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Solar PV Power Forecasting For Smart Grid System

(A Case Study of Solar PV Power Plant at Singh Durbar K3 Substation Kathmandu, Nepal)

By

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The undersigned certify that they have read and recommended to the Institute of Engineering for acceptance, a thesis entitled **"SOLAR PV POWER FORECASTING FOR SMART GRID SYTEM: A CASE STUDY OF SOLAR PV POWER PLANT AT SINGHDURBAR K3 SUBSTATION"** submitted by Mr. Shamvu Prasad Mandal, in partial fulfilment of the requirements for the degree of Master of science in Renewable Energy Engineering.

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ABSTRACT

The Photovoltaic (PV) systems are considered as clean and efficient sources of renewable energy with its rapid growth in market and technology over the past years. However, the power output of the PV system is an intermittent and non-stationary random process because of the variability of solar irradiation and weather characteristics. To ensure stable, secure operation and economic integration of solar PV system in smart-grids which is growing in the world as a major source of energy and development in solar technology this power is going to be economical. Data analysis and power forecasting of solar PV power is an important issue for reliability and energy management in the smart grid.

In this research, the real power data of Singhdarbar substation (K3), Kathmandu, Nepal has been analysed. The data proposed here has been analysed first to ensure the correlation of solar PV power with different metrological parameters such as Irradiance, temperature and wind. After analysis, the mathematical expression of power in terms of irradiance has been developed by 4^{th} order polynomial regression modelling. The use of multilayer neural network (MNN) and long-short term memory recurrent neural network (LSTM-RNN) to forecasting the output power of PV systems. The use of LSTM further reduces forecasting error compared with the other methods. The proposed forecasting method can be a helpful tool for planning and energy management in the smart grid.

This study presents, solar Photovoltaic (PV) power modelling using polynomial regression and artificial neural deep learning techniques. This method has been developed and validated using a 35.58 kWp Solar PV system installed inside the K3 substation of Singhdarbar, Kathmandu Nepal. In this study, first, the PV power data is statistically analyzed and modelled by using the polynomial regression technique and further modelled by using two different neural network namely multilayer neural network (MNN) and long short – term memory networks (LSTM) are examined. For PV power data modelling using deep learning techniques, all recorded data is used and parted into two as 90% for training and 10% for prediction in the various structure of both deep learning techniques in order to find the best deep learning structure in terms of low loss error. With these best models, prediction results show the long short term memory network has a better performance compared to the multilayer neural network and polynomial regression technique.

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LIST OF ABBREVIATION

AI: Artificial Intelligence 23

ANN: Artificial Neural Network 22

c_t: Cell State 29

DC: Direct Current 21

ft: Foreget gate 30

LSTM: Long Short Term Memory 28

MNN: Multilayer Artificial Neural Network 27

MoEn: Ministry of Energy 20

MoF: Ministry of Finance 20

MoFA: Ministry of Foreign Affair 20

NWP: Numerical Weather Prediction 22

$O_{t:}$: Output Gate 30

PV: Photovoltaic 14

ReLU: Rectified Linear Unit 27

RES: Renewable Energy Source 22

RMSE: Root Mean Square Error 37

RNN: Recurrent Neural Network 28

STC: Standard Test Condition 16

SVMs: Support Vector Machines 33

CHAPTER ONE: INTRODUCTION

1.1 Background

Renewable Energy technology has been viable alternative to the conventional Non-Renewable Sources of Energy. Solar PV power is highly dependent on solar irradiance and weather parameters. Especially, when all our basic needs are based on this type of energy. Solar PV power is available everywhere in the world and it is free of cost. The cost of solar energy taping is decreasing day by day in the growing market. It is utilized mostly for personal demand but if its use can be commercialized for the stable system where the smart grid energy management system is designed according to the load management system. Load management system does not manage according to installed capacity but if managed according to power generation over the year, for this actual and accurate power forecasting would be very important.

Nepal's energy situation reflects its challenging terrain (over 75% mountainous) and very low-income levels of the people. About 25% of Nepal's population i.e. 26.5 million people live below the poverty line, which varies by region but averaged earning of 19,261 Nepali Rupees per year in the Fiscal year 2010/2011. The per capita annual income is 917 USD in Fiscal Year 2011/2012. (Bureau, 2015)

Energy is an important development indicator, which provides vital inputs for survival and economic development. Energy supply and consumption are still in a traditional state in Nepal. At present, renewable energy generation capacity of the country is still significantly very low due to technological and economic barriers. But the average efficiency of renewable energy technologies is good in performance and also environmentally safe.

As data recorded in 2016 shows only seventy-six percent of people have access to electricity in Nepal (GIZ, 2016) out of which fifteen percent of the rural population gets electricity from the off-grid renewable energy source as of National census 2011.

The average global solar radiation in Nepal varies from 3.6-6.2 $kWh/m^2/day$, the sun shines for about 300 days a year, the number of sunshine hours amounts to almost 2100 hours per year and average insolation intensity about 4.7 $kWh/m^2/day$ (=16.92 $MJ/m^2/day$). (K. R. Adhikari, n.d.) Thus, Nepal lies in a favourable insolation zone in the world.

The Photovoltaic (PV) systems are considered as clean and efficient sources of renewable energy with its rapid growth in market and technology over the past years. Solar energy obtained from a solar PV cell is fluctuating in nature affected by external environment conditions like solar irradiance and cell temperature. Solar PV power generation is highly dependent on solar irradiance. The amount of power extracted from the PV system is a function of the PV module voltage and current. In this regard, many different studies have been conducted in the literature to obtain PV characteristics for the PV model. Due to the rapid growth in PV system technology, a better understanding of PV systems performance and supervisor of power output has become an important subject for research. The improper supervision system in PV systems reduces the efficiency of the systems. Also, the power output of the PV system is an intermittent and non-stationary random process because of the variability of solar irradiation and weather characteristics. In the Smart grid, the solar PV power is an important energy source, and controlling the PV system is needed for optimal performance achievement for Smart Grid. Therefore, the prediction of the power output of the PV system has been considered as an interesting research topic for Smart Grid.

In this research different Artificial Neural Deep Learning Techniques are studied for photovoltaic power data analysis and modelling. The method has been developed and validated from a 35.84 kWp photovoltaic system which is installed at the Singhdarbar –K3 Substation site Kathmandu Nepal.

There are 19 plants installed in Singhdarbar at various offices rooftop and parking areas. The total capacity of all installed plant is about 1.1 MWp. Data logger at K3 substation of Singhdarbar records all the PV power data through the internet of different sites. These studies are carried out on the K3 plant only which is installed at the rooftop of substation building of Nepal Electricity Authority at Singhdarbar. In this plant there are two grid-tie inverter installed each having a capacity of 19.5 kW. The total plant capacity of K3 is 35.84 kW. Rating of each PV panel is 280W with 8.91 A. The map of the system and its surrounding is shown in Figure 1-1

Currently the use of Artificial Intelligence Tools is becoming more and more common due to their capacity of solving highly complex problems. The improvement in the computers and in the algorithms performance also helped for solving not only engineering problems, but also in many areas like medicine, finances and literature. Therefore these tools are becoming more popular and can still make some progress and can be applied in more areas. In Table 1.1 there are some examples of application of Artificial Intelligence Tools in different study fields.

Table 1.1: Artificial intelligence use in different field of study

Field	**Description**
Banking	Credit application evaluators, cash forecasting, firm classification, stock and exchange rate forecasting
Automotive	Automotive automatic guidance systems, automatic braking systems, misfire detection, virtual emission sensors
Electronics	Code sequence prediction, process control, chip failure analysis, nonlinear modelling
Medical	Medical data analysis, Breast cancer cell analysis, EEG and ECG analysis, optimization of transplant times, emergency
Telecommunications	Image and data compression, automated information services, real-time translation of spoken language, customer
Speech	Natural Language Processing, Speech recognition, speech compression, vowel classification, text to speech synthesis

The challenge of climate and energy crisis, renewable energy generation including solar power generation has experienced significant growth. Increasingly high penetration level of photovoltaic (PV) power generation arises complexity in smart grid. Solar power is intermittent and variable and is highly dependent on cloud cover variability, atmospheric aerosol levels, and other atmosphere parameters. The large-scale of Solar PV Power generation introduces significant challenges to smart grid energy management. Accurate forecasting of solar power/irradiance is critical to secure economic operation of the smart grid (Wan, et al., Dec 2015).

Due to intermittent and stochastic characteristics of Solar PV Power has brought great challenges to smart grid system in terms of operation, regulation and planning. Power forecasting is an important factor for optimal utilization of power grid system and assessing the working performance of PV systems.

1.2 Problem Statement

In Nepal, we have many solar micro grid systems. Some of them are connected to the national grid and some are planning to connect soon without any study. The fluctuating nature of solar PV power generation has a great impact on the PV system planning, operation, and its economic analysis. Thus it is good if it has a better prediction method for smart grid system.

In most of the cases, the PV cell performances given in the module datasheets are defined under standard test conditions (STC) i.e. irradiance 1000W/m^2, and the cell temperature 25^{0}C. But in practical case the environmental conditions are different that affect the performance of PV panels. Therefore, there is a need to investigate the relation between the solar PV power performance and external environment conditions like solar irradiance, cell temperature and wind speed. Since these are uncertain factors, the power output of these resources also experiences uncertainty. Furthermore, ability to estimate the amount of power that can be generated by these resources is important for the investors who plan on building and adding such resources to the grid. The ultimate objective of this work is the development of real-time solar PV data prediction and modelling as a function of solar irradiance with low complexity and acceptable modelling accuracy.

In addition, many different studies have been conducted in the literature to obtain PV characteristics for PV power modelling and prediction. Due to the rapid growth in PV system technology, a better understanding of PV systems performance and prediction of power output has become an important subject for research. The improper analysis and prediction method in PV systems reduced the efficiency of the whole systems and make system ultimate failure. Therefore, the proper prediction algorithm for PV systems will help to estimate the accurate production of the electricity under the normal operating conditions, and adding such resources to the grid if the plants produce abnormally low power for some time.

1.3 Objectives

1.3.1 Main Objective

To study solar PV power forecasting for the smart grid system by using Deep Machine Learning Techniques (DMLT).

1.3.2 Specific Objectives

The specific study of this research is:

- To carry out data analysis between Solar PV power with Irradiance, Temperature and Wind to find the relationship between these parameters.
- To develop a real-time solar PV power forecasting model and evaluate the model by calculating RMSE between actual and forecasted power.
- To recommend the model with high accuracy for solar PV power forecasting.

1.4 Limitation

- This study is carried out considering only four different month hourly recorded data.
- Data recorded at K3 site are not stored when the internet server is down.
- Load demand is not considered in this research.

1.5 Case study site and experimental setup

1.5.1 Study site Google map image

Figure 1-1 Location Map of the Photovoltaic (PV) System of 35.84 KWp Capacity inside Singhdarbar, Kathmandu, Nepal

This project is located in the courtyard and surrounding area of Home Ministry which is in Singhdarbar, Kathmandu, Nepal at east longitude 85^0 19’28” and north latitude $27^0$41’52”.

1.5.2 Measuring instrument installed at the site

Figure 1-2 Measuring instrument connected on the rooftop of the K3 substation.

Figure 1-2 shows the all measuring instrument connected at the K3 substation site. Installed measuring equipment is the solar panel of Yingli Energy (China) Co. Ltd, Humidity sensor, temperature sensor, wind velocity detector, pyrometer and wind direction detector. All devices are installed on the rooftop of K3 substation in Singhdarbar Kathmandu Nepal.

Table 1.2 Specification of Solar PV Module

S.N.	Description	Rating
1	Rated power	280.0 W(0/+5w)
2	Rated voltage	31.4V
3	Rated Current	8.91A
4	Maximum series fuse	15 A
5	Open circuit Voltage	39.3 V
6	Short Circuit Current	9.38 A

Figure 1-3 Power production on 2018-10-30

Figure 1-3 is a Data logger print screenshot on 2018-10-30 at 14:21. It shows the power generation from different plant at that time. Power generation from K3 Substation is 15.584 kW, Ministry of Energy (MoEn) is 37.145 kW, Ministry of Foreign Affair (MoFA) is 37.558 kW, Ministry of Finance (MoF) is 13.316 kW.

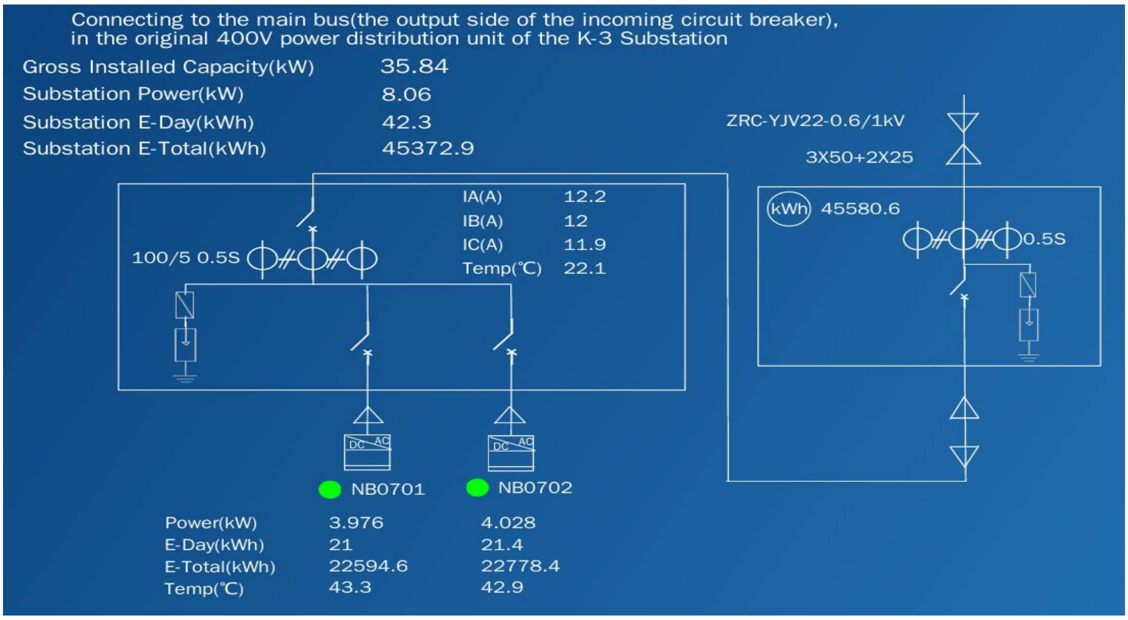


Figure 1-4: Connection diagram of installed Solar PV System

Figure 1-4 is a print screenshot of the connection diagram. In the K3 substation plant, there is two smart inverters having a capacity of 19.5 kW, three-phase 380/400V output voltage, input DC voltage is 640V. There are three CT's 100/5 A. It also shows the installed capacity is 35.84 kW, power generation 8.06 kW, inverter temperature 43.3°C and 42.9 °C and energy generation.

CHAPTER TWO: LITERATURE REVIEW

2.1 Solar PV Power Forecast

Solar PV Power forecasting and modelling has been carried out in various research papers using different techniques in many countries. Day- ahead forecasting of Solar Power Output from PV plant in the American Southwest was published in Renewable Energy 91 in 2016. This paper in (Larson, et al., 2016) presents relevant research work on Forecasting for hourly-averaged, day-ahead power output from PV power plant based on least-square optimization of Numerical Weather prediction (NWP). Three various forecasting method are evaluated against power output data from two non-tracking plants in California for 2011-2014. The research validate the performance of the proposed methodology as compared with previous studies.

Solar PV Power is highly dependent on external meteorological conditions. This paper (Lee, et al., 2017) presents the solar photovoltaic (PV) power output modelling using least mean square algorithm. The algorithm is applied to data which are obtained from the experimental site at the Hae-Nam, Korea. This modelling includes the correlation of solar PV power output and solar irradiation. The results obtained from this modelling indicate that under normal condition, the solar irradiation and PV power output have a very strong positive correlation.

The main characteristics of the output power of the PV systems are randomness and intermittency. These characteristics can lead to unexpected fluctuations in the voltages and PV power for the PV systems and can cause many problems in power systems, such as power quality, generation control, and storage devices protection. In essence, it is necessary to accurately predict PV power generation to ensure the safe operation and economic integration of the power system (Wang, et al., 2017). In this paper, the historical Solar PV Power data used are collected by Elia, Belgium’s electricity transmission system. The training dataset is applied to train the RNN network and extract the nonlinear features hidden in the PV power data, and the testing dataset is used to evaluate the prediction performance of the proposed method.

(Haykin, 2009) In this paper, it describes four different approaches i.e. statistical approach, artificial, physical and hybrid approach for solar PV power forecasting and suggested that solar power forecasting is essential to overcome some technological and economic issues.

The Statistical Approach is based on data-driven formulation using historically measured data to forecast time series solar PV power data (Bacher, et al., 2009). Statistics is a form of mathematical analysis that uses quantified models, representations for a given set of experimental data or real-life studies. Statistics studies methodologies to gather, review, analyse and draw conclusions from data.

Artificial intelligence (AI) approaches utilize artificial neural networks (ANN) to construct solar constructors, which can be also classified into the category of the statistical approach (Sfetsos & Coonick, 2000). It refers to the simulation of human intelligence in machines that are programmed to think like humans and mimic their actions. The term may also be applied to any machine that exhibits traits associated with a human mind such as learning and problem-solving. The ideal characteristic of artificial intelligence is its ability to rationalize and take actions that have the best chance of achieving a specific goal.

The physical model is based on numerical weather prediction (NWP) or satellite image that predicts solar irradiance and PV generation (Perez, et al., 2013).

The hybrid model is a combination of all the above three models to forecast solar PV power (Nanou, et al., 2015, oct). A hybrid campaign might be a mix of impression-based (CPM) and performance-based (CPC or CPA), or a mix of two performance-based models. Hybrid deals are sometimes seen as a way to further split the risk between publishers and advertisers

2.2 Machine Learning

Machine learning is an application of artificial intelligence (AI) that provides systems the ability to automatically learn and improve from experience without being explicitly programmed. Machine learning focuses on the development of computer programs that can access data and use it to learn for themselves. The process of learning begins with observations or data, such as examples, direct experience, or instruction, in order to look for patterns in data and make better decisions in the future based on the examples that we provide. The primary aim is to allow the computers to learn automatically without human intervention or assistance and adjust actions accordingly.

Machine learning and artificial intelligence make data engineers evaluate results with high accuracy. Comparing deep learning techniques for solar PV power forecasting.

(Paudel & Jang, 2018) In his paper presents photovoltaic power modeling using artificial neural deep learning techniques. Two different neural networks have tested in this paper, namely the multilayer neural network (MNN) and long short –term memory network (LSTM). PV power data, the whole day real power output has used and parted into 70% data for training and 30% data for testing and prediction. Both models have tested in terms of having low error output results obtained from the training data. The prediction result of this research show the LSTM has better performance compare to MNN. This paper recommends further forecasting can be done to improve modeling result with one-year historical data for more accurate prediction.

2.2.1 Deep Learning

Deep learning is a subset of machine learning where artificial neural networks, algorithms inspired by the human brain, learn from large amounts of data. Similarly to how we learn from experience, the deep learning algorithm would perform a task repeatedly, each time tweaking it a little to improve the outcome. We refer to 'deep learning' because the neural networks have various (deep) layers that enable learning.

Deep Learning for Time Series Forecasting. Deep learning methods, such as Multilayer Perceptron, Convolutional Neural Networks, and Long Short-Term Memory Networks, can be used to automatically learn the temporal dependence structures for challenging time series forecasting problems. Neural networks may not be the best solution for all-time series forecasting problems, but for those problems where classical methods fail and machine learning methods require elaborate feature engineering, deep learning methods can be used with great success (Brownlee, 2019).

2.2.1.1 Recurrent Neural Networks (RNN)

Recurrent Neural Networks or RNN as they are called in short, are very important variant of neural networks heavily used in Natural Language Processing. In general neural network, the input is processed through a number of layers and an output is produced, with an assumption that two successive inputs are independent of each other.

2.3 Solar PV Power Prediction Application in Smart Grid System

With large-scale penetration of Solar PV Power in smart grid, it reduces stability and reliability of the system and especially effects the energy management of smart grid

(Ropp, et al., 2008). This arise the problems of voltage fluctuation, power flow, grid losses, short-circuit current of distribution networks (Aguro & Steffel, 2011). Solar PV Power prediction could provide meaningful guidance for system operators, electricity participants as well as decision makers of electric power planning. Forecasting models with different prediction periods have been employed for smart grid energy management. Short-time fluctuation of PV outputs can be extremely large, depending on weather conditions, such as cloud passing. The accurate very short-time Solar PV Power prediction model with prediction period from 30s to several minutes could help to smooth the PV outputs, so as to avoid large fluctuations of voltage and frequency of smart grid. To limit the ramp rate of PV generations, various strategies have been applied to smooth the PV outputs. An electric double-layer capacitor, battery storage system, and fast ramping generators are commonly utilized technologies to absorb the rapid fluctuations of Solar PV Power generation. Various strategies are proposed (Cheng, 2010) to schedule intraday electric power of smart grids with Solar PV Power generation integration. Intelligent energy management systems with both grid-connected and islanded operations are modelled which consider the capacity and charging rate of storage, residential load variations, and distribution network electricity price as well. In the smart grid environment, the development of day ahead energy management tools for next-generation Solar PV installations, including storage units and demand response, causes flexibility and uncertainty to smart grid operators. A price based day-ahead energy management system with storage system and demand response to cover the fluctuations of the uncertainties of the PV outputs is proposed. In addition, day ahead power scheduling is becoming an important part of power systems considering the thermal generators with slow ramp limitation. The effects of forecast accuracy of large-scale aggregated photovoltaic power generation is evaluated. Day-ahead scheduling of PV generation combined with battery storage in the unit commitment problems are proposed. Another application of day-ahead prediction model is the bidding strategy of PV companies participating in the day ahead electricity markets (Awad, et al., 2012) (Ho, et al., 2009).

Solar PV Power forecasting techniques improve the quality of the energy delivered to the grid and minimize the additional cost associated with weather dependency.

2.4 Research Gap

The supply and demand for energy are determining the course of global development in every sphere of human activity. Sufficient supplies of clean energy are intimately linked with global stability, economic prosperity, and quality of life. Finding energy sources to satisfy the world‘s growing demand is one of society‘s foremost challenges for the next half-century. The importance of this pervasive problem and the perplexing technical difficulty of solving it require a concerted national effort marshalling our most advanced scientific and technological capabilities.

Solar forecasting is a stepping stone to these challenges. Solar PV power forecasting depends on factors like knowledge of the sun‘s path, the atmosphere‘s condition, the scattering process and the characteristics of a solar energy plant that utilizes the sun‘s energy to create solar PV power. Solar photovoltaic systems transform solar energy into electric power. The output power depends on the incoming radiation and on the solar panel characteristics. Photovoltaic power production is increasing nowadays. Forecast information is essential for efficient use, the management of the electricity grid and solar energy trading. Various solar forecasting research activities get motivated due to the factors that accurate solar forecasting techniques improve the quality of the energy delivered to the grid and minimize the additional cost associated with weather dependency. Solar forecasts on multiple time horizons play an important role in storage management of PV systems, control systems in buildings, hospitals, schools, etc., control of solar thermal power plants, as well as for the grids ‘regulation and power scheduling. It allows grid operators to adapt the load in order to optimize the energy transport, allocate the needed balance energy from other sources if no solar energy is available, plan maintenance activities at the production sites and take necessary measures to protect the production from extreme events.

CHAPTER THREE: GENERAL RESEARCH METHODOLOGY

The research methodology of this study was conducted in general methods then specific to particular according to the objectives which include defining a problem, literature review, research algorithms, data collection, data preparation and analysis, evaluating algorithms modeling, improvement of results, and final results and conclusion.

3.1 Defining a Problem

The photovoltaic output is highly dependent on external meteorological conditions. The inherent variability of large-scale solar generation introduces significant challenges to smart grid energy management. Since the smart grid control system requires energy management for stability and reliability and decisions making to invest in the power system. Proper energy management requires deep knowledge of power generation and consumption demand. Easy to handle and accurate forecasting models are very important in power systems and energy planning. Solar PV power forecasting models for practical field data are very suitable for big investors in the power sector. Machine learning and artificial intelligence are some of the trending topics in the tech world today. It makes data engineers evaluate results with low error and high accuracy.

3.1.1 Regression-Based PV Output Modelling:

Under normal conditions, we found that the solar irradiance and power measurements follow a strong linear relationship, which shows that dependency on solar PV power output is very high on solar irradiation.

The first step of data analysis is to model power vs. irradiation. Elimination of observations corresponding to the low sunlight levels at which the solar PV module produces significantly low power outputs, and corresponding zero power output is done. In order to detect the linearity, the plot of power output as a function of irradiance was examined using the data obtained from the experimental site. The strong correlation between the power and irradiance was found.

The output power from the PV module can be computed at any given irradiance using a polynomial function. A polynomial is a function describing the form of a length of line which is constructed out of known constants and variables. This function uses the operations of addition, subtraction, multiplication and non-negative integer exponents to describe the form of the line.

The output power of the PV system can be computed at any given solar irradiation using the polynomial function. Firstly, we apply the Polynomial regression in different months' power output as a function of irradiance. Modelling the curvature in power data is to formulate a "fourth-order polynomial model" with one quantitative predictor i.e. irradiance. Equation of polynomial linear regression is shown in equation 1 below,

$$Y = b_1 + b_2X_1^1 + b_2X_2^2 \dots \dots \dots \dots + b_nX_n^n \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots . (1)$$

Where,

Y = Predicted Outcome

b = Regression Coefficient

X = value of our independent variable

For our PV data modelling, 4^{th} – order Polynomial equation will be,

$$P_{Solar} = b_1 + b_2I_1^1 + b_2I_2^2 + b_3I_3^3 + b_4I_4^4 \dots \dots \dots \dots \dots \quad \dots \dots \dots \dots \dots \dots . \dots \dots \dots \dots . . (2)$$

Where,

Y = Predicted Power Output

b = Regression Coefficient

I = value of our Solar irradiance

3.1.2 Multilayer Artificial Neural Network (MNN) Algorithms

A multi-layered feed-forward artificial neural network consists of at least three layers of nodes. This three-layer is input, hidden and output layers. MNN is a supervised neural network so they require the desired output to be trained. In the MNN, each layer is made up of a number of interconnected nodes that use an activation function. Here, in this work, we use the rectified linear unit (ReLU) as an activation function. The input layer communicates to one or more hidden layers, where the actual processing is done via a system of weighted connections and the final output is provided by the output layer. The general MNN structure is shown in Figure 3-1 below.

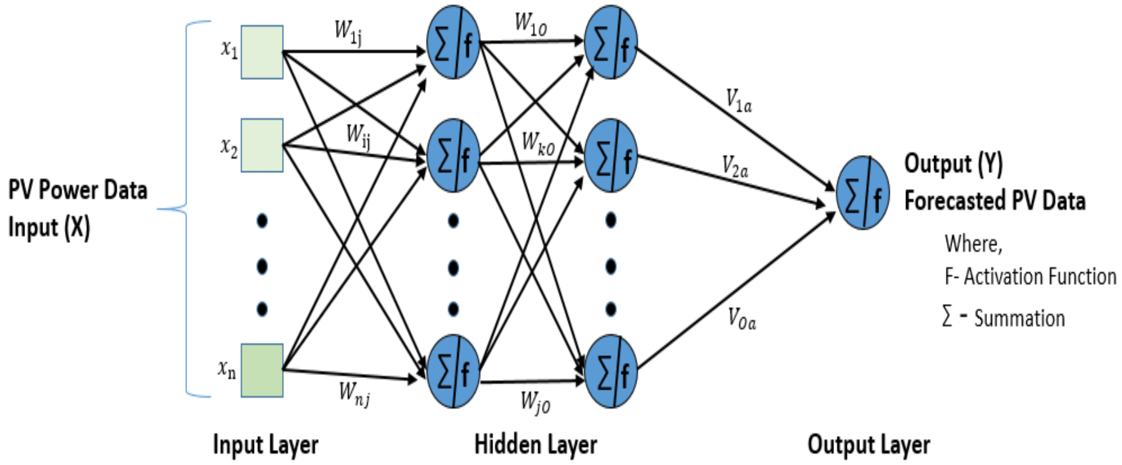


Figure 3-1 Multilayer Artificial Neural Network Structure (Haykin, 2009)

The MNN general structure is shown above. Where input is the PV power data, X= [$x1$,2… xn], having two hidden layers activated by ReLU function and output is Y. The weighting values connected between the input and the first hidden layer are [$w1j$, 2j… wnj], between the two hidden layers are [$w1o$,2o… wjo] and from second hidden layer to output layer are [$v1a$,$v2a$… voa] (Haykin, 2009).

$$W.X = w_1x_1 + w_2x_2 + \ldots\ldots\ldots w_mx_m = \sum_{i=1}^{m} w_ix_i \ldots\ldots\ldots\ldots(3)$$

3.1.3 Long Short-Term Memory (LSTM) Network Algorithms

LSTMs are a special kind of RNNs that can learn short-term as well as long-term dependencies (Grish, 2012). Unlike RNNs, LSTMs were designed to avoid the long-term dependency problem. LSTM network is trained using back propagation through time, and it overcomes the vanishing gradient problem. The traditional neural networks have neurons, in turn, LSTM networks have memory blocks that are connected through successive layers. Each block contains gates that handle the state of the block and the output. In the LSTM unit, there are three types of gates: forget, input and output. The task of each gate can be summarized as follows:

– **Forget gate** sets what information to throw away from the block-based on certain conditions.

– **Input gate** sets which value from the input to update the memory state based on certain conditions.

– **Output gate** sets what to output based on input and the memory of the block based on certain conditions.

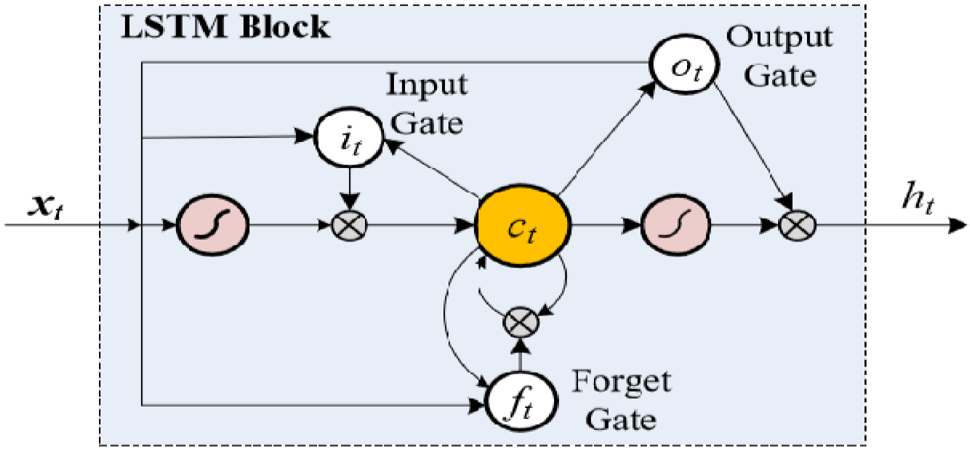


Figure 3-2 LSTM unit (Hochreiter, 1997)

As shown in Figure 3-2: LSTM block receives an input sequence and then each gate uses activation units to decide whether they are triggered or not. This operation makes the change of state and addition of information that flows through the block conditional. The gates have weights that can be learned during the training phase. Indeed, the gates make the LSTM blocks smarter than classical neurons and enable them to memorize recent sequences. Each LSTM unit contains a cell which has a state c_t at time t. This cell can be considered as a memory unit. Reading/modifying this cell is controlled through the input gate (a sigmoidal gate), forget gate f_t and output gate o_t. The LSTM unit receives inputs from two external sources at each of the four terminals (i.e., the three gates and the input) at each time step (Hochreiter, 1997). The two external sources are:

– The Power sample x_t.

– The previous hidden states of all LSTM units in the same layer h_{t-1}

Each gate has an internal source, the cell state c_{t-1} of its cell block. The LSTM sums the inputs coming from different sources with a bias. The gates are activated by inputting their total input into the logistic function. The total input at the input terminal is passed through the tanh non-linearity. The LSTM multiplies the resulting activation by the activation of the input gate and then sums the result of the multiplication to the cell state after multiplying the cell state by the activation of the forget gate ft. The LSTM passes the updated cell state through a tanh non-linearity and then multiply it with the activations of the output gate O_t to determine the final output from the LSTM unit ht. The previous steps and the updates of the LSTM can be formulated as follows.

$$i_t = \sigma(W_{xi} X_t + W_{hi} h_{t-1} + W_{ci} c_{t-1} + b_i) \qquad (4)$$

$$f_t = \sigma(W_{xf} X_t + W_{hf} h_{t-1} + W_{cf} c_{t-1} + b_f) \qquad (5)$$

$$c_t = f_t c_{t-1} + i_t \tanh(W_{xc} X_t + W_{hc} h_{t-1} b_c) \qquad (6)$$

$$o_t = \sigma(W_{xo} X_t + W_{ho} h_{t-1} + W_{co} c_t + b_o) \qquad (7)$$

$$h_t = o_t \tanh(c_t) \qquad (8)$$

The main advantage of using the LSTM unit, unlike the traditional neurons used in RNN, is that its cell state accumulates activities over time. Since derivatives distribute over sums, the derivatives of the error do not vanish quickly as they are sent back into time. In this way, LSTM can carry out tasks over long sequences and discover long-range features.

The LSTM shown in above Figure 3-3 has inputted PV power data X_t, output Y_t, and three gates i_t, f_t and o_t, where t represents the time period.

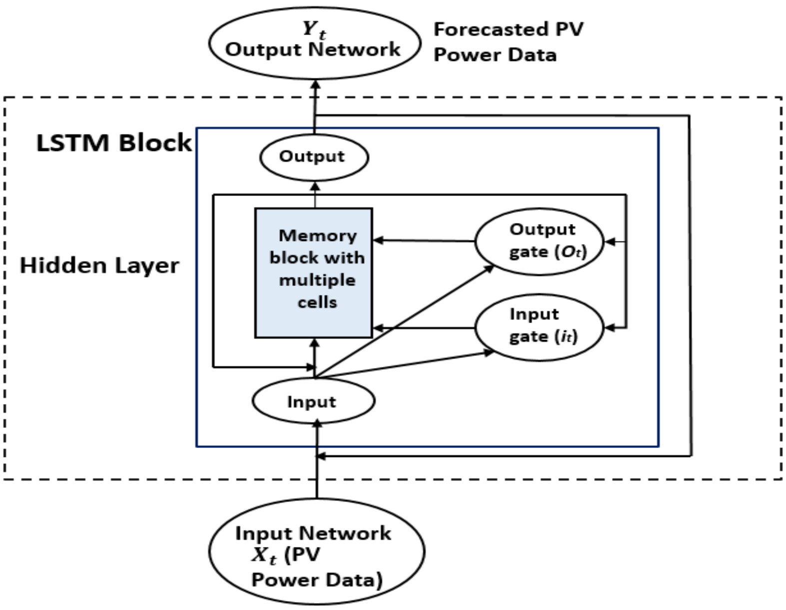


Figure 3-3 Long Short-Term Memory (LSTM) (Paudel & Jang, 2018) Network Structure

The best way to get started using Python for machine learning is to work through a project end-to-end and cover the key steps like loading data, summarizing data, evaluating algorithms and making some predictions. This gives a replicable method that can be used dataset after dataset. You can also add further data and improve the results.

3.1.4 Libraries and Packages

To understand machine learning, basic knowledge of Python programming is needed. In addition, there are a number of libraries and packages generally used in performing various machine learning tasks as listed below and shown in figure 3-4.

Numpy − is used for its N-dimensional array objects. It is the most fundamental packages in Python, NumPy is a general-purpose array-processing package. It provides high-performance multidimensional array objects and tools to work with the arrays. NumPy is an efficient container of generic multi-dimensional data.

Keras - is Tensor Flow’s high-level API for building and training Deep Neural Network code. It is an open-source neural network library in Python. With Keras, statistical modeling, working with images and text is a lot easier with simplified coding for deep learning.

Tensor flow- Tensor Flow is an AI library that helps developers to create large-scale neural networks with many layers using data flow graphs. Tensor Flow also facilitates the building of Deep Learning models, pushes the state-of-the-art in ML/AI and allow easy deploy of ML-powered applications.

Pandas − *Pandas* is an open-source Python package that provides high-performance, easy-to-use data structures and data analysis tools for the labeled data in Python programming language. Pandas stand for *Python Data Analysis Library*. Pandas is a perfect tool for data wrangling or mugging. It is designed for quick and easy data manipulation, reading, aggregation, and visualization. Pandas take data in a CSV or TSV file or a SQL database and create a Python object with rows and columns called a data frame.

Matplotlib − Matplotlib is the plotting library for Python that provides an object-oriented API for embedding plots into applications. It is a close resemblance to MATLAB embedded in Python programming language. is a 2D plotting library for creating graphs and plots

Scikit-learn − Scikit Learn is a robust machine learning library for Python. It features ML algorithms like SVMs, random forests, k-means clustering, spectral clustering, mean shift, cross-validation and more... Even NumPy.

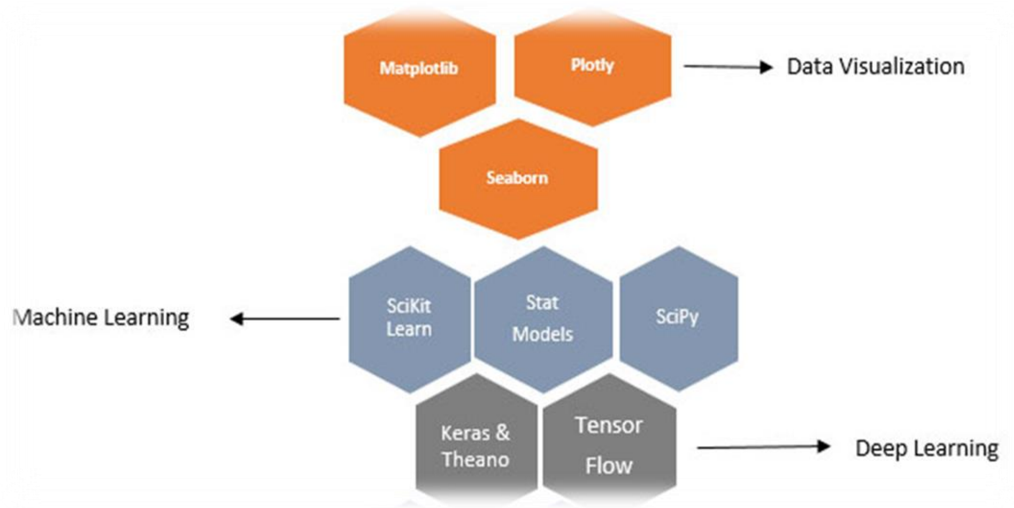


Figure 3-4 Showing Various Libraries use in different Purpose

3.1.5 Concepts and Types of Learning

In this chapter, we describe the concept and types of learning which are used in machine learning technology. We will learn about the training data our programs will access and how the learning process is automated and how the success and performance of such machine learning algorithms are evaluated.

3.1.5.1 Concepts of Learning

Learning is the process of converting experience into expertise or knowledge. Learning can be broadly classified into three categories, as mentioned below, based on the nature of the learning data and interaction between the learner and the environment.

- Supervised Learning
- Unsupervised Learning
- Semi-supervised Learning

Similarly, there are four categories of machine learning algorithms as shown below −

- Supervised learning algorithm
- Unsupervised learning algorithm

- Semi-supervised learning algorithm
- Reinforcement learning algorithm

However, the most commonly used ones are

Supervised Learning: In supervised learning, learning data comes with a description, labels, targets or desired outputs and the objective is to find a general rule that maps inputs to outputs. This kind of learning data is called labelled data. The learned rule is then used to label new data with unknown outputs. Supervised learning deals with learning a function from available training data. There are many supervised learning algorithms such as Logistic Regression, Neural networks, Support Vector Machines (SVMs), and Naive Bayes classifiers.

Supervised learning can be further classified into two types - Regression and Classification.

- **Regression -** trains on and predicts a continuous-valued response.
- **Classification** - attempts to find the appropriate class label, such as analyzing positive/negative sentiment, male and female persons, benign and malignant tumors, secure and unsecured loans, etc.

Unsupervised Learning: Unsupervised learning is used to detect anomalies, outliers, such as fraud or defective equipment, or to group customers with similar behaviours for a sales campaign. It is the opposite of supervised learning. There is no labelled data here. When learning data contains only some indications without any description or labels, it is up to the coder or to the algorithm to find the structure of the underlying data, to discover hidden patterns, or to determine how to describe the data. This kind of learning data is called unlabelled data.

Semi-supervised Learning: If some learning samples are labelled, but some others are not labelled, then it is semi-supervised learning. It makes use of a large amount of unlabelled data for training and a small amount of labelled data for testing. Semi-supervised learning is applied in cases where it is expensive to acquire a fully labelled dataset while more practical to label a small subset. For example, it often requires skilled experts to label certain remote sensing images, and lots of field experiments to locate oil at a particular location while acquiring unlabelled data is relatively easy.

Reinforcement Learning: Here learning data gives feedback so that the system adjusts to dynamic conditions in order to achieve a certain objective. The system evaluates its performance based on the feedback responses and reacts accordingly. The best-known instances include self-driving cars and chess master algorithm Alpha Go.

3.1.6 Types of Data

Training dataset: A training dataset is a dataset of examples used for learning, that is to fit the parameters (e.g., weights) of Most approaches that search through training data for empirical relationships tend to overfit the data, meaning that they can identify and exploit apparent relationships in the training data that do not hold in general. The actual dataset that we use to train the model (weights and biases in the case of Neural Network). The model sees and learns from this data.

Test dataset: A test dataset is a dataset that is independent of the training dataset, but that follows the same probability distribution as the training dataset. If a model fit to the training dataset also fits the test dataset well, minimal overfitting has taken place (see figure below). A better fitting of the training dataset, as opposed to the test dataset, usually points to overfitting.

A test set is, therefore, a set of examples used only to assess the performance (i.e. generalization) of a fully specified classifier. (A. Shah, S. C. Kaushik, S. N. Garg, 2009) (Y.Cui, Y. C. Sun, Z. L. Chang, 2013)

3.1.7 Correlation Coefficient, r

The quantity r is called the linear correlation coefficient. It measures the strength and the direction of a linear relationship between two variables.

The mathematical formula for computing r is:

$$r = \frac{n\sum xy - (\sum x)(\sum y)}{\sqrt{n(\sum x^2) - -(\sum x)^2}\sqrt{n(\sum y^2) - (\sum y)^2}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.\ldots\ldots \quad (9)$$

Where n is the number of pairs of data.

The value of r is such that -1 < r < +1. The + and – signs are used for positive linear correlations and negative linear correlations respectively.

Positive Correlation: If x and y have a strong positive linear correlation, r is close to +1 i.e. r-value of exactly +1 indicates a perfect positive fit. Positive values indicate a relationship between x and y variables such that as values for x increases, values for y also increase.

Negative Correlation: If x and y have a strong negative linear correlation, r is close to -1. An r value of exactly -1 indicates a perfect negative fit. Negative values indicate a relationship between x and y such that as values for x increase, values for y decrease.

No Correlation: If there is no linear correlation or a weak linear correlation, r is close to 0. A value near zero means that there is a random, nonlinear relationship between the two variables.

3.1.8 Root Mean Square Error (RMSE):

The root means square error (RMSE) has been used as a standard statistical metric to measure model performance in meteorology. The root means square error (RMSE) is regularly employed in model evaluation studies (Chai & Draxler, 2014). Root Mean Square Error (RMSE) is a standard way to measure the error of a model in predicting quantitative data. Formally it is defined as follows:

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{\left(\widehat{P_i} - P_i\right)^2}{n}} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (10)$$

Here, $\hat{P}_1, \hat{P}_2, \hat{P}_3, \dots\dots\dots\dots\dots. \hat{P}_n$ are predicted solar PV power and
$P_1, P_2, P_3, \dots\dots\dots\dots\dots. P_n$ are measured values where n is the no of observations.
The RMSE for training and test set should be very similar then developed model is best fit model. If the RMSE for test set is much higher than that of the training set then data are badly over fitted

3.2 Literature Review

This step has been done in chapter two to depict all possible researches that have been attempted around the world and various related research and research term logy concerned with data analysis and solar PV power modelling with machine learning were studied.

3.3 Research Algorithms and Flow Chart

The photovoltaic (PV) market and technology have shown rapid growth over the past years, representing today a mature technology for power production from renewable energy sources and a common on-site electricity generation strategy. A prediction algorithm for PV systems can provide an accurate estimate of the electricity production under normal operating conditions and detect PV system problem periods of abnormally low power production when the system produces.

```
Power data from CSV file
For each forecast do
 Filter data based on availability;
 Arrange dataset in the array;
 Partition the dataset into 90% training and 10% test set;
 Define a parameter set (e.g. look back);
 Define model structure
    For each model, structure do for
        Configure model;
            Model fit;
            Evaluate the model using loss value;
            Predict values for the training set;

        End
            Calculate the average RMSE on the training sets;

        End
        Determine optimal hyperparameters (i.e. lowest RMSE);
        Test model on all test data with optimal hyperparameters;
        Evaluate the model on the test set (i.e. the 10% of data);
End
```

Figure 3-4. Deep learning Algorithms

Figure 3-4 shows an overview of the applied deep learning algorithms performed for each model. The solar PV power data is hourly based on four-month data. The whole data set is divided into 90% and 10% to train and test in the various model structures. Detailed methodology is explained below,

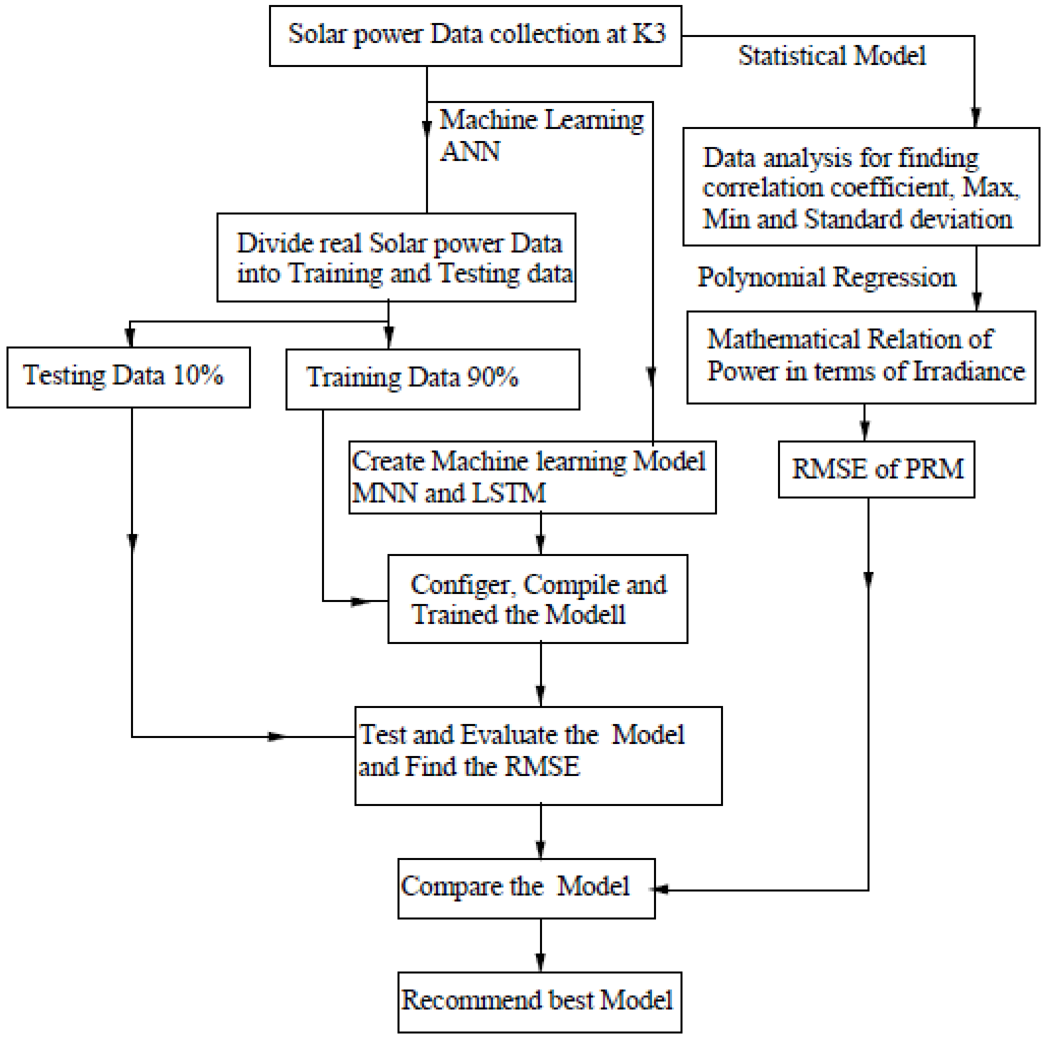


Figure 3-5. Research Flow Chart

The above Figure 3-5 shows a block diagram of proposed work. Here, real solar PV power data is collected from the PV station site, installed at the K3 substation of Singhdarbar, Kathmandu, Nepal.

The recorded data are visualized and analysed individually then performed from the pool of regression algorithms. For this propose, the top tested Polynomial Linear Regression modelling algorithm is used because the collected data are highly scattered and having polynomial by nature. From this analysis, the correlation coefficient between powers with solar irradiance is obtained.

The polynomial linear regression algorithms will apply to predict the PV power as a function of solar irradiation. And also evaluate the root mean square error (RMSE) for four-month data individually as well as the combination of all data.

The recorded historic PV power data was modelled by using deep neural networks mainly multiple neural networks (MNN) and Long Short Term Memory (LSTM) algorithm analysing with each different structure to get the best modelling prediction result having a minimum root mean square error (RMSE). Figure 3-5, illustrates the block diagram of our proposed work, which starts initially with analyzation of recorded data from our PV system site.

Detail procedure of implementing deep learning Algorithms for forecasting recorded PV Data is clearly shown in Figure 3-5. And its implementation was shown in Figure 3-6

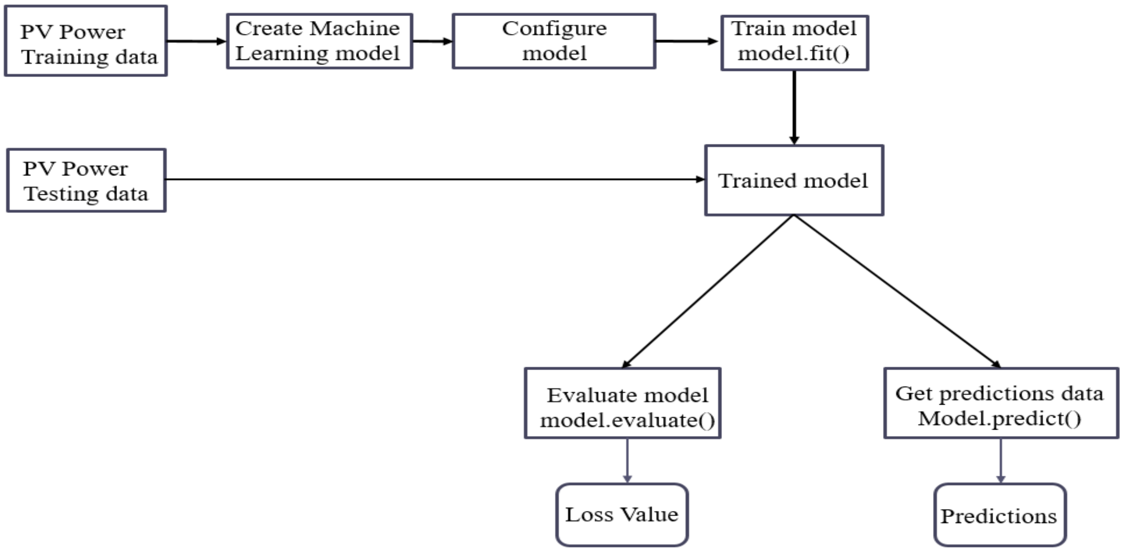


Figure 3-6. Implementation of Machine Learning Algorithms for Forecasting PV Data in Details (Abdel Nasser & Mahmoud, 2017)

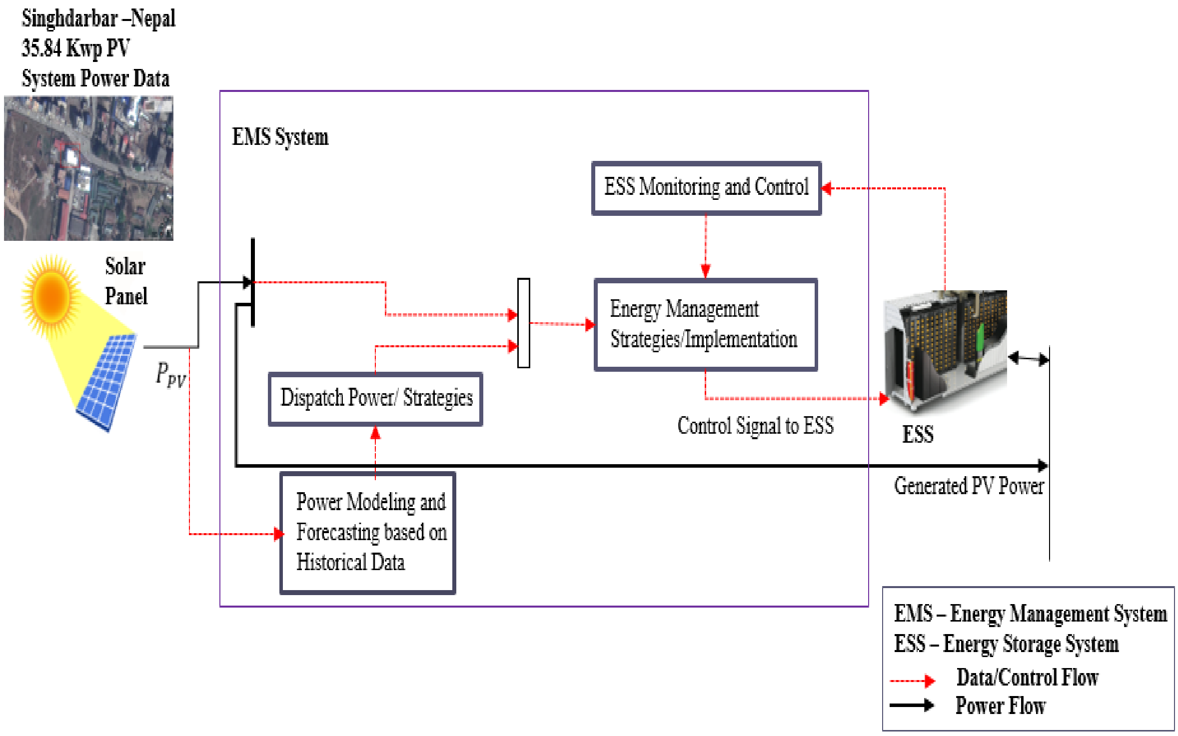


Figure 3-7 Implementation of the Photovoltaic (PV) Power modeling and forecasting System for 35.84 kWp Capacity system inside Singhdarbar, Kathmandu, Nepal

CHAPTER FOUR: DATA COLLECTION AND DATA ANALYSIS

Data analysis is the process of inspecting, cleansing, transforming and modelling the data for the purpose of discovering useful information, suggesting conclusions and supporting decision-making and of course for future prediction.

4.1 Data Collection

In this research, Historical Solar PV power and environmental data are taken from a 35.84 KWp photovoltaic system which is installed at the rooftop of K3 Substation at Singhdarbar site, Kathmandu, Nepal. PV module is installed with the climate data collection device and remote power data acquisition device; the details of equipment are described below.

The climatic data collection device has an anemometer for the wind speed measurement, and two separate temperature sensors for each PV module to measure the ambient temperature. Two pyrometers are used to measure solar irradiance, one for perpendicular and another for inclination solar irradiance. This device measures the real-time I-V output of the PV modules along with solar irradiance, wind speed, and temperature data. The PV power output is varying in the season so for experimental purposes, we mainly choose 4-month data (March, June, September and December of 2018). Measurements recorded hourly basis, covering the period of March 1 to December 31, 2018, (which represent different power pattern) of the solar irradiation and dc power output were used to develop accurate PV data modelling approach

There are 19 solar plants installed at different offices, parking areas and rooftop of the office building in Singhdarbar, Kathmandu. Solar PV power data is recorded on the hourly basis of all 19 plants at the K3 substation data logger. In this study, we only considered the data of the K3 plant. For the analysis and forecasting. We select the different season hourly data, they are namely data of March, Jun, September and December of 2018 to reflect all season of the year. This graph is shown in Figure 4-1, Figure 4-2, Figure 4-3 and Figure 4-4 for 35.84 kWp Capacity systems inside Singhdarbar, Kathmandu, Nepal.

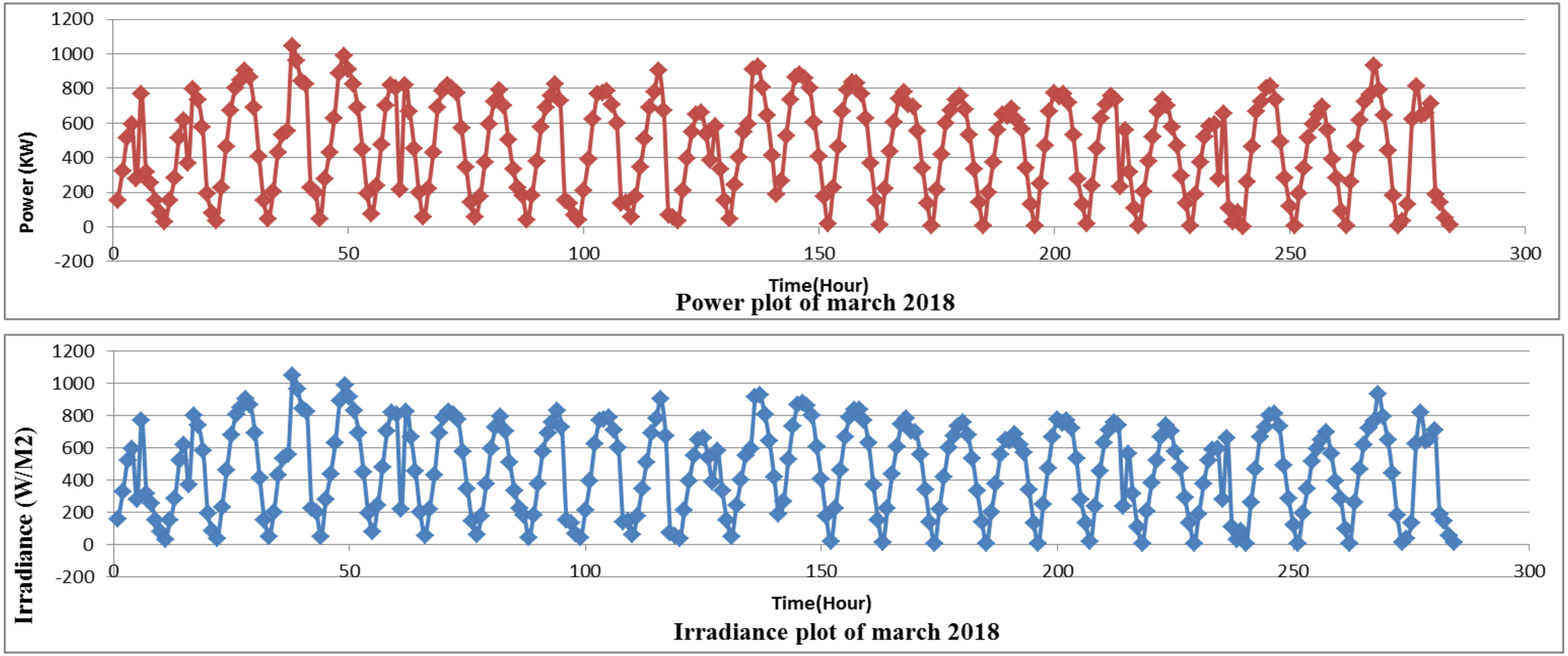
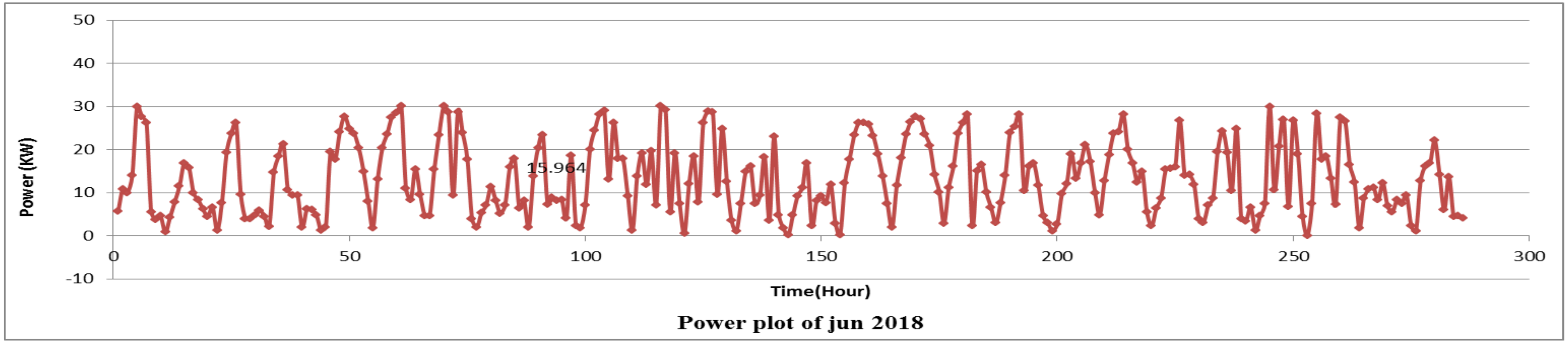


Figure 4-1 Solar Irradiance and Power plot of March 2018

Figure 4-1 is the graph of Solar PV power and Irradiance recorded in the data logger station at K3 substation, Singhdarbar, Kathmandu, Nepal of March 1st to March 30^{th,} 2018. The data logger records the data on an hourly basis. In this graph only 7:00 AM to 6:00 PM everyday data has considered.



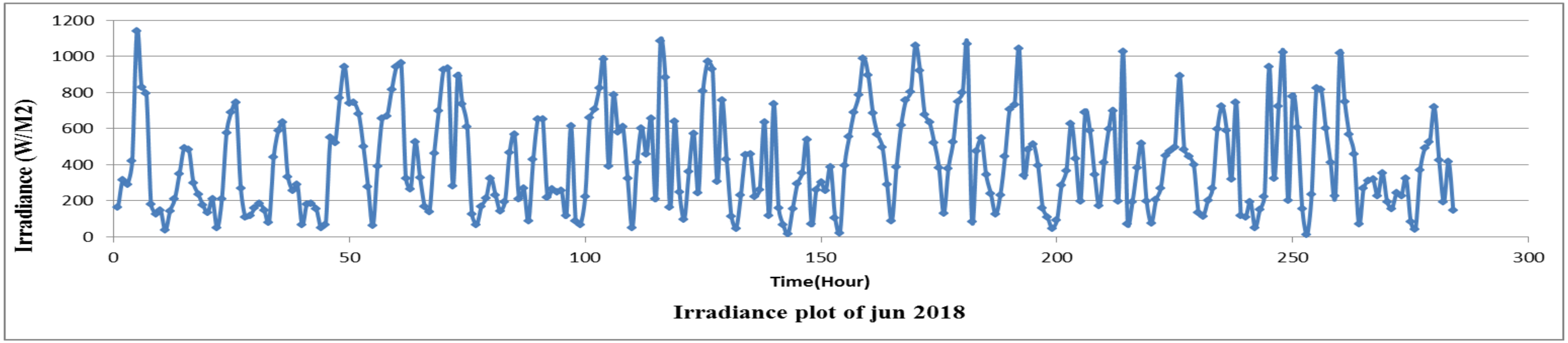


Figure 4-2 Solar Irradiance and Power plot of Jun 2018

Figure 4-2 is the graph of Solar PV power and Irradiance recorded in the data logger station at K3 substation, Singhdarbar, Kathmandu, Nepal of Jun 1st to Jun 30th, 2018. The data logger records the data on an hourly basis. In this graph only 7:00 AM to 6:00 PM everyday data has considered.

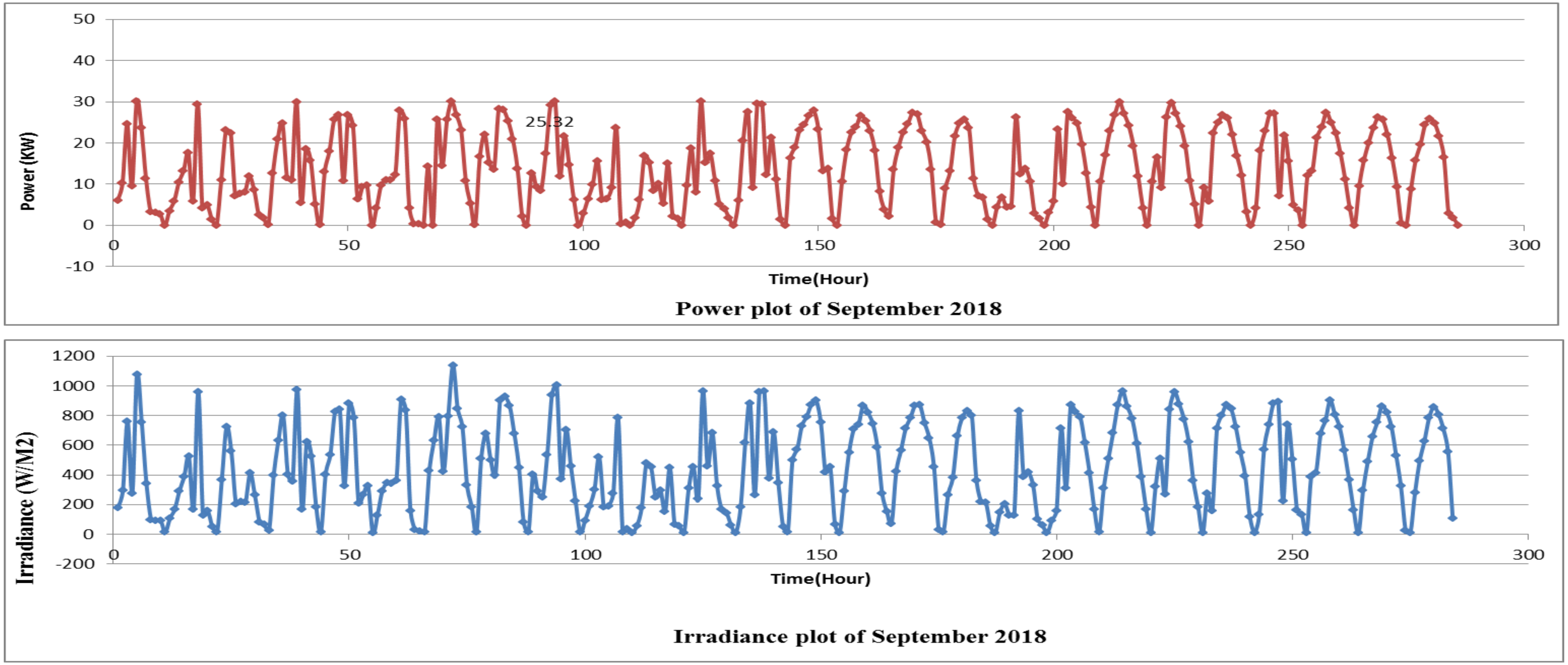


Figure 4-3 Solar Irradiance and Power plot of September 2018

Figure 4-3 is the graph of Solar PV power and Irradiance recorded in the data logger station at K3 substation, Singhdarbar, Kathmandu, Nepal of September 1st to September 30th, 2018. The data logger records the data on an hourly basis. In this graph only 7:00 AM to 6:00 PM everyday data has considered.

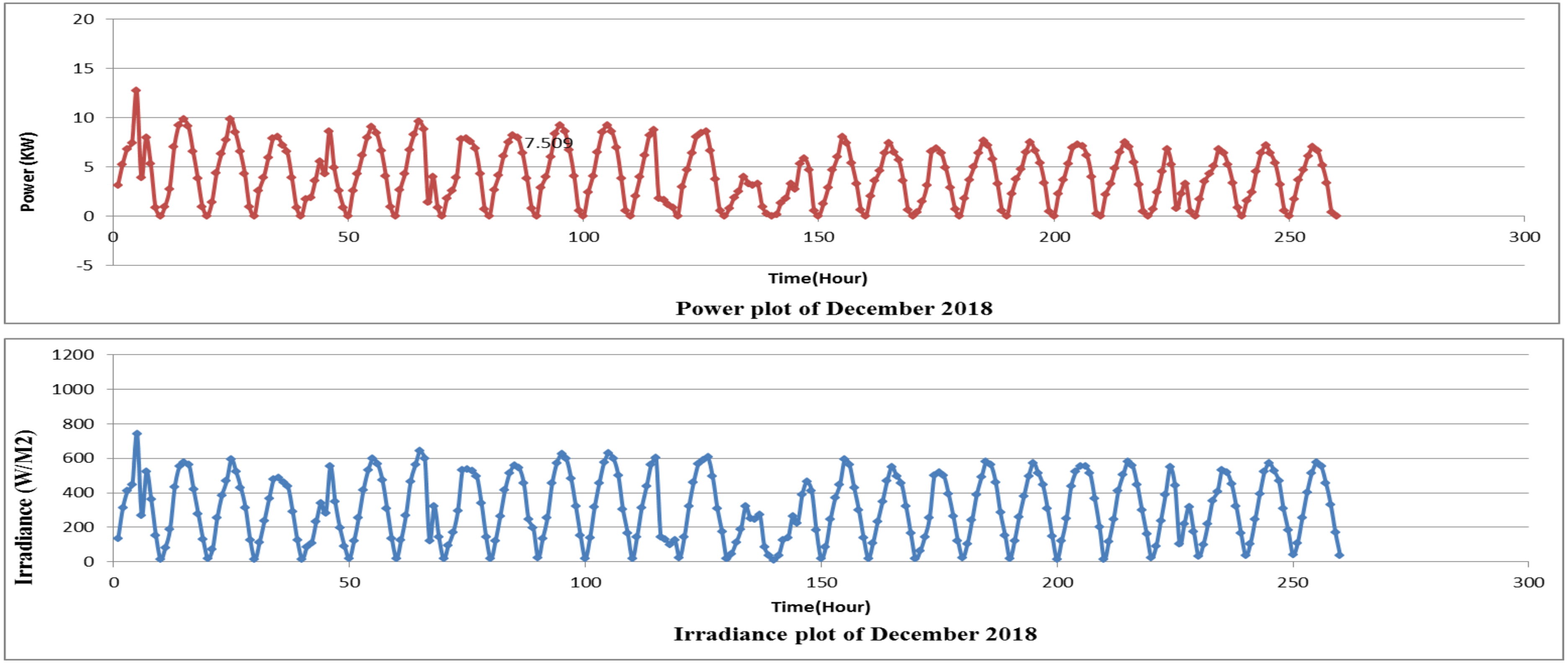


Figure 4-4 Solar Irradiance and Power plot of December 2018

Figure 4-4 is the graph of Solar PV power and Irradiance recorded in the data logger station at K3 substation, Singhdarbar, Kathmandu, Nepal of December 1st to December 30th, 2018. The data logger records the data on an hourly basis. In this graph only 7:00 AM to 6:00 PM everyday data have considered.

4.2 Recorded Solar PV power, Irradiance, wind speed, and temperature data analysis

Hourly measured data are briefly analysed here. In this study, we mainly take the Solar PV Power data and corresponding solar irradiance values of four different months' data covering from March to December of 2018.

4.2.1 Scatter Plot Analysis

The scatterplot is a useful summary of a set of bivariate data (two variables), usually drawn before working out a linear correlation coefficient or fitting a regression line. It gives a good visual picture of the relationship between the two variables and aids the interpretation of the correlation coefficient or regression model.

4.2.1.1 Scatter plot of March 2018

Solar PV power vs. irradiance, solar PV power vs. temperature and solar PV power vs. wind speed of different day recorded data of March month are plotted to see the correlation between them.

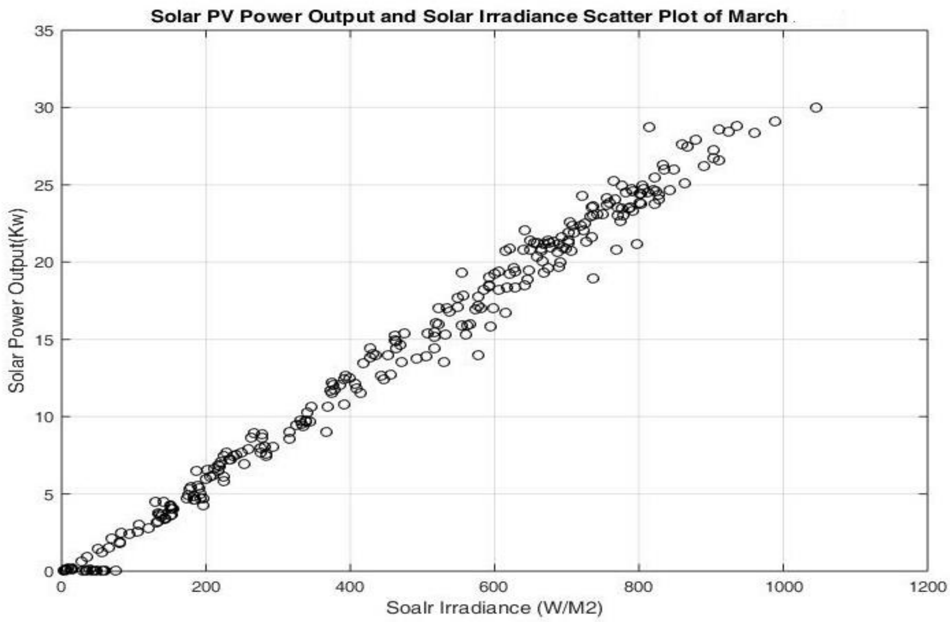


Figure 4-5 Scatter Plot of March PV module Power Vs. Solar Irradiation Data

Figure 4-5 is the scatter plot of solar PV power and irradiance of March 2018. Which are highly correlated to each other and the correlation coefficient is 0.9942.

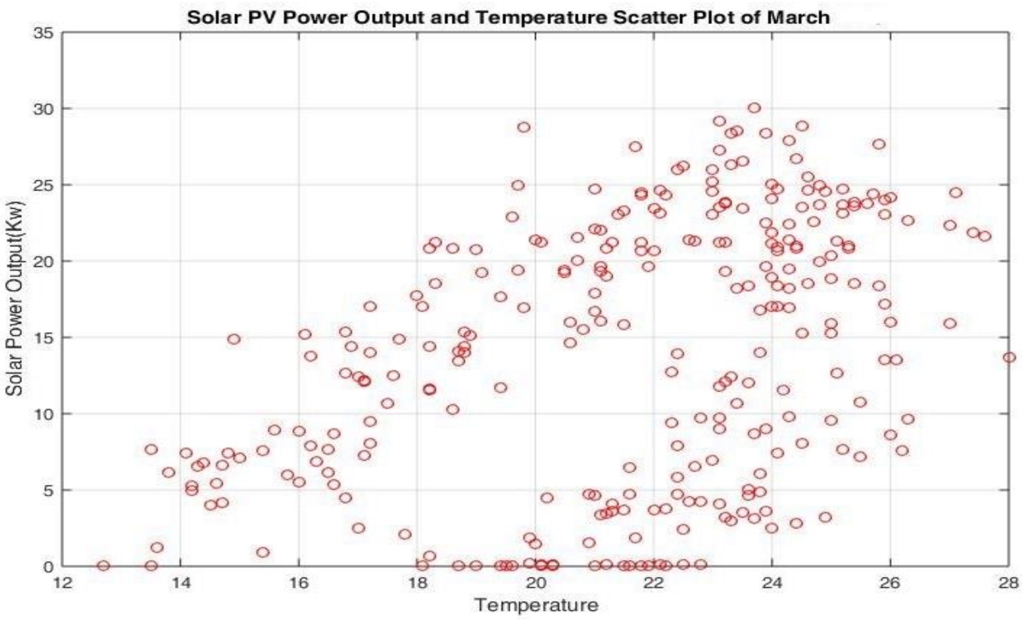


Figure 4-6 Scatter Plot of March PV module Power Vs. Temperature Data

Figure 4-6 is the scatter plot of solar PV power and Temperature of March 2018. Which are highly scattered to each other and having a correlation coefficient is 0.4022. From this, it is cleared that the effect of temperature on solar PV power production is not so much accountable.

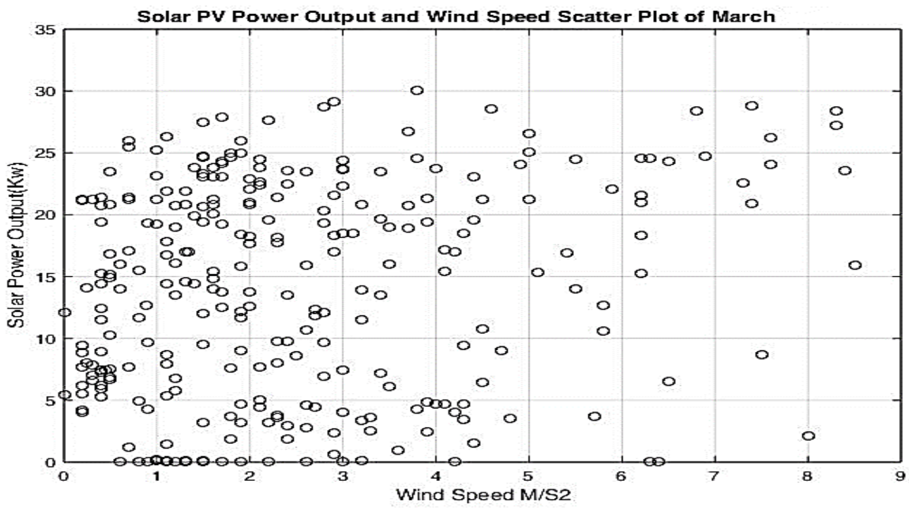


Figure 4-7 Scatter Plot of March PV module Power Vs wind speed Data

Figure 4-7 is the scatter plot of solar PV power and wind speed of March 2018. Which are highly scattered to each other and having a correlation coefficient is 0.1982. From this, it has been cleared that the effect of wind on solar PV power production is not accountable.

4.2.1.2 Scatter plot of Jun 2018

Here, we plot the solar PV power vs. irradiance, solar PV power vs. temperature and solar PV power vs. wind speed of different day recorded data of Jun month to see the correlation between them.

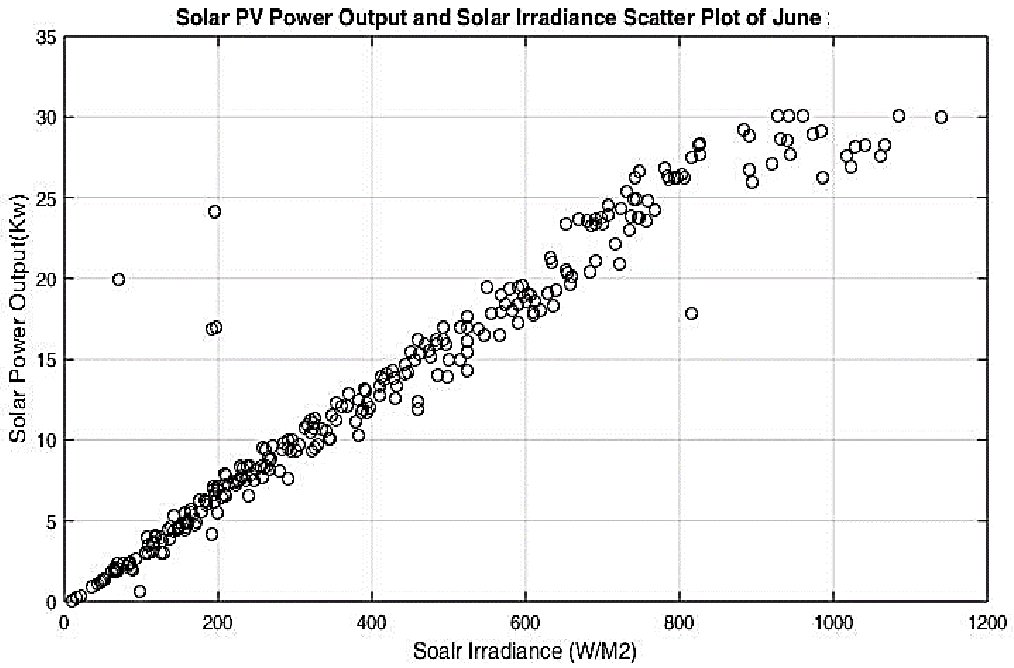


Figure 4-8 Scatter Plot of PV module Power vs. Solar Irradiation Data of June 2018

Figure 4-8 is the scatter plot of solar PV power and irradiance of Jun 2018. Which are highly correlated to each other and the correlation coefficient is 0.9664.

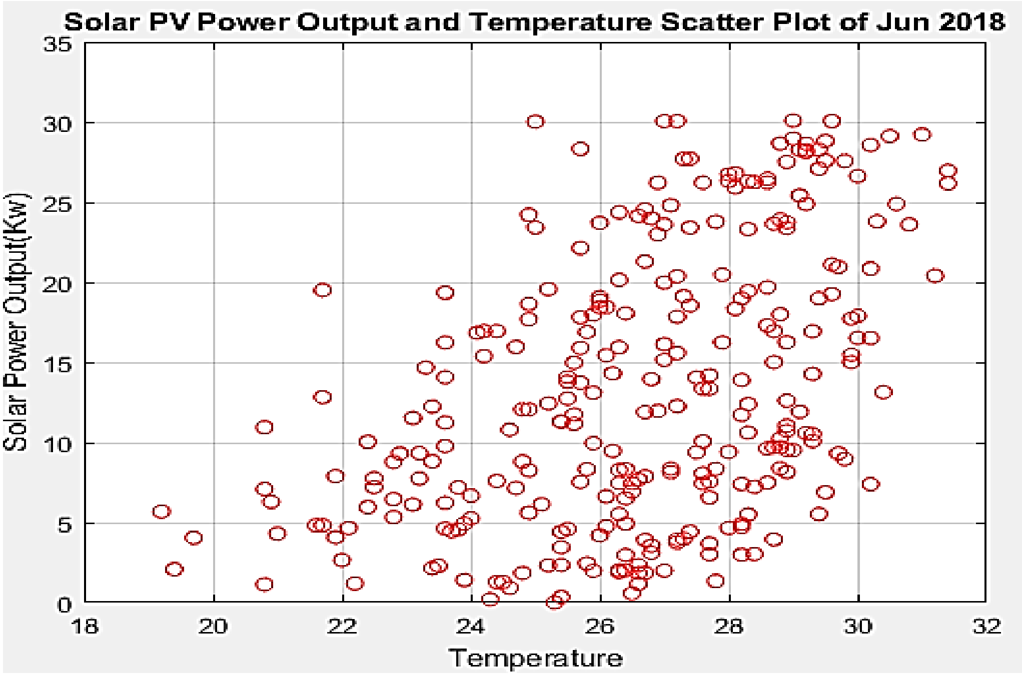


Figure 4-9 Scatter Plot of Jun 2018 PV module Power vs. Temperature Data

Figure 4-9 is the scatter plot of solar PV power and Temperature of Jun 2018. Which are highly scattered to each other and having a correlation coefficient is 0.4226. From this, it has cleared that the effect of temperature on solar PV power production is not so much accountable.

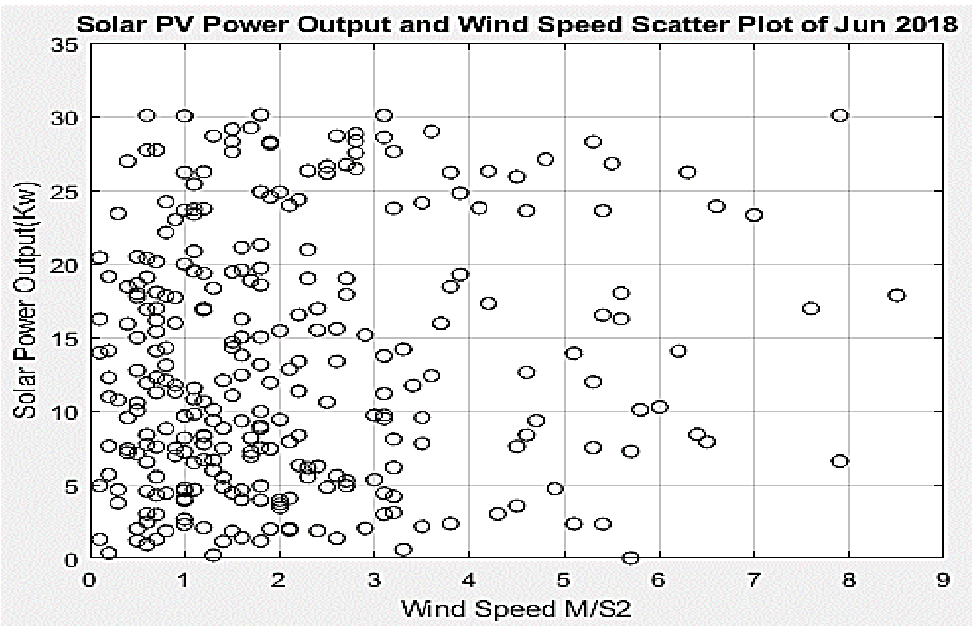


Figure 4-10 Scatter Plot of Jun 2018 PV module Power Vs. wind speed Data

Figure 4-10 is the scatter plot of solar PV power and wind speed of June 2018. Which are highly scattered to each other and having a correlation coefficient is 0.1118. From this, it has cleared that the effect of wind on solar PV power production is not accountable.

4.2.1.3 Scatter plot of September 2018

In this, we plot the solar PV power vs. irradiance of the different day recorded data of September month to see the correlation between them.

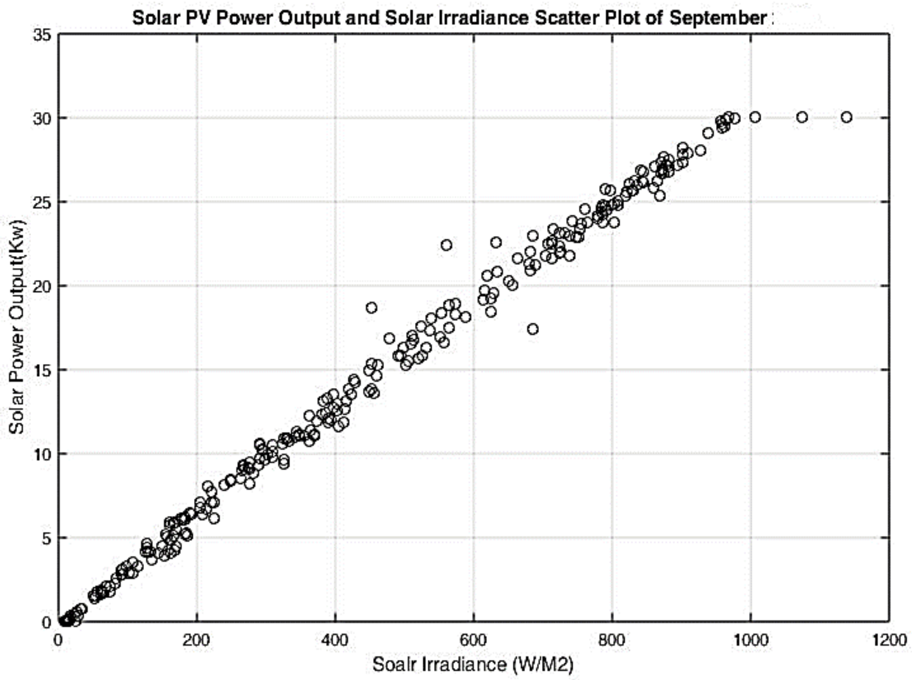


Figure 4-11 Scatter Plot of Power vs. Solar Irradiation Data of September 2018

Figure 4-11 is the scatter plot of solar PV power and irradiance of September 2018. Which are highly correlated to each other and the correlation coefficient is 0.9959.

4.2.1.4 Scatter plot of December 2018

In this, we plot the solar PV power vs. irradiance of the different day recorded data of December month to see the correlation between them.

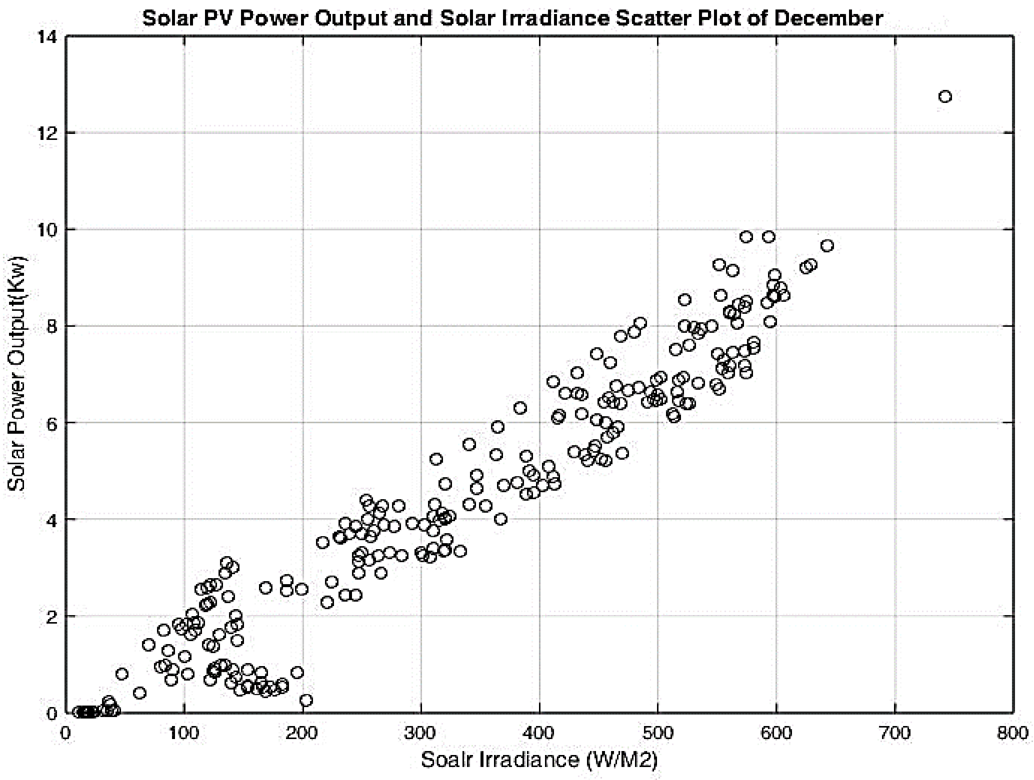


Figure 4-12 Scatter Plot of Solar PV power Vs. Solar Irradiation Data of December 2018

Figure 4-12 is the scatter plot of solar PV power and irradiance of December 2018. Which are highly correlated to each other and the correlation coefficient is 0.9663. But less correlation value compared to the other three months. Which was mainly happened due to someday missing data.

From the above scatter plot of each month's solar PV power vs. irradiance, we can see the strong correlation between power and irradiance. Therefore, from this scatter plot analysis it can be inferred that the solar PV power output highly depends on the solar irradiance value. From this analysis, we further use power as a function of irradiance in our modelling propose. The calculated correlation coefficient between the power and solar irradiance of each day-recorded data of different months are illustrated in Table 4.1

Table 4.1 Correlation Coefficient of the Hourly measurements of solar PV data

Data Taken Month	Correlation Coefficient		
	Power and Irradiance	Power and Temperature	Power and wind
March, 2018	0.9942	0.4022	0.1982
June, 2018	0.9664	0.4626	0.1118
September, 2018	0.9959	0.4942	0.1070
December, 2018	0.9663	0.3744	-0.0715
All data	0.9374		

From Table 4.1, it is clear that the correlation coefficient of PV power with solar irradiance is found to be greater than 0.937 in all cases. The correlation coefficient of power with wind is found to be less than 0.19. Similarly the correlation coefficient of power with temperature have also less than 0.49. Therefore, under normal condition, solar irradiance and Solar PV Power are highly correlated, Solar PV Power and temperature are weakly correlated and Solar PV Power and wind are independent.

Histograms are one of the most common graphs used to display numeric data. The histogram is used to plot the frequency of score occurrences in a continuous data set that has been divided into classes, called bins. The x-axis of histogram plots are the solar PV power and irradiance data and y-axis of the histogram shows the number of repetition of the generated same amount of power and irradiance.

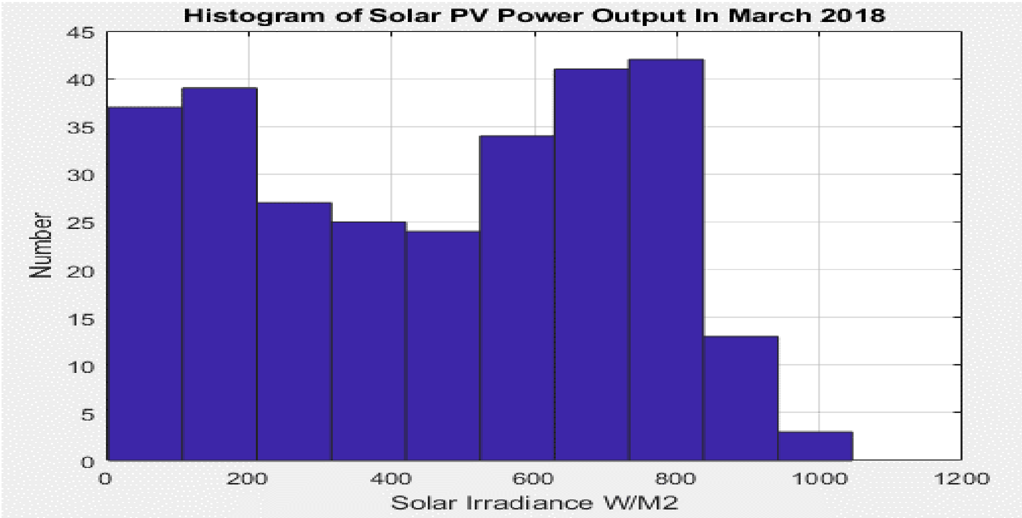


Figure 4-13 Histogram Plot of different dated Solar Irradiation

From this histogram plot of solar irradiance of different dated data of March 2018. The maximum solar irradiance value was 1046 w/m^2 but it is only less than 5 times but 800 w/m^2 were more than 40 times in a month of March 2018.

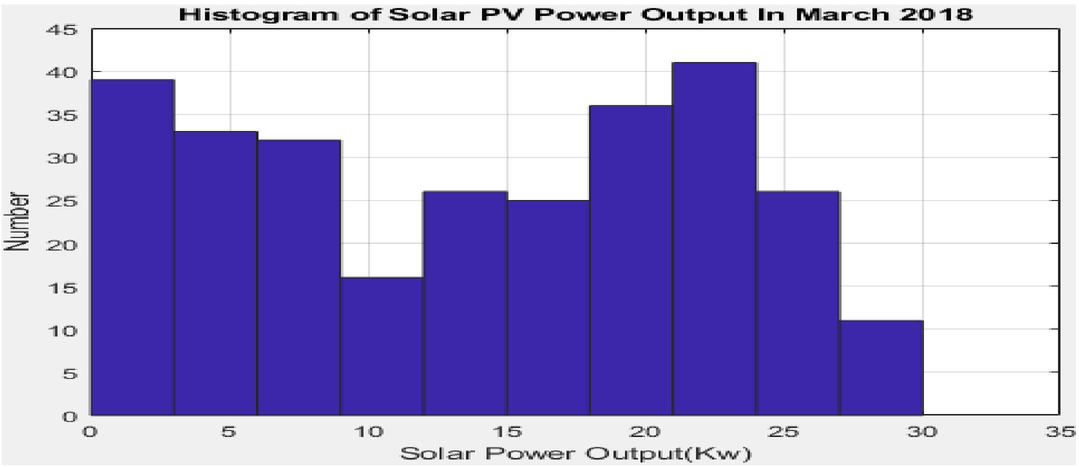


Figure 4-14 Histogram Plot of different dated PV Power of March 2018

From this Histogram plot of PV power data of different dated of March 2018. The maximum power was 30.027 kW at 1046 w/m^2 which was only less than 12 times of total occurrence. The minimum power was 0.005 kW at irradiance 3 w/m^2 which was around 38 times in a month.

Table 4.2 Basic Statistics of the Hourly measurements of solar PV and irradiance data of different Months.

Data Taken Date	Measurement	Min. Value	Max. Value	Value Mean	Stand. Deviation
March, 2018	Power (Kw)	0.005	30.027	13.784	8.651
	Irradiance (W/m2)	3.000	1046.000	458.480	276.445
June, 2018	Power (Kw)	0.008	30.090	13.284	8.472
	Irradiance (W/m2)	11.000	1140.000	416.080	275.002
September, 2018	Power (Kw)	0.003	30.061	13.703	9.430
	Irradiance (W/m2)	8.000	1138.000	437.328	304.167
December, 2018	Power (Kw)	0.003	12.751	4.139	2.878
	Irradiance (W/m2)	11.000	743.000	310.161	189.039

From the above statistical analysis Table 4.2, the minimum power generation is 0.003 kW at irradiance less than 11 W/m^2 in September and December of 2018. March, June, and September have the maximum irradiance value i.e. greater than 1046 W/m^2 with maximum PV power output i.e. greater than 30 kW. The mean and standard deviation of PV power output and solar irradiance of month March, Jun and September of 2018 have nearly closed value but the mean and standard deviation of December data have different value. Therefore March, Jun and September have nearly similar pattern of Solar PV Power output but December have different pattern of data. From the all month solar power data plot it is cleared that the data of different season of 2018 recorded in K3 substation are complex in nature.

CHAPTER FIVE: RESULTS AND DISCUSSION

5.1 Case 1: Polynomial Linear Regression Modelling

5.1.1 March 2018, PV Power Data

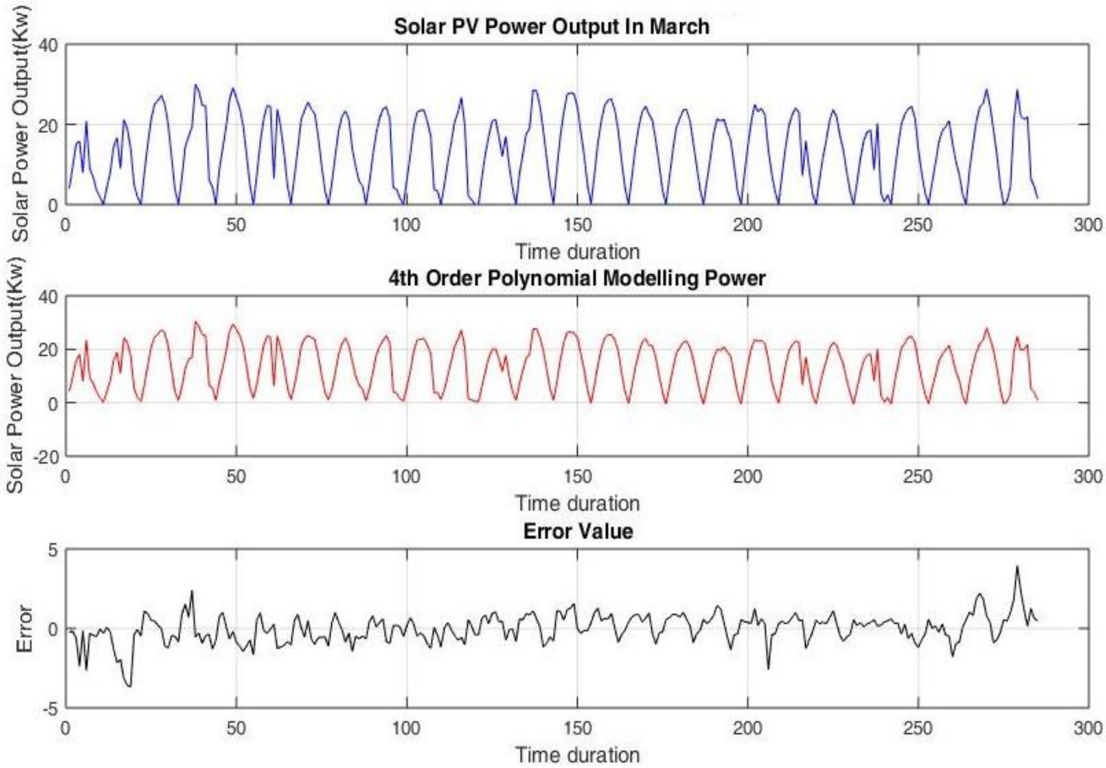


Figure 5-1 Plot of actual Power, Polynomial Linear Regression Modelled Power and Error value of March 2018

From the above Figure 5-1, the actual power and forecasted power follow the same pattern. It has concluded that the polynomial regression of the 4th order was the best fitted model for the monthly obtained solar PV power data. and the RMSE obtained from it is 0.924.

$$P_{Solar(March)} = -7.1926e^{-12}I^4 + 8.152e^{-09}I^3 - 2.5519e^{-06}I^2 + 0.0318I - 0.6439 \dots\dots\dots\dots\dots\dots.(11)$$

5.1.2 June 2018, PV Power Data

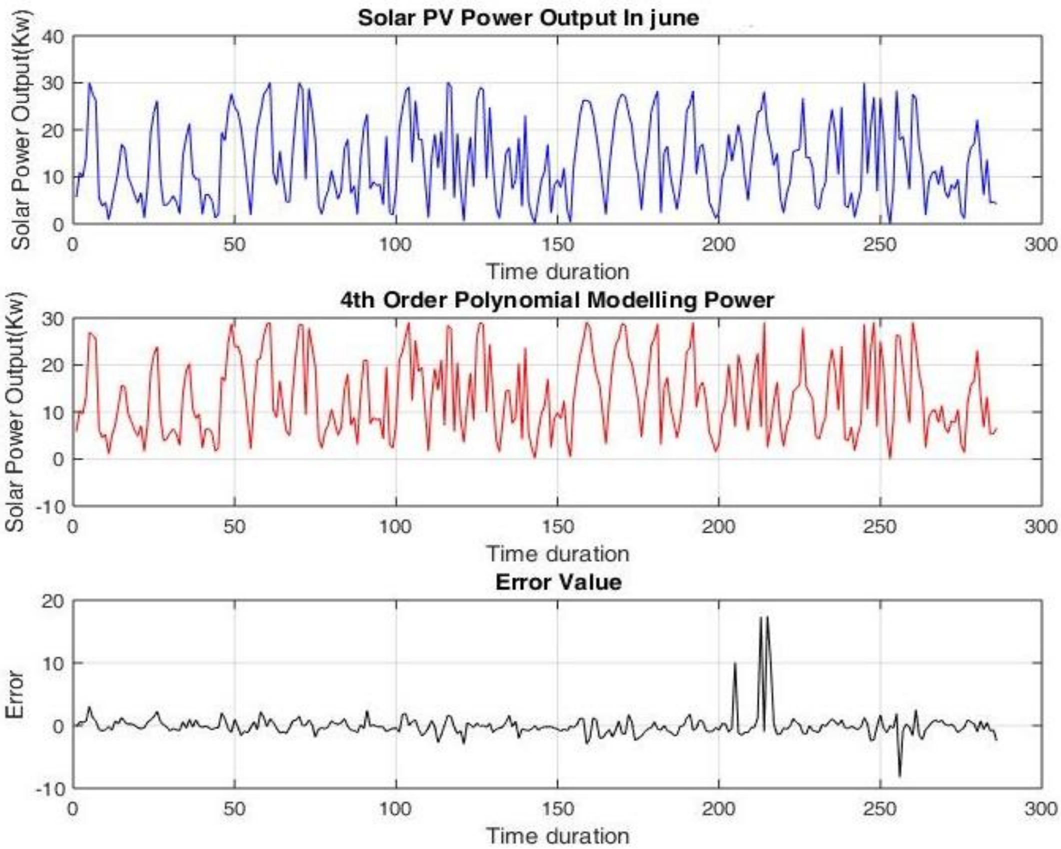


Figure 5-2 Plot of actual Power, Polynomial Linear Regression Modelled Power and Error Data of June 2018

From the above Figure 5-2, the actual power and forecasted power follow the same pattern. From this, it has concluded that the polynomial regression of the 4th order was the best-fitted model for the monthly obtained solar PV power data. and the RMSE obtained from it is 2.031.

$$P_{Solar(June)} = -6.76e^{-11}I^4 + 1.254e^{-07}I^3 - 7.6075e^{-05}I^2 + 0.048I - 0.5412 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \ldots (12)$$

5.1.3 September 2018, PV Power Data

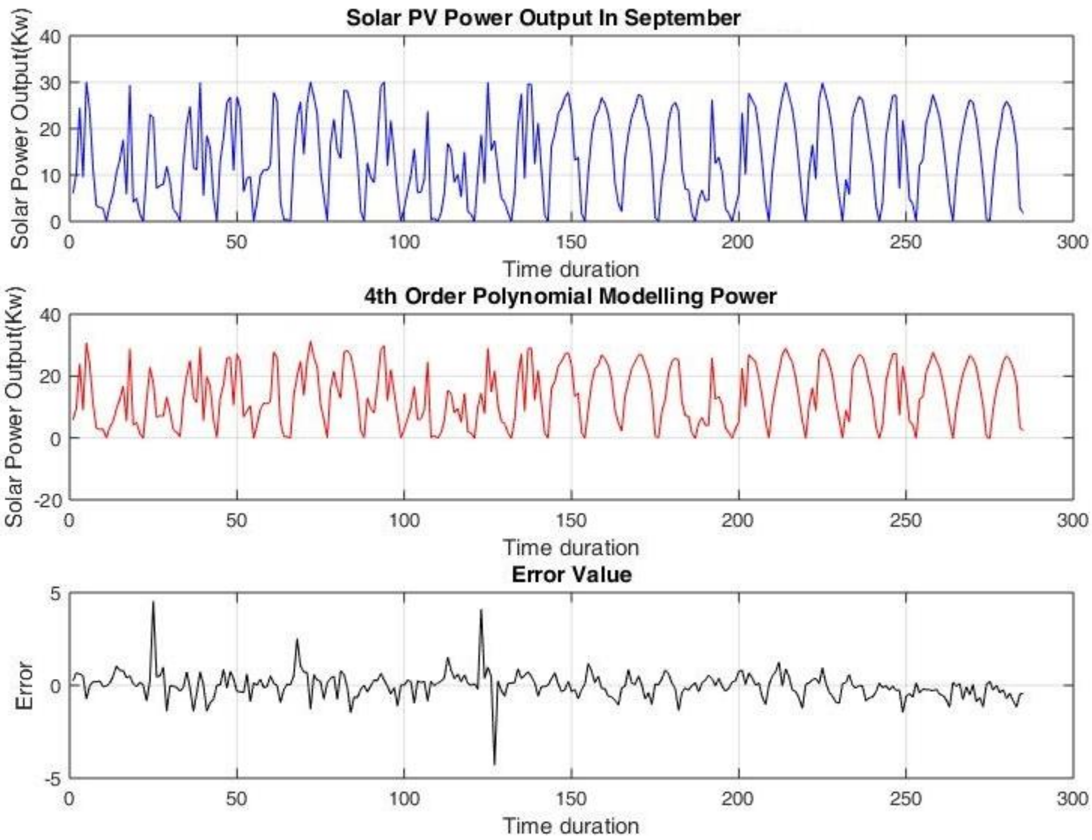


Figure 5-3 Plot of actual Power, Polynomial Linear Regression Modelled Power and Error Data of September 2018

From the above Figure 5-3, the actual power and forecasted power follow the same pattern. From this, it is concluded that the order polynomial regression of the 4th order was the best-fitted model for the monthly obtained solar PV power data and the RMSE obtained from it is 0.72.

$$P_{Solar(September)} = -1.9187e^{-11}I^4 + 3.44e^{-08}I^3 - 2.37e^{-05}I^2 + 0.0387I - 0.542 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(13)$$

5.1.4 December 2018, PV Power Data

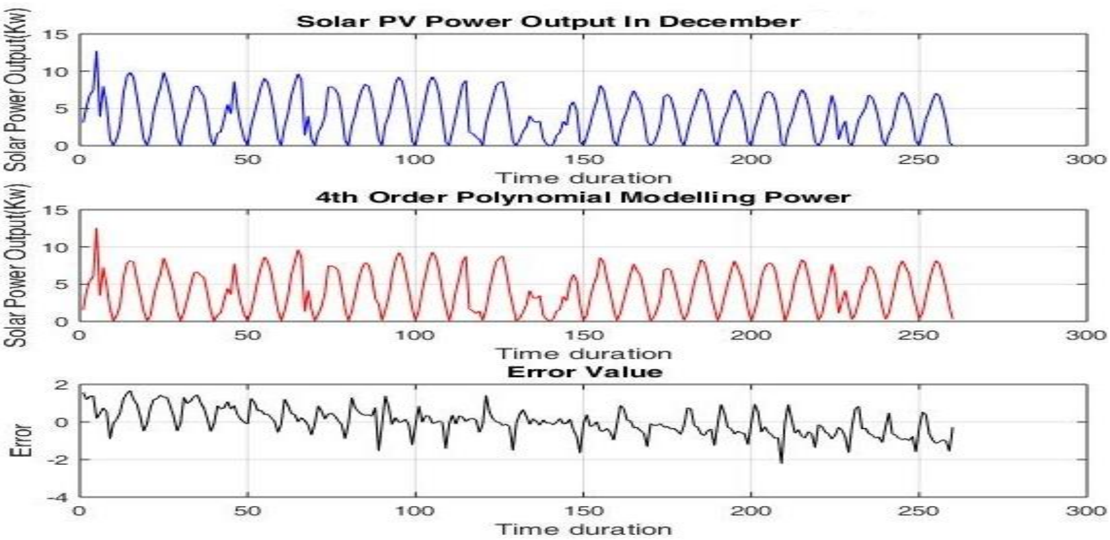


Figure 5-4 Plot of actual Power, Polynomial Linear Regression Modelled Power and Error Data of December 2018

From the above Figure 5-3, the actual power and forecasted power follow the same pattern. From this, it has concluded that the order polynomial regression of the 4th order was the best-fitted model for the monthly obtained solar PV power data and the RMSE obtained from it is 0.72

$P_{Solar(December)} = 5.7383e^{-11}I^4 - 6.7192e^{-08}I^3 + 2.9215e^{-05}I^2 + 0.0088I - 0.0573 \ldots \ldots \ldots \ldots \ldots \ldots \ldots (14)$

5.1.5 All 4 month data of 2018

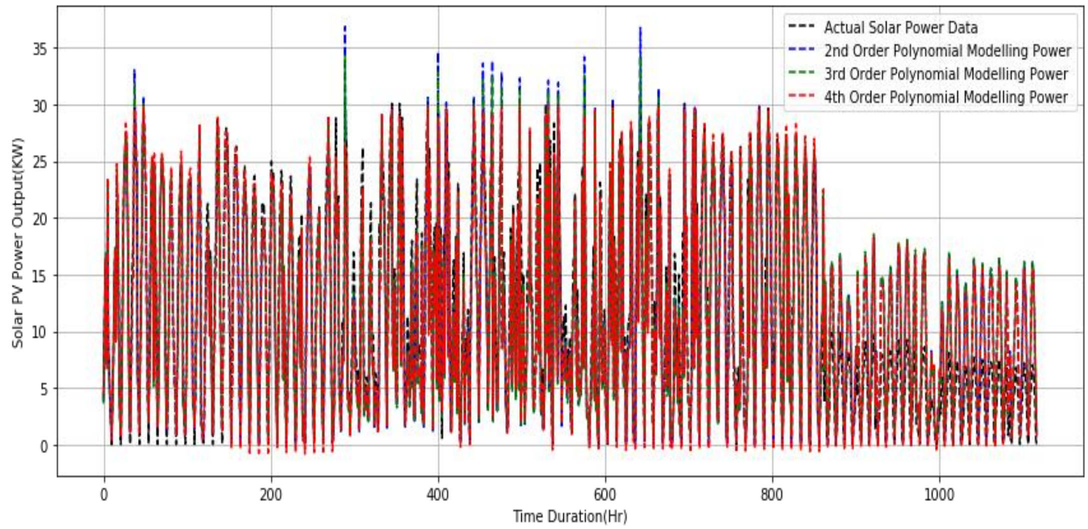


Figure 5-5. Comparison of all four Polynomial Linear Regression Modelled Power Data Plot of All 4 Month, 2018

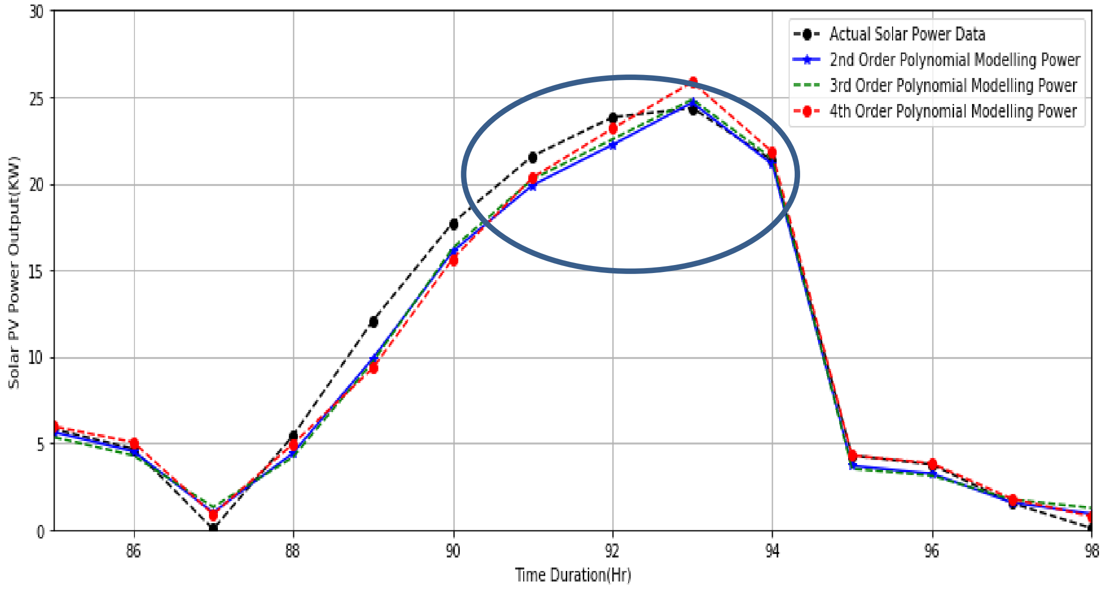


Figure 5-6. Zoom out of Comparison of all four Polynomial Linear Regression Modelled Power Data Plot of All 4 Month, 2018

$$P_{Solar(All\ data\ )} = -1.173e^{-10}I^4 + 2,25e^{-07}I^3 - 1.26e^{-04}I^2 + 0.0492I - 0.9749 \ldots (15)$$

From equation 11-15, it is concluded that among four various polynomial regression modelling, 4th order polynomial regression modelling only have less RMSE.

5.1.6 Polynomial Regression Modelling Results

Table 5.1 Root Mean Square Error (RMSE) of Real Power and Forecasted Power

March	Jun	September	December	All 4 Month data
0.924	2.031	0.72	0.72	2.92

4^{th} order polynomial regression modelling worked best in individual month data as shown in Polynomial Regression Modelling Results

Table 5.1. In the big data modelling including four-month power data, the 4^{th} order polynomial regression was not able to model properly in-compare to individual months due to the fluctuating nature of solar PV power data in four different months. Thus, this concludes that polynomial regression modelling only works for steady time series data. Polynomial regression modelling could not predict efficiently this fluctuating solar PV power data.

This analysis concludes that due to the highly fluctuating nature of PV power data polynomial regression modelling cannot model PV power data accurately. Therefore machine learning techniques would be better for these types of highly fluctuating data forecasting

5.2 Case 2: Multilayer Neural Network-Based Solar PV power Modelling:

A multi-layered feed-forward artificial neural network (MNN) consists of at least three layers of nodes. This three-layer is input, hidden and output layers. MNN is a supervised neural network so they require the desired output to be trained. In the MNN, each layer is made up of a number of interconnected nodes that use an activation function. Here, in this work, we use the rectified linear unit (ReLU) as an activation function. The input layer communicates to one or more hidden layers, where the actual processing is done via a system of weighted connections and the final output is provided by the output layer.

Here, the input for the MNN model is PV power obtain from the PV system at K3 substation in Singhdarbar, Nepal each day data from morning 8 am to 7 pm of 4-month duration. For better modelling, this collected 4 month PV power data is further divided into 90% for training and 10% for prediction and applying in the MNN algorithm using Python programming. From the training data, different structures of MNN have been trained and evaluated to choose the best models that are used to perform the prediction of the PV power output.

To select the best models from MNN, the mean squared error (RMSE) of the model has been evaluated. At 400 epochs for the training process, the error is converged and the training is stopped. The RMSE obtained from different MNN structure during the training and testing process are shown in Table 5.2 below.

Table 5.2 MNN Model Result

C.N.	MNN Structure	Optimizer	Learning Rate	Epochs	Train RMSE	Test RMSE
1	2 Hidden layer (5 and 10 node)	Adam	DEFAULT VALUE	Epoch =400	6.54	2.94
2	2 Hidden layer (50 and 100 node)	Adam	DEFAULT VALUE	Epoch =400	6.43	2.96
3	**3 Hidden layer (5, 10 and 5 node)**	**Adam**	**DEFAULT VALUE**	**Epoch =400**	**6.53**	**2.92**
4	3 Hidden layer (50, 100 and 50 node)	Adam	DEFAULT VALUE	Epoch =400	6.43	2.93

In the MNN Model Adam Optimizer has used due to perform optimization and is one of the best optimizers at present**.** Which default learning rate has decaying the running average of the gradient β1= 0.9, decaying the running average of the square of gradient β2 = 0.999, Step size parameter 0.001.

Four different MNN were trained and test with same data having Adam optimizer, default learning rate and for 400 epoch. The result obtained from third MNN structure have lowest RMSE i.e. 2.92. The 3rd MNN structure having three hidden layer, first hidden layer H1 have 5 node, second hidden layer H2 have 10 node and third hidden layer H3 have 5 node with Adam optimizer and default learning rate structure are best MNN structure for K3 site data.

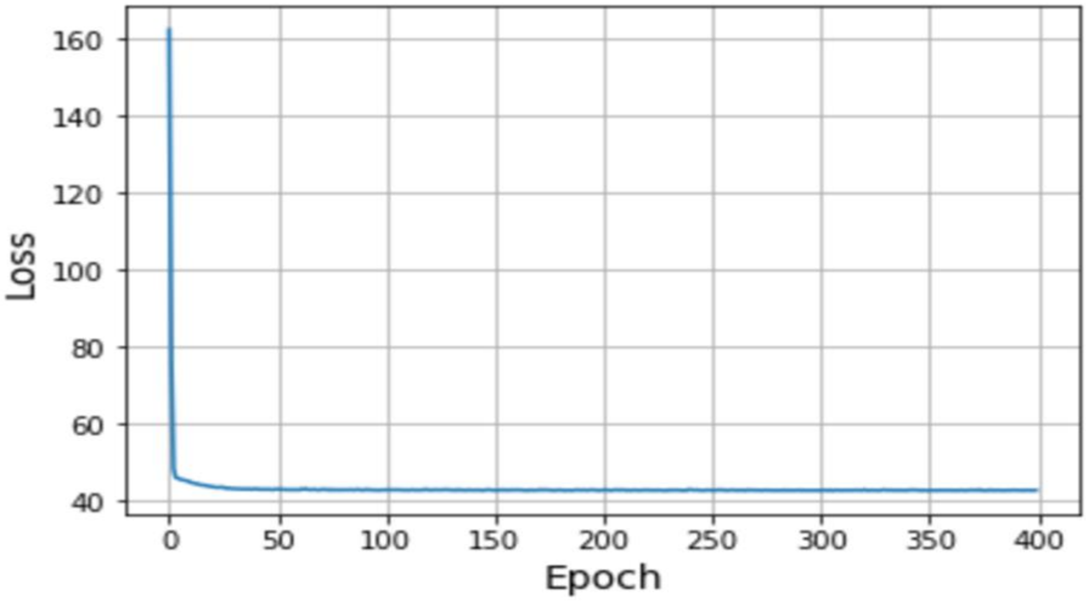


Figure 5-7: For Condition 3 Epoch

From Figure 5-7 learning rate of the Multilayer Neural Network (MNN) model vanished at Epoch 400. And the error value became saturate.

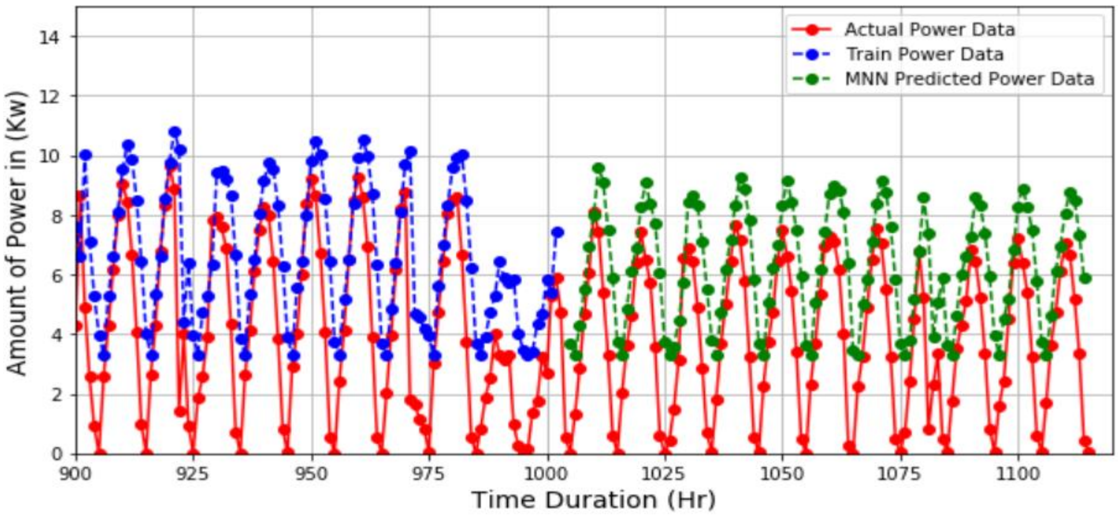


Figure 5-8: For Condition 3 Power Curve

Figure 5-8 is the modelling graph of Training PV output power data, Actual Figure 5-7: For Condition 3 EpochPV output Power data and predicted PV output power data reported from MNN structure with one input (In (1)) node, first hidden layer with five nodes (H1 (5)), second hidden layer with ten nodes (H2 (10)), third hidden layer with five nodes (H3 (5)), and one output node (Out (1)).

5.3 Case 3: Long Short-Term Memory (LSTM) Network-Based Solar PV power Modelling

Here, the input for the LSTM model is PV power obtain from the PV system at K3 substation in Singhdarbar, Kathmandu, Nepal. Each day data from morning 8:00 am to 7:00 pm of 4-month duration are collected and used. For better modelling, this collected 4 month PV power data is further divided into 90% for training and 10% for prediction. From the training data, different structures of LSTM have been trained and evaluated to choose the best models that are used to perform the prediction of the PV power output.

To select the best models from LSTM, the root mean squared error (RMSE) of the model has been evaluated. At 50 epochs for the training process, the error is converged and the training is stopped. The RMSE obtained from different LSTM structure during the training and testing process are shown in Table 5.3 below.

Table 5.3 LSTM Model Results

C.N.	LSTM Structure	Learning Rate	Epochs	Train RMSE	Test RMSE
1	2 Hidden layer (5 and 10 node)	default value	Epoch =50	5.20	1.35
2	2 Hidden layer (50 and 100 node)	default value	Epoch =50	4.06	1.31
3	3 Hidden layer (5, 10 and 5 node)	default value	Epoch =50	5.35	1.67
4	**3 Hidden layer (50, 100 and 50 node)**	**default value**	**Epoch =50**	**3.02**	**1.21**

Four different LSTM model were trained and test with same data having Adam optimizer, default learning rate and for 50 epoch. The result obtained from fourth LSTM structure have lowest RMSE.

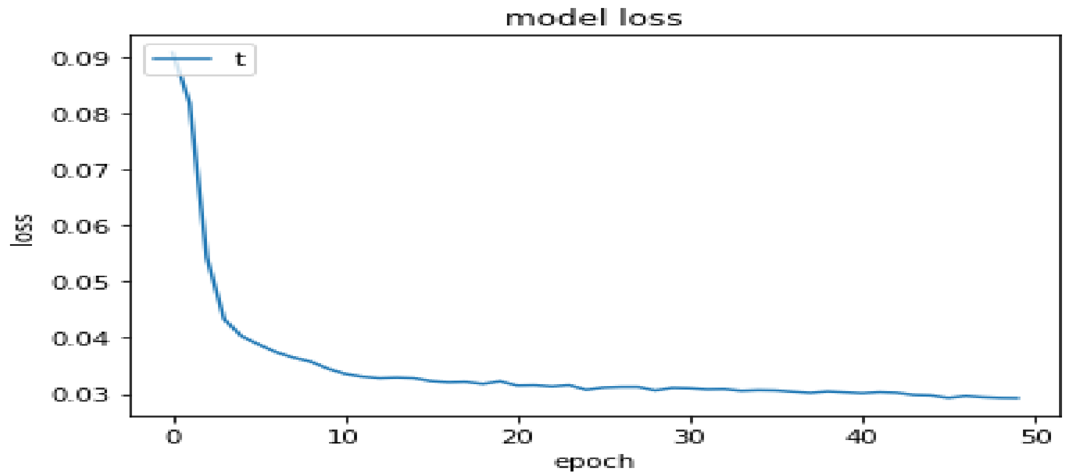


Figure 5-9: Epoch for Condition 4

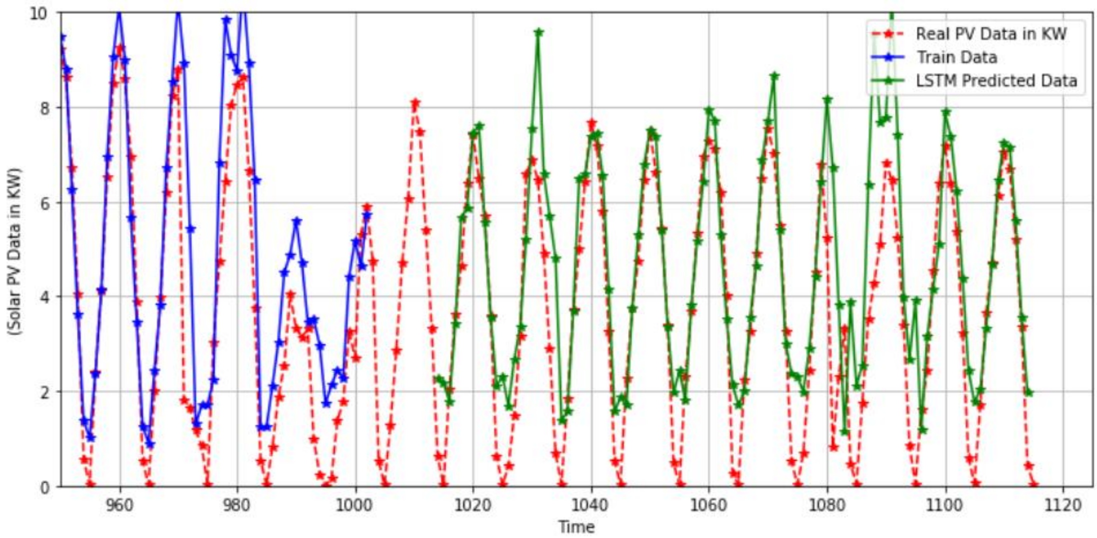


Figure 5-10: Power Test Result for Condition 4

From the training and testing RMSE evaluations of LSTM modelling, it can be observed that the best LSTM structure is with one input (In (1)) node, first hidden layer with fifty nodes (H1 (50)), second hidden layer with hundred nodes (H2 (100)), third hidden layer with fifty nodes (H3 (50)), and one output node (Out (1)). Among the four LSTM structure evaluations, we found this structure model has less RMSE error with 3.02 in training and 1.21 in testing.

Table 5.4 Model Output Comparison Summary

S. N	Number of Hidden Layer	Hidden Layer Nodes	LSTM Model		MNN Model	
			Train RMSE	Prediction RMSE	Train RMSE	Prediction RMSE
1	2	H1(5)-H2(10)	5.20	1.35	6.54	2.94
2	2	H1(50)-H2(100)	4.06	1.31	6.43	2.96
3	3	H1(5)-H2(10)-H3(5)	5.35	1.67	6.53	2.92
4	3	H1(50)-H2(100)-H3(50)	3.02	1.21	6.43	2.93

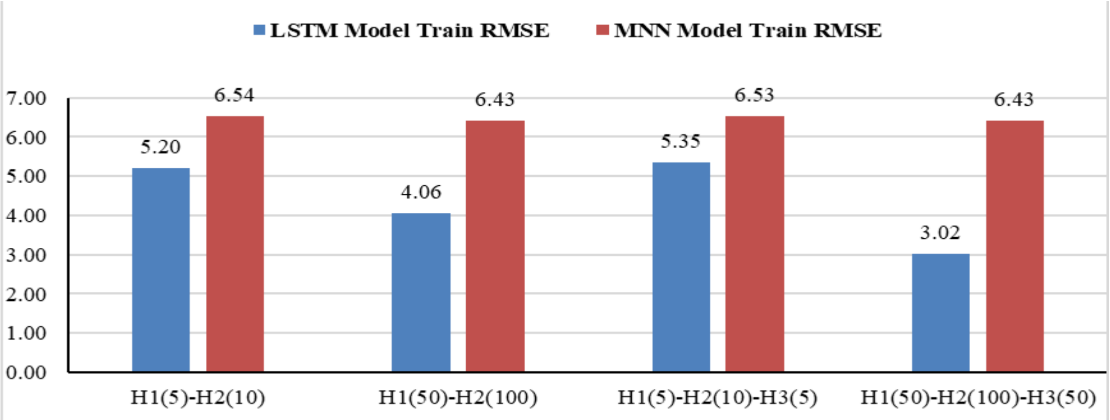


Figure 5-11. Bar chart of training error of MNN and LSTM

From this bar chart, it can be concluded that for this PV Solar PV power Data obtained from K3 substation Singdarbar, Kathmandu Nepal, Neural network having 3 hidden layers with first hidden layer H1 have 50 nodes, second hidden layer H2 have 100 nodes and third hidden layer H3 have 50 nodes fitted best model. Root mean square error (RMSE) of both LSTM and MNN trained model are 3.02 and 6.43 respectively.

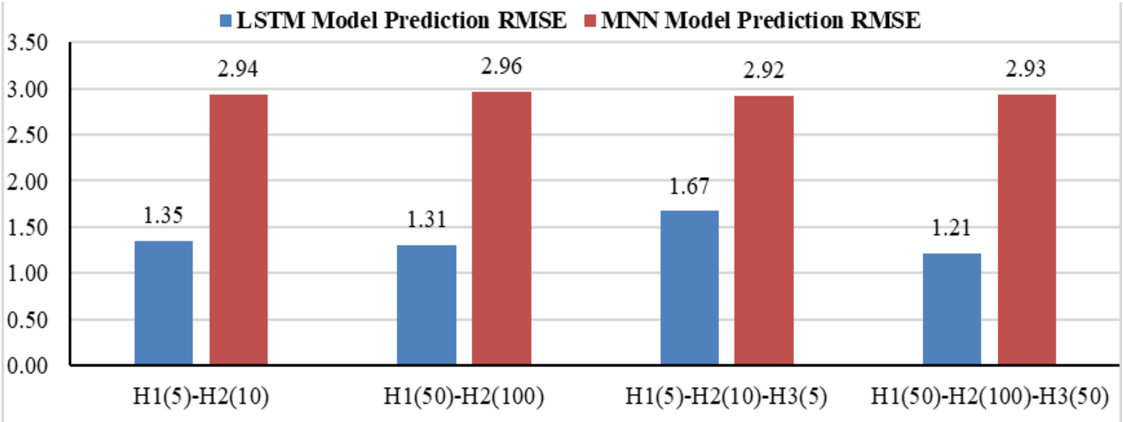


Figure 5-12 Model Output Comparison of LSTM and MNN Model

Table 5.5. Comparison Between The best Model

S.N	Number of Hidden Layer	Hidden Layer Nodes	LSTM Model		MNN Model	
			Train RMSE	Prediction RMSE	Train RMSE	Prediction RMSE
1	3	H1(5)-H2(10)-H3(5)	5.35	1.67	6.53	2.92
2	3	H1(50)-H2(100)-H3(50)	3.02	1.21	6.43	2.93

From Figure 5-12, LSTM and MNN structure was te

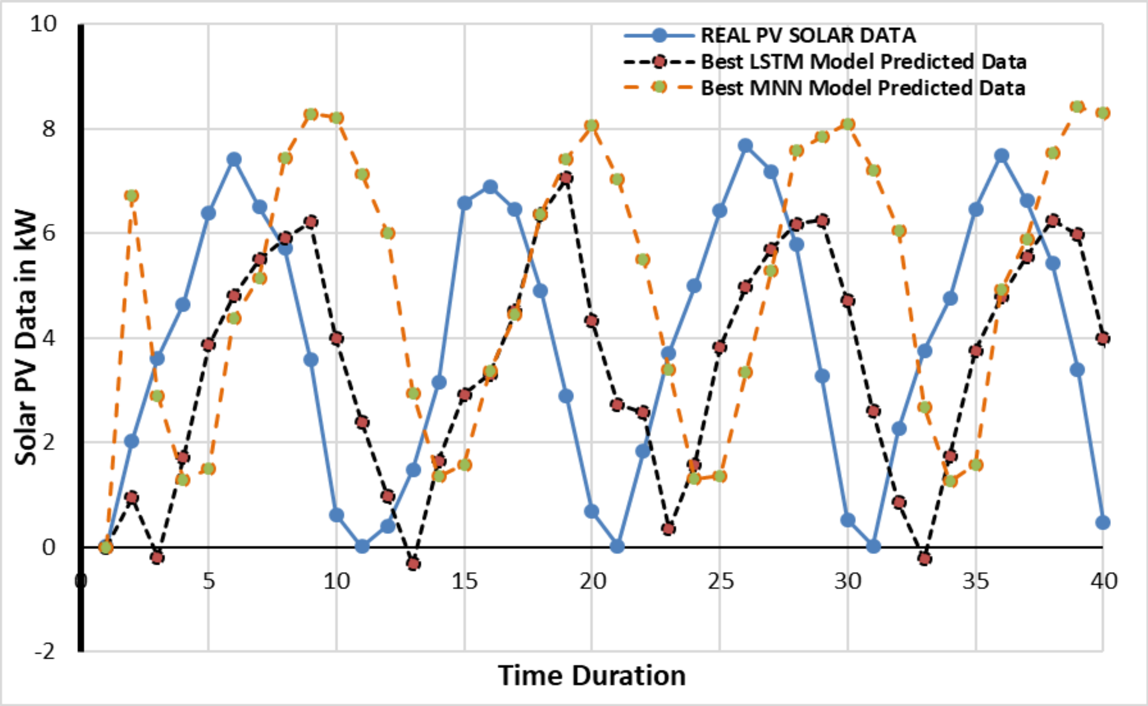


Figure 5-13. Model Comparison Graph with actual Power

From the Comparison of MNN and LSTM for four testing models reveals LSTM achieves the better prediction performance. LSTM has 50% more accurate RMSE compared to that of MNN.

Table 5.6. Model Result Comparison with other Research paper Result for Validation

SN.	Name of Research Paper	Training RMSE		Prediction RMSE	
		MNN	LSTM	MNN	LSTM
1	Comparing Deep Learning Techniques for modelling PV Power Output (Paudel & Jang, 2018)	5.005	2.21	9.56	3.12
2	Our Thesis Result	6.43	3.02	2.92	1.21

CHAPTER SIX: CONCLUSION AND RECOMMENDATION

6.1 Conclusion

- The correlation coefficient between the solar PV power with Irradiation, temperature and wind has calculated to understand the relationship between the parameters. The correlation coefficient between the power and irradiance was found greater than 0.93, power and temperature has less than 0.49 and power and wind was found less than 0.19. This showed that power and irradiance has strong relationship.
- Polynomial Regression, Multi-layer Neural Network, and Long Short Term Memory Neural Network model were developed for real time solar PV power forecasting. The RMSE between the actual and forecasted power by Polynomial Regression was found 2.92. The value of RMSE obtained by MNN and LSTM was found 2.92 and 1.21 respectively.
- The purposed LSTM model decreased the error by 100% compared to Polynomial Regression and MNN model, therefore the LSTM model has recommended as the best model for solar PV power forecasting in our case.
- Solar PV Power forecasting techniques improve the quality of the energy delivered to the grid and minimize the additional cost associated with weather dependency and it help for future generation expansion planning.

6.2 Recommendation

- This forecast can help to make important decisions in the field of solar PV power forecasting.
- This research is limited to K3 substation as a case study for academic purpose. If the experimental set up can be done properly at others stations of Nepal, similar forecasting can be carried out.
- There is space for researcher in other forecasting model comprising of Neural Network and check whether the other model could forecast more accurately.

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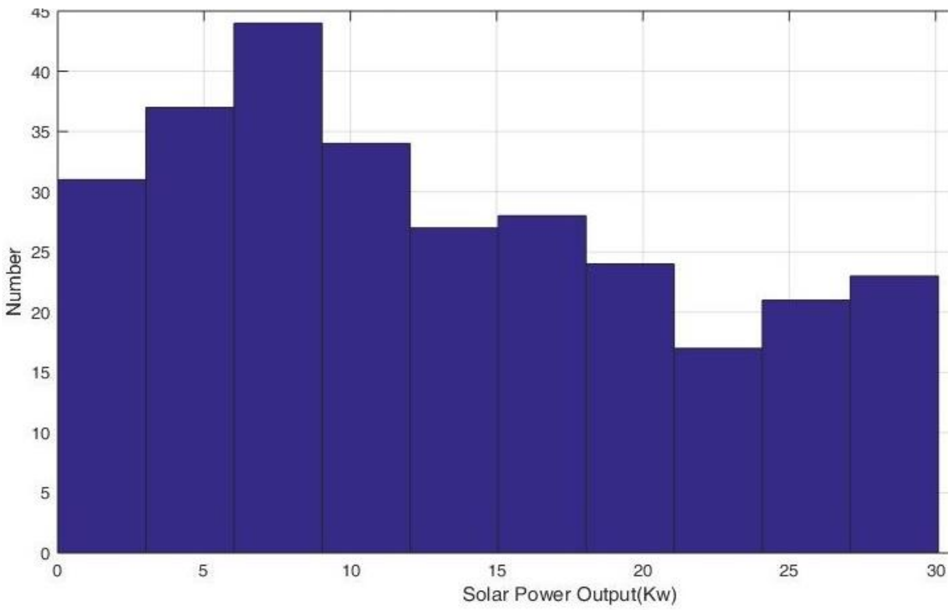
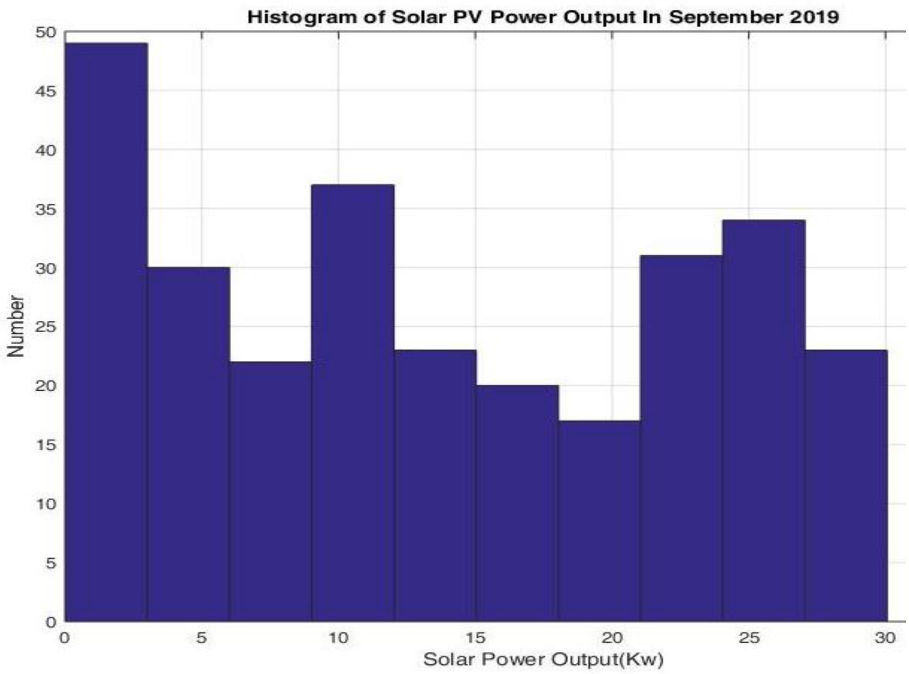
Appendix A: Histogram Plot of Solar PV power and Solar Irradiance.



From the above Histogram plot of Solar PV power Data of Different day of Jun, 2018. It has cleared that the min power = 0.008 kW, Maximum Power obtained on that month was 30.09 kW, Mean Value = 13.284 and Standard deviation = 8.472.



From the above Histogram plot of Solar PV power Data of Different day of September, 2018. It has cleared that the min power = 0.003 kW, Maximum Power obtained on that month was 30.061 kW, Mean Value = 13.70 and Standard deviation = 9.4307.

Appendix B: Error Comparison Power Data Sheet of Both Model

S.N	REAL PV SOLAR DATA kW	LSTM MODEL PREDICTED POWER DATA kW	MNN MODEL PREDICTED POWER DATA kW	LSTM ERROR kW	MNN ERROR kW
1	0.016	0.94135249	6.71862888	-0.92535249	-6.70262888
2	2.029	-0.19422446	2.89156699	2.22322446	-0.86256699
3	3.616	1.71580696	1.2971189	1.90019304	2.3188811
4	4.649	3.86606693	1.49176121	0.78293307	3.15723879
5	6.397	4.80400562	4.37445736	1.59299438	2.02254264
6	7.419	5.50130272	5.1455555	1.91769728	2.2734445
7	6.499	5.89672899	7.44972086	0.60227101	-0.95072086
8	5.706	6.21180868	8.28837681	-0.50580868	-2.58237681
9	3.59	3.9827373	8.21393204	-0.3927373	-4.62393204
10	0.62	2.39015913	7.13804483	-1.77015913	-6.51804483
11	0.014	0.97931927	6.01293278	-0.96531927	-5.99893278
12	0.407	-0.31979647	2.94945359	0.72679647	-2.54245359
13	1.484	1.64893436	1.35148096	-0.16493436	0.13251904
14	3.15	2.91602993	1.57727909	0.23397007	1.57272091
15	6.58	3.30584383	3.36593795	3.27415617	3.21406205
16	6.893	4.51027012	4.44273233	2.38272988	2.45026767
17	6.455	6.35893106	6.37091494	0.09606894	0.08408506
18	4.909	7.05249834	7.42638159	-2.14349834	-2.51738159
19	2.885	4.32295465	8.06383705	-1.43795465	-5.17883705
20	0.685	2.73241496	7.03608942	-2.04741496	-6.35108942
21	0.025	2.5741241	5.50974321	-2.5491241	-5.48474321
22	1.834	0.34406435	3.383986	1.48993565	-1.549986
23	3.711	1.58039212	1.30236816	2.13060788	2.40863184
24	4.993	3.83248878	1.36590743	1.16051122	3.62709257
25	6.437	4.9816227	3.33624268	1.4553773	3.10075732
26	7.677	5.70274019	5.29285336	1.97425981	2.38414664
27	7.187	6.17549038	7.58248663	1.01150962	-0.39548663
28	5.787	6.24394274	7.84402752	-0.45694274	-2.05702752
29	3.265	4.7086978	8.095788	-1.4436978	-4.830788
30	0.527	2.59648108	7.20396376	-2.06948108	-6.67696376
31	0.019	0.84626549	6.06261301	-0.82726549	-6.04361301
32	2.259	-0.2234325	2.68639088	2.4824325	-0.42739088
33	3.76	1.74668598	1.25887561	2.01331402	2.50112439

S.N	REAL PV SOLAR DATA kW	LSTM MODEL PREDICTED POWER DATA kW	MNN MODEL PREDICTED POWER DATA kW	LSTM ERROR kW	MNN ERROR kW
34	4.749	3.75598431	1.58557105	0.99301569	3.16342895
35	6.463	4.77226591	4.91980028	1.69073409	1.54319972
36	7.497	5.55453062	5.88675022	1.94246938	1.61024978
37	6.627	6.2444191	7.53628397	0.3825809	-0.90928397
38	5.425	5.97140455	8.41162395	-0.54640455	-2.98662395
39	3.397	4.00439739	8.29612541	-0.60739739	-4.89912541
40	0.478	2.2984221	7.2087903	-1.8204221	-6.7307903
41	0.013	0.8963927	5.99601793	-0.8833927	-5.98301793
42	2.29	-0.39456338	2.59392238	2.68456338	-0.30392238
43	3.689	1.75162697	1.30667186	1.93737303	2.38232814
44	5.341	3.77325773	1.76309967	1.56774227	3.57790033
45	6.95	4.66471624	4.89019156	2.28528376	2.05980844
46	7.29	5.97287226	6.03339815	1.31712774	1.25660185
47	7.109	6.6430068	7.78215742	0.4659932	-0.67315742
48	6.193	7.22138119	8.50296974	-1.02838119	-2.30996974
49	4.003	3.83296323	8.16642094	0.17003677	-4.16342094
50	0.253	2.47901344	7.24405336	-2.22601344	-6.99105336
51	0.012	1.07173407	5.97472763	-1.05973407	-5.96272763
52	2.225	-0.58653545	3.22156262	2.81153545	-0.99656262
53	3.26	2.04495835	1.28443551	1.21504165	1.97556449
54	4.89	3.81145263	1.83094168	1.07854737	3.05905832
55	6.495	4.44865942	4.91167974	2.04634058	1.58332026
56	7.536	5.47827148	5.77774572	2.05772852	1.75825428
57	7.027	6.30793476	7.5185771	0.71906524	-0.4915771
58	5.507	7.63469553	8.69917583	-2.12769553	-3.19217583
59	3.246	3.49394679	8.29047775	-0.24794679	-5.04447775
60	0.513	2.14763021	7.70578241	-1.63463021	-7.19278241
61	0.022	0.65737593	6.20134068	-0.63537593	-6.17934068
62	0.68	-0.42602351	2.52132726	1.10602351	-1.84132726
63	2.433	1.97154057	1.30405092	0.46145943	1.12894908
64	4.509	3.14345956	1.63916349	1.36554044	2.86983651
65	6.789	4.13478899	3.47731209	2.65421101	3.31168791
66	5.23	5.55168962	4.81498814	-0.32168962	0.41501186
67	0.812	6.75105572	7.18386459	-5.93905572	-6.37186459
68	2.286	5.30604935	7.67928553	-3.02004935	-5.39328553
69	3.335	2.47323608	7.30437136	0.86176392	-3.96937136
70	0.459	1.62432432	5.58955908	-1.16532432	-5.13055908
71	0.033	2.29233623	3.62614393	-2.25933623	-3.59314393
72	1.752	1.47738469	3.50169086	0.27461531	-1.74969086
73	3.508	2.42499661	1.39480436	1.08300339	2.11319564
74	4.287	4.53652859	1.26746607	-0.24952859	3.01953393

S.N	REAL PV SOLAR DATA kW	LSTM MODEL PREDICTED POWER DATA kW	MNN MODEL PREDICTED POWER DATA kW	LSTM ERROR kW	MNN ERROR kW
75	5.095	6.08644772	3.82045436	-0.99144772	1.27454564
76	6.817	7.55544138	6.28755331	-0.73844138	0.52944669
77	6.451	6.53385162	6.30094528	-0.08285162	0.15005472
78	5.249	6.49491453	6.25314474	-1.24591453	-1.00414474
79	3.38	4.44195652	6.94535351	-1.06195652	-3.56535351
80	0.838	2.31531191	6.11655092	-1.47731191	-5.27855092
81	0.036	1.38032794	5.98038197	-1.34432794	-5.94438197
82	1.606	-0.1952929	2.81267595	1.8012929	-1.20667595
83	2.434	1.13153017	1.3817327	1.30246983	1.0522673
84	4.539	3.23414826	1.66452909	1.30485174	2.87447091
85	6.386	3.79114008	4.30781937	2.59485992	2.07818063
86	7.194	5.18956661	4.5052948	2.00443339	2.6887052
87	6.403	6.33508348	6.82740545	0.06791652	-0.42440545
88	5.378	6.41962433	8.14778328	-1.04162433	-2.76978328
89	3.222	4.23806906	7.92872334	-1.01606906	-4.70672334
90	0.59	2.56797409	7.1628561	-1.97797409	-6.5728561
91	0.044	0.7356019	5.97372484	-0.6916019	-5.92972484
92	1.698	-0.19807185	3.11458182	1.89607185	-1.41658182
93	3.658	2.04256439	1.32724333	1.61543561	2.33075667
94	4.71	3.54906678	1.5412035	1.16093322	3.1687965
95	6.133	4.57143307	3.8952806	1.56156693	2.2377194
96	7.038	5.4292841	5.88142443	1.6087159	1.15657557
97	6.691	5.89399624	7.46467543	0.79700376	-0.77367543
98	5.202	6.12368917	7.91737938	-0.92168917	-2.71537938
99	3.351	3.93792105	7.84794664	-0.58692105	-4.49694664
100	0.434	2.21385694	7.07071733	-1.77985694	-6.63671733
101	0.039	1.04434323	5.79616022	-1.00534323	-5.75716022

Appendix C: K-3 Meteorological Data Daily Report Log Sheet

Date & time	Irradiance (W/M^2)	Temperature (^0C)	Wind speed (m/s)	Power (Kw)
2018/03/01 08:00:00	155	14.5	0	4.009
2018/03/01 09:00:00	325	17.2	0.2	9.457
2018/03/01 10:00:00	517	18.9	0.5	15.13
2018/03/01 11:00:00	595	21.5	1.9	15.83
2018/03/01 12:00:00	276	22.4	1.1	7.935
2018/03/01 13:00:00	768	24.4	2	20.84
2018/03/01 14:00:00	315	23.9	4.7	8.997
2018/03/01 15:00:00	253	23	2.8	6.916
2018/03/01 16:00:00	150	21.3	2.3	3.592
2018/03/01 17:00:00	80	19.9	2.4	1.863
2018/03/01 18:00:00	0	18.7	1.9	0.007
2018/03/01 19:00:00	0	18.2	1.7	0
2018/03/02 08:00:00	151	14.7	0	0
2018/03/02 09:00:00	281	17.2	0	0.66
2018/03/02 10:00:00	517	18.8	0.4	4.201
2018/03/02 11:00:00	616	21	0	8.024
2018/03/02 12:00:00	367	23.1	1.9	14.44
2018/03/02 13:00:00	797	23.1	5	16.71
2018/03/02 14:00:00	736	24	3.5	9.011
2018/03/02 15:00:00	578	23.8	5.5	21.2
2018/03/02 16:00:00	192	23.6	2.1	18.96
2018/03/02 17:00:00	81	21.7	1.8	14
2018/03/02 18:00:00	0	20.3	2.6	5.025
2018/03/02 19:00:00	0	15.2	0.7	1.85
2018/03/03 08:00:00	229	13.5	0	0
2018/03/03 09:00:00	462	14.9	0.5	1.116
2018/03/03 10:00:00	675	18.3	0.2	7.693
2018/03/03 11:00:00	804	19.7	1.8	14.92
2018/03/03 12:00:00	848	23	0	21.23
2018/03/03 13:00:00	904	23.1	8.3	24.97
2018/03/03 14:00:00	863	24	5	25.96
2018/03/03 15:00:00	691	24.8	1.4	27.25
2018/03/03 16:00:00	408	23.1	2.7	25.07

Date & time	Irradiance (W/M^2)	Temperature (^0C)	Wind speed (m/s)	Power (Kw)
2018/03/03 17:00:00	152	21.5	5.7	19.95
2018/03/03 18:00:00	0	20.1	6.3	11.81
2018/03/03 19:00:00	0	19.2	3.4	3.681
2018/03/04 08:00:00	201	14.3	0	0
2018/03/04 09:00:00	427	16.9	0	1.112
2018/03/04 10:00:00	534	19.8	2.9	6.568
2018/03/04 11:00:00	554	21.1	0.9	14.41
2018/03/04 12:00:00	1046	23.7	3.8	16.98
2018/03/04 13:00:00	960	23.9	8.3	19.33
2018/03/04 14:00:00	843	25.2	1.8	30.03
2018/03/04 15:00:00	823	24.6	6.3	28.37
2018/03/04 16:00:00	225	23.8	3.5	24.69
2018/03/04 17:00:00	197	22.6	3.8	24.61
2018/03/04 18:00:00	0	21.5	4.2	6.1
2018/03/04 19:00:00	0	20	2.7	4.27
2018/03/05 08:00:00	277	16	0	0
2018/03/05 09:00:00	432	18.7	0	1.708
2018/03/05 10:00:00	629	20.5	0.4	8.862
2018/03/05 11:00:00	890	22.5	7.6	14.05
2018/03/05 12:00:00	988	23.1	2.9	19.4
2018/03/05 13:00:00	911	23.5	5	26.22
2018/03/05 14:00:00	828	24	7.6	29.14
2018/03/05 15:00:00	689	23.9	3.4	26.57
2018/03/05 16:00:00	446	23.3	2.7	24.09
2018/03/05 17:00:00	192	22.4	4	19.67
2018/03/05 18:00:00	0	21	0.6	12.38
2018/03/05 19:00:00	0	19.9	3.5	4.688
2018/03/06 08:00:00	238	14.8	0.4	0
2018/03/06 09:00:00	475	16.8	1.6	1.17
2018/03/06 10:00:00	702	20	0.4	7.419
2018/03/06 11:00:00	819	22.1	1.5	15.38
2018/03/06 12:00:00	803	21.8	5.5	21.39
2018/03/06 13:00:00	217	21.6	4.5	24.65
2018/03/06 14:00:00	821	23.2	4	24.47
2018/03/06 15:00:00	668	23.2	2.8	26.47
2018/03/06 16:00:00	455	22.3	5.8	23.76
2018/03/06 17:00:00	196	20.9	1.9	19.31
2018/03/06 18:00:00	0	19.4	6.4	12.7
2018/03/06 19:00:00	0	18.4	2.6	4.727
2018/03/07 08:00:00	219	14.4	0	0

Date & time	Irradiance (W/M^2)	Temperature (^0C)	Wind speed (m/s)	Power (Kw)
2018/03/07 09:00:00	428	16.2	2	1.301
2018/03/07 10:00:00	690	20.1	0.7	6.748
2018/03/07 11:00:00	786	22	0.5	13.79
2018/03/07 12:00:00	821	24.6	0.7	21.2
2018/03/07 13:00:00	802	25.6	1.6	23.48
2018/03/07 14:00:00	774	26.3	2.1	25.5
2018/03/07 15:00:00	573	24.3	5.4	23.8
2018/03/07 16:00:00	345	22.8	2.8	22.65
2018/03/07 17:00:00	144	21.1	3.2	16.92
2018/03/07 18:00:00	0	19	1.5	9.709
2018/03/07 19:00:00	0	18.2	0.6	3.376
2018/03/08 08:00:00	177	14.2	0.4	0
2018/03/08 09:00:00	375	17.1	0	0.752
2018/03/08 10:00:00	592	18.3	3	5.31
2018/03/08 11:00:00	723	21.1	2	12.21
2018/03/08 12:00:00	792	21.5	1.5	18.5
2018/03/08 13:00:00	702	23.2	1.6	22.06
2018/03/08 14:00:00	505	22.4	3.2	23.31
2018/03/08 15:00:00	334	22.3	4.3	21.23
2018/03/08 16:00:00	225	22.4	1.2	13.92
2018/03/08 17:00:00	183	21	4.1	9.417
2018/03/08 18:00:00	0	19	1.7	5.812
2018/03/08 19:00:00	0	18	1	4.669
2018/03/09 08:00:00	179	14.6	0	0
2018/03/09 09:00:00	377	17.1	0	1.033
2018/03/09 10:00:00	577	18	2.3	5.433
2018/03/09 11:00:00	692	20.7	2.9	12.07
2018/03/09 12:00:00	759	23.2	2.1	17.73
2018/03/09 13:00:00	827	21.8	6.5	21.58
2018/03/09 14:00:00	727	22.7	3.9	23.82
2018/03/09 15:00:00	151	22.8	0.9	24.35
2018/03/09 16:00:00	133	22.2	2.3	21.34
2018/03/09 17:00:00	66	20.9	4.4	4.281
2018/03/09 18:00:00	0	20.1	1.2	3.771
2018/03/09 19:00:00	0	18.9	1.1	1.537
2018/03/10 08:00:00	210	13.8	0	0
2018/03/10 09:00:00	391	17	0	1.51
2018/03/10 10:00:00	620	19.1	1	6.163
2018/03/10 11:00:00	770	21.4	1.7	12.4
2018/03/10 12:00:00	777	23.5	2.6	19.26

Date & time	Irradiance (W/M^2)	Temperature (^0C)	Wind speed (m/s)	Power (Kw)
2018/03/10 13:00:00	788	25.4	2.4	23.06
2018/03/10 14:00:00	707	24.1	3.7	23.46
2018/03/10 15:00:00	598	24.1	4.2	23.58
2018/03/10 16:00:00	135	22	1.8	20.7
2018/03/10 17:00:00	144	21.2	4.3	17.04
2018/03/10 18:00:00	0	19.6	0.8	3.692
2018/03/10 19:00:00	0	18.9	0	3.48
2018/03/11 08:00:00	175	14.2	0	0
2018/03/11 09:00:00	346	17.5	0	0.975
2018/03/11 10:00:00	508	18.8	4.1	4.923
2018/03/11 11:00:00	688	22	1.5	10.66
2018/03/11 12:00:00	778	23	1.6	15.39
2018/03/11 13:00:00	904	24.4	3.7	20.65
2018/03/11 14:00:00	673	21.9	4.4	23.04
2018/03/11 15:00:00	70	17.8	8	26.7
2018/03/11 16:00:00	0	13.6	0.7	19.6
2018/03/11 17:00:00	0	12.7	0.9	2.134
2018/03/13 08:00:00	211	14.7	0.5	0
2018/03/13 09:00:00	393	16.8	0	1.141
2018/03/13 10:00:00	549	18.1	0.7	6.663
2018/03/13 11:00:00	649	21.2	1.3	12.64
2018/03/13 12:00:00	659	21.8	0.3	17.06
2018/03/13 13:00:00	538	23.8	0.5	20.83
2018/03/13 14:00:00	386	23.6	1.5	21.23
2018/03/13 15:00:00	581	24	1.3	16.82
2018/03/13 16:00:00	331	23.1	2.4	12.03
2018/03/13 17:00:00	150	21.3	3	17.03
2018/03/13 18:00:00	0	19.5	2.2	9.729
2018/03/13 19:00:00	0	18.9	1.6	4.054
2018/03/14 08:00:00	241	15.4	0	0
2018/03/14 09:00:00	399	17.6	0	1.432
2018/03/14 10:00:00	548	19.4	2	7.559
2018/03/14 11:00:00	593	21.2	1.2	12.53
2018/03/14 12:00:00	911	23.4	4.6	17.66
2018/03/14 13:00:00	925	23.3	6.8	19.01
2018/03/14 14:00:00	807	24.1	6.9	28.55
2018/03/14 15:00:00	642	24.6	3.1	28.41
2018/03/14 16:00:00	414	24.2	3.2	24.74
2018/03/14 17:00:00	184	23.6	2.6	18.5
2018/03/17 08:00:00	267	15.6	0	0

Date & time	Irradiance (W/M^2)	Temperature (^0C)	Wind speed (m/s)	Power (Kw)
2018/03/17 09:00:00	523	17.2	0	2.015
2018/03/17 10:00:00	732	19.6	2	8.921
2018/03/17 11:00:00	867	21.7	1.5	16.99
2018/03/17 12:00:00	879	24.3	1.7	22.93
2018/03/17 13:00:00	859	25.8	2.2	27.46
2018/03/17 14:00:00	800	25.7	3	27.89
2018/03/17 15:00:00	606	24.3	2	27.64
2018/03/17 16:00:00	407	23.2	2.8	24.41
2018/03/17 17:00:00	174	21.6	4.3	18.24
2018/03/17 18:00:00	15	19.9	1	12.11
2018/03/17 19:00:00	0	18.5	0	4.714
2018/03/18 08:00:00	225	14.1	0	0
2018/03/18 09:00:00	461	16.1	0.4	1.945
2018/03/18 10:00:00	665	18.6	1.6	7.451
2018/03/18 11:00:00	789	21	1.5	15.23
2018/03/18 12:00:00	835	22.4	0.7	20.86
2018/03/18 13:00:00	833	23.3	1.1	24.72
2018/03/18 14:00:00	770	23.1	8.4	26.01
2018/03/18 15:00:00	628	23.6	6.2	26.28
2018/03/18 16:00:00	369	23.4	5.8	23.54
2018/03/18 17:00:00	152	23.1	4.2	18.36
2018/03/18 18:00:00	0	20.3	1.3	10.64
2018/03/19 08:00:00	221	15	0	0
2018/03/19 09:00:00	435	17.2	0.6	1.746
2018/03/19 10:00:00	606	19.7	1.5	7.065
2018/03/19 11:00:00	742	22.1	1	13.99
2018/03/19 12:00:00	782	23	3.8	19.42
2018/03/19 13:00:00	704	24.7	7.3	23.12
2018/03/19 14:00:00	694	24.4	2	24.53
2018/03/19 15:00:00	555	25	8.5	22.55
2018/03/19 16:00:00	338	24.3	2.3	20.98
2018/03/19 17:00:00	138	23.5	4.8	15.94
2018/03/19 18:00:00	0	22.1	1.5	9.777
2018/03/19 19:00:00	0	20.3	0	3.495
2018/03/20 08:00:00	217	16.3	0	0
2018/03/20 09:00:00	418	18.7	0	1.523
2018/03/20 10:00:00	600	20.5	1.7	6.886
2018/03/20 11:00:00	674	22.6	0.7	13.49
2018/03/20 12:00:00	735	24.5	3.4	19.23
2018/03/20 13:00:00	755	24.8	3	21.37

Date & time	Irradiance (W/M^2)	Temperature (^0C)	Wind speed (m/s)	Power (Kw)
2018/03/20 14:00:00	678	25.3	6.2	23.52
2018/03/20 15:00:00	531	25	6.2	23.7
2018/03/20 16:00:00	332	25	1.5	20.98
2018/03/20 17:00:00	140	23.9	3.3	15.28
2018/03/20 18:00:00	0	21.9	3	9.539
2018/03/20 19:00:00	0	20.7	0.3	3.65
2018/03/21 08:00:00	200	15.8	0	0
2018/03/21 09:00:00	373	18.2	0	1.036
2018/03/21 10:00:00	557	21	1.1	5.985
2018/03/21 11:00:00	650	24.3	2.3	11.65
2018/03/21 12:00:00	639	25.3	0.5	17.86
2018/03/21 13:00:00	682	25.1	4.5	21.37
2018/03/21 14:00:00	618	25.8	2.9	20.81
2018/03/21 15:00:00	566	26	3.5	21.28
2018/03/21 16:00:00	339	26.3	0.9	18.36
2018/03/21 17:00:00	132	24.9	1.9	15.96
2018/03/21 18:00:00	0	22.2	1.5	9.68
2018/03/21 19:00:00	0	21	0	3.181
2018/03/23 08:00:00	249	16.5	0	0
2018/03/23 09:00:00	470	20.6	1.3	2.143
2018/03/23 10:00:00	665	21.8	0.4	7.657
2018/03/23 11:00:00	776	24.8	1.9	14.63
2018/03/23 12:00:00	749	25.2	4.4	20.71
2018/03/23 13:00:00	766	25.9	4.9	24.97
2018/03/23 14:00:00	720	27	3	23.11
2018/03/23 15:00:00	530	26.1	3.4	22.5
2018/03/23 16:00:00	276	25.2	2.1	22.34
2018/03/23 17:00:00	131	23.7	2.2	16.89
2018/03/23 18:00:00	15	22.8	1.5	7.664
2018/03/23 19:00:00	0	21.9	3.3	3.161
2018/03/24 08:00:00	235	17.1	0	0.004
2018/03/24 09:00:00	452	18.8	0	2.086
2018/03/24 10:00:00	627	21.1	2.2	7.236
2018/03/24 11:00:00	708	24.3	2.1	13.98
2018/03/24 12:00:00	756	26	1.7	19.61
2018/03/24 13:00:00	736	25.9	1.5	22.39
2018/03/24 14:00:00	232	25.5	3.4	24.13
2018/03/24 15:00:00	562	27	2.6	23.03
2018/03/24 16:00:00	315	26	2.5	7.221
2018/03/24 17:00:00	106	24	3.3	15.89

Date & time	Irradiance (W/M^2)	Temperature (^0C)	Wind speed (m/s)	Power (Kw)
2018/03/24 18:00:00	0	22.5	1.1	8.589
2018/03/25 08:00:00	206	16.5	0	0
2018/03/25 09:00:00	378	19.4	1.9	1.731
2018/03/25 10:00:00	518	21.1	1.2	6.154
2018/03/25 11:00:00	668	24	0.2	11.72
2018/03/25 12:00:00	736	25.2	3	16.06
2018/03/25 13:00:00	703	27.4	1.1	21.17
2018/03/25 14:00:00	577	25.9	4.1	23.65
2018/03/25 15:00:00	472	25.9	2.4	21.89
2018/03/25 16:00:00	292	24.5	2.3	17.2
2018/03/25 17:00:00	133	23.2	1.5	13.5
2018/03/25 18:00:00	0	21.8	1.3	8.045
2018/03/25 19:00:00	0	20.8	0	3.195
2018/03/26 08:00:00	189	16	0	0.01
2018/03/26 09:00:00	374	18.2	0	1.731
2018/03/26 10:00:00	522	20.6	0.6	5.508
2018/03/26 11:00:00	585	23.4	2.3	11.55
2018/03/26 12:00:00	593	25.4	0	16.01
2018/03/26 13:00:00	277	23.7	7.5	18.18
2018/03/26 14:00:00	658	25	2.8	18.5
2018/03/26 15:00:00	108	23.3	2.4	8.657
2018/03/26 16:00:00	28	18.2	2.9	20.32
2018/03/26 17:00:00	83	17	3.9	2.983
2018/03/26 18:00:00	0	18.1	0	0.66
2018/03/26 19:00:00	0	17.4	1.6	2.465
2018/03/27 08:00:00	259	16.2	0	0.008
2018/03/27 09:00:00	464	18.2	0	2.238
2018/03/27 10:00:00	666	20.7	1.6	7.863
2018/03/27 11:00:00	726	23.9	2.4	14.4
2018/03/27 12:00:00	801	25.4	1.4	20.07
2018/03/27 13:00:00	813	27.1	2.1	22.51
2018/03/27 14:00:00	735	27.6	6.2	23.82
2018/03/27 15:00:00	491	28	1.7	24.48
2018/03/27 16:00:00	283	26.2	1.8	21.6
2018/03/27 17:00:00	120	24.4	2.6	13.72
2018/03/27 18:00:00	0	22.8	3.2	7.594
2018/03/27 19:00:00	0	21.6	1.6	2.817
2018/03/28 08:00:00	190	16.6	1.1	0.006
2018/03/28 09:00:00	341	18.6	0.5	1.663
2018/03/28 10:00:00	516	20.8	0.8	5.358

Date & time	Irradiance (W/M^2)	Temperature (^0C)	Wind speed (m/s)	Power (Kw)
2018/03/28 11:00:00	592	24.1	1.9	10.3
2018/03/28 12:00:00	648	24.3	3.9	15.48
2018/03/28 13:00:00	698	24.1	7.4	18.39
2018/03/28 14:00:00	560	24.5	5.1	19.45
2018/03/28 15:00:00	391	25.5	4.5	20.91
2018/03/28 16:00:00	283	24.1	3	15.31
2018/03/28 17:00:00	93	22.5	2.9	10.77
2018/03/28 18:00:00	0	21.2	1	7.442
2018/03/28 19:00:00	0	20.3	2	2.4
2018/03/29 08:00:00	262	16.6	1.1	0.021
2018/03/29 09:00:00	464	17.7	1.6	2.92
2018/03/29 10:00:00	616	19	1.2	8.659
2018/03/29 11:00:00	721	22.2	1.7	14.87
2018/03/29 12:00:00	764	23	1	20.73
2018/03/29 13:00:00	935	24.5	7.4	24.3
2018/03/29 14:00:00	792	24.9	6.2	25.23
2018/03/29 15:00:00	645	25	3.7	28.83
2018/03/29 16:00:00	442	25.1	2	24.59
2018/03/29 17:00:00	182	23.8	3.9	18.87
2018/03/29 18:00:00	0	22.8	1.1	12.63
2018/03/29 19:00:00	0	21.5	0.8	4.843
2018/03/30 08:00:00	35	15.4	3.6	0.021
2018/03/30 09:00:00	130	16.8	2.1	6.635
2018/03/30 10:00:00	620	18.2	3.2	0.915
2018/03/30 11:00:00	814	19.8	2.8	4.465
2018/03/30 12:00:00	642	21	5.9	20.85
2018/03/30 13:00:00	655	21.3	1	28.76
2018/03/30 14:00:00	710	24	1.3	22.07
2018/03/30 15:00:00	187	22.7	6.5	21.23
2018/03/30 16:00:00	142	20.2	2.7	21.9
2018/03/30 17:00:00	50	20	1.1	6.524
2018/03/30 18:00:00	0	18.9	8.1	4.459
2018/03/30 19:00:00	0	16.1	5.5	1.429
2018/06/01 08:00:00	165	19.2	0.2	0.02
2018/06/01 09:00:00	317	20.8	0.2	1.358
2018/06/01 10:00:00	291	22.4	0	5.685
2018/06/01 11:00:00	419	23.6	0.7	10.95
2018/06/01 12:00:00	1140	25	1	10.03
2018/06/01 13:00:00	827	27.4	0.7	14.07
2018/06/01 14:00:00	793	27.6	3.8	30.02

Date & time	Irradiance (W/M^2)	Temperature (^0C)	Wind speed (m/s)	Power (Kw)
2018/06/01 15:00:00	179	24.9	2.6	27.71
2018/06/01 16:00:00	127	27.2	0	26.21
2018/06/01 17:00:00	148	25.5	1	5.605
2018/06/01 18:00:00	36	24.6	0	3.759
2018/06/01 19:00:00	0	23.3	0	4.599
2018/06/02 08:00:00	142	21	0.7	0.84
2018/06/02 09:00:00	208	21.9	2.1	1.964
2018/06/02 10:00:00	347	23.1	0	4.307
2018/06/02 11:00:00	493	24.4	0.7	0
2018/06/02 12:00:00	483	25.7	0.4	11.52
2018/06/02 13:00:00	297	25.9	1.8	16.95
2018/06/02 14:00:00	237	25.8	2.2	15.9
2018/06/02 15:00:00	176	23.6	2.4	9.95
2018/06/02 16:00:00	134	23.7	1.5	8.328
2018/06/02 17:00:00	208	24	1.2	6.222
2018/06/02 18:00:00	49	24.5	0.7	4.459
2018/06/02 19:00:00	0	22.3	0.5	6.674
2018/06/03 08:00:00	211	23.2	1.2	2.219
2018/06/03 09:00:00	578	23.6	1.2	3.303
2018/06/03 10:00:00	691	26	1.1	7.751
2018/06/03 11:00:00	743	26.9	1	19.35
2018/06/03 12:00:00	270	28.6	1	23.71
2018/06/03 13:00:00	107	27.3	1.6	26.21
2018/06/03 14:00:00	119	19.7	1	9.629
2018/06/03 15:00:00	160	21.7	2.5	3.997
2018/06/03 16:00:00	184	22.4	1.3	4.049
2018/06/03 17:00:00	148	23.8	0.6	4.83
2018/06/03 18:00:00	81	23.4	3.5	5.958
2018/06/03 19:00:00	0	22.8	0	4.563
2018/06/04 08:00:00	443	23.3	0	2.555
2018/06/04 09:00:00	590	26.1	0.4	4.036
2018/06/04 10:00:00	633	26.7	1.8	14.67
2018/06/04 11:00:00	334	28.3	1.2	18.45
2018/06/04 12:00:00	258	29	0.4	21.3
2018/06/04 13:00:00	291	28.9	3.5	10.62
2018/06/04 14:00:00	66	26.4	2.1	9.521
2018/06/04 15:00:00	182	20.9	0	9.537
2018/06/04 16:00:00	185	23.1	2.3	2.023
2018/06/04 17:00:00	157	23.9	0.1	6.292
2018/06/04 18:00:00	49	24.4	0.1	6.128

Date & time	Irradiance (W/M^2)	Temperature (^0C)	Wind speed (m/s)	Power (Kw)
2018/06/04 19:00:00	0	23.2	2.4	4.932
2018/06/05 08:00:00	68	19.4	1.2	0.052
2018/06/05 09:00:00	549	21.7	0	0.289
2018/06/05 10:00:00	523	24.9	0.9	2.08
2018/06/05 11:00:00	768	24.9	0.8	19.51
2018/06/05 12:00:00	944	27.3	0.6	17.69
2018/06/05 13:00:00	741	29.2	1.8	24.21
2018/06/05 14:00:00	745	30.3	4.1	27.7
2018/06/05 15:00:00	683	31.2	0.1	24.89
2018/06/05 16:00:00	500	28.7	1.8	23.79
2018/06/05 17:00:00	279	27.6	3.2	20.41
2018/06/05 18:00:00	62	26.3	2.1	15
2018/06/05 19:00:00	0	22.7	2	8.067
2018/06/06 08:00:00	391	25.9	0.8	2.395
2018/06/06 09:00:00	654	27.2	0.6	9.33
2018/06/06 10:00:00	668	28.7	1	13.1
2018/06/06 11:00:00	815	28.9	2.8	20.37
2018/06/06 12:00:00	941	30.2	3.1	23.65
2018/06/06 13:00:00	961	29.6	7.9	27.51
2018/06/06 14:00:00	324	28.9	1.5	28.57
2018/06/06 15:00:00	263	27.8	4.6	30.06
2018/06/06 16:00:00	524	29.9	2.4	11.04
2018/06/06 17:00:00	329	28.8	3	8.345
2018/06/06 18:00:00	169	28.2	4.9	15.48
2018/06/06 19:00:00	0	22.5	2.1	9.694
2018/06/07 08:00:00	139	22.1	0.3	4.537
2018/06/07 09:00:00	461	24.2	0.7	2.855
2018/06/07 10:00:00	700	25	0	4.659
2018/06/07 11:00:00	927	27.2	0.6	15.39
2018/06/07 12:00:00	932	29.2	1.3	23.42
2018/06/07 13:00:00	283	28	2	30.05
2018/06/07 14:00:00	890	29.5	2.8	28.65
2018/06/07 15:00:00	737	28.8	6.6	9.404
2018/06/07 16:00:00	611	29.9	0.5	28.81
2018/06/07 17:00:00	125	27.2	2	23.91
2018/06/07 18:00:00	66	25.9	1.9	17.74
2018/06/07 19:00:00	0	23.9	0	3.949
2018/06/08 08:00:00	167	22.8	3	1.979
2018/06/08 09:00:00	214	23.8	1	5.94
2018/06/08 10:00:00	325	25.4	2.2	5.336

Date & time	Irradiance (W/M^2)	Temperature (^0C)	Wind speed (m/s)	Power (Kw)
2018/06/08 11:00:00	233	26.3	1.2	7.197
2018/06/08 12:00:00	142	24	2.7	11.33
2018/06/08 13:00:00	194	24.7	0.4	8.275
2018/06/08 14:00:00	468	24.7	0.9	5.263
2018/06/08 15:00:00	567	25.9	0.5	7.152
2018/06/08 16:00:00	210	26.4	0.6	15.96
2018/06/08 17:00:00	267	27.1	1.7	17.98
2018/06/08 18:00:00	87	26.3	2.9	6.513
2018/06/08 19:00:00	0	25	2.1	8.145
2018/06/09 08:00:00	429	25.5	0	2.694
2018/06/09 09:00:00	653	27.9	0.5	5.257
2018/06/09 10:00:00	652	28.9	1.1	13.79
2018/06/09 11:00:00	220	30.2	0.4	20.47
2018/06/09 12:00:00	265	29.8	1.8	23.38
2018/06/09 13:00:00	248	28.9	1	7.388
2018/06/09 14:00:00	256	28.8	6.4	8.957
2018/06/09 15:00:00	119	21.9	2.1	8.152
2018/06/09 16:00:00	612	24.9	0.5	8.384
2018/06/09 17:00:00	86	25.8	0.6	4.077
2018/06/09 18:00:00	66	24.8	0.8	18.65
2018/06/09 19:00:00	0	23.9	0.7	2.447
2018/06/10 08:00:00	223	22.5	1.7	0.033
2018/06/10 09:00:00	659	26.3	0.7	3.943
2018/06/10 10:00:00	707	26.7	1.9	7.213
2018/06/10 11:00:00	824	29.1	1.9	20.15
2018/06/10 12:00:00	984	30.5	1.5	24.55
2018/06/10 13:00:00	390	30.4	1.8	28.25
2018/06/10 14:00:00	786	31.4	2.5	29.12
2018/06/10 15:00:00	582	28.8	5.6	13.14
2018/06/10 16:00:00	610	30	2.7	26.17
2018/06/10 17:00:00	322	29.7	4.7	18
2018/06/10 18:00:00	51	27.8	2.6	17.9
2018/06/10 19:00:00	0	25.7	6.8	9.321
2018/06/11 08:00:00	412	26.8	0.1	1.905
2018/06/11 09:00:00	603	27.3	0.2	7.393
2018/06/11 10:00:00	460	29.1	0	13.95
2018/06/11 11:00:00	658	28.6	1.8	19.12
2018/06/11 12:00:00	208	28.4	5.7	11.91
2018/06/11 13:00:00	1086	29	1.8	19.69
2018/06/11 14:00:00	884	31	1.7	7.234

Date & time	Irradiance (W/M^2)	Temperature (^0C)	Wind speed (m/s)	Power (Kw)
2018/06/11 15:00:00	164	29.4	2.3	30.09
2018/06/11 16:00:00	640	29.6	3.9	29.22
2018/06/11 17:00:00	247	28.6	5.3	5.528
2018/06/13 08:00:00	361	24.9	1.4	2.204
2018/06/13 09:00:00	573	26	3.8	6.438
2018/06/13 10:00:00	244	26.7	6.5	12.06
2018/06/13 11:00:00	807	28.3	4.2	18.45
2018/06/13 12:00:00	973	29	3.6	7.882
2018/06/13 13:00:00	931	28.8	2.6	26.3
2018/06/13 14:00:00	305	28.7	3.1	28.96
2018/06/13 15:00:00	759	27.1	3.9	28.66
2018/06/13 16:00:00	430	28.9	4.6	9.702
2018/06/13 17:00:00	114	26.8	4.5	24.8
2018/06/13 18:00:00	47	26.6	1.8	12.61
2018/06/13 19:00:00	0	25.9	0.6	3.56
2018/06/14 08:00:00	230	24.4	0.2	2.989
2018/06/14 09:00:00	456	25.6	0.5	5.022
2018/06/14 10:00:00	460	27.9	1.6	7.596
2018/06/14 11:00:00	224	27.6	1.4	14.98
2018/06/14 12:00:00	261	27.5	2	16.24
2018/06/14 13:00:00	635	28.1	1.3	7.441
2018/06/14 14:00:00	116	27.7	2	9.384
2018/06/14 15:00:00	735	26.9	0.9	18.34
2018/06/14 16:00:00	161	28.2	1.8	3.694
2018/06/14 17:00:00	67	26.6	1.5	22.99
2018/06/17 08:00:00	157	21.6	0	0.26
2018/06/17 09:00:00	294	22.9	1.6	2.022
2018/06/17 10:00:00	354	23.6	0.7	4.838
2018/06/17 11:00:00	538	25.8	0.6	9.307
2018/06/17 12:00:00	69	23.5	1	11.24
2018/06/17 13:00:00	260	24.9	1.2	16.89
2018/06/17 14:00:00	301	23.2	1.3	2.299
2018/06/17 15:00:00	257	26.6	0.6	8.255
2018/06/17 16:00:00	388	26.7	0	9.327
2018/06/17 17:00:00	105	26.4	0.7	7.701
2018/06/17 18:00:00	21	25.4	0.2	11.89
2018/06/17 19:00:00	0	23.9	6.9	2.977
2018/06/18 08:00:00	393	23.4	0	1.215
2018/06/18 09:00:00	555	25.7	0.8	3.651
2018/06/18 10:00:00	690	27.4	0.3	12.24

Date & time	Irradiance (W/M^2)	Temperature (^0C)	Wind speed (m/s)	Power (Kw)
2018/06/18 11:00:00	785	28	2.3	17.82
2018/06/18 12:00:00	987	28.4	1.2	23.41
2018/06/18 13:00:00	895	28.1	4.5	26.32
2018/06/18 14:00:00	686	28.3	7	26.25
2018/06/18 15:00:00	568	29.4	2.3	25.92
2018/06/18 16:00:00	498	28.2	5.1	23.32
2018/06/18 17:00:00	290	27.7	4.5	19
2018/06/18 18:00:00	89	27	0.5	13.9
2018/06/18 19:00:00	0	25.5	1.8	7.57
2018/06/19 08:00:00	386	25.6	0.9	1.688
2018/06/19 09:00:00	620	26.4	0.7	6.809
2018/06/19 10:00:00	756	27	5.4	11.74
2018/06/19 11:00:00	802	28.6	2.8	18.06
2018/06/19 12:00:00	1061	29.5	3.2	23.6
2018/06/19 13:00:00	920	29.4	4.8	26.46
2018/06/19 14:00:00	679	30.8	4.6	27.6
2018/06/19 15:00:00	634	29.7	2.3	27.09
2018/06/19 16:00:00	523	29.3	0.8	23.61
2018/06/19 17:00:00	383	28.8	6	20.95
2018/06/19 18:00:00	130	28.2	3.1	14.27
2018/06/19 19:00:00	0	26.9	1.9	10.25
2018/06/20 08:00:00	379	25.6	0	1.666
2018/06/20 09:00:00	524	27	0.7	5.968
2018/06/20 10:00:00	748	27.8	3.2	11.17
2018/06/20 11:00:00	798	28.6	6.3	16.13
2018/06/20 12:00:00	1067	29.2	5.3	23.78
2018/06/20 13:00:00	85	26.6	5.1	26.22
2018/06/20 14:00:00	476	27	2.9	28.25
2018/06/20 15:00:00	545	30.2	5.4	2.339
2018/06/20 16:00:00	344	29.3	1.3	15.15
2018/06/20 17:00:00	239	27.7	7.9	16.51
2018/06/20 18:00:00	126	27.7	4.3	10.08
2018/06/20 19:00:00	0	26.4	2.7	6.569
2018/06/21 08:00:00	231	22.5	0	0.063
2018/06/21 09:00:00	444	25.5	0.2	1.05
2018/06/21 10:00:00	708	26.8	2.1	7.764
2018/06/21 11:00:00	732	29.1	1.1	14.08
2018/06/21 12:00:00	1041	29.4	1.5	23.98
2018/06/21 13:00:00	340	29.2	2.5	25.42
2018/06/21 14:00:00	483	28.9	5.6	28.28

Date & time	Irradiance (W/M^2)	Temperature (^0C)	Wind speed (m/s)	Power (Kw)
2018/06/21 15:00:00	514	28.7	7.6	10.58
2018/06/21 16:00:00	393	28.2	3.4	16.25
2018/06/21 17:00:00	159	28	1.1	16.95
2018/06/21 18:00:00	109	28.4	0.6	11.72
2018/06/21 19:00:00	0	26.5	1.7	4.665
2018/06/23 08:00:00	46	22.2	0.5	0.042
2018/06/23 09:00:00	92	22	1	0.341
2018/06/23 10:00:00	286	23.6	1.1	1.196
2018/06/23 11:00:00	367	24.8	0.8	2.655
2018/06/23 12:00:00	628	26	0.6	9.766
2018/06/23 13:00:00	432	27.7	2.2	12.06
2018/06/23 14:00:00	197	29.3	2.4	19.07
2018/06/23 15:00:00	691	29.6	1.6	13.35
2018/06/23 16:00:00	590	28.6	4.2	16.94
2018/06/23 17:00:00	345	27.6	5.8	21.11
2018/06/23 18:00:00	171	26.4	2.7	17.3
2018/06/23 19:00:00	0	25.5	1.2	10.06
2018/06/24 08:00:00	410	25.5	0.5	1.159
2018/06/24 09:00:00	597	26	1.7	7.062
2018/06/24 10:00:00	699	28.9	1.2	12.74
2018/06/24 11:00:00	196	26.6	3.5	18.85
2018/06/24 12:00:00	1028	29.2	1.9	23.74
2018/06/24 13:00:00	71	27	1	24.14
2018/06/24 14:00:00	192	24.1	1.2	28.12
2018/06/24 15:00:00	382	25.2	1.6	19.98
2018/06/24 16:00:00	515	29.9	0	16.85
2018/06/24 17:00:00	199	28.3	1.4	12.43
2018/06/24 18:00:00	76	25.2	5.4	15.01
2018/06/25 08:00:00	204	22.8	1.1	1.215
2018/06/25 09:00:00	268	24.8	1.4	2.074
2018/06/25 10:00:00	451	26.1	2	6.464
2018/06/25 11:00:00	474	27.2	2.6	8.812
2018/06/25 12:00:00	497	26.3	3.7	15.44
2018/06/25 13:00:00	891	28	2.7	15.57
2018/06/25 14:00:00	485	27.5	6.2	15.94
2018/06/25 15:00:00	446	27.7	3.3	26.73
2018/06/25 16:00:00	398	26.9	5.3	14.06
2018/06/25 17:00:00	136	26.7	1	14.18
2018/06/25 18:00:00	115	26.8	3.2	11.96
2018/06/25 19:00:00	0	24.9	1.5	3.919

Date & time	Irradiance (W/M^2)	Temperature (^0C)	Wind speed (m/s)	Power (Kw)
2018/06/26 08:00:00	200	20.8	0.5	0.011
2018/06/26 09:00:00	267	22.8	0	1.118
2018/06/26 10:00:00	595	25.2	0	7.091
2018/06/26 11:00:00	723	26.3	2.2	8.78
2018/06/26 12:00:00	589	28.3	1.5	19.57
2018/06/26 13:00:00	320	29.3	0.5	24.37
2018/06/26 14:00:00	744	30.6	2	19.44
2018/06/26 15:00:00	119	28.7	1.8	10.52
2018/06/26 16:00:00	109	25.4	2	24.88
2018/06/26 17:00:00	195	26.1	1.3	3.948
2018/06/26 18:00:00	52	23.9	1.6	3.459
2018/06/26 19:00:00	0	22.3	0	6.633
2018/06/27 08:00:00	149	23.6	0	1.535
2018/06/27 09:00:00	224	26.5	0.9	3.03
2018/06/27 10:00:00	943	27	3.1	4.635
2018/06/27 11:00:00	324	28.9	0.3	7.452
2018/06/27 12:00:00	722	30.2	1.1	30.05
2018/06/27 13:00:00	1023	31.4	0.4	10.72
2018/06/27 14:00:00	200	29.5	1.7	20.85
2018/06/27 15:00:00	780	28.1	5.5	26.96
2018/06/27 16:00:00	607	28.2	2.7	6.893
2018/06/27 17:00:00	156	27.4	3.1	26.8
2018/06/27 18:00:00	0	25.3	5.7	19
2018/06/27 19:00:00	0	25.6	2.2	4.426
2018/06/28 08:00:00	236	25.7	0.7	1.129
2018/06/28 09:00:00	826	25.7	2.8	7.05
2018/06/28 10:00:00	815	27.2	8.5	7.536
2018/06/28 11:00:00	601	27.4	1.8	28.32
2018/06/28 12:00:00	411	27.6	2.6	17.85
2018/06/28 13:00:00	225	28.2	1.9	18.56
2018/06/28 14:00:00	1018	29.8	1.5	13.36
2018/06/28 15:00:00	748	30	2.5	7.406
2018/06/28 16:00:00	566	30	2.2	27.57
2018/06/28 17:00:00	460	28.3	3.6	26.62
2018/06/28 18:00:00	69	26.7	2.4	16.52
2018/06/28 19:00:00	0	24.8	3.4	12.39
2018/06/29 08:00:00	268	23.4	1.8	0.84
2018/06/29 09:00:00	313	24.6	1.1	3.823
2018/06/29 10:00:00	320	25.4	0.9	8.815
2018/06/29 11:00:00	228	26.4	1.2	10.8

Date & time	Irradiance (W/M^2)	Temperature (^0C)	Wind speed (m/s)	Power (Kw)
2018/06/29 12:00:00	354	27.2	0.7	11.27
2018/06/29 13:00:00	193	26.5	0.9	8.337
2018/06/29 14:00:00	157	26.3	0.7	12.27
2018/06/29 15:00:00	242	27.1	0.6	6.933
2018/06/29 16:00:00	227	26.3	1.8	5.528
2018/06/29 17:00:00	325	26.2	3.1	8.363
2018/06/29 18:00:00	84	25.4	3.8	7.462
2018/06/29 19:00:00	0	23.9	2.5	9.469
2018/06/30 08:00:00	43	20.8	1.4	0.754
2018/06/30 09:00:00	370	21.7	2.1	2.327
2018/06/30 10:00:00	493	23.6	0.1	1.134
2018/06/30 11:00:00	524	24.2	1.2	12.82
2018/06/30 12:00:00	717	25.7	0.8	16.24
2018/06/30 13:00:00	426	26.2	1.5	16.96
2018/06/30 14:00:00	195	25.1	3.2	22.13
2018/06/30 15:00:00	416	25.7	3.1	14.31
2018/06/30 16:00:00	148	25.4	0.8	6.147
2018/06/30 17:00:00	153	26.1	1	13.73
2018/06/30 18:00:00	191	26	3.2	4.421
2018/06/30 19:00:00	0	24.5	1.3	4.769
2018/09/01 08:00:00	178	23.8	1.4	0.442
2018/09/01 09:00:00	295	23.4	1.6	1.669
2018/09/01 10:00:00	761	26.5	2.3	6.036
2018/09/01 11:00:00	276	29.2	1.3	10.24
2018/09/01 12:00:00	1075	30.7	2.4	24.53
2018/09/01 13:00:00	755	30.2	3.9	9.477
2018/09/01 14:00:00	344	30.5	3.2	30.05
2018/09/01 15:00:00	99	27.9	3	23.72
2018/09/01 16:00:00	90	24.8	1.3	11.31
2018/09/01 17:00:00	92	24.4	0.4	3.309
2018/09/01 18:00:00	0	24.4	3	3.032
2018/09/01 19:00:00	0	23.9	1.4	2.807
2018/09/02 08:00:00	108	21.5	0	0.03
2018/09/02 09:00:00	168	22.2	0.6	0.895
2018/09/02 10:00:00	291	23.1	0.9	3.551
2018/09/02 11:00:00	388	23.7	0	5.95
2018/09/02 12:00:00	524	26	2.9	10.49
2018/09/02 13:00:00	166	25.5	1.4	13.29
2018/09/02 14:00:00	959	28.3	2.7	17.55
2018/09/02 15:00:00	126	26.2	3	5.812

Date & time	Irradiance (W/M^2)	Temperature (^0C)	Wind speed (m/s)	Power (Kw)
2018/09/02 16:00:00	157	24.8	0.9	29.4
2018/09/02 17:00:00	50	24.4	2	4.137
2018/09/02 18:00:00	0	23.9	1.9	5.028
2018/09/02 19:00:00	0	23.5	1.2	1.533
2018/09/03 08:00:00	370	23.9	0.7	0.079
2018/09/03 09:00:00	724	26	1.3	2.291
2018/09/03 10:00:00	560	25.4	1.5	11.09
2018/09/03 11:00:00	204	27.7	1.8	23.11
2018/09/03 12:00:00	222	27.7	1.7	22.4
2018/09/03 13:00:00	216	26	3.6	7.097
2018/09/03 14:00:00	412	27.4	1.3	7.749
2018/09/03 15:00:00	263	27.4	0.7	8.026
2018/09/03 16:00:00	84	26	5	11.86
2018/09/03 17:00:00	64	25.3	0	8.534
2018/09/03 18:00:00	0	25	0.9	2.545
2018/09/03 19:00:00	0	24.3	0.7	1.778
2018/09/04 08:00:00	398	24.9	0.7	0.464
2018/09/04 09:00:00	634	25.8	1.2	5.173
2018/09/04 10:00:00	799	26.9	3.3	12.71
2018/09/04 11:00:00	405	29.3	0.4	20.87
2018/09/04 12:00:00	355	28.7	1.1	24.8
2018/09/04 13:00:00	977	32.2	2.2	11.63
2018/09/04 14:00:00	170	31.9	2.1	11.07
2018/09/04 15:00:00	625	30.6	3	29.98
2018/09/04 16:00:00	525	30.1	2	5.546
2018/09/04 17:00:00	183	28.1	2.4	18.48
2018/09/04 18:00:00	0	25.6	1.7	15.85
2018/09/04 19:00:00	0	24.2	1.1	5.214
2018/09/04 20:00:00	0	24.3	0.7	0.112
2018/09/05 08:00:00	403	25.8	1.5	0.26
2018/09/05 09:00:00	538	25.9	2.6	2.378
2018/09/05 10:00:00	829	28.3	0.5	12.99
2018/09/05 11:00:00	841	28.9	0.1	18.04
2018/09/05 12:00:00	326	28.7	4.7	25.65
2018/09/05 13:00:00	882	29.3	1.9	26.87
2018/09/05 14:00:00	786	29.1	1.7	10.92
2018/09/05 15:00:00	208	28.6	2.6	26.82
2018/09/05 16:00:00	267	27.5	1.6	24.28
2018/09/05 17:00:00	325	28.1	2.8	6.387
2018/09/05 18:00:00	0	24.5	2.4	9.286

Date & time	Irradiance (W/M^2)	Temperature (^0C)	Wind speed (m/s)	Power (Kw)
2018/09/05 19:00:00	0	20.5	0.7	9.647
2018/09/06 08:00:00	129	23.4	1.2	0.242
2018/09/06 09:00:00	290	24.4	0	2.778
2018/09/06 10:00:00	347	25.8	0.8	4.166
2018/09/06 11:00:00	342	28.7	1.1	9.752
2018/09/06 12:00:00	363	27.4	3.7	11.1
2018/09/06 13:00:00	909	27.8	2.2	10.98
2018/09/06 14:00:00	836	29	3.6	12.24
2018/09/06 15:00:00	159	28.7	1.8	27.9
2018/09/06 16:00:00	29	25.3	1.5	0
2018/09/06 17:00:00	23	21.4	4.2	0
2018/09/06 18:00:00	0	21.6	0	0.354
2018/09/06 19:00:00	0	22.2	2.8	0.432
2018/09/07 06:00:00	0	21	0.8	0
2018/09/07 08:00:00	428	24.3	1.2	0.031
2018/09/07 09:00:00	632	27.1	0.4	2.713
2018/09/07 10:00:00	790	27.6	0.6	14.28
2018/09/07 11:00:00	426	29.3	1.2	0
2018/09/07 12:00:00	798	29	3	25.76
2018/09/07 13:00:00	1138	30	2	14.42
2018/09/07 14:00:00	845	31.6	2.4	25.64
2018/09/07 15:00:00	724	28.2	3.1	30.05
2018/09/07 16:00:00	331	28.7	2.5	26.79
2018/09/07 17:00:00	184	28.3	2.1	23.13
2018/09/07 18:00:00	15	26.3	0.5	10.91
2018/09/07 19:00:00	0	25.1	0.9	5.241
2018/09/08 08:00:00	512	24.9	0	0.176
2018/09/08 09:00:00	681	26.8	2.3	5.566
2018/09/08 10:00:00	502	27.4	1.1	16.76
2018/09/08 11:00:00	397	28.2	1.7	22.05
2018/09/08 12:00:00	902	30.2	2.7	15.31
2018/09/08 13:00:00	927	31.1	1.8	13.57
2018/09/08 14:00:00	868	28.3	4.2	28.22
2018/09/08 15:00:00	681	28.9	7.8	28.09
2018/09/08 16:00:00	448	27.6	7.7	25.32
2018/09/08 17:00:00	81	25.2	6.6	20.94
2018/09/08 18:00:00	0	24.5	3.5	13.71
2018/09/08 19:00:00	0	24.2	1.6	2.271
2018/09/09 08:00:00	403	24.2	0	0.027
2018/09/09 09:00:00	289	26.1	0.6	2.912

Date & time	Irradiance (W/M^2)	Temperature (^0C)	Wind speed (m/s)	Power (Kw)
2018/09/09 10:00:00	249	25.2	1.2	12.62
2018/09/09 11:00:00	536	26.4	4.5	9.356
2018/09/09 12:00:00	939	28.8	3.2	8.4
2018/09/09 13:00:00	1006	28.4	6.4	17.36
2018/09/09 14:00:00	373	27.2	3.4	29.12
2018/09/09 15:00:00	703	29.1	2.7	30.06
2018/09/09 16:00:00	460	26.9	7.7	11.97
2018/09/09 17:00:00	224	27	2.8	21.76
2018/09/09 18:00:00	0	24.7	6.5	14.63
2018/09/09 19:00:00	0	24.5	1.4	6.19
2018/09/10 08:00:00	91	21.9	0	0.003
2018/09/10 09:00:00	190	22.2	0	0.314
2018/09/10 10:00:00	301	23.8	0	2.84
2018/09/10 11:00:00	520	25.1	1.9	6.473
2018/09/10 12:00:00	183	26.9	0.5	9.961
2018/09/10 13:00:00	191	25.6	2.7	15.65
2018/09/10 14:00:00	274	26.3	2.9	6.209
2018/09/10 15:00:00	786	28.3	2.1	6.364
2018/09/10 16:00:00	17	24.5	6.2	9.132
2018/09/10 17:00:00	34	22.4	2	23.77
2018/09/10 18:00:00	0	22.3	0	0.364
2018/09/10 19:00:00	0	22.2	2	0.747
2018/09/11 08:00:00	56	20.4	1.2	0.001
2018/09/11 09:00:00	177	20.6	0.8	1.923
2018/09/11 10:00:00	478	21.5	0	1.798
2018/09/11 11:00:00	452	22.3	1.7	6.159
2018/09/11 12:00:00	248	23.1	1.6	16.83
2018/09/11 13:00:00	295	25.6	1.2	15.32
2018/09/11 14:00:00	155	23.6	3.4	8.434
2018/09/11 15:00:00	449	23	3.1	10.18
2018/09/11 16:00:00	68	21.6	5.4	5.225
2018/09/11 17:00:00	55	20.4	1.6	14.97
2018/09/13 08:00:00	309	22.8	1.3	0.097
2018/09/13 09:00:00	453	24.8	0.6	2.666
2018/09/13 10:00:00	239	26.4	0.5	9.796
2018/09/13 11:00:00	967	27.5	0.9	18.65
2018/09/13 12:00:00	461	28.2	0.8	8.139
2018/09/13 13:00:00	686	26	2.2	30.05
2018/09/13 14:00:00	329	25.4	4.9	15.26
2018/09/13 15:00:00	166	26.2	1.2	17.41

Date & time	Irradiance (W/M^2)	Temperature (^0C)	Wind speed (m/s)	Power (Kw)
2018/09/13 16:00:00	144	25	1.6	10.89
2018/09/13 17:00:00	61	23.6	1.7	5.119
2018/09/13 18:00:00	0	23.5	0.5	4.077
2018/09/13 19:00:00	0	22.8	2.1	1.865
2018/09/14 08:00:00	182	22.7	0.1	0.027
2018/09/14 09:00:00	620	24.4	1.4	2.213
2018/09/14 10:00:00	882	27	0.6	6.071
2018/09/14 11:00:00	267	25.2	2.2	20.61
2018/09/14 12:00:00	959	29.2	1.9	27.52
2018/09/14 13:00:00	963	27.4	1.5	9.222
2018/09/14 14:00:00	380	25.8	4	29.63
2018/09/14 15:00:00	689	27.1	3.2	29.45
2018/09/14 16:00:00	347	25.2	5.6	12.38
2018/09/14 17:00:00	52	24.2	2.3	21.23
2018/09/17 08:00:00	498	24.1	0.2	0.189
2018/09/17 09:00:00	573	25.9	0.4	3.128
2018/09/17 10:00:00	732	26.1	2.3	16.29
2018/09/17 11:00:00	792	29	0.7	18.95
2018/09/17 12:00:00	874	31.7	1.2	23.17
2018/09/17 13:00:00	902	28.6	5.7	24.46
2018/09/17 14:00:00	753	28	6.5	26.71
2018/09/17 15:00:00	416	27.7	7.6	27.85
2018/09/17 16:00:00	453	26.9	6.3	23.35
2018/09/17 17:00:00	66	25.8	2.1	13.15
2018/09/17 18:00:00	0	24.6	3.6	13.82
2018/09/17 19:00:00	0	23.7	1.5	1.72
2018/09/18 08:00:00	291	22.5	2.1	0.101
2018/09/18 09:00:00	553	24.3	0.1	2.022
2018/09/18 10:00:00	708	26.7	2.1	10.63
2018/09/18 11:00:00	742	28.1	2.6	18.41
2018/09/18 12:00:00	870	31.4	1.3	22.51
2018/09/18 13:00:00	820	28.9	5.2	23.87
2018/09/18 14:00:00	747	28.7	7.2	26.68
2018/09/18 15:00:00	588	28.2	3.7	25.37
2018/09/18 16:00:00	277	26.7	7.4	22.93
2018/09/18 17:00:00	153	26.5	2.5	18.1
2018/09/18 18:00:00	0	25	3.6	8.204
2018/09/18 19:00:00	0	24.2	3.9	3.9
2018/09/19 08:00:00	423	22.9	2.8	0.275
2018/09/19 09:00:00	565	24.9	1.8	3

Date & time	Irradiance (W/M^2)	Temperature (^0C)	Wind speed (m/s)	Power (Kw)
2018/09/19 10:00:00	712	27.1	0.3	13.54
2018/09/19 11:00:00	785	27.9	1.7	18.87
2018/09/19 12:00:00	870	30.2	2.4	22.63
2018/09/19 13:00:00	872	31.4	2.6	24.63
2018/09/19 14:00:00	752	28.3	2.5	27.35
2018/09/19 15:00:00	650	28.1	5.8	26.94
2018/09/19 16:00:00	456	27.3	2.7	22.92
2018/09/19 17:00:00	32	26.6	1.6	20.25
2018/09/19 18:00:00	0	23.5	0.9	13.61
2018/09/19 19:00:00	0	21.7	0.8	0.772
2018/09/20 08:00:00	265	22.9	0.1	0.148
2018/09/20 09:00:00	383	23.8	2.1	5.095
2018/09/20 10:00:00	663	26.2	0.6	8.969
2018/09/20 11:00:00	787	27.9	0.5	13.16
2018/09/20 12:00:00	831	29.2	1.1	21.65
2018/09/20 13:00:00	803	31.6	1.7	24.77
2018/09/20 14:00:00	364	27.2	5.9	25.67
2018/09/20 15:00:00	222	27.8	1.6	23.74
2018/09/20 16:00:00	214	25.2	0	11.36
2018/09/20 17:00:00	54	25.2	2.3	7.09
2018/09/20 18:00:00	0	24.9	0.1	6.713
2018/09/20 19:00:00	0	24.2	0.4	1.511
2018/09/21 08:00:00	149	21.3	1.3	0.067
2018/09/21 09:00:00	204	22.1	2.2	1.742
2018/09/21 10:00:00	128	22.4	0.4	4.48
2018/09/21 11:00:00	127	22.7	0	6.79
2018/09/21 12:00:00	833	25.3	1.1	4.398
2018/09/21 13:00:00	387	25.4	4.7	4.628
2018/09/21 14:00:00	419	26.6	6.4	26.25
2018/09/21 15:00:00	333	27.1	2.2	12.44
2018/09/21 16:00:00	101	26.5	1	13.86
2018/09/21 17:00:00	62	23.8	0.5	10.73
2018/09/21 18:00:00	0	22.8	1.5	2.863
2018/09/21 19:00:00	0	22.5	0	1.647
2018/09/23 08:00:00	93	22.4	1.3	0
2018/09/23 09:00:00	160	24	1.6	2.833
2018/09/23 10:00:00	714	25.7	3.5	3.147
2018/09/23 11:00:00	310	26	0	5.938
2018/09/23 12:00:00	874	27.2	8.9	23.37
2018/09/23 13:00:00	0	0	0	10.09

Date & time	Irradiance (W/M^2)	Temperature (^0C)	Wind speed (m/s)	Power (Kw)
2018/09/23 14:00:00	790	27.1	3.4	27.63
2018/09/23 15:00:00	616	26.4	8.3	0
2018/09/23 16:00:00	414	26.3	6.6	24.74
2018/09/23 17:00:00	169	25.2	3.2	19.72
2018/09/23 18:00:00	0	23.9	2.8	12.7
2018/09/23 19:00:00	0	23	3.3	4.461
2018/09/24 08:00:00	310	23.7	0.2	0.017
2018/09/24 09:00:00	511	23.9	0.6	3.844
2018/09/24 10:00:00	685	25.7	0.9	10.56
2018/09/24 11:00:00	872	27.6	2.1	17.05
2018/09/24 12:00:00	964	27.3	6.1	22.94
2018/09/24 13:00:00	861	28.1	4.8	26.88
2018/09/24 14:00:00	779	27	7.5	29.88
2018/09/24 15:00:00	614	27.1	1.6	27.09
2018/09/24 16:00:00	390	27.3	3.9	24.17
2018/09/24 17:00:00	168	25.3	1.6	19.2
2018/09/24 18:00:00	0	24.1	3	11.86
2018/09/25 08:00:00	323	22.7	0.9	0
2018/09/25 09:00:00	509	25.8	0	2.793
2018/09/25 10:00:00	269	26.9	1.5	10.59
2018/09/25 11:00:00	843	26.6	3	16.58
2018/09/25 12:00:00	957	27.3	2.4	9.123
2018/09/25 13:00:00	878	27.2	8.1	26.26
2018/09/25 14:00:00	778	28.1	4.1	29.8
2018/09/25 15:00:00	625	27	5.6	27.18
2018/09/25 16:00:00	362	27	1.9	24.03
2018/09/25 17:00:00	186	24.8	2.8	19.27
2018/09/25 18:00:00	0	23.6	5.8	10.78
2018/09/25 19:00:00	0	23	1.2	5.11
2018/09/26 08:00:00	276	22.2	0.7	0.005
2018/09/26 09:00:00	160	24.2	0.3	1.88
2018/09/26 10:00:00	712	25.8	0	9.106
2018/09/26 11:00:00	802	28.5	0	5.78
2018/09/26 12:00:00	872	29.2	4	22.48
2018/09/26 13:00:00	845	29.7	1.2	24.92
2018/09/26 14:00:00	723	30.5	2.7	26.9
2018/09/26 15:00:00	551	28.3	1.4	26.16
2018/09/26 16:00:00	394	26.7	4	21.98
2018/09/26 17:00:00	115	24.8	3	16.92
2018/09/26 18:00:00	0	23.8	2.5	12.06

Date & time	Irradiance (W/M^2)	Temperature (^0C)	Wind speed (m/s)	Power (Kw)
2018/09/26 19:00:00	0	23.3	3.5	3.327
2018/09/27 08:00:00	133	22.8	0	0
2018/09/27 09:00:00	573	25.4	2.8	1.492
2018/09/27 10:00:00	738	27.6	2	4.154
2018/09/27 11:00:00	882	29.2	1.3	18.26
2018/09/27 12:00:00	894	30	1.3	22.99
2018/09/27 13:00:00	225	26.5	1.2	27.11
2018/09/27 14:00:00	738	28.5	4.4	27.17
2018/09/27 15:00:00	505	26.3	4.1	7.077
2018/09/27 16:00:00	163	25.3	5.7	21.79
2018/09/27 17:00:00	134	24.9	2.4	15.56
2018/09/27 18:00:00	0	23.7	1.2	4.857
2018/09/27 19:00:00	0	23.1	0.8	3.682
2018/09/28 08:00:00	389	22.2	0	0
2018/09/28 09:00:00	415	24.1	1.1	1.624
2018/09/28 10:00:00	680	25.1	1.2	12.12
2018/09/28 11:00:00	765	27.9	4.5	13.15
2018/09/28 12:00:00	902	28.3	0.9	21.3
2018/09/28 13:00:00	808	27.4	4.3	23.79
2018/09/28 14:00:00	723	26.8	7.4	27.33
2018/09/28 15:00:00	565	27.1	4.6	25.02
2018/09/28 16:00:00	370	26.1	8.1	22.35
2018/09/28 17:00:00	163	24.9	5.5	17.48
2018/09/28 18:00:00	0	23.4	2.3	11.15
2018/09/28 19:00:00	0	22.8	4.2	4.12
2018/09/29 08:00:00	298	22.6	0.9	0.018
2018/09/29 09:00:00	491	24.2	1.9	3.226
2018/09/29 10:00:00	656	25.1	1.2	9.61
2018/09/29 11:00:00	755	26	2.6	15.83
2018/09/29 12:00:00	865	28.8	2.4	20.05
2018/09/29 13:00:00	821	26.2	4.7	23.67
2018/09/29 14:00:00	725	26.7	5.8	26.22
2018/09/29 15:00:00	531	27.7	4.6	25.62
2018/09/29 16:00:00	326	26.3	2.6	21.99
2018/09/29 17:00:00	27	24.5	1.8	16.31
2018/09/29 18:00:00	0	23.5	1.8	9.39
2018/09/29 19:00:00	0	23	1.1	0.563
2018/09/30 08:00:00	281	23.9	0	0.001
2018/09/30 09:00:00	495	25	0.8	1.98
2018/09/30 10:00:00	629	26.9	0	8.874

Date & time	Irradiance (W/M^2)	Temperature (^0C)	Wind speed (m/s)	Power (Kw)
2018/09/30 11:00:00	785	28.9	1.7	15.85
2018/09/30 12:00:00	859	30.6	1.1	19.59
2018/09/30 13:00:00	808	27.9	4.7	24.37
2018/09/30 14:00:00	712	28.5	3.8	25.87
2018/09/30 15:00:00	557	26.8	4.4	24.8
2018/09/30 16:00:00	107	25.9	3.1	21.66
2018/09/30 17:00:00	74	25.1	2.4	16.6
2018/09/30 18:00:00	0	23.9	2.8	2.923
2018/09/30 19:00:00	0	23.3	2.3	1.806
2018/12/01 08:00:00	136	11.7	0	0
2018/12/01 09:00:00	313	13.1	0	0.157
2018/12/01 10:00:00	411	16.2	0.2	3.112
2018/12/01 11:00:00	448	17.2	1.7	5.248
2018/12/01 12:00:00	743	19.6	2.8	6.848
2018/12/01 13:00:00	269	17.4	3.7	7.413
2018/12/01 14:00:00	523	18.1	0.4	12.75
2018/12/01 15:00:00	363	18.5	1.7	3.896
2018/12/01 16:00:00	154	17	4.3	7.99
2018/12/01 17:00:00	0	15.2	2.8	5.325
2018/12/01 18:00:00	0	14.3	2.1	0.885
	80	23.2	0.7	0
2018/12/02 08:00:00	186	24	0	0.039
2018/12/02 09:00:00	432	24.5	1	0.944
2018/12/02 10:00:00	552	27.8	1.4	2.74
2018/12/02 11:00:00	575	26.2	1.5	7.028
2018/12/02 12:00:00	563	25.4	0.9	9.27
2018/12/02 13:00:00	422	28	0	9.855
2018/12/02 14:00:00	277	25.9	4.4	9.153
2018/12/02 15:00:00	131	25.6	4.2	6.596
2018/12/02 16:00:00	18	24.7	1.8	3.848
2018/12/02 17:00:00	0	23.3	2.3	0.976
2018/12/02 18:00:00	70	9.2	0	0
2018/12/03 08:00:00	253	11.6	0.6	0.073
2018/12/03 09:00:00	383	14	0	1.408
2018/12/03 10:00:00	468	16.3	1.2	4.388
2018/12/03 11:00:00	593	18	0	6.308
2018/12/03 12:00:00	523	19.8	1.2	7.775
2018/12/03 13:00:00	431	19.4	2.8	9.854
2018/12/03 14:00:00	312	17.7	4.5	8.537
2018/12/03 15:00:00	126	16.4	4.4	6.597

Date & time	Irradiance (W/M^2)	Temperature (^0C)	Wind speed (m/s)	Power (Kw)
2018/12/03 16:00:00	0	14.7	2	4.318
2018/12/03 17:00:00	0	14.2	0.7	0.913
2018/12/03 18:00:00	114	9.9	0	0
2018/12/04 08:00:00	236	12.1	0	0.156
2018/12/04 09:00:00	365	14.4	1.8	2.555
2018/12/04 10:00:00	479	15.7	1.3	3.927
2018/12/04 11:00:00	485	17.1	0	5.924
2018/12/04 12:00:00	460	16.2	5.2	7.875
2018/12/04 13:00:00	436	17.2	2.9	8.053
2018/12/04 14:00:00	292	17.4	2.5	7.235
2018/12/04 15:00:00	124	16.2	4.2	6.578
2018/12/04 16:00:00	0	14.7	0.9	3.927
2018/12/04 17:00:00	0	13.6	1.2	0.859
2018/12/04 18:00:00	83	9.5	0	0
2018/12/05 08:00:00	108	10.5	0	0.028
2018/12/05 09:00:00	231	12.5	0	1.703
2018/12/05 10:00:00	340	14.1	1.6	1.852
2018/12/05 11:00:00	281	15.6	1.1	3.635
2018/12/05 12:00:00	553	17.3	0.6	5.539
2018/12/05 13:00:00	347	18.1	0	4.288
2018/12/05 14:00:00	199	18.1	1.8	8.642
2018/12/05 15:00:00	90	16.4	4.2	4.921
2018/12/05 16:00:00	0	14.7	1.6	2.564
2018/12/05 17:00:00	0	13.5	1.1	0.902
2018/12/05 18:00:00	120	9.4	0	0
2018/12/06 08:00:00	256	12.1	0	0.137
2018/12/06 09:00:00	417	13.5	1.4	2.577
2018/12/06 10:00:00	530	15.7	0.9	4.288
2018/12/06 11:00:00	598	18	1.4	6.158
2018/12/06 12:00:00	568	20.1	1.8	7.976
2018/12/06 13:00:00	475	18.3	1.4	9.053
2018/12/06 14:00:00	310	19.8	1.4	8.46
2018/12/06 15:00:00	135	16.7	2.4	6.679
2018/12/06 16:00:00	0	15.1	0	4.059
2018/12/06 17:00:00	0	13.9	1.7	0.968
2018/12/06 18:00:00	127	8.7	0	0
2018/12/07 08:00:00	267	11.6	0.1	0.113
2018/12/07 09:00:00	465	13.1	2.2	2.637
2018/12/07 10:00:00	561	15	0.9	4.275
2018/12/07 11:00:00	643	18	1	6.75

Date & time	Irradiance (W/M^2)	Temperature (^{0}C)	Wind speed (m/s)	Power (Kw)
2018/12/07 12:00:00	597	18.8	2	8.308
2018/12/07 13:00:00	121	17.1	3.9	9.661
2018/12/07 14:00:00	320	16.5	1.6	8.854
2018/12/07 15:00:00	141	15.8	2.7	1.407
2018/12/07 16:00:00	0	14.5	1.4	3.992
2018/12/07 17:00:00	0	13.5	1.5	0.906
2018/12/07 18:00:00	95	8.9	0	0
2018/12/08 08:00:00	169	10.1	0	0.078
2018/12/08 09:00:00	293	11.8	1	1.84
2018/12/08 10:00:00	534	14.1	0	2.571
2018/12/08 11:00:00	536	17.4	0	3.924
2018/12/08 12:00:00	526	18.7	2.2	7.842
2018/12/08 13:00:00	498	17.4	4.1	7.926
2018/12/08 14:00:00	341	16.6	8.3	7.594
2018/12/08 15:00:00	143	16.1	2.2	6.887
2018/12/08 16:00:00	0	14.3	2.9	4.322
2018/12/08 17:00:00	0	13.4	3.5	0.733
2018/12/08 18:00:00	122	8.8	0	0
2018/12/09 08:00:00	265	11.2	0.2	0.11
2018/12/09 09:00:00	415	12.7	0	2.649
2018/12/09 10:00:00	515	15.6	1	4.122
2018/12/09 11:00:00	560	18.4	2.3	6.102
2018/12/09 12:00:00	0	0	0	7.509
2018/12/09 13:00:00	0	0	0	8.255
2018/12/09 14:00:00	0	0	0	8.004
2018/12/09 15:00:00	0	0	0	6.44
2018/12/09 16:00:00	0	0	0	3.856
2018/12/09 17:00:00	0	0	0	0.824
2018/12/09 18:00:00	0	0	0	0
2018/12/10 08:00:00	0	0	0	0
2018/12/10 09:00:00	0	0	0	0
2018/12/10 10:00:00	573	14.7	2	0
2018/12/10 11:00:00	625	18.7	1.3	0
2018/12/10 12:00:00	597	20.4	1.4	8.384
2018/12/10 13:00:00	483	19.4	1.4	9.217
2018/12/10 14:00:00	324	18.2	1.6	8.631
2018/12/10 15:00:00	154	16.9	1.9	6.725
2018/12/10 16:00:00	0	14.8	0.5	4.06
2018/12/10 17:00:00	0	13.6	1.5	0.561
2018/12/10 18:00:00	137	9	1.2	0

Date & time	Irradiance (W/M^2)	Temperature (^0C)	Wind speed (m/s)	Power (Kw)
2018/12/11 08:00:00	318	11.6	1.8	0
2018/12/11 09:00:00	458	14.3	0	0
2018/12/11 10:00:00	575	16.4	2	4.114
2018/12/11 11:00:00	629	16.5	1.8	6.523
2018/12/11 12:00:00	598	20	1.8	8.497
2018/12/11 13:00:00	502	19.9	0.7	9.255
2018/12/11 14:00:00	303	18.4	3.9	8.598
2018/12/11 15:00:00	166	16.3	3.1	6.95
2018/12/11 16:00:00	0	14.7	1.3	3.882
2018/12/11 17:00:00	0	14.7	2	0.5
2018/12/11 18:00:00	0	14.7	2	0.3
2018/12/13 08:00:00	144	9.6	0	0
2018/12/13 09:00:00	315	11.9	1.3	0.052
2018/12/13 10:00:00	436	13.6	0	2.018
2018/12/13 11:00:00	564	15.9	2.9	3.97
2018/12/13 12:00:00	603	17.3	1.1	6.183
2018/12/13 13:00:00	145	18.2	0.6	8.229
2018/12/13 14:00:00	129	16.6	1.7	8.779
2018/12/13 15:00:00	100	16.3	0.5	1.816
2018/12/13 16:00:00	126	16.7	0.1	1.63
2018/12/13 17:00:00	0	14.2	0	1.171
2018/12/13 18:00:00	0	12.9	0	0.843
2018/12/14 08:00:00	141	9.1	0	0
2018/12/14 09:00:00	321	11.3	0	0.089
2018/12/14 10:00:00	462	14	0	3.017
2018/12/14 11:00:00	567	15.7	0	4.724
2018/12/14 12:00:00	592	16.5	2.8	6.423
2018/12/14 13:00:00	606	18.9	1.7	8.049
2018/12/14 14:00:00	494	19.6	1.3	8.48
2018/12/14 15:00:00	310	17.6	4.6	8.624
2018/12/14 16:00:00	173	16.3	1.5	6.642
2018/12/14 17:00:00	0	14.1	4	3.76
2018/12/14 18:00:00	0	14.2	3.9	0.02
2018/12/17 08:00:00	47	6.1	1.3	0
2018/12/17 09:00:00	112	7.8	1	0.022
2018/12/17 10:00:00	186	9.9	0.2	0.814
2018/12/17 11:00:00	320	13.1	0.9	1.873
2018/12/17 12:00:00	250	13.5	1.4	2.533
2018/12/17 13:00:00	247	14.4	2	4.036
2018/12/17 14:00:00	273	17.1	0.7	3.326

Date & time	Irradiance (W/M^2)	Temperature (^0C)	Wind speed (m/s)	Power (Kw)
2018/12/17 15:00:00	84	15.8	0	3.137
2018/12/17 16:00:00	36	15.8	0.7	3.307
2018/12/17 17:00:00	0	14.4	0	0.97
2018/12/17 18:00:00	0	13.8	0	0.24
2018/12/18 08:00:00	37	9.2	0	0
2018/12/18 09:00:00	125	10.6	0.3	0
2018/12/18 10:00:00	140	11.9	1	0.157
2018/12/18 11:00:00	264	13.7	2.9	1.373
2018/12/18 12:00:00	224	13.4	3.4	1.774
2018/12/18 13:00:00	389	14.5	2.2	3.258
2018/12/18 14:00:00	466	14.6	3.9	2.712
2018/12/18 15:00:00	413	14.8	8	5.314
2018/12/18 16:00:00	182	14.1	4.4	5.899
2018/12/18 17:00:00	0	12.6	2.2	4.741
2018/12/18 18:00:00	0	11.7	1.5	0.526
2018/12/19 08:00:00	87	8.8	0	0
2018/12/19 09:00:00	247	11	1.1	0.034
2018/12/19 10:00:00	370	12.4	1.9	1.286
2018/12/19 11:00:00	448	14.8	0	2.874
2018/12/19 12:00:00	595	16.5	1.8	4.699
2018/12/19 13:00:00	563	17	2.7	6.055
2018/12/19 14:00:00	429	16.7	0	8.102
2018/12/19 15:00:00	300	16.6	3.6	7.465
2018/12/19 16:00:00	140	16	2.1	5.412
2018/12/19 17:00:00	0	14.1	1.8	3.326
2018/12/19 18:00:00	0	12.6	0.7	0.615
2018/12/20 08:00:00	107	7.3	0	0
2018/12/20 09:00:00	232	10.4	0	0.053
2018/12/20 10:00:00	347	11.6	1.1	2.029
2018/12/20 11:00:00	468	14.4	1.4	3.616
2018/12/20 12:00:00	551	16	0.8	4.649
2018/12/20 13:00:00	496	17.2	0	6.397
2018/12/20 14:00:00	457	17.8	1.5	7.419
2018/12/20 15:00:00	322	17.5	1.9	6.499
2018/12/20 16:00:00	165	15.4	3.4	5.706
2018/12/20 17:00:00	0	13.5	1.6	3.59
2018/12/20 18:00:00	0	12.2	2.7	0.62
2018/09/12 08:00:00	62	9.3	0	0
2018/09/12 09:00:00	145	10.8	0.8	0.015
2018/09/12 10:00:00	256	12.5	0.8	0.407

Date & time	Irradiance (W/M^2)	Temperature (^0C)	Wind speed (m/s)	Power (Kw)
2018/09/12 11:00:00	500	13.1	3	1.484
2018/09/12 12:00:00	517	13.8	0.8	3.15
2018/09/12 13:00:00	499	16.3	2.7	6.58
2018/09/12 14:00:00	395	16.7	3	6.893
2018/09/12 15:00:00	266	15.7	5.6	6.455
2018/09/12 16:00:00	122	14.5	3.3	4.909
2018/09/12 17:00:00	0	12.9	0.4	2.885
2018/09/12 18:00:00	0	11.8	1.3	0.685
2018/12/23 08:00:00	102	7.1	0	0
2018/12/23 09:00:00	240	9.2	0	0.036
2018/12/23 10:00:00	391	13.2	1.5	1.834
2018/12/23 11:00:00	491	15	0.9	3.711
2018/12/23 12:00:00	581	15.4	1	4.993
2018/12/23 13:00:00	561	17.6	2.2	6.437
2018/12/23 14:00:00	462	20	1.9	7.677
2018/12/23 15:00:00	284	20.2	1.3	7.187
2018/12/23 16:00:00	154	16.7	2.9	5.787
2018/12/23 17:00:00	0	14.4	1.7	3.265
2018/12/23 18:00:00	0	12.8	0	0.527
2018/12/24 08:00:00	120	6.5	0	0
2018/12/24 09:00:00	260	10.4	0	0.027
2018/12/24 10:00:00	381	11.6	0.9	2.259
2018/12/24 11:00:00	498	13.7	0	3.76
2018/12/24 12:00:00	573	16.5	2	4.749
2018/12/24 13:00:00	516	18	2.1	6.463
2018/12/24 14:00:00	446	18	0.2	7.497
2018/12/24 15:00:00	310	17.7	5.9	6.627
2018/12/24 16:00:00	147	16.4	1	5.425
2018/12/24 17:00:00	0	14.2	3.4	3.397
2018/12/24 18:00:00	0	12.9	0.7	0.478
2018/12/25 08:00:00	122	7.2	0	0
2018/12/25 09:00:00	249	9	0	0.019
2018/12/25 10:00:00	438	11.9	0.2	2.29
2018/12/25 11:00:00	521	14.9	0.3	3.689
2018/12/25 12:00:00	556	18	1.1	5.341
2018/12/25 13:00:00	554	17.9	2.6	0
2018/12/25 14:00:00	513	17.6	5.8	7.29
2018/12/25 15:00:00	367	17.2	6.4	7.109
2018/12/25 16:00:00	203	16.2	5.9	6.193
2018/12/25 17:00:00	0	13.7	2.2	4.003

Date & time	Irradiance (W/M^2)	Temperature (^0C)	Wind speed (m/s)	Power (Kw)
2018/12/25 18:00:00	0	12.3	0.5	0.253
2018/12/26 08:00:00	118	5.6	0	0
2018/12/26 09:00:00	247	8.5	0	0.018
2018/12/26 10:00:00	411	10.8	1.1	2.225
2018/12/26 11:00:00	503	12.5	0.9	3.26
2018/12/26 12:00:00	581	14.6	0.8	4.89
2018/12/26 13:00:00	559	16.4	1.3	6.495
2018/12/26 14:00:00	447	17.7	3.6	7.536
2018/12/26 15:00:00	301	16.4	2.7	7.027
2018/12/26 16:00:00	161	14	2	5.507
2018/12/26 17:00:00	0	12.3	1.3	3.246
2018/12/26 18:00:00	0	11.1	0.7	0.513
2018/12/27 08:00:00	89	7.9	1.5	0
2018/12/27 09:00:00	236	9.4	0.7	0
2018/12/27 10:00:00	389	11.7	1.5	0.68
2018/12/27 11:00:00	549	13.4	7.4	2.433
2018/12/27 12:00:00	441	13.6	4.2	4.509
2018/12/27 13:00:00	103	13.2	2.7	6.789
2018/12/27 14:00:00	220	13.6	0.8	5.23
2018/12/27 15:00:00	319	14.4	2.7	0.812
2018/12/27 16:00:00	176	13.9	1.6	2.286
2018/12/27 17:00:00	0	11.6	0.7	3.335
2018/12/27 18:00:00	0	10.3	3	0.459
2018/12/28 08:00:00	98	5	0	0
2018/12/28 09:00:00	217	7.2	0	0.028
2018/12/28 10:00:00	355	10.7	0.5	1.752
2018/12/28 11:00:00	407	11.2	2.8	3.508
2018/12/28 12:00:00	534	15	0.9	4.287
2018/12/28 13:00:00	518	15.8	2.1	5.095
2018/12/28 14:00:00	452	15	0.7	6.817
2018/12/28 15:00:00	321	15.8	1.5	6.451
2018/12/28 16:00:00	165	13.1	0.5	5.249
2018/12/28 17:00:00	0	11.5	2.5	3.38
2018/12/28 18:00:00	0	10.3	1.8	0.838
2018/12/29 08:00:00	105	5.5	0	0
2018/12/29 09:00:00	244	7.9	0.7	0.03
2018/12/29 10:00:00	395	9.8	0.3	1.606
2018/12/29 11:00:00	524	11.9	0	2.434
2018/12/29 12:00:00	573	15.4	1.4	4.539
2018/12/29 13:00:00	526	15.7	0	6.386

Date & time	Irradiance (W/M^2)	Temperature (^0C)	Wind speed (m/s)	Power (Kw)
2018/12/29 14:00:00	470	16.2	1	7.194
2018/12/29 15:00:00	308	16.7	1.9	6.403
2018/12/29 16:00:00	183	15	2.5	5.378
2018/12/29 17:00:00	0	12.8	0.8	3.222
2018/12/29 18:00:00	0	11.2	0	0.59
2018/12/30 08:00:00	109	5.4	0	0
2018/12/30 09:00:00	257	8.4	0	0.019
2018/12/30 10:00:00	402	10.4	0.7	1.698
2018/12/30 11:00:00	514	12.6	1.4	3.658
2018/12/30 12:00:00	575	17.2	0.5	4.71
2018/12/30 13:00:00	552	16.9	0.7	6.133
2018/12/30 14:00:00	456	17.5	2	7.038
2018/12/30 15:00:00	333	16.3	3.8	6.691
2018/12/30 16:00:00	169	15.6	3	5.202
2018/12/30 17:00:00	0	13.6	2.2	3.351
2018/12/30 18:00:00	0	11.9	0	0.434