust generation every five minutes in response to changes in electricity demand and wind output. While the capability to adapt will vary from grid to grid, the application of a solar forecast largely remains the same. Traditionally, power forecasts typically were derived from numerical weather prediction models, but currently machine learning techniques are increasingly being used in conjunction with the numerical models to produce more accurate and adaptive forecasts . The goal of this undergraduate project is to discover which machine learning techniques provide the best short term predictions of solar energy production.

C. Forecasting Approaches

The solar power forecasting can be performed by several methods; the two big categories are the cloud

imagery combined with physical models, and the machine learning models. Machine learning is a subfield of computer science in which a model can solve problems which are impossible to be represented by explicit algorithms. The machine learning models find relations between inputs and outputs even if the representation is impossible; this characteristic allow the use of machine learning models in many cases, for example in pattern recognition, classification problems, forecasting problems. In global horizontal irradiance forecasting the models can be used in three different ways:

- structural models which are based on other meteorological and geographical parameters
- time-series models which only consider the historically observed data of solar irradiance as input features
- hybrid models which consider both, solar irradiance and other variables as exogenous variables

II. COLLECTION OF SOLAR IRRADIATION DATA FOR MACHINE LEARNING

For training a machine learning model it is essential that we have enough data in the specified domain. Machine learning algorithms learn from data. It is therefore critical to choose the right data and prepare them properly to enable the problem to be solved effectively. Moreover, if we need to predict the solar power generation in Varanasi, it is best that we ue the data collected in Varanasi. For this purpose, we implemented a solar data acquisition system and deployed it in order to gather sufficient data for the machine learning model using a Pyranometer. Although due to time constraints, we were only able to collect enough data for validation purposes.

III. SOLAR IRRADIATION

There are many ways to measure solar irradiation depending on the way the measuring instrument is oriented. The most important measures of solar irradiation are listed int the following table. Forecasting of global horizontal irradiance (GHI) is the first and most essential step in most PV power prediction systems. This is because GHI is the measure corresponding to solar power generation in fixed PV installations. Global Horizontal Irradiation (GHI) combines Direct Normal Irradiation (DNI) and Diffuse Horizontal Irradiation (DHI). Both are linked in the formula for GHI:

$$GHI = DHI + DNI.cos(\theta) \qquad (1)$$

(where theta is the solar zenith angle)

| Type	Description	Instrument
Global Horizontal Irradiation (GHI)	The total radiation received by a horizontal surface. GHI value includes both DHI and DNI. Application: • Fixed PV installations.	• Pyranometer (horizontal)
Global Tilted Irradiation (GTI)	The total direct and diffuse radiation received a tilted surface. Application: • Fixed PV installations.	• Pyranometer tilted in the same angle as the solar module
Direct Normal Irradiation (DNI)	It is the amount of solar radiation received per unit area by a surface that is always held perpendicular to the direction of the sun at its current position. Application: • Concentrated Solar Power (CSP) • Concentrated PV (CPV) • Fixed PV installations	• Pyrheliometer installed on a sun tracker • Rotating Shadowband Irradiometer
Diffuse Horizontal Irradiation (DHI)	Diffuse Horizontal Irradiation is the amount of radiation received per unit area by a surface that does not arrive on a direct path from the sun, but has been scattered by the atmosphere and comes equally from all directions. Application: • Fixed PV installations.	• Pyranometer with shadow ball or shadow ring, installed in a sun tracker • Rotating Shadowband Irradiometer

(a) Global Horizontal Irradiation

(b) Global Tilted Irradiation

$\alpha = 90°$

(c) Direct Normal Irradiation

(d) Diffuse Horizontal Irradiation
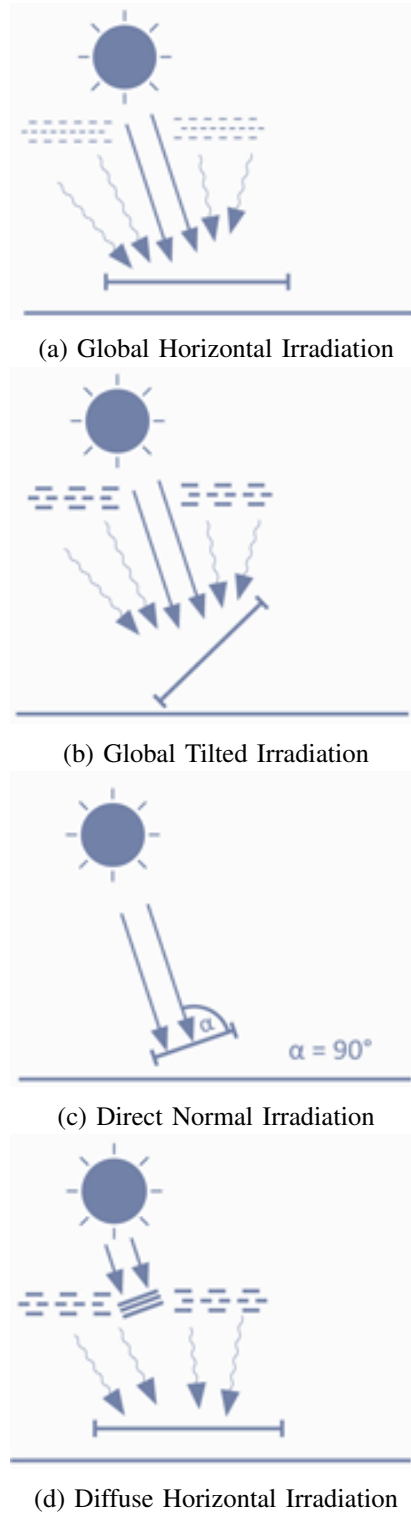
Figure 1: Types of Radiation

IV. PYRANOMETER

A. Introduction

The Solar Radiation Sensor, or solar pyranometer, measures global radiation, the sum at the point of measurement of both the direct and diffuse components of solar irradiance. The sensor's transducer, which converts incident radiation to electrical current, is a silicon photodiode with wide spectral response.The sensor outputs a voltage proportional to the amount of solar irradiance. The outer shell shields the sensor body from thermal radiation and provides an airflow path for convection cooling of the body, minimizing heating of the sensor interior. It includes a cutoff ring for cosine response, a level indicator, and fins to aid in aligning the sensor with the sun's rays. The space between the shield and the body also provides a runoff path for water, greatly reducing the possibility of rain- or irrigation-water entrapment. The diffuser is welded to the body for a weather-tight seal; it provides an excellent cosine response. The transducer is an hermetically-sealed silicon photodiode with integrated amplifier . Spring-loaded mounting screws, in conjunction with the level indicator, enable rapid and accurate leveling of the sensor. Each sensor is calibrated against a secondary standard Pyranometer in natural daylight.

B. Specification

- Transducer : Silicon photodiode
- Spectral Response : 400 to 1100 nanometers
- Temperature Coefficient : 0.12% per C
- Reference temperature : 25 C
- Housing Material : UV-resistant PVC plastic
- Weight : 250 g
- Range : 0 to 1800 W/m2
- Accuracy : 5% of full scale
- Drift : up to 2% per year
- Output : 0 to 5 VDC (0- 1800 w/m2)
- Power supply : 7- 24 VDC 1mA (typical)

C. Solar Data Acquisition System(short-term) using Arduino and Pyranometer

A short-term solar data acquisition system was built using a Pyranometer and an Arduino UNO Module . The pyranometer was deployed in rooftop so that no buildings, constructions, trees or obstructions are above it. The device itself was mounted in the horizontal plane while taking care that there is no obstruction to the path of sunlight since this affects the measurement of direct GHI. Moreover,it is located far from any kind of obstruction, which might reflect sunlight (or sun shadow) onto the pyranometer itself. The pyranometer requires a 12 V DC source which was provided using a DC adapter. The pyranometer outpus an analog value proportional to the irradiance at the current location. The output of the pyranometer needs to be caliberated before we can make accurate measurements. The analog ouput is interfaced to the Arduino module. The ADC of the Arduino is
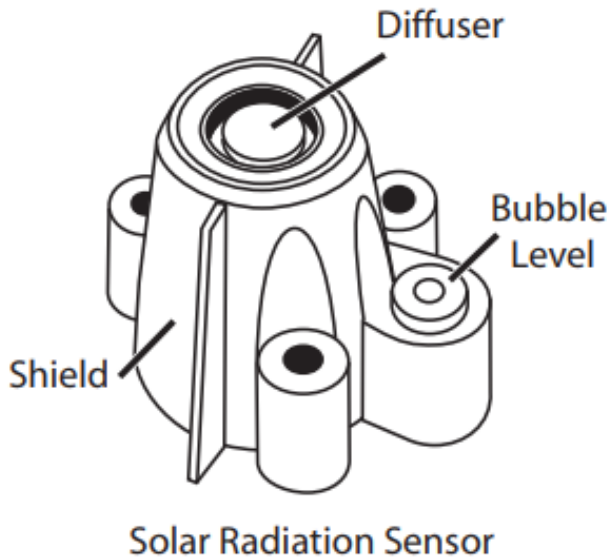
(a) Apparatus Diagram
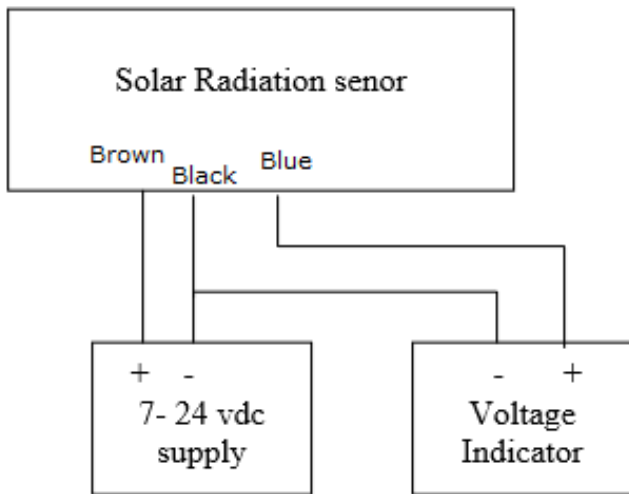
(b) Wiring Diagram

Figure 2: Pyranometer

used to convert this analog signal (0 to 5 V) to a digital value (0 to 1023). Since the long term operation of the device requires that it can go offline (due to power cuts), we cannot use the main memory to store the recorded data since it is a volatile media. Instead,we used the inbuilt EEPROM of Arduino UNO Module which is non volatile and retains the data even after the power is cut. Since the Arduino UNO has a rather limited EEPROM memory(1024 bytes) the data was downsampled before storage (8 bytes). With a recording interval of 5 min per day (12 hours), at a maximum, the device can store 3

days worth of solar GHI data. The arduino itself is also powered by the DC apdapter(12 V). After a period of 3 days, the Arduino automatically stops recording. Then the Arduino can be used to read out the EEPROM data to a computer where it can be logged and then processed. Range of analog output- 0 to 5V Range of digital output of Arduino-0 to 1023 Actual Pyranometer output range-0 to 1800 Watt/meter squared
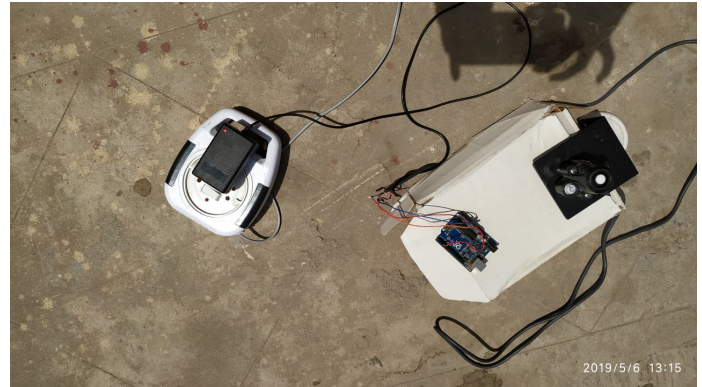

Figure 3: Complete Setup

The digital output is converted into actual Irradiance through appropriate conversion formulae.

Assuming linear relation between solar irradiation intensity and analog output of the pyranometer :

$$V_{analog} = \frac{V_{max} - V_{min}}{I_{max} - I_{min}} I_{GHI} .$$

$$V_{analog} = \frac{5}{1800} I_{GHI}$$

$$V_{analog} = 0.00277 I_{GHI} .$$

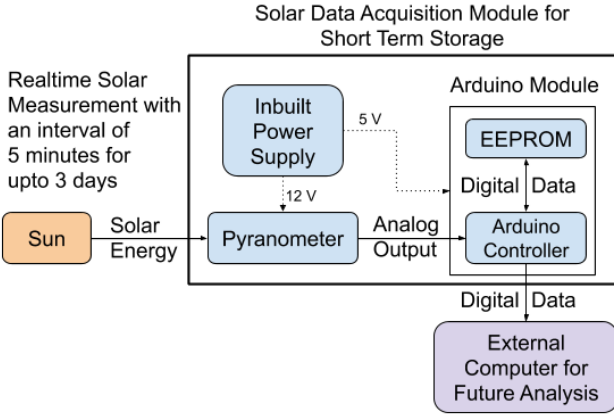where, V_{analog} is the output voltage and I_{GHI} is the Global Horizontal Irradiance

Figure 5: Block Diagram

Figure 7: Irradiance Plot vs Time

```
#include <EEPROM.h>
int n;
int led = 13;
void setup()
{
  n=1024;
  pinMode(3,INPUT);
  Serial.begin(9600);
  pinMode(led, OUTPUT);
  digitalWrite(led, LOW);
  while(!digitalRead(3));
  digitalWrite(led, HIGH);
}
int i =0;
void loop()
{
  if(Serial.available() and Serial.read()=='s') while(true);
  if (i>n-4 or not digitalRead(3) ) digitalWrite(led, LOW);
  else{
    digitalWrite(led, HIGH);
    for(int j=0;j<1000;j++) delay(180);
    int val = analogRead(0) / 4;
    Serial.println(val);
    EEPROM.write(i, val);
    i++;
    EEPROM.write(n-1,i&255);
    EEPROM.write(n-2,i>>8);
  }
}
```

Figure 6: Arduino Code

V. RESULT

The data was collected for 15 days for a period of 12 hours starting from 10 April,2019 to 30 April,2019 and then analyzed. Following is a plot of data collected on 15 April,2019 from 6 AM to 6 PM.
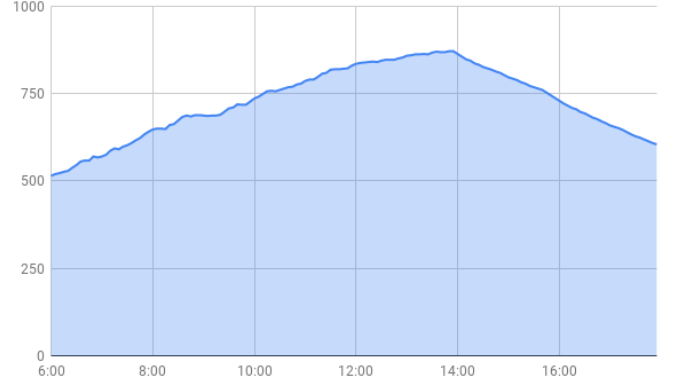
VI. FUTURE WORK

- Try different models like Artificial Neural Network (ANN), Recurrent Neural Network (RNN), Long-Short-Term-Memory(LSTM), Auto Regressive Integrated Moving Average(ARIMA).
- Analyze the collected data.
- Currently the data acquisition system is limited by the amount of storage space. In the future we plan to use a Raspberry Pi Module along with an SD Card so as to greatly expand the amount of data that we can store.
- Collection of Global Tilted Irradiations (GTI) data using pyranometer. Since GTI more closely approximates the actual PV panels which are tilted for maximum sunlight.

VII. ACKNOWLEDGMENT

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