M. Tech. (Power System) KOMAL SINGH 2023

AI based Approach for Power Prediction and Performance Evaluation of the Solar PV Modules with Varying Dust Accumulation Levels

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

MASTER OF TECHNOLOGY
IN
POWER SYSTEM

SUBMITTED BY

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(2K21/PSY/03)

UNDER THE SUPERSVISION OF

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CANDIDATE'S DECLARATION

I, **Komal Singh**, Roll No. **2K21/PSY/03**, M.Tech. (Power System), hereby declare that the project Dissertation titled "**AI based Approach for Power Prediction and Performance Evaluation of the Solar PV Modules with Varying Dust Accumulation Levels**" which is submitted by me to the Department of Electrical Engineering, Delhi Technological University, Delhi in partial fulfillment of the requirement for the award of the degree of Master of Technology, is not imitated from any source without proper citation and is authentic. This work has not beforehand formed the root for the award of any Degree, Diploma, Fellowship, Associateship or any other similar title or acknowledgment.

Komal Singh

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CERTIFICATE

I, hereby certify that the Project Dissertation titled "**AI based Approach for Power Prediction and Performance Evaluation of the Solar PV Modules with Varying Dust Accumulation Levels**" which is submitted by Komal Singh, Roll No. 2K21/PSY/03, Department of Electrical Engineering, Delhi Technological University, Delhi in partial fulfillment of the requirement for the award of the degree of Master of Technology is a testimony of the project work carried out by the student under our supervision. To the best of our awareness this work has not been submitted in part or full for any Degree or Diploma to this University or to a different place

31.05.23

Place: **Delhi** **Prof. M. Rizwan**

Date: **(Supervisor)**

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ABSTRACT

Solar energy has shown to be the undisputed leader among renewable energy sources since it is clean and environmentally benign. A photovoltaic module's output power and longevity are controlled by a number of parameters, including solar insolation, clouds, cell temperature and other shading effects such as dust deposition, meteorological conditions, geographical location, module orientation, and so on.

Energy demand and concerns over greenhouse gases have made the integration of solar PV into the grid imperative. Solar power forecasting models must have a high prediction accuracy to address the intermittent nature of solar irradiation. Solar PV power is significantly affected by the dust deposited on the PV panel surface.

The impact of dust collection on the operation of the 5 kW photovoltaic system set up on the rooftop of the UEE laboratory at Delhi Technological University is initially investigated in this work. The performance of the 5 kW photovoltaic system is evaluated for 62 days, with the panels left naturally uncleaned for the first 31 days and then cleaned on a regular basis for the next 31 days. The performance ratio, capacity factor, system energy yield, and reference energy yield are all calculated. The pragmatic 5 kW system's performance analysis results were afterwards compared to the PVsyst software results.

Later on, the amount of dust deposited on PV panel as one of the input parameters to predict solar PV power and solar irradiation is also studied. Multivariate analysis of three deep learning techniques that is LSTM (Long short-term memory), 1D CNN (Convolution Neural Network) and BilSTM (Bidirectional Long short-term memory) to predict the solar PV power and solar irradiation with varying dust accumulated levels for the 335-watt PV module set up on the rooftop of the lab at Delhi Technological University is presented. An artificial dust scenario is created by continually incrementing the dust level by 1.258 mg/cm^2.

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LIST OF ABBREVIATIONS

ANN	Artificial Neural Networks
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregression and Moving Average
BiLSTM	Bidirectional Long Short Term Memory
BIPV	Building-Integrated Photovoltaics
CF	Capacity Factor
CNN	Convolutional Neural Network
COVID 19	Coronavirus Disease
DBLSTM	Double Layer Bidirectional Long Short Term Memory
DNN	Deep Neural Network
ELM	Extreme Learning Machine
EU	European Union
FNN	Feedforward Neural Network
GAN	Generative Adversarial Networks
GBRT	Gradient Boosted Regression Trees
GDP	Gross Domestic Product
GHG	Greenhouse Gases
GPR	Gaussian Progress Regression
GPU	Graphics Processing Unit
GRU	Gated Recurrent Unit
GW	Giga Watt
GWO	Grey Wolf Optimization
IEC	International Electrotechnical Commission
KNN	K Nearest Neighbor
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error

ML	Machine Learning
MLP	Multilayer Perceptron
MPPT	Maximum Power Point Tracking
NASA	National Aeronautics and Space Administration
NREL	National Renewable Energy Laboratory
PR	Performance Ratio
PV	Photo-Voltaic
ReLU	Rectified Linear Activation Unit
RMSE	Root Mean Square Error
RNN	Recurrent Neural Network
SLFN	Single Layer Feed-Forward Network
SMA	System, Mess and Anlagentechnik
STC	Standard Temperature Condition
SVM	Support Vector Machine
Si- Poly	Silicon Polycrystalline
SVR	Support Vector Regression
XGBoost	Extreme Gradient Boosting

LIST OF SYMBOLS

Y_R	Reference energy yield
Y_S	System energy yield
P_{mpp}	Maximum peak power
V_{mpp}	Volage at maximum peak
I_{mpp}	Current at maximum peak
V_{oc}	Open circuit voltage
I_{sc}	Short circuit current
kWhAC	Energy in kilo-watts hours on AC (inverter) side.
i_k	Input gate
f_k	Forget gate
O_k	Output gate
σ	Sigmoid function
Ψ_k	Input at current timestamp
W_x	Weight of the respective (x) gate neurons
h_k	Output of the LSTM Block
b_x	Bias of the respective gates (x)
C_k	Cell state (memory) at timestamp k
C'_k	Represents candidate for cell state at timestamp k
μ	Mean
σ	Standard deviation
X	Feature
R^2	R Squared Error
R^2_a	Adjusted R squared error
^0C	Degree celsius
W/m^2	Watts per meters square
mg/cm^2	Milli gram per centimeter square

kW	Kilo watt
kWh	Kilo watt hour
Wp	Peak power
kWDC	Kilo watt at DC side
D	Considering dust as parameter for forecasting
WD	Not considering dust as parameter for forecasting
µm	Micro meters

CHAPTER 1

INTRODUCTION

1.1 GENERAL

Photovoltaics (PV) systems are a form of renewable energy technology that converts sunlight directly into electricity. Renewable energy sources play a great role in cutting GHG emissions. PV systems utilize the photovoltaic effect, which is the process by which certain materials generate an electric current when exposed to light. These systems have gained significant popularity as a clean and sustainable energy solution.

The benefits of PV systems are numerous. They offer a clean and renewable source of electricity, reducing dependence on fossil fuels and minimizing greenhouse gas emissions. PV systems can also provide electricity in areas with limited or no access to the grid, enabling energy independence and improving energy security. Furthermore, the operational and maintenance costs of PV systems are relatively low, making them economically viable in the long run.

As the technology continues to advance, photovoltaics hold great potential for meeting the world's energy needs in a sustainable and environmentally friendly manner. Ongoing research and development efforts aim to increase the efficiency of solar cells, reduce costs, and improve the integration of PV systems into existing infrastructure.

With increase in the dependency over renewable energy and to meet the sustainability goals, solar PV panels plays a major role. Due to intermittency of solar, solar power forecasting accuracy needs to be as accurate as possible. The effect of partial shading, dust accumulation, hotspots etc. on the power output of solar PV needs to be minimized. Solar forecasting and performance analysis of solar PV is studied and analyzed in this research.

1.2 PERFORMANCE RATIO

Performance ratio (PR) measures the quality of PV system and hence is also popular as quality factor in the solar energy sector [10]. Performance analysis can solely be used for making the right decisions for current and future installations [12]. In [13] authors calculated the performance ratio of the 6 kW PV system for four months. Performance ratio (PR) is a globally known metric used by countries like Australia, the United States, and Europe to assess the performance of solar panels. With the assistance of such a study, these countries were able to improve the efficacy of their PV plants by identifying the deficit and thereby make smarter investment decisions. The Performance ratio has a better predictive value than the PV plant's final yield because it closely accounts for actual solar radiation [14]. EU performance report signifies that a well performing system should have a performance ratio of 0.8 and higher [15]. As per SM, performance ratio measures the percentage of the energy that can be exported to the grid, after subtracting arbitrary energy losses and consumption [16]. Weather variability is a strong determinant of PR regardless of the plant's location or system size. [17]-[19] presents the performance ratio overview for different countries. In [20], the authors reviewed the effect of dust on the performance of photovoltaic panels in the North Africa, Middle East, and the Far East region. Due to limited water resources and high dust accumulation rates throughout the year, most countries in these regions have always struggled with cleaning their PV panels [21]. Therefore, while studying the impact of dust on the performance of PV panels, location is of utmost importance.

1.3 CAPACITY FACTOR

Net capacity factor refers to the unitless ratio of actual electricity production over a period of time to theoretical energy production. Although capacity factor (CF) can be used to measure the performance of grid-connected solar systems, it does not take threshold irradiation into account, hence it is unable to provide an accurate picture of PV plant performance. Moreover, it does not take into account environmental factors, grid availability, and system faults and hence crippling its performance analyzing potential [14]. Investors occasionally utilize capacity factor to calculate the return on investment of their solar PV installations.

1.4 PVSYST SOFTWARE

PVsyst software is used to examine, size, model, and analyse photovoltaic arrays. PVsyst features a database of solar system component data and diverse meteorological data sources such as meteonorm, NREL etc. [22]-[24] presents PVsyst simulation of photovoltaic system for different locales. It is typically used to identify the optimal tilt angle, azimuth angle, and PV module and inverter for improving PV plant performance and minimizing losses [24].

1.5 SOLAR POWER FORECASTING

Solar power forecasting is the process of collecting and analysing data in order to predict solar power generation over various time periods in order to reduce the impact of solar intermittency. Forecasts of solar power are utilised for effective grid management and power trading.

Generally, the solar forecasting techniques depend on the forecasting horizon

1. Nowcasting (forecasting 2-5 hours ahead),
2. Short-term forecasting (up to week ahead)
3. Long-term forecasting (weeks, months, years)

In PV power forecasting, many methodologies such as physical, heuristic, statistical, and machine learning are often applied.

To generate PV power forecasts, statistical and machine learning (ML) approaches are employed utilising historical data. While heuristic models focus on the detailed definition of mathematical processes, statistical models necessitate the selection of a model that takes into account prior information about the system. ML approaches necessitate the selection of a predictive algorithm based on its empirical capabilities. ML techniques include SVM, KNN, regression models etc whereas statistical models include ARIMA, ARMA, VAR etc.

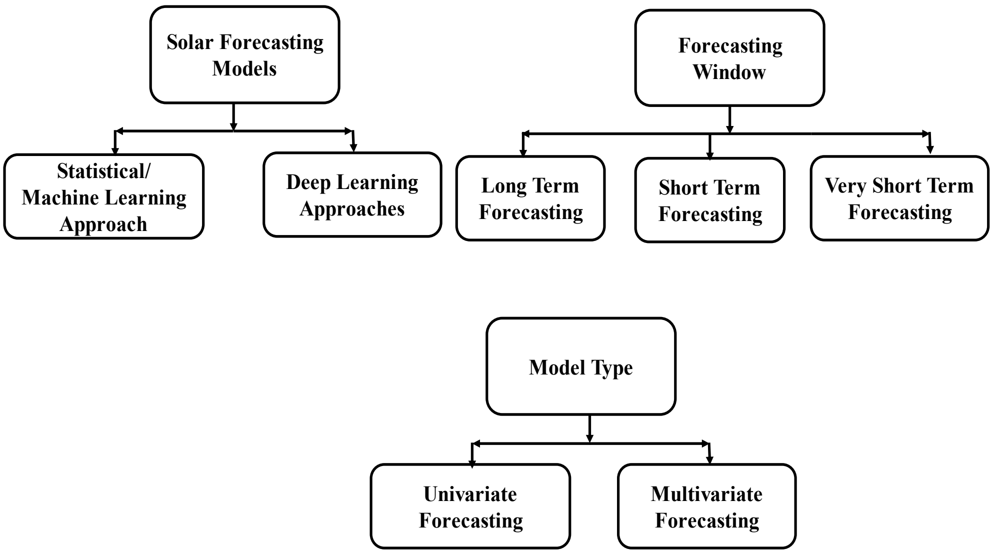

Fig 1.1: - Approaches to Solar Power Forecasting

Time series forecasting entails predicting the future values of a time series. A univariate, bivariate, or multivariate time series can exist. A univariate time series contains only one variable, whereas a bivariate time series has two variables and a multivariate time series has more than two variables.

1.6 DEEP LEARNING TECHNIQUES

Deep learning is a machine learning technique that trains computers to do things that come naturally to humans. A computer model learns to execute task categories directly from images, text, or sound in deep learning. Deep learning models can attain outstanding accuracy, sometimes outperforming humans. Models are trained utilising an extensive amount of labelled data and multi-layered neural network architectures.

Deep learning necessitates a large amount of processing power. High-performance GPUs have efficient parallel architectures for deep learning. When paired with clusters or cloud computing, development teams can reduce deep learning network training time from weeks to hours or less. Applications of deep learning techniques comes in automated driving, aerospace and defense, medical and forecasting.

Deep learning techniques can be classified as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNNs), Generative Adversarial Networks (GAN) and many more. LSTM and gated RNNs are very popular RNN techniques. To solve the problem of exploding and vanishing gradient, we go for various non linear functions such as tanh, ReLU, Softmax, sigmoid etc. A rectified linear unit (ReLU) is an activation function that implements nonlinearity to a deep learning network. The differentiation for the ReLU is relatively simple in the computation of neural network backpropagation. The sole assumption we will make is that the derivative at point 0 is also zero.

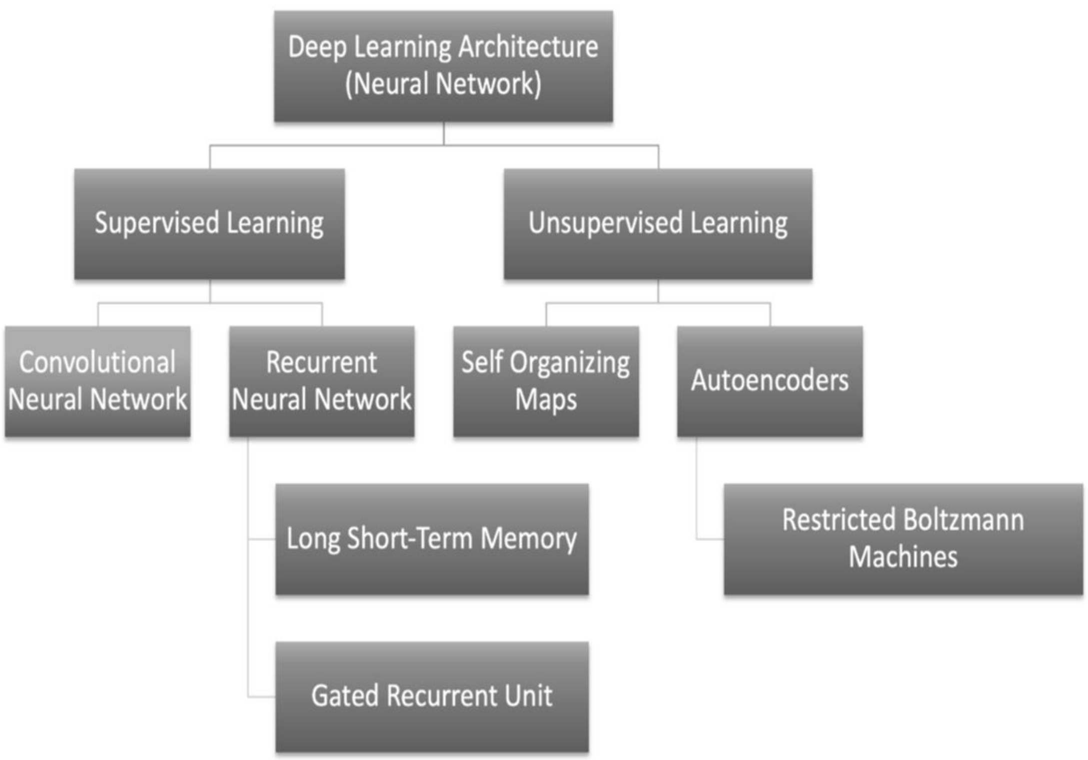

Fig 1.2: - Types of Deep Learning Techniques

1.7 SUMMARY OF THE WORK

This report shows the performance analysis for May and June 2022 of the 5 kW photovoltaic system setup on the lab roof at Delhi Technological University. In May, the panels weren't cleaned at all, but in June, they were cleaned regularly. In May and June, 5 kW photovoltaic system data of system energy (kWh), peak power (Wp), and operating hours was collected daily from the inverter unit. Due to the PV system being out of service for 5 days in May, a few days from April and July were also added to the statistics for May and June, respectively. For both months, comparisons are made between the reference energy yield (Y_R), system energy yield (Y_S), performance ratio (PR), capacity factor (CF), and peak power (W).

Also, solar power and irradiation forecasting of the 335 watt module that is setup on the rooftop of the lab at Delhi Technological University is performed. The parameters such as temperature (^{0}C), irradiation (W/m^2), PV power (W) and dust (mg/cm^2) are collected. The temperature, irradiation and PV power are measured using a solar system PV analyzer. The dust level is incremented daily at regular levels by 1.258 mg/cm^2. PV power and solar irradiation prediction is performed using three ANN models: LSTM, BiLSTM and 1D CNN. The data is preprocessed using standardization and then passed through the ANN models for analysis. The performance metrics were compared for LSTM, 1D CNN and BiLSTM for with considering dust as input parameter and without considering dust as input parameter. Dust accumulation on PV panels has a significant adversative impact on the solar cells' performance, especially in hot and arid regions [40]. Dust as a factor for solar PV forecasting is rarely done in the literature.

1.8 OUTLINE OF DISSERTATION

This dissertation is divided into six chapters including this chapter. The summary of various chapters is given below: -

Chapter 1: - This chapter provides the introduction of the dissertation, the performance parameters such as performance ratio, capacity factor etc. are explained. The solar forecasting techniques are also described

Chapter 2: - Chapter 2 tabulates the relevance of literature in work along with scope of work.

Chapter 3: - The chapter 3 deals with the methodology of the research. Performance analysis and PVsyst analysis are included in performance analysis of 5 kW PV system. AI techniques that are LSTM, BiLSTM and CNN-1D are also explained briefly.

Chapter 4: - This chapter consists of the experimental setup of 5 kW PV system, that are used to study the effect of dust on the performance. The results of the effect of dust accumulation on the performance ratio of the 5 kW PV system. The results are explained in the form of tables and plots.

Chapter 5: - This chapter consists of the experimental setup of 335-Watt PV module, forecasting accuracy of solar PV modules. The solar forecasting accuracy results with and without considering dust accumulation as an input parameter are compared to assess the forecasting accuracy. The results are explained in the form of tables and plots.

Chapter 6: - This chapter includes the final conclusion and future scope of the research.

CHAPTER 2

LITERATURE REVIEW

2.1 GENERAL

Despite the huge disruptions associated with the global pandemic and the collapse in GDP, wind and solar capacity increased by a colossal 238 GW in 2020 – almost double its previous highest annual increase [1]. This growth tendency is consistent with Agenda 2030's decarbonization targets. Soiling occurs due to the deposition of sand, dust particles, an organic layer, bird droppings, snow, and plant products which affect the power output of solar panels [2]. The aberrant operating circumstances created by dust accumulation on the surface of solar PV panels significantly limit energy output by solar systems.

In order for photovoltaics to be efficient, a considerable amount of unalterable and alterable factors must be taken into account; dust is one such unalterable factor that significantly reduces PV module efficiency [3]. It is imperative that PV panels needs to be cleaned frequently depending on their site location, as the Saharan region has strong solar energy potential, but is plagued with sand and dust accumulation, wind as well as high temperatures [4].

In [5], the effect of dust on the solar panel was analyzed for different modular technologies; the impact of dust on voltage, power and current of the respective modules was studied and quantitative performance degradation was observed. Power performance can be significantly reduced up to 60-70% due to the deposition of dust on the surface of PV panel [6]. The size and shape of dust particles accumulated vary with location [7] and hence type of dust soiling can significantly have a varying effect on PV performance [8]. The deposit of coal dust on PV panels causes a significant performance drop compared to that caused by fly ash [9], gypsum, and fertilizer industry dust [6].

According to government data, India's power consumption increased by 13.6% year on year to 112.81 billion units in November 2022. Approximately 770 million tonnes of coal equivalent (MTCE) will be consumed by 2030, rising annually thereafter before reaching a peak in the early 2030s in India. Over the next decade, coal is expected to continue to increase in definite terms, reaching a peak around 2030. However, its contribution to electricity generation is projected to drop from just under 75 percent to just under 55 percent. More than 60 percent of the growth in power demand will come from renewable energy sources, and 35 percent of electricity will come from renewable sources by 2030 - solar PV alone will account for more than 15 percent of the energy mix [25]. With such a high contribution of solar PV, the efficiency of solar PV in power production plays a crucial role.

The stochastic, volatile, and variable nature of solar power generation threatens the economic viability and stability of energy systems as well as its use as a renewable resource [26]. Solar source is irregular in nature as a result, PV power is intermittent and is highly dependent on irradiance, temperature level and other atmospheric parameters [27]. There are various factors affecting the power output of PV modules such as partial shading [28], dust [29], hotspots [30] and faults. Dust is a varying factor that can significantly affect PV power production. Smart grids may suffer from grid stability and reliability issues due to the high penetration of solar PV. Therefore, solar PV power forecasting plays a vital role in integrating renewable energy generation efficiently and reducing volatility in distributed generation systems [31].

There are various factors affecting the solar PV power forecast accuracy such as forecasting horizon, input parameters, weather classification etc [32]. There are two major approaches to predict solar PV output such as direct and indirect approach. The direct approach involves directly calculating the PV system's power output, whereas the indirect approach begins with calculating the solar irradiation, then uses a PV performance model to determine the PV system's power output. Cloud imagery and numerical weather prediction techniques are used in the indirect method, whereas machine learning is used in the direct method [33].

Solar forecasting can be accomplished using various statistical models such as

ARIMA (autoregressive integrated moving average) [34], ARMA (autoregression and moving average) [35], VAR (vector autoregression); machine learning models [36] such as linear regression, SVM (support vector machine), KNN (K nearest neighbor) etc.; deep learning models [37] such as LSTM (long short-term memory), GRU (gated recurrent unit), autoencoders, Conv1D or CNN-1D (convolutional neural network). The irradiance can be predicted using machine learning techniques and statistical models such as artificial neural networks (ANN), support vector machines (SVM), vector autoregressive (VAR), autoregressive moving average (ARMA) and many more. However, they lack accuracy because they cannot capture long-term dependency [38]. Bi-LSTM is comprised of basically two LSTMs: a forward LSTM that utilizes past information and a backward or reverse LSTM that takes future information into use. Bi-LSTM achieves more accurate performance than LSTM and RNN (recurrent neural network) in general because it can use both past and future information [39].

2.2 RELEVANCE OF LITERATURE IN WORK

The literature review is done of the below shown papers and the relevance of the literature in the work is shown in the below table 2.1

Table 2.1: - Literature Review

Ref. No.	**Title**	**Agenda**	**Relevance in Work**
1	"Statistical Review of World Energy 2021,"	2010-2020 country wise contribution and consumption of different forms of energy	Impact of COVID 19 on solar and wind capacity
2	Modeling Effect of Dust Particles on Performance Parameters	The patterns of different shapes, lightness% and density printed on the	Effect of dust on power output of solar panels

	of the Solar PV Module	transparent sheets to simulate the effect of dust on PV panels	
3	Comparison between performance of man-made and naturally cleaned PV panels in a middle of a desert	Effect of cleaning PV panels in the kingdom of Bahrain. BIPV should be employed with self-cleaning Nano technology.	Study of the various factors affecting the frequency of PV panel cleaning.
4	Impact of dust accumulation on PV panel performance in the Saharan region	Noticeable reduction in the power performance of solar module due to the accumulation of dust with percentage of 20% in the Sahara Region.	Apart from solar insolation, factors such as shading and dust also strongly affect the solar PV power output.
5	Evaluating the Performance of Different PV Modules Technology Due to Dust Accumulation in Tripoli Region	Effect of dust on monocrystalline, polycrystalline and amorphous solar modules was studied in Tripoli region.	The performance of amorphous solar modules was most affected by dust
6	Effects of coal and fly ash dust deposition of photovoltaic panel performance: A photovoltaic system at coal-fired power plant case study	PV panels were subjected to four distinct types of dust deposit conditions: coal particles, fly ashes, regular environmental dust, and a clean PV panel on a daily basis.	Dust varies based on location – agricultural – rice husk dust, industrial – coal dust ,constructional site-fly ash etc.
7	Dust Accumulation and Its Effect on PV Performance in Tropical Climate and Rice Farm Environment	The deposition of dust on PV modules deployed in PV power facilities near rice farms in Thailand is discussed. For the rice field	Power and energy losses due to soiling were around 3-4% each month during the dry season.

		setting, dust particle size was found to be in the 10-20 μm range.	
8	An experimental study on effect of dust on power loss in solar photovoltaic module.	Data were acquired for dust samples of various weights with changes in power loss in a PV module at three solar irradiation levels of 650, 750, and 850 W/m^2.	Dust from different fields such as constructional sites, agricultural land and industrial areas will affect solar PV in coming time
9	Effect of industrial dust deposition on photovoltaic module performance: Experimental measurements in the tropical region.	The investigation included dust from the fertiliser, gypsum, aggregate crusher, and coal mining industries. Coal dust has the greatest impact on PV module output performance.	Dust collection on the Si-Poly PV module reduced output power and short-circuit current while having no effect on open-circuit voltage.
10	Photovoltaic system performance – Part 3: Energy evaluation method	IEC 61724 -3	IEC-61724-3 provides guidelines on evaluation methods and data collection for performance of long-term capacity and short-term system
11	Photovoltaic system performance – Part 2: Capacity evaluation method	IEC 61724 -2	IEC 61724-2 provides the evaluation of power output during

			reference conditions (a few relatively sunny days)
12	Performance Evaluation of Grid Interactive Photovoltaic System	It shows the performance of a 40kWp grid interactive PV system installed in Agra, India. The impact of battery storage on the performance ratio is discussed.	Array Yield, Reference Yield, Final Yield, Performance Ratio, and Capacity Factor are among the performance parameters examined.
13	Performance Analysis of PV Grid-Connected in Fours Special Months of the Year	The PV plant has a capacity of 6 kWp and is divided into three mini-plants of 2 kWp of Polycrystalline, Monocrystalline, and Amorphous silicon.	November, August, May and January are critical months to analyse PV panel performance.
14	Performance ratio – Crucial parameter for grid connected PV plants	The main purpose of this study is to emphasise the significance of PR as a critical performance indicator by citing literature and research advances.	Adoption of monitoring guidelines and international codes such as IEC 61724 could improve performance and reliability measurements of the grid PV systems
15	Performance Monitoring Guidelines for Photovoltaic Systems.	This report summarised the progress to date, the approach to developing guidelines, and the loss probability derivation, as	The suggested practises are being enhanced to include life-cycle monitoring and

		well as some examples of new guidelines in development.	system output maximisation.
16	Performance Ratio-Quality Factor for the PV plants	Performance ratio is and its function	PR – Calculation and factors affecting it.
17	Performance and Availability Analyses of PV Generation Systems in Taiwan	To analyse the PV operational performance and system availability, monthly final energy yield and failure data from 202 PV systems deployed in Taiwan were collected.	Comparison of performance analysis with other countries.
18	Review of the performance of residential PV systems in Belgium	Analyse the operational data of 993 installations to assess the state of the art in residential PV systems in Belgium.	Key parameters that most influence PV panel quality
19	Performance analysis of A grid-connected solar PV plant in Niš, republic of Serbia Energy	2 kW (rooftop) solar PV plant in Ni (Republic of Serbia), as well as the equipment for estimating its performance and energy efficiency based on real-world climate conditions.	To compare the effective energy production of PV solar facilities located in various parts of the world.
20	A review of dust accumulation on PV panels in the MENA and the Far East regions	The effect of dust on the performance of solar panels in the Middle East, North Africa, and the Far East, as well as cleaning techniques	Many ways have been explored to remove dust from the surface of PV panels, including manual and self-cleaning systems.

21	Influence of seasonal effect on dust accumulation on Photovoltaic panels that operate light posts	The purpose of this study is to investigate the seasonal impacts on the performance of the dust mitigation strategy for PV panels used to power street light posts.	Summer month requires more cleaning of PV panels as compared to winter months.
22	Modeling and simulation of 15MW grid-connected photovoltaic system using PVsyst software	Complete modeling and simulation of 15MW solar photovoltaic grid connected at the site of Oued Kebrite a town and commune in Souk Ahras Province in north-eastern Aigeria using PVsyst software.	Calculation of PR, plotting energy graphs, setting location, importing libraries and datasheets of inverter and PV system using PV syst software.
23	Simulation of a Dubai based 200 KW power plant using PVsyst Software	This research investigates the feasibility of installing a 200 kWp on-grid monocrystalline silicon solar plant in Dubai International Academic City using PVsyst software.	Study of PV panel with PVsyst software, in different scenarios, to analyse different scenarios before final investment in the PV plant.
24	Simulation and performance analysis of a 1kWp photovoltaic system using PVsyst	1kWp photovoltaic system is designed and simulated using PVsyst software for Hamirpur, Himachal Pradesh, India using measured data of the location	Design of a PV system is entirely location dependent, Performance ratio is very important parameter for evaluating the system performance.
25	International Energy	Provides essential analyses	Intermittent nature

	Agency, World energy outlook 2022. OECD, 2022.	and insights into the ramifications of the significant and ongoing shock to global energy systems.	of Solar gives challenges in integrating solar in grid, grid stability is threatened.
26	Taxonomy research of artificial intelligence for deterministic solar power forecasting	Taxonomy research of the existing solar power forecasting models based on AI algorithms	Different types of ways of solar forecasting. The vision of solar integration in grid.
27	Solar photovoltaic power forecasting using optimized modified extreme learning machine technique	The authors employ an extreme learning machine (ELM) technique for real-time PV power forecasting.	To train single layer feed-forward network (SLFN), ELM algorithm is implemented.
28	Photovoltaic array reconfiguration under partial shading conditions for maximum power extraction: A state-of-the-art review and new solution method	Knight's tour is a novel reconfiguration strategy for extracting maximum output from photovoltaic (PV) arrays in partial shadowing conditions.	Effect of partial shading on output of PV panels and accuracy of solar forecasting models.
29	Experimental investigation on solar PV panel dust cleaning with solution method	To remove dust and grime from solar PV panels, three different chemical solutions created in a laboratory are applied with a solar PV panel cleaning robot.	The power harvested from the PV panel cleaned with proposed Solution 1 (2-propanol) has risen by 15%.
30	Power Enhancement and Hotspot Reduction	There are two alternative configurations: in the first,	Power enhancement by derouting the

	of a Rooftop Solar PV Array Using MOSFETs	MOSFETs are connected across every 14 modules, while in the second, alternate bypass diodes and MOSFETs are connected across each module.	current in different paths to mitigate hotspots and improve Solar PV output efficiency.
31	A hybrid intelligent approach for solar photovoltaic power forecasting: Impact of aerosol data	To anticipate PV power, a newly developed intelligent approach based on grey wolf optimisation (GWO) and multilayer perceptron (MLP) was utilised.	Hybrid techniques and aerosol data information can improve the forecasting accuracy of PV panels
32	A review and evaluation of the state-of-the-art in PV solar power forecasting: Techniques and optimization	Forecasting techniques are examined, and it is shown that convolutional neural networks excel in eliciting a model's deep underlying non-linear input-output correlations. PV panel performance can also be evaluated using economic utility measurements.	For network training and forecasting, the optimal data cleansing procedures are normalisation and wavelet transforms, as well as augmentation utilising generative adversarial networks.
33	Machine learning methods for solar radiation forecasting: A review	Give an overview of forecasting methods of solar irradiation using machine learning approaches	In terms of prediction quality, the ANN and ARIMA approaches can be considered equivalent.
34	Statistical modeling for global solar radiation forecasting in Bogotá	Statistical modeling based on time series was made to forecast the accumulated	It was found that the series which better fitted to the one

		mean daily global solar radiation in Bogotá	built with experimentally measured data, can be obtained using the ARIMA model
35	A Guide to Solar Power Forecasting using ARMA Models	Summarize a step-by-step methodology to forecast power output from a PV system	Learn about statistical models to perform solar forecasting
36	Solar radiation prediction using different machine learning algorithms and implications for extreme climate events.	To estimate solar radiation, 12 machine learning models were constructed to predict and compare daily and monthly values, as well as a stacking model combining the best of these methods.	The stacking model, which incorporated the GBRT, XGBoost, GPR, and random forest models, and the XGBoost model are good models for monthly solar radiation forecast.
37	Deep learning models for solar irradiance forecasting: A comprehensive review	Several deep learning models, including long short-term memory, deep belief network, echo state network, convolution neural network, and others, have been evaluated for effectiveness and efficacy.	Over CNN, LSTM, GRU, RNN, and DNN, hybrid CNN-LSTM may improve prediction accuracy by 3.62%, 25.29%, 34.66%, 37.37%, and 26.20%, respectively.
38	Solar irradiance forecasting using deep neural networks.	Deep recurrent neural networks (DRNNs) are used to predict solar irradiance and compare results with other methods such as SVR	According to the results of the performance tests, deep learning neural networks beat all

		and FNN	other methods.
39	Novel double-layer bidirectional LSTM network with improved attention mechanism for predicting energy consumption	Novel double-layer BLSTM with improved attention mechanism is proposed.	Experimental results indicate that the presented DBLSTM achieves superior performance compared to other methods.
40	Impact of dust accumulation on photovoltaic panels: a review paper	Artificial intelligence models used to forecast PV performance, as well as their accuracy in terms of data amount and complexity	Prediction models available and their advancement and scope.

2.3 CONCLUSION

The literature review of the work is presented in this chapter, the papers consisting of performance ratio, capacitor factor, system yield are dealt, papers dealing with solar forecasting models are also reviewed.

CHAPTER 3

METHODOLOGY USED FOR PERFORMANCE ANALYSIS AND SOLAR POWER FORECASTING

3.1 PERFORMANCE ANALYSIS:

The performance ratio (PR) is location-independent and is sometimes referred to as the quality factor because it accurately assesses the quality of the PV plant. The performance ratio (PR) describes the relationship between the ideal and actual PV system energy outputs. PV plant energy is strongly reliant on solar insolation, and the performance ratio compensates for the incident solar irradiation, making it a powerful performance assessment tool.

$$Y_R = \frac{\textbf{Measured insolation in kWh/m}^2}{\textbf{Reference irradiation in kW/m}^2} \qquad 3.1$$

$$Y_S = \frac{\textbf{AC Energy output in kWh}}{\textbf{Nameplate rated output in kW}} \qquad 3.2$$

$$PR = \frac{\textbf{System Energy Yield } (\mathbf{Y_S})}{\textbf{Reference Energy Yield } (\mathbf{Y_R})} \qquad 3.3$$

The ratio of energy produced (kWhAC) from the PV plant divided by the PV plant's theoretical peak energy production during a given period is known as the capacity factor (CF) for a photovoltaic system. However, because it excludes the insolation from the sun, this element is not the best performance evaluation criteria.

$$CF = \frac{\textbf{Actual Energy output of system in kWh}}{\textbf{24} * \textbf{ Nameplate rated output in kW}} \qquad 3.4$$

The capacity factor and performance ratio can alternatively be stated as percentages. PR values for solar PV systems typically vary from 65-95%, with capacity factor values ranging from 15-25%.

3.2 PVSYST ANALYSIS

PVsyst software is a powerful solar design tool utilised by thousands of researchers and professionals worldwide. PVsyst is quickly becoming the industry standard for large and utility-scale solar projects.

The performance ratio (PR) is location-independent and is sometimes referred to as the quality factor because it accurately assesses the quality of the PV plant. The performance ratio (PR) describes the correlation between the ideal and actual energy outputs of a PV system. PV plant energy is strongly reliant on solar insolation, and the performance ratio compensates for this worldwide incident irradiation, making it a potent performance assessment tool.

It is also occasionally used to evaluate the performance reduction of previously installed PV systems. The software's main parts are project design, simulation, and utilities. The project design includes grid-connected, freestanding, and pumping systems. The system allows users to customize PV system power and select appropriate PV modules, inverters, and batteries.

The simulation is run in hourly stages over a year and results a detailed report with graphs, tables, and diagrams. Databases and tools are examples of utilities. Monthly and hourly climatic data are stored in databases. Climate data compatible with PVsyst can also be imported from other sources. Unlisted PV modules, inverters, and batteries can also have their datasheets added. The behaviour of a PV installation may be readily approximated and visualised with the use of tools, and it also offers access to compare PV systems and simulation by importing measured data from actual PV installations.

PVsyst supports the import of solar radiation data as well as the use of built-in

Meteonorm, NASA, Solcast, and NREL data. It comprises a library of PV modules, solar inverters, pumps and generators from different manufacturers. If it is not listed, there is an option to import or change the existing datasheet of PV modules, inverters, and so on.

3.3 LSTM (LONG SHORT-TERM MEMORY)

LSTM is a recurrent type of neural network that can resolve the problem associated with vanishing and exploding gradients. Each unit of the LSTM contains information about the previous state. Instead of the same feedback loop connection, LSTM uses different paths for long and short-term memories. Unlike basic vanilla recurrent neural networks, LSTM is based on a much more complicated unit. The lack of weights allows long-term memories to flow through a series of unrolled units without causing the gradient to explode or vanish. At various stages, the sigmoid activation function determines the amount that LSTM remembers. A cell that acts as a memory can store, read or write information. In-coming information is stored when the cell reads, writes, or erases through the opening and closing of the gates. There are four neural network layers in the LSTM instead of one, each of which interacts with the others in a unique manner.

$$i_k = \sigma\ (W_i[h_{k-1}\ , \Psi_k\ ] + b_i \qquad 3.4$$

$$f_k = \sigma\ (W_f[h_{k-1}\ , \Psi_k\ ] + b_f \qquad 3.5$$

$$O_k = \sigma\ (W_o[h_{k-1}\ , \Psi_k\ ] + b_o \qquad 3.6$$

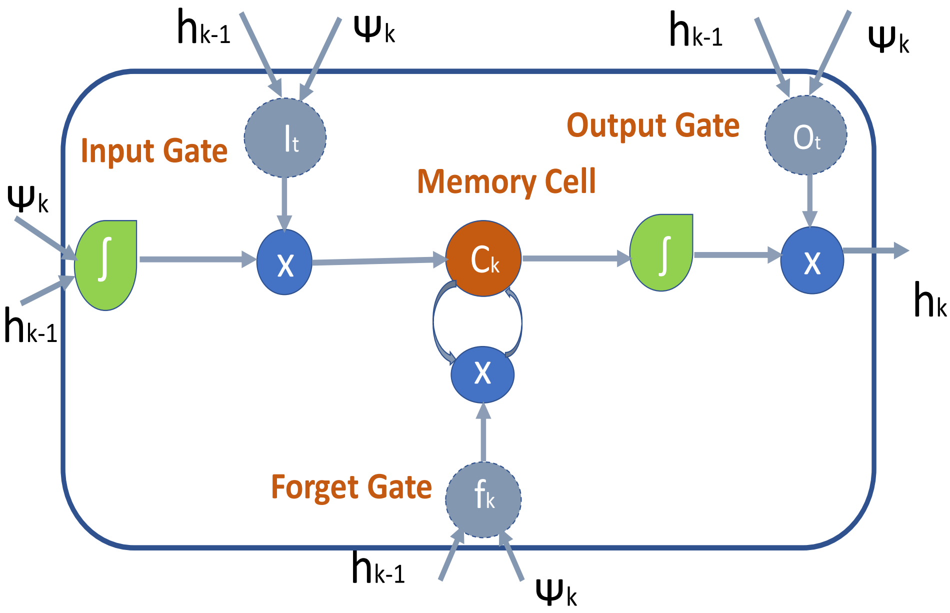

Fig. 3.1: - LSTM Structure

$C_k' = tanh\ (W_C\ [h_k - 1, \Psi_k] + b_c$ 3.7

$C_k = f_k * C_{k-1} + i_k * C_k'$ 3.8

$h_k = O_k\ *\ tanh(C_k)$ 3.9

$\mathrm{i_k}$ = input gate, $\mathrm{f_k}$ = forget gate, $\mathrm{O_k}$ = Output gate

σ = sigmoid function,

Ψ_k = input at current timestamp ,

W_x = weight of the respective (x) gate neurons

$h_k - 1$ = output of the previous LSTM Block

$\mathrm{b_x}$ = bias of the respective gates (x)

$\mathrm{C_k}$ = Cell state (memory) at timestamp k

$\mathrm{C_k'}$ = represents candidate for cell state at timestamp k

The Cell state is the core concept of the LSTM technique LSTM networks comprise of different gates that contain information about the previous state. The first step of the long short-term memory unit is forget gate that determines what percentage of the long term memory is to be remembered. The second step is the input gate that determines how often long-term memory needs to be updated. The final stage of the LSTM updates the short-term memory, as this short-term memory is the output from this entire LSTM unit; this stage is known as the output gate.

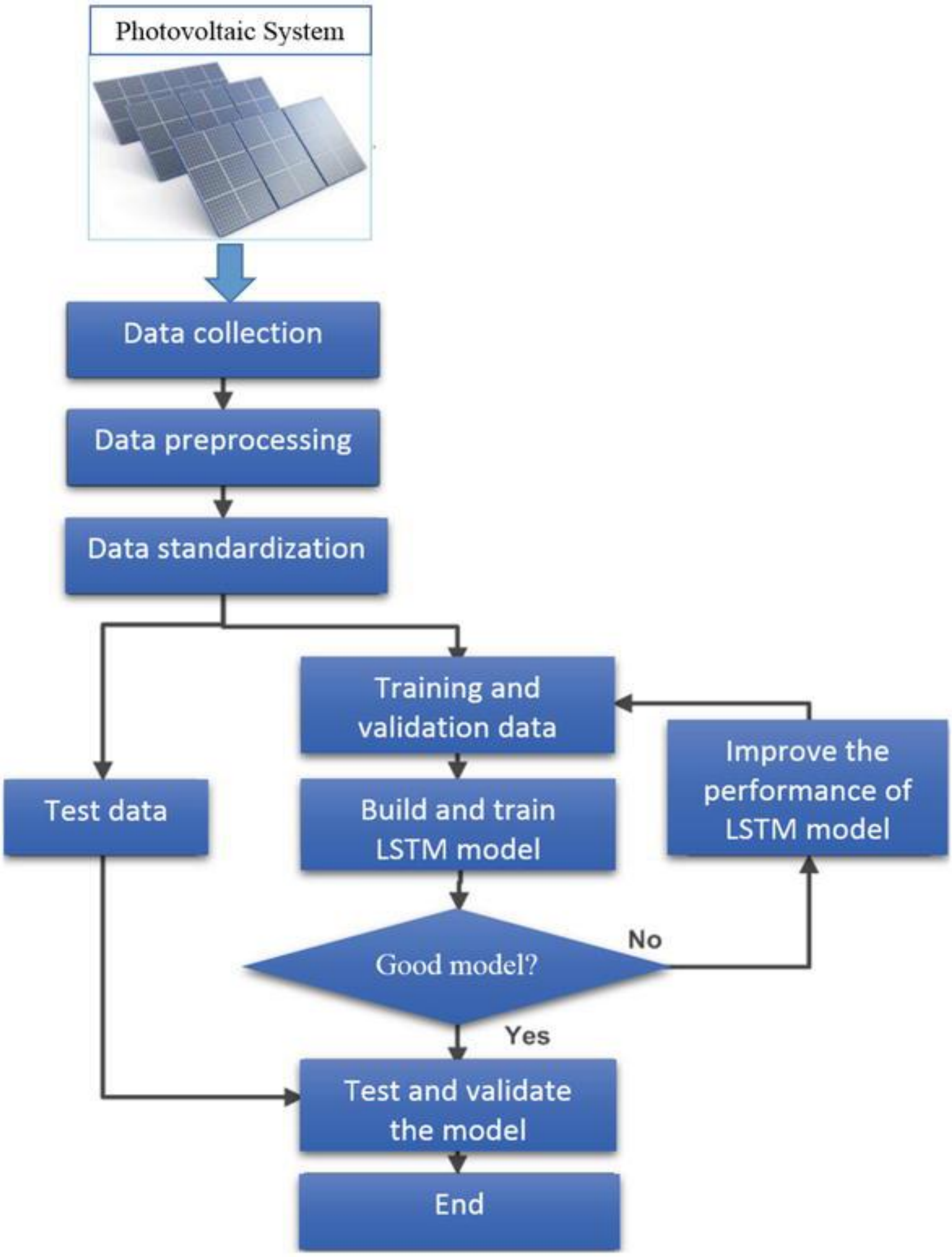

Fig. 3.2: - Flowchart of Solar Power Forecasting using LSTM

3.4 BILSTM (BIDIRECTIONAL LSTM)

A BiLSTM, or bidirectional LSTM, is a sequence processing model made up of two LSTMs, one forward and one backward. BiLSTMs significantly increase the amount of information given to the network, hence enhancing the context offered to the algorithm.

Bidirectional LSTM encodes a sequence in both forward and reverse directions and concatenates the results of forward and reverse LSTMs. Bidirectional LSTM trains two models. The first model learns the sequence of the specified input data samples, while the second model attempts to learn the inverted sequence in the reverse direction.

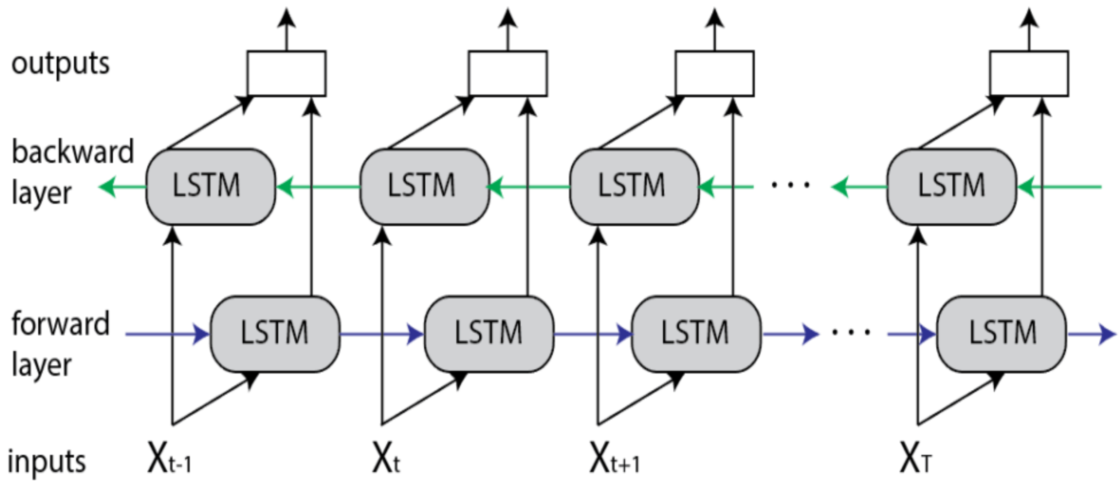

Fig 3.3: - BiLSTM Structure

The merge step involves combining of both models; Merging can be done with one of the following operations:

- Concatenation (default)
- Sum
- Multiplication
- Averaging

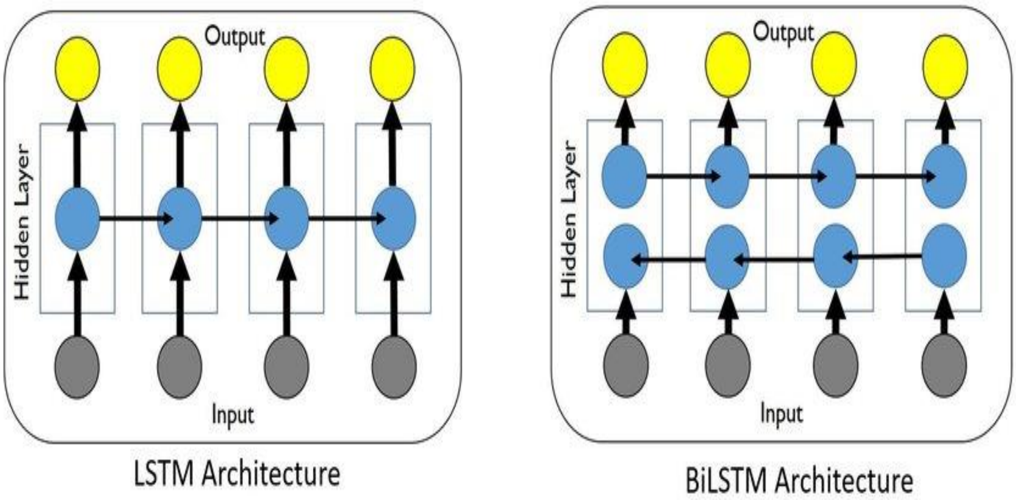

Fig. 3.4: - Comparison of LSTM and BiLSTM Architecture

3.5 1D CNN (CONVOLUTIONAL NEURAL NETWORK)

For handling 1-dimensional data, 1D-CNN or Conv1D is a suitable approach. Under identical conditions, the computational complexity of 1D-CNN is lower than that of its 2D counterpart. The types of layers present in a CNN architecture are CNN layers, flatten layers, dropout layers, fully connected dense layers or MLP (multilayer perceptron) layers. Configuration of a 1 D CNN comprises of a number of hidden CNN and MLP neurons, filter size and subsampling factor in each CNN layer and the choice of pooling and activation function.

A feature map can be obtained by using the filtering operation repeatedly on the layers. A feature map specifies the different attributes linked to the data samples. Convolution is a linear operation involving the multiplication of inputs with a certain set of weights. In 1D CNN, the inputs are multiplied by the kernel, that is a 1D array of weights. Executing this multiplication operation returns a unique value with each go, and with number of passes or go’s, multiple values are obtained constituting a feature map.

After the feature map is obtained, each component is passed through an activation function. The ReLU activation function can be used to improve the performance of the model and also to overcome the problem of the vanishing gradient.

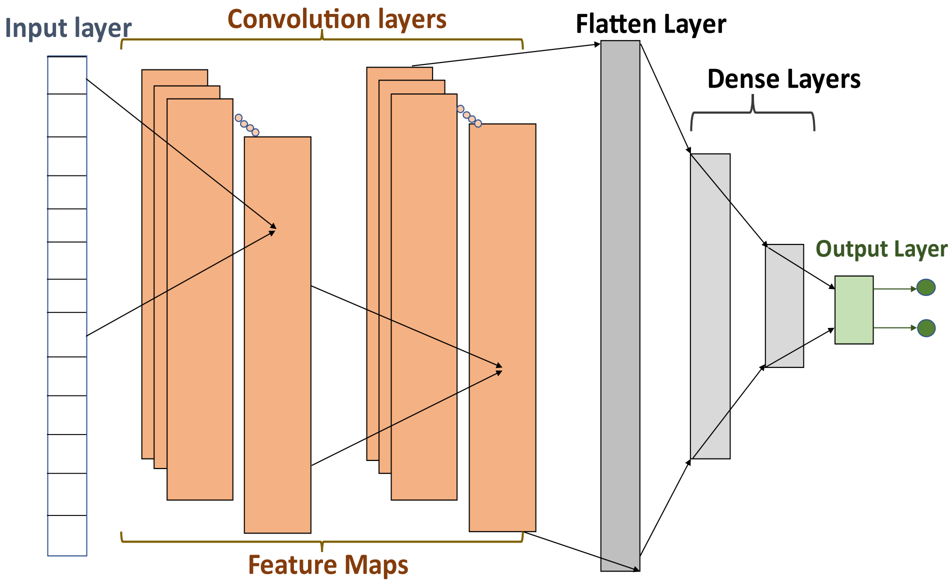

Fig. 3.5: - CNN Architecture

For aa 1D input sequence X $\in R^n$ and a filter k$\in R^{2m+1}$, the convolution operation is as shown in equation (7)

$$\mathrm{h(t)} = x * z(t) = \sum_{z=-m}^{m} x(t-z).k(z) \tag{3.10}$$

3.6 DATA PREPROCESSING

Feature scaling is an important step in data preprocessing. Daily solar PV data is bell-shaped in nature, so standardization is a suitable preprocessing approach. ANN models perform better when the predictors are on the same scale. In standardization, all features follow the reduced central normal distribution.

$$X_{standarized} = \frac{X-\mu}{\sigma} \tag{3.11}$$

μ = Mean

σ = Standard deviation

X = feature

3.7 STATISTICAL INDICATORS

The statistical indices are used to test and examine the performance of the models. The performance metrics used are MAE (Mean Absolute Error), R^2 (R Squared Error), RMSE (Root Mean Square Error) and R_a^2 (Adjusted R squared error).

$$MAE = \frac{1}{N} \sum_{i=1}^{n} |Y_i - Y_i'| \quad 3.12$$

Where Y_i is the actual result, Y_i' is the predicted result and N is the number of samples.

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{n} (Y_i - Y_i')^2} \quad 3.13$$

RMSE is the square root of the average of squared residuals. Residuals are estimated by subtracting the predicted value from the actual value.

$$R^2 = 1 - \frac{Mean\ Squared\ Error\ (Model)}{Mean\ Squared\ Error\ (Baseline)} \quad 3.14$$

R squared error is another popular metric used for the evaluation of regression models, also known as the coefficient of Determination. The R-squared indices allow us to assess the performance of the model to a constant baseline. To determine a constant baseline, the mean of the data is taken and, a line is drawn through it.

As the number of input features is increasing the R^2 score is improved, even if the model is not improving. It may mislead the researchers; hence adjusted R^2 can also be calculated.

To overcome the problem of R square, adjusted R squared is used, which always returns a lower value than R2. This is due to the fact that it adjusts the values of increasing predictors and only shows improvement if there is a genuine improvement.

$$R_a^2 = 1 - [\frac{n-k}{n-k-1} * (1 - R^2)] \quad 3.15$$

‘n’ is the number of data points and ‘k’ denotes the number of features or independent variable

3.8 CONCLUSION

This chapter presented the approaches and methods used in this research for obtaining the results presented in upcoming two chapters. PVsyst analysis and performance analysis are described that are used for studying the effect of dust deposition on the performance ratio of the 5 W PV system. AI techniques such as LSTM, CNN 1D and BiLSTM are also briefly explained, that are used for solar power forecasting.

CHAPTER 4

PERFORMANCE ANALYSIS OF 5 kW PV SYSTEM

4.1 DESCRIPTION OF HARDWARE SETUP

4.1.1 5 kW PV System

Fig. 4.1 depicts the reference PV system. The 5 kW photovoltaic system is made up of 20 modules, each having a rated output of 250 Wp and connected in two parallel strings of ten modules in each string. Table 4.1 displays the STC ratings for the 250 Wp module.

Fig. 4.1: - 5 kW Photovoltaic System

The 5 kW PV system shown in Fig. 4.1 is a polycrystalline type of material. Each module has in total 60 cells. The PV system is grid connected and an MPPT inverter is also connected in the system. The PV panels are inclined at a tilt angle of 29^0 and azimuth of 10^0.

Table 4.1: - 250 W_p Module Ratings at STC

Cell type	Polycrystalline
Rated output (P_{mpp})	250 Wp
Rated voltage (V_{mpp})	30.48 V
Rated current (I_{mpp})	8.21 A
Open Circuit Voltage (V_{oc})	37.47 V
Short circuit current (I_{sc})	8.81 A
Module Efficiency	15.4 %
Number of Cells	60
Module size	1640*992*35 mm
Number of diodes	03

4.1.2 MPPT Inverter

The 5.5 kW_{AC} MPPT based inverter in shown in Fig. 4.2 and the ratings of this inverter are depicted in Table 4.2.

Fig. 4.2: - 5.5 kW_{AC} MPPT Inverter

Table 4.2: - 5.5 kW_{AC} Inverter Ratings

Max. AC output active power	5.5 kW
MPP Voltage Range	200-900 V
Maximum Input Voltage	1000 V
Maximum Input Current	2*11 A
ISC PV (absolute maximum)	2*16.5 A
Maximum Continuous Output Current	3*8.5 A
Rated Grid Voltage	380/400 V

The MPPT-based inverter is capable of providing with the 5 kW photovoltaic system's daily system energy (kWh), daily peak power (W), and daily operable. The ratings of the 5.5 kWp inverter are defined in Table 4.2.

4.1.3 PVsyst 5 kW PV System

PV module and inverter datasheets, as stated in Tables 4.1 and 4.2, as well as tilt angle and azimuth angle, as depicted below in Fig. 4.1, were imported into PVsyst software for simulation. The coordinates of Delhi Technological University is 28.74950 N and 77.11840 E. The most recent NASA daily global irradiation data for the above area is used to calculate the performance ratio (PR).

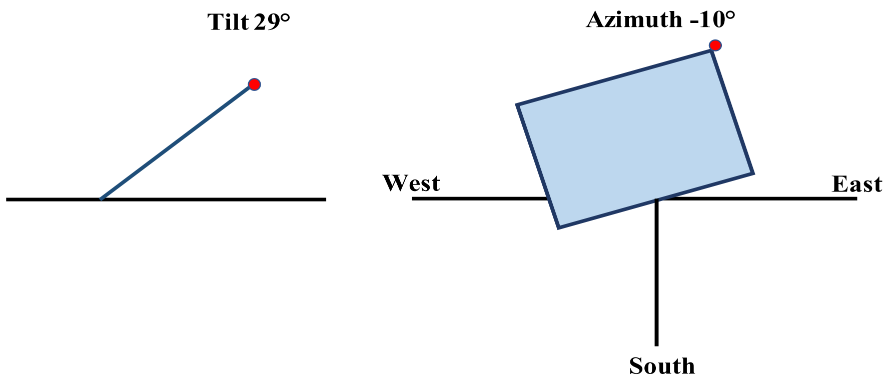

Fig. 4.3: - Tilt angle and Azimuth angle in PVsyst

Table 4.3: - PVsyst Parameters

Field Type	Fixed-tilted plane
Number of 250 Wp modules	20
Module area	33 m^2
Nominal PV power	5 kWDC
Nominal AC power	5.5 kWAC
Modules in series	10
Number of Strings	2
Site Latitude	28.7495^0 N
Site Longitude	77.1184^0 E
Altitude	300 m

Table 4.3 shows the PVsyst parameters obtained in PVsyst after importing the the datasheets of module and inverter along with the tilt and azimuth angle of the PV system into the software.

The data is collected from the inverter unit over a period of 62 days, and the 5 kW PV system operates every day for 10-15 hours. The panels were left naturally unclean in May, whereas they were cleaned on a regular basis in June, and because the PV system was down for 5 days in May, the data consists of some dates from April and July. The comparison of reference energy yield (Y_R), system energy yield (Y_S), performance ratio (PR), capacity factor (CF), and peak power (W) is shown in Figs. 4.4-4.9.

4.2 PERFORMANCE ANALYSIS RESULTS

4.2.1 Comparison of Reference Energy Yield of both Months

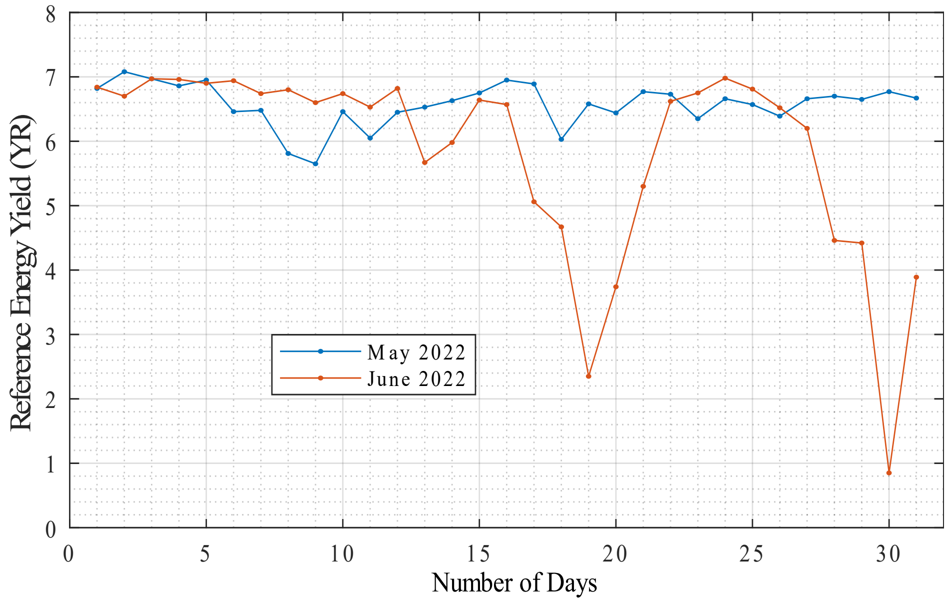

Fig. 4.4: - Comparison of Reference Energy Yield of both Months

In Fig. 4.4 above, the reference energy yields for the two months are compared. It is clear that the reference energy yield for June suddenly plummeted for a few days due to the frequent rainfall, which caused the panels to naturally clean themselves and drop in temperature. Additionally, it can be identified that May has a higher solar energy potential than June.

4.2.2 Comparison of Reference Energy Yield and System Energy Yield of both Months

Fig. 4.5 and Fig. 4.6 compare the reference Energy yield (Y_R) and system Energy yield (Y_S) in May and June, respectively.

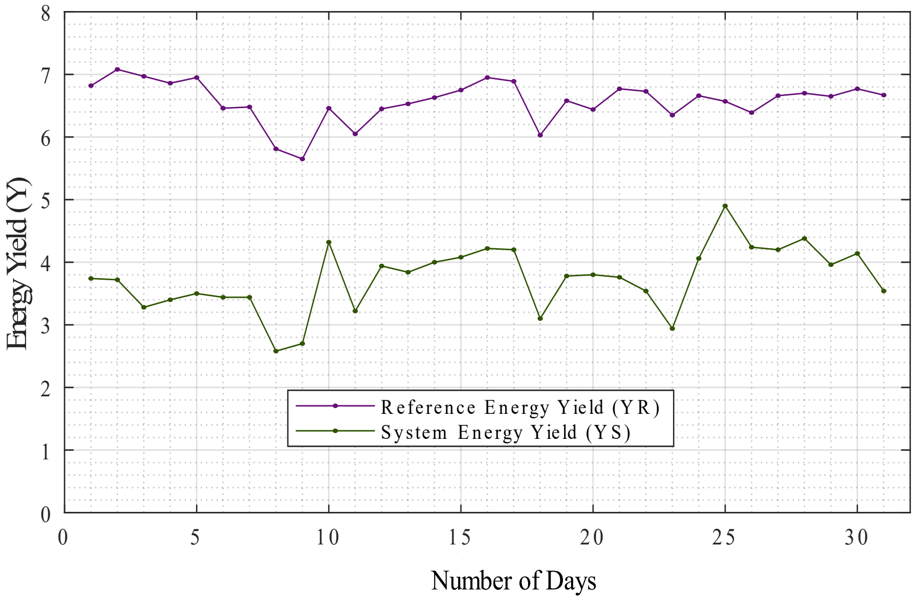

Fig 4.5: - Comparison of Reference Energy Yield (Y_R) and System Energy Yield (Y_s) in May 2022

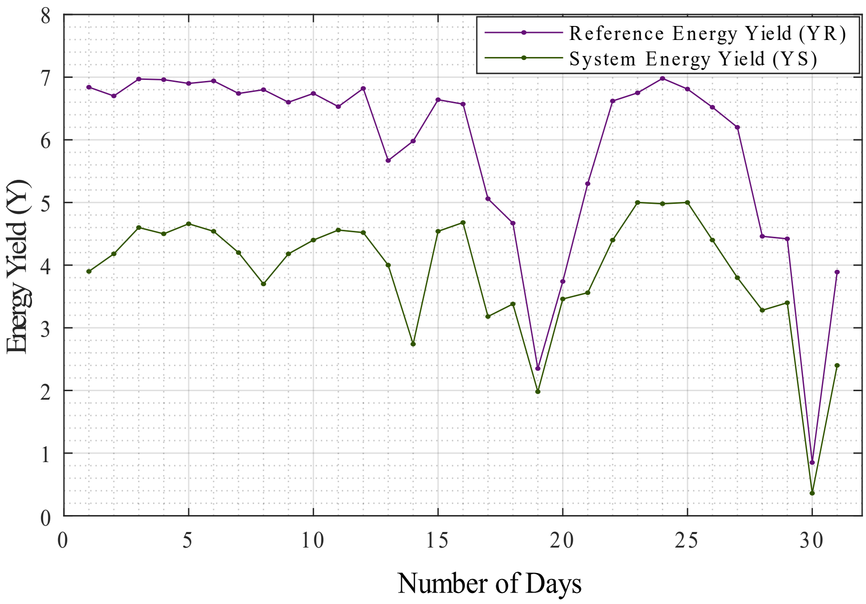

Fig 4.6: - Comparison of Reference Energy Yield (Y_R) and System Energy Yield (Y_s) in June 2022

From Fig 4.5 and 4.6, it is evident that in June, the system energy yield approaches the reference energy yield more than in May, implying that more power is extracted from the PV system.

4.2.3 Comparison of Capacity Factor and Performance Ratio of both Months

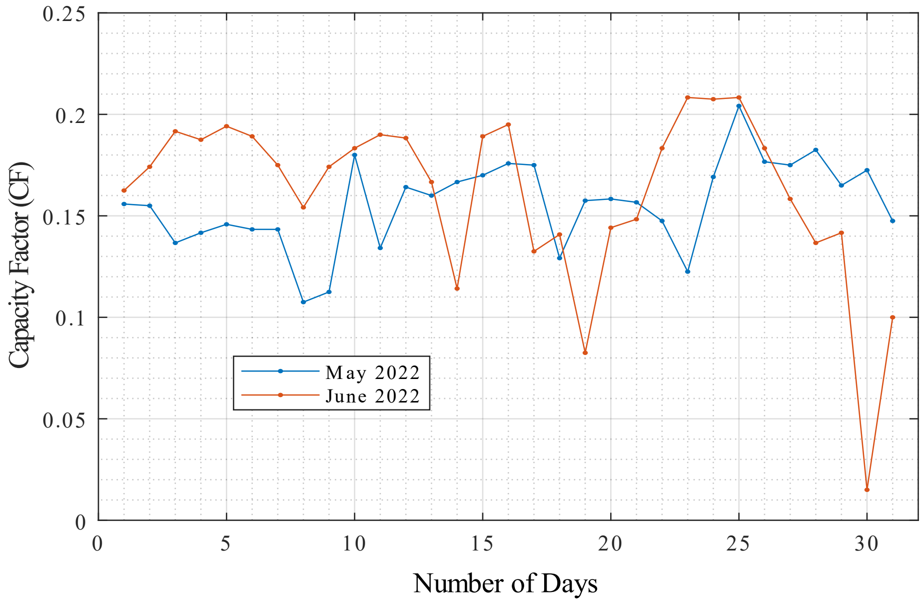

Fig. 4.7: - Comparison of Capacity Factor per Day of both Months

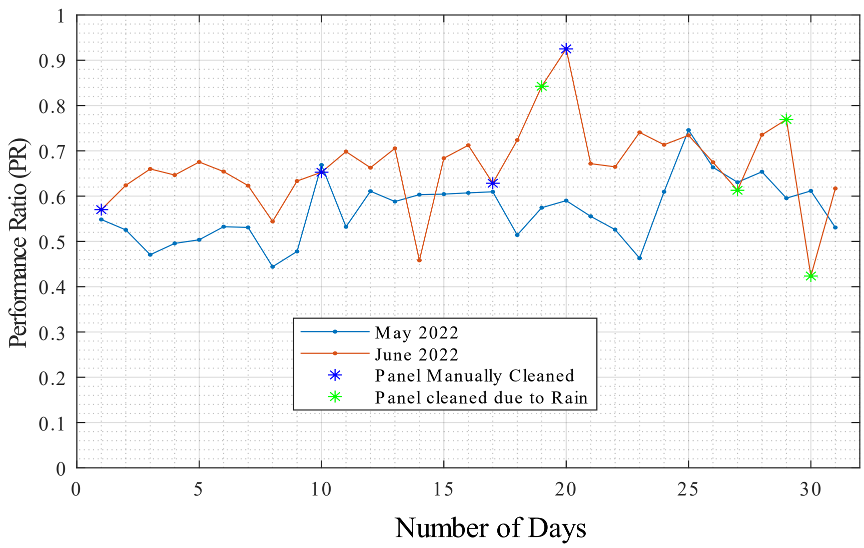

Fig. 4.8: - Comparison of Performance Ratio per Day of both Months

The daily capacity factor of the two months is compared in Fig. 4.7, but since the capacity factor does not take into account environmental factors like irradiance, it is unable to derive any conclusions. In contrast, Fig. 4.8 shows the performance ratio comparison of the two months, and it can be seen that, with the exception of 5 days, the PR of June is greater than the PR of May. Due to frequent panel cleaning, a high PR of 0.925 was recorded in June, and a minimum PR of 0.42 was recorded during the same month due to a lot of grey days. The highlighted parts indicate the days when the solar panels were either naturally washed by rain or manually cleaned.

4.2.4 Comparison of Peak Power of both Months

It is the maximum power that can be sustained by a power supply for a short period of time, and it is sometimes called the peak surge power.

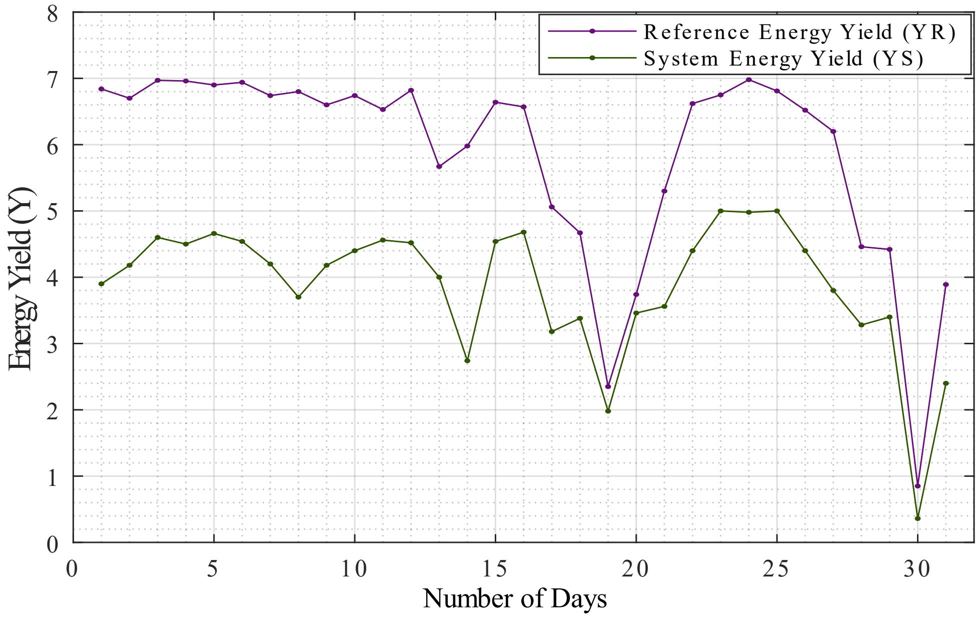

Fig 4.9: - Comparison of Peak Power (W) per day of both Months

As can be seen in Fig. 4.9, the daily peak power of June exceeds that of May on most days as a result of regular panel cleaning. In June, the highest peak power was 4490 W, and the lowest peak power was 452 W due to frequent grey days.

4.2.5 Performance Analysis Summary

Table 4.1 compares the reference energy yield (Y_R), system energy yield (Y_S), capacity factor (CF), performance ratio (PR), and peak power (in W) of both months

Table 4.4: - Comparison of Monthly Average Values of Both Months

Month / Average	May 2022	June 2022
Reference Energy Yield	6.57	5.839
System Energy Yield	3.741	3.886
Capacity Factor	0.156	0.162
Performance Ratio	0.568	0.667
Peak Power	2864.80 W	3203.484 W

Table 4.4 compares the monthly average values of different quantities for the two months, and it can be seen that June's system energy yield, capacity factor, performance ratio, and peak power are higher than May's corresponding values. However, June's monthly reference energy yield is lower than May's. Solar energy potential is higher in May, but performance is better in June. The performance ratio showed a striking 10% improvement in June compared to May. As seen in Fig. 4.9, the peak power likewise saw a considerable improvement in June.

4.3 PVSYST ANALYSIS RESULTS

After running the simulation in PVsyst the following daily system output energy is shown in Fig. 4.10 is obtained for whole year. The data of May and June are exported from this graph for comparative analysis of PVsyst 5 kW system with the practical 5 kW system.

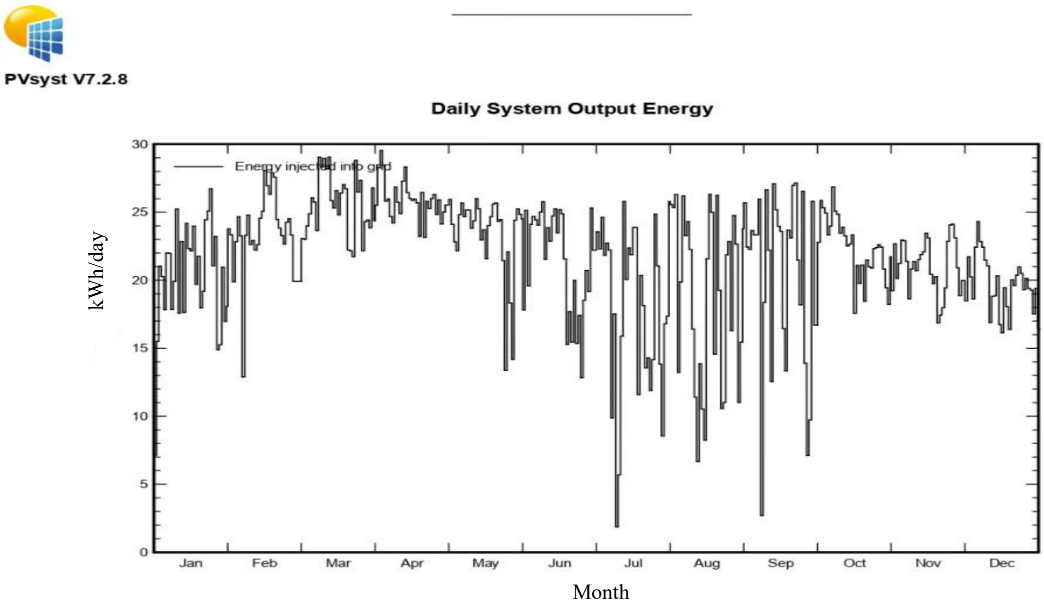

Fig. 4.10: - Whole Year Daily System Output Energy in PVsyst Software

4.4 COMPARISON OF PVSYST 5 kW SYSTEM AND PRACTICAL 5 kW SYSTEM

Table 4.5 compares the total system energy of the real system and the PVsyst system.

Table 4.5. Total System Energy Comparison of Both Months

Month / Energy	May 2022	June 2022
Total Practical System Energy (kWh)	580	602
PVsyst Total System Energy (kWh)	798	716

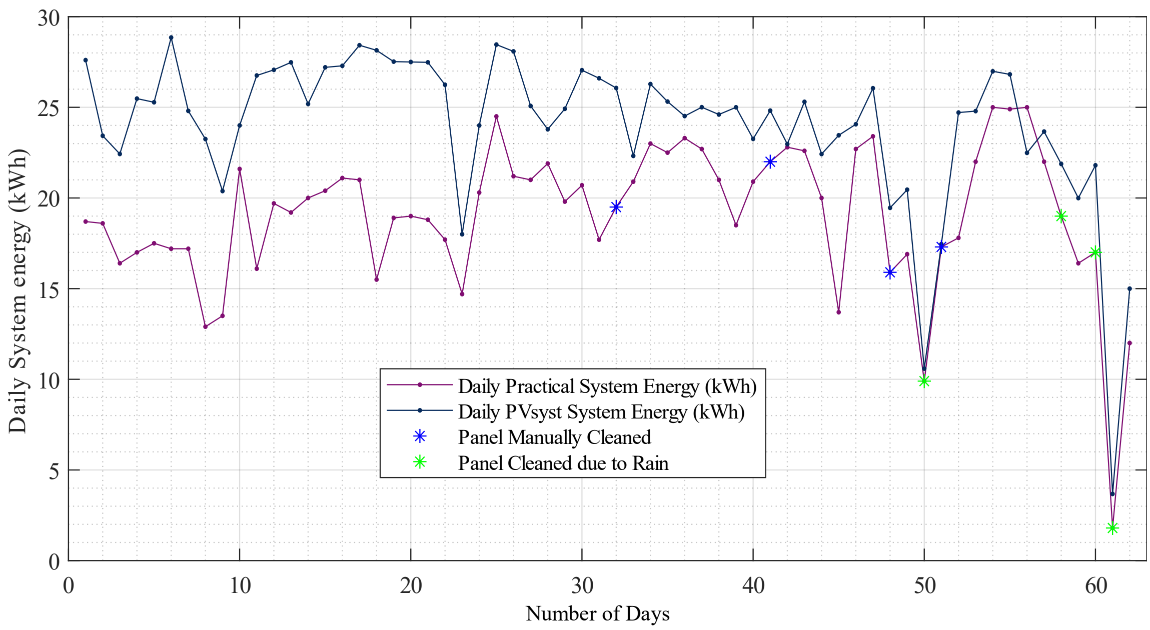

Fig. 4.11: - Over 62 Days, The Energy Consumption of the Practical 5 kW PV System And The Pvsyst 5 kW PV System was Compared on a Daily Basis.

The daily system energy of the practical PV system and simulation is compared and presented in Fig. 4.11 for 62 days after simulating the 5 kW solar system in PVsyst. The practical system energy in June was higher than the PVsyst energy in May, and on one crucial day, the practical system energy exceeded the PVsyst energy. Table 4.5 indicates that cleaning the panel on a regular basis significantly improves the monthly total system energy.

Despite the greater PVsyst daily system energy for May, the higher practical system energy for June is mostly due to regular panel cleaning. The entire practical system energy for the 62 days is 1182.2 kWh, as opposed to the overall PVsyst system energy of 1513.37 kWh. Total system losses compared to PVsyst energy for 62 days are 331.7 kWh, with 217.96 kWh in May and 113.21 kWh in June. Energy losses were reduced by 104.75 kWh in June as a result of frequent PV panel cleaning.

Table 4.6 Comparison of PR For Practical System and PVsyst System for both Months

Performance Ratio / **Month**	**Practical 5 kW PV System**	**PVsyst 5 kW PV System**
May 2022	0.57	0.78
June 2022	0.67	0.78

Table 4.6 compares the performance ratios of the simulation and real systems for both months. The performance ratio is a worldwide recognised criterion for measuring the efficiency of a PV system, and it can be seen that there was a considerable 10% improvement in PR in June.

4.5 CONCLUSION

This chapter consists of the experimental setup of 5 kW PV system, that are used to study the effect of dust on the performance. The results of the effect of dust accumulation on the performance ratio of the 5 kW PV system are presented. The results are explained in the form of tables and plots.

CHAPTER 5

SOLAR POWER FORECASTING OF 335 W PV MODULE

5.1 DESCRIPTION OF HARDWARE SETUP

The Fig. 5.1 shows the experimental setup of the solar power forecasting of the 335 watt module, The setup present on the rooftop of the laboratory is shown in Fig. 5.1.

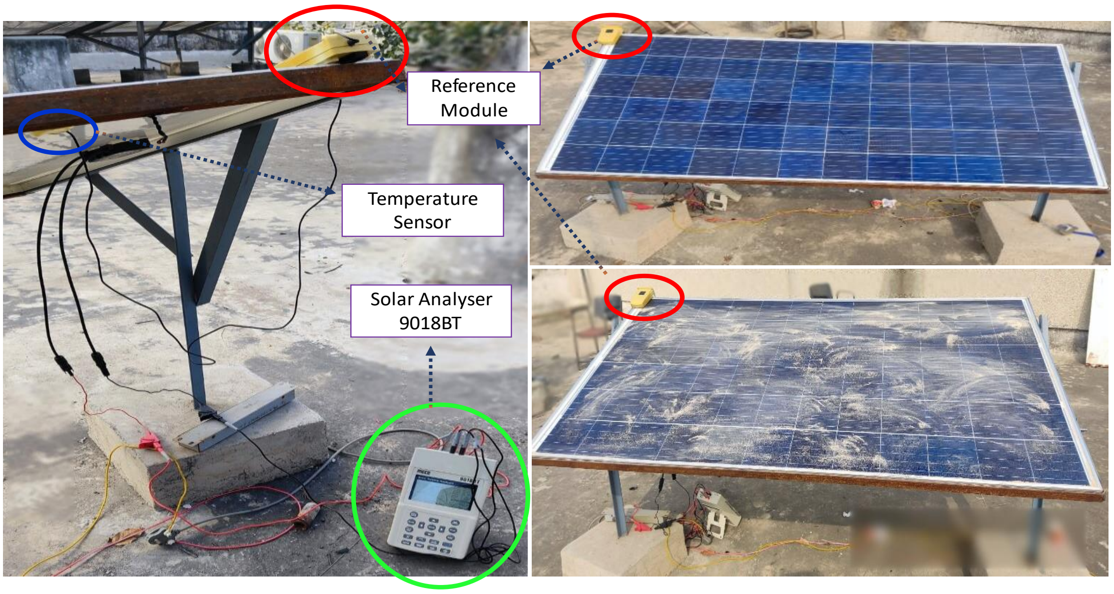

Fig. 5.1: - Experimental Setup of solar forecasting with Dust as Input Parameter

Fig. 5.1 shows the experimental setup for solar PV forecasting with dust as one of the input parameters. The 335 watt PV module is located on the rooftop of the laboratory and the data is collected from the solar system analyzer at intervals of 1 minute, and a total of around 2000 samples are collected.

The remote solar detector (reference module) measures the incident solar irradiation on the 335 watt module and the cell temperature. The considered parameters for the forecasting model are solar irradiation incident on the module (W/m^2), cell temperature (^{0}C), module output power (W) and dust (mg/cm^2). The dust is varied with an increment of 1.258 mg/cm^2 at regular intervals.

5.1.1 335 Watt PV Module

The ratings of the 335-watt module are shown in the below table: -

Table 5.1: - 335 W_p Module Ratings at STC

Cell type	Polycrystalline
Rated output (P_{mpp})	335 W_p
Rated voltage (V_{mpp})	35 V
Rated current (I_{mpp})	7.10 A
Open Circuit Voltage (V_{oc})	40 V
Short circuit current (I_{sc})	7.5 A
Tolerance	± 8 %
Number of Cells	60
Module Area	1.9878 m^2
Bypass diode rating	10 A

5.1.2 Solar System Analyser

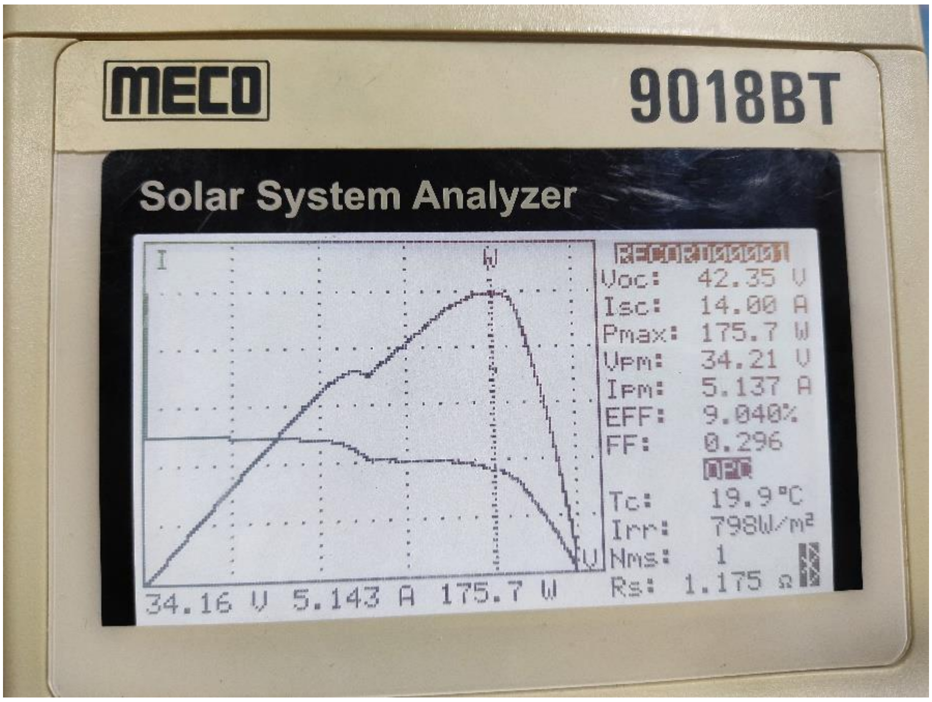

Fig. 5.2: - PV, IV plot of a Sample in Solar System Analyser

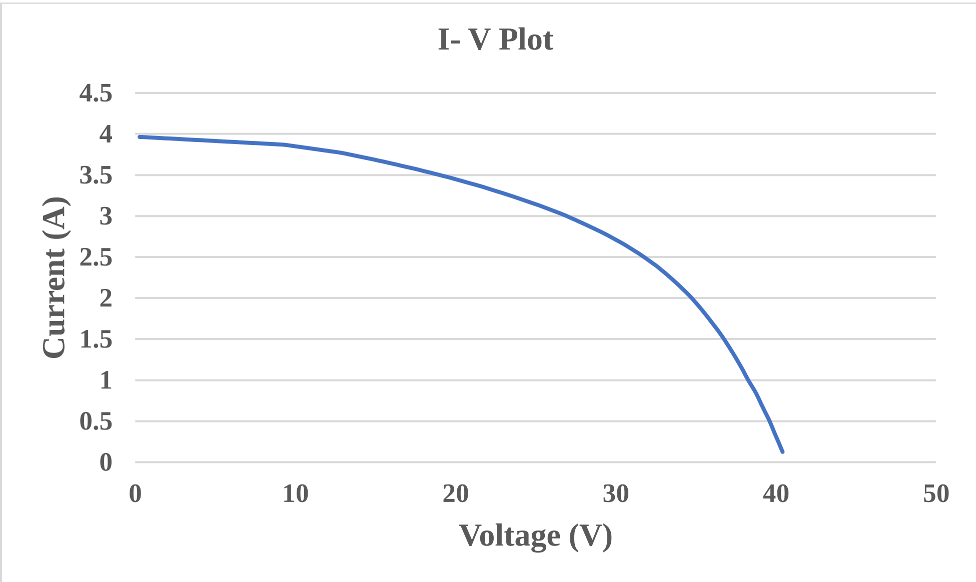

Fig. 5.3: - I-V plot of a Single Sample Reading taken from Solar System Analyser

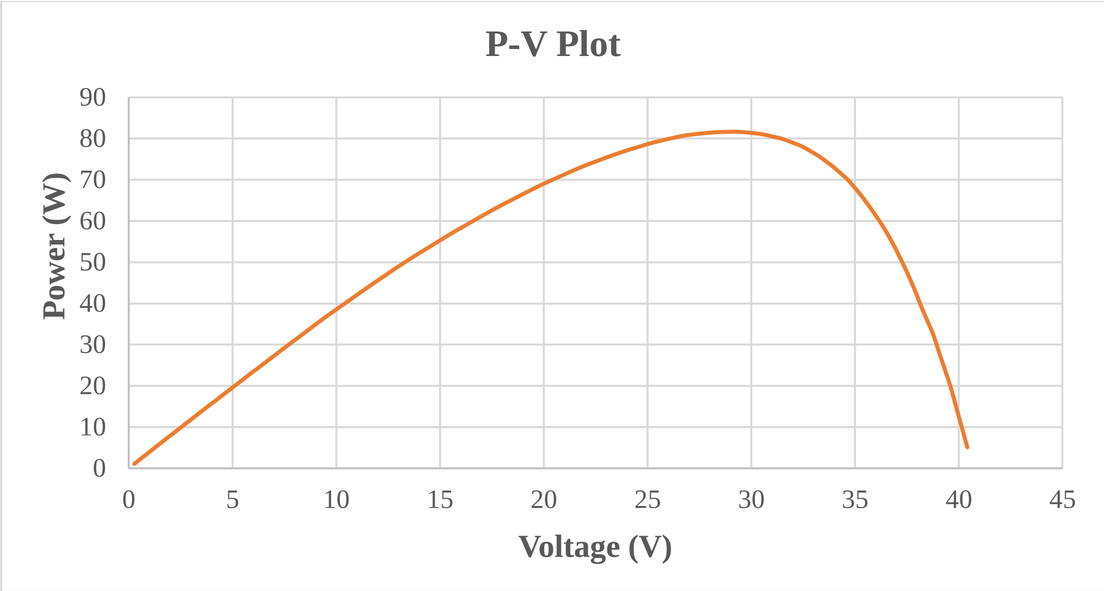

Fig. 5.4: - P-V plot of a Single Sample Reading taken from Solar System Analyser

5.2 RESULTS OF SOLAR POWER FORECASTING OF 335-WATT MODULE

5.2.1 Solar Forecasting Data

Fig. 5.5 and Fig. 5.6 show the solar irradiation (W/m^2) and solar power (W) data.

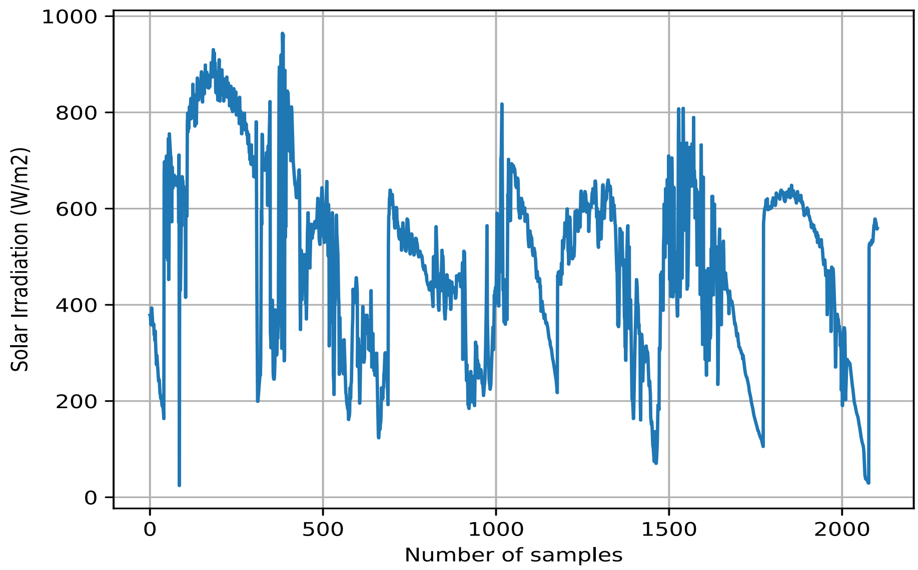

Fig. 5.5: - Solar Irradiation (W/m^2) Versus Number of samples

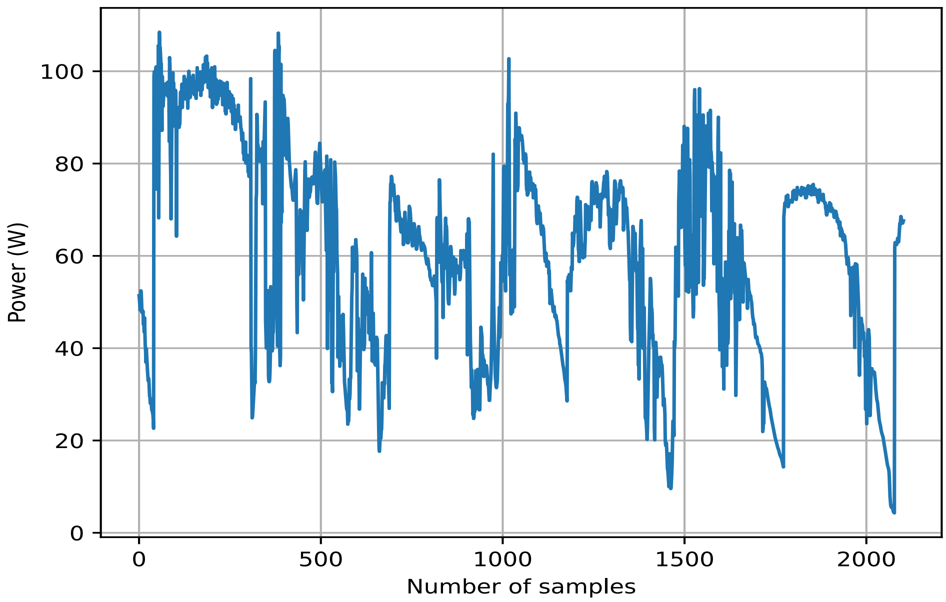

Fig. 5.6 - Power (W) Versus Number of samples

The data is forecasted for three deep learning models; LSTM, 1D CNN and BiLSTM using a python jupyter environment. Multivariate forecasting is used to predict results for irradiation and power with other features as input parameters.

5.2.2 Model Parameters of LSTM, CNN 1D and BI-LSTM

The parameters for each model are shown in Table 5.2.

Table 5.2: - Model Parameters LSTM, 1D CNN and BI-LSTM

		1D CNN	LSTM	BiLSTM
Total Features		4 and 3	4 and 3	4 and 3
Layers	Number of Hidden layer /Neurons/ Activation function	1/64/ ReLU	1/64/ ReLU	1/64/ ReLU

	Number of Dense layer/Neurons/ Activation function	1/8/ ReLU + 1/1/ linear	1/8/ ReLU + 1/1/ linear	1/8/ ReLU + 1/1 /linear
	Number of flatten layer	1	1	1
Kernel Size		2	Not valid	Not valid
No. of Trainable Parameters		2641	18,193	36, 369
Epochs		50	50	50
Optimizer/ learning rate		Adam/ 0.001	Adam/ 0.001	Adam/ 0.001

Table 5.2 shows the model parameters; total number of features is considered as 4 for the case that considers dust as the input parameter and for the case without dust as the input parameter, the total number of features is 3. The parameters for all three models are kept equal to compare them at a level.

The Fig. 5.7-5.16 shows the comparison of all three models, with dust as an input parameter denoted with ‘D’ and without dust as an input parameter denoted as ‘WD’ with the actual results and it can be observed that the predictions are significantly improved for with dust as the input parameter case than as compared to the case that does not consider dust as input parameter for all three models.

5.2.3 Comparison of Different AI Models for With Dust and Without Dust as Input Parameter

As can be seen from Fig. 5.7 to 5.16 and Table 5.3 and Table 5.4, the BiLSTM model has the highest prediction accuracy compared to LSTM and Conv1D (1D

Convolution neural network) models. The Conv1D model also gives very close results to the BilSTM model. Conv1D model has the least number of trainable parameters, and hence it takes the least time to get executed. As can be seen from Table 5.5 and Table 5.6, RMSE and MAE is least for BiLSTM for all cases, whereas R^2 is highest for BiLSTM compared to other models.

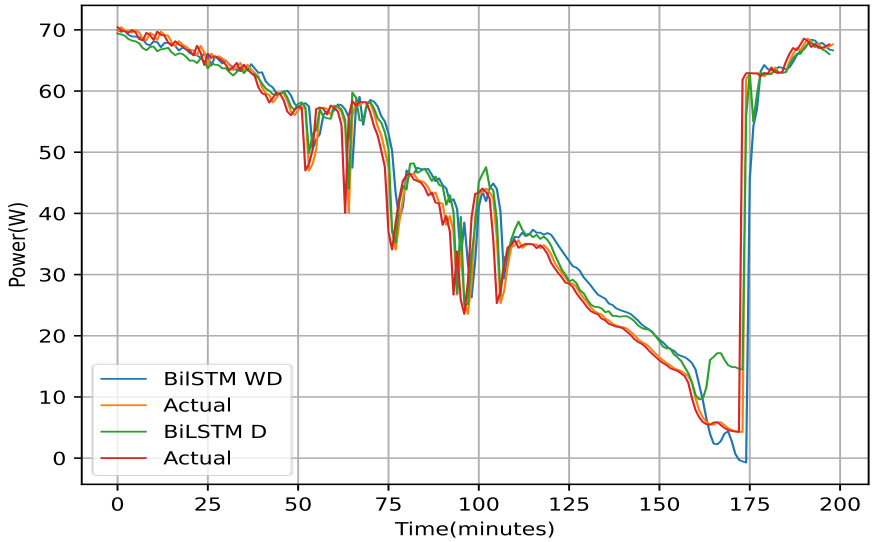

Fig. 5.7: - Solar Power Forecasting for BiLSTM model for with Dust as Input Parameter (D) and without Dust as Input Parameter (WD)

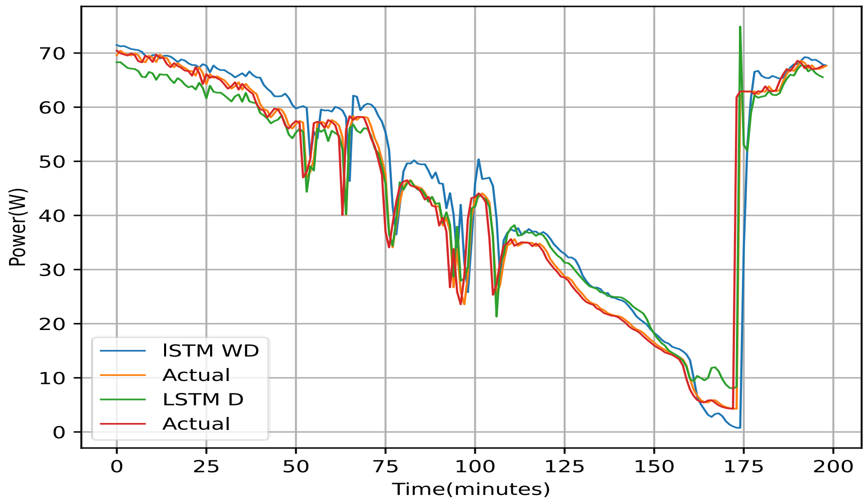

Fig 5.8: - Solar Power Forecasting for BiLSTM model for with Dust as Input Parameter (D) and without Dust as Input Parameter (WD)

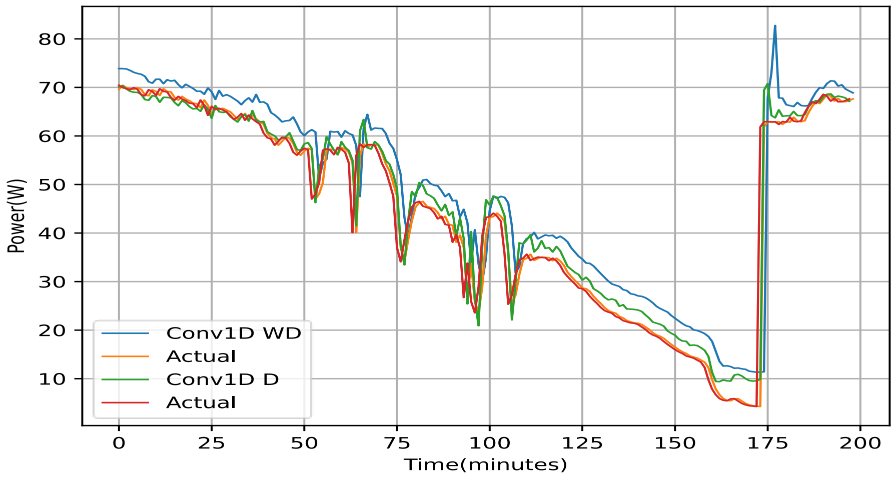

Fig. 5.9: - Solar Power Forecasting for Conv1D Model for with Dust As Input Parameter (D) and without Dust as Input Parameter (WD)

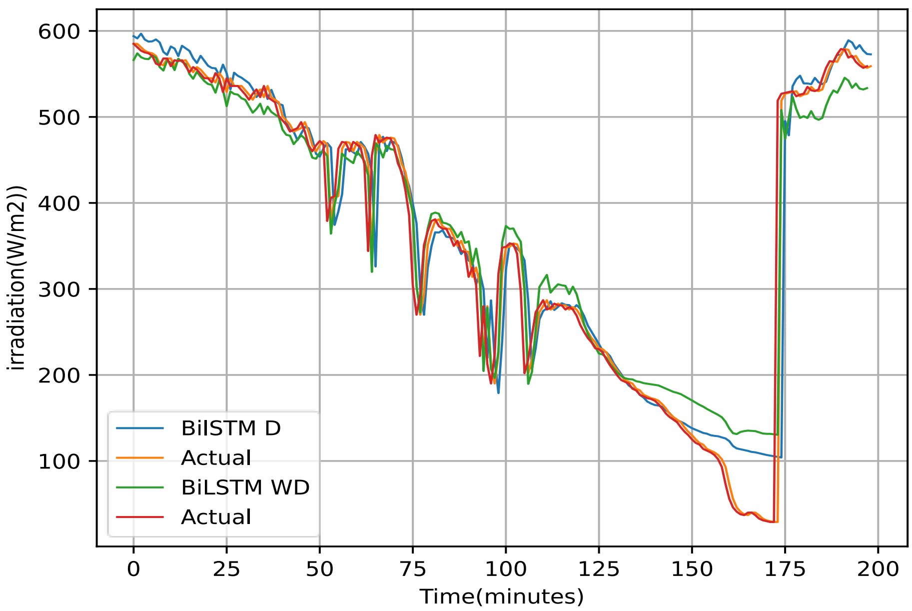

Fig. 5.10: - Solar Irradiance Forecasting for BILSTM Model for with Dust as Input Parameter (D) and without Dust as Input Parameter (WD)

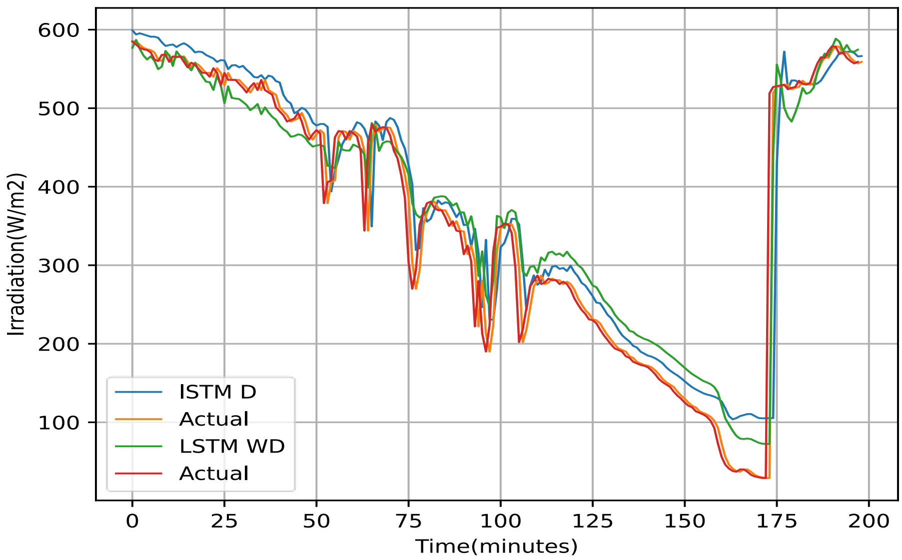

Fig. 5.11: - Solar Irradiance Forecasting for LSTM Model for with Dust as Input Parameter (D) and without Dust as Input Parameter (WD)

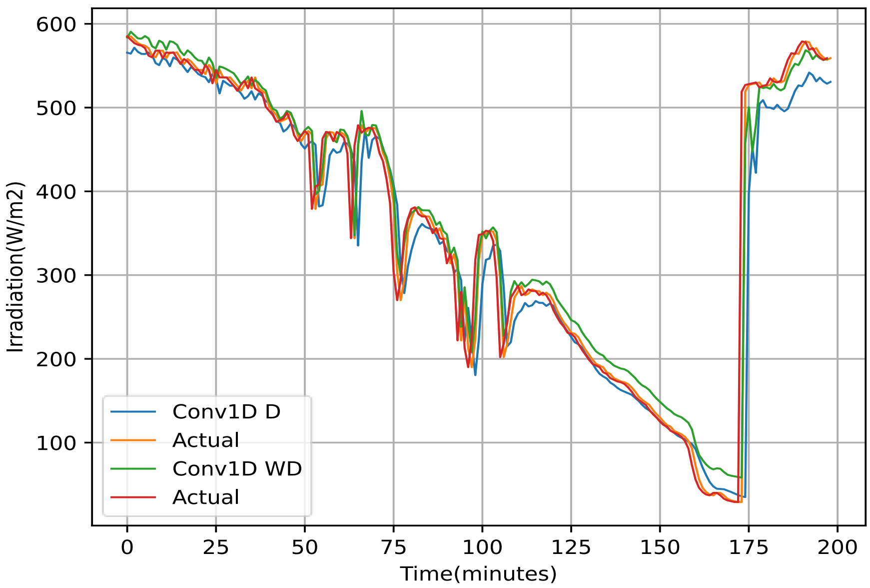

Fig. 5.12: - Solar Irradiance Forecasting for Conv1D Model for with Dust as Input Parameter (D) and without Dust as Input Parameter (WD)

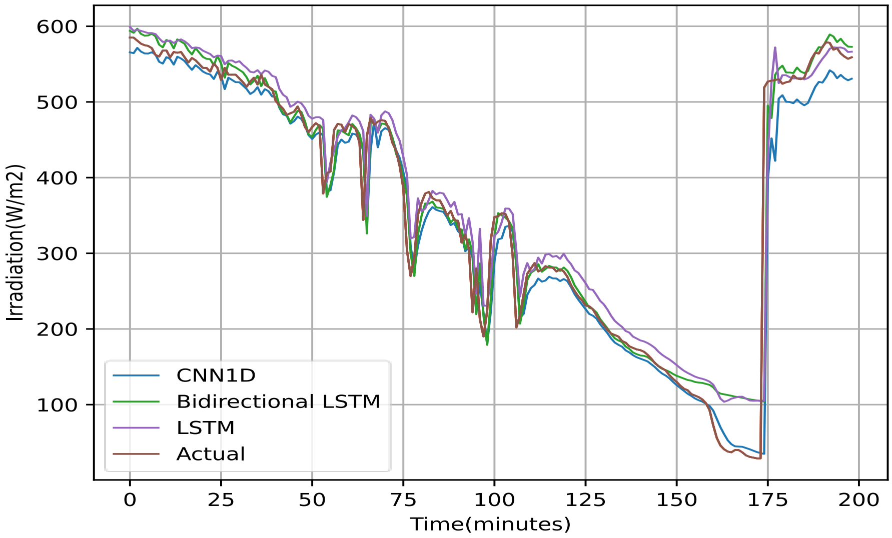

Fig 5.13: - Comparison of Different Models for Predicting Irradiation with the Actual Irradiation Results with Dust as an Input Parameter

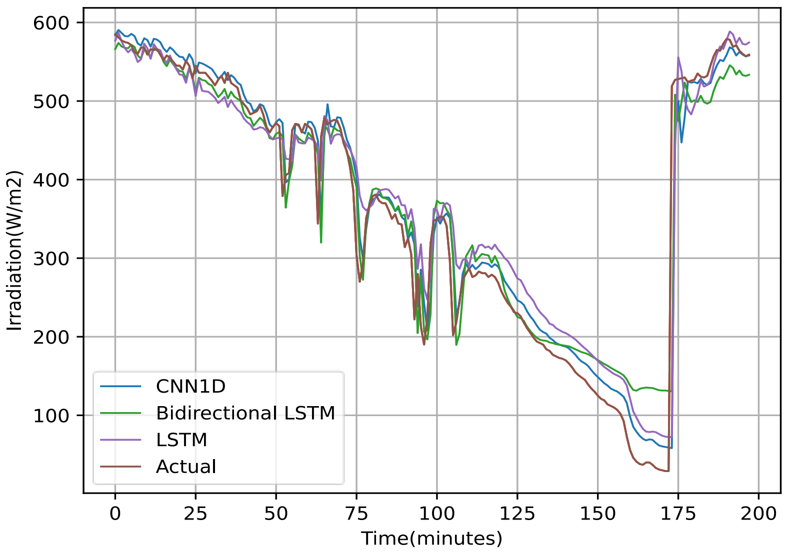

Fig. 5.14: - Comparison of Different Models for Predicting Irradiation with the Actual Irradiation Results without Dust as an Input Parameter

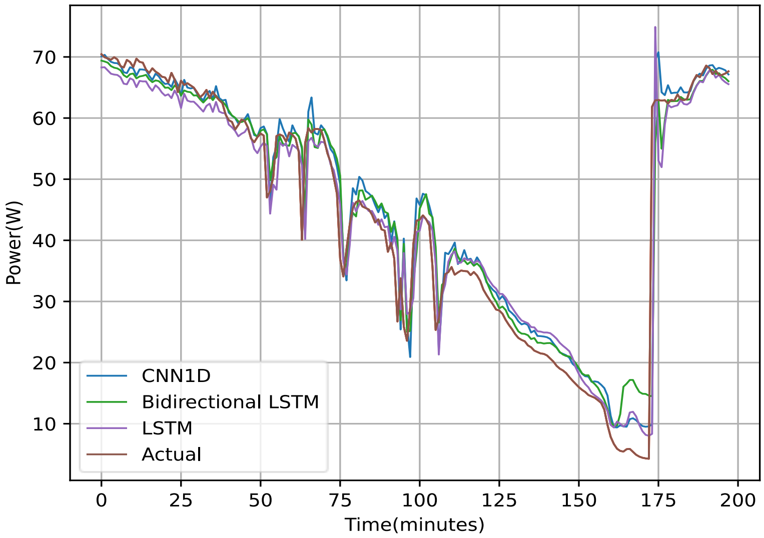

Fig. 5.15: - Comparison of Different Models For Predicting Power with the Actual Power Results with Dust as an Input Parameter

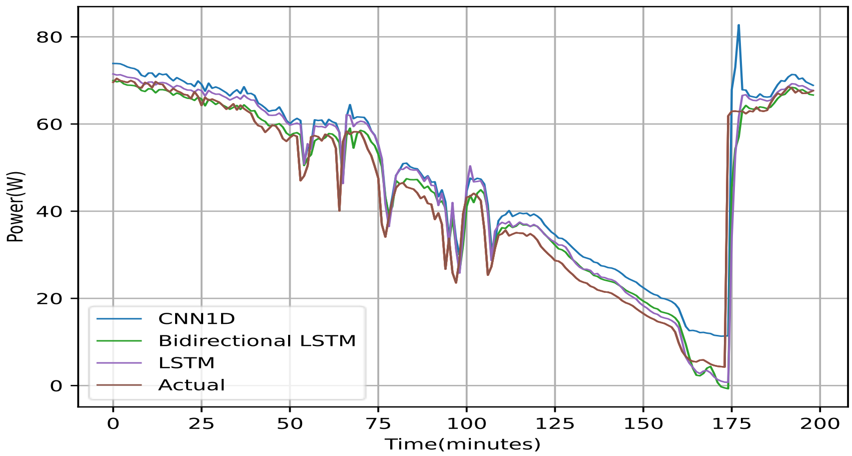

Fig. 5.16: - Comparison Oof Different Models For Predicting Power with the Actual Power Results without Dust as n Input Parameter

Table 5.3: - Performance Comparison of Various Models for Predicting Power (W)

Power (W)		RMSE (W)	MAE (W)	R^2	Adjusted R^2
Dust	CNN 1D	5.35	5.12	0.937	0.89
	LSTM	5.35	4.8	0.931	0.86
	BiLSTM	5.32	4.65	0.94	0.90
Without Dust	CNN 1D	6.74	5.6	0.891	0.80
	LSTM	6.36	5.23	0.903	0.82
	BiLSTM	5.8	5.15	0.919	0.85

Table 5.4: - Performance Comparison of Various Models for Predicting Irradiation (W/m^2)

Irradiation(W)		RMSE (W/m^2)	MA (W/m^2)	R^2	Adjusted R^2
Dust	CNN – 1D	42.7	33.8	0.938	0.89
	LSTM	44.84	35.2	0.932	0.87
	BiLSTM	40.3	31.3	0.944	0.91
Without Dust	CNN – 1D	43.09	33.9	0.937	0.88
	LSTM	49.62	33.0	0.9174	0.84
	BiLSTM	42.4	32.7	0.92	0.86

5.3 CONCLUSION

This chapter consists of the experimental setup of 335 watt PV module. The results of the solar forecasting accuracy results with and without considering dust accumulation as an input parameter are shown. The results are explained in the form of tables and plots. Next chapter includes the final conclusion and future scope of the research.

CHAPTER 6

CONCLUSION AND FUTURE SCOPE

6.1 CONCLUSION

The 5 kW photovoltaic system's performance is analysed for 62 days. The panels were left naturally unclean for the first 31 days before being cleaned on a regular basis for the next 31 days. Although May has a higher potential for solar energy, June has a good performance ratio due to regular panel cleaning in June. PV panels consider rainfall to be a significant factor when analysing performance; while grey skies impede the sun's insolation, rainfall cleans the panels and lowers their temperature, resulting in improved production on days of sunlight following rainfall. In June, there was a significant 10% improvement in performance ratio as a result of routinely cleaning the panels as compared to PR of May. In terms of PVsyst energy, June's practical system energy was higher than May's, and on one crucial day, practical system energy outperformed PVsyst output, according to PVsyst study.

Dust is a significant factor affecting the performance of PV panels. Solar forecasting accuracy can be improved by considering dust as one of the parameters. The BiLSTM model has the highest forecasting accuracy but also has the highest number of trainable parameters, hence it will take more time to get executed, on the other hand 1D CNN has good accuracy but has a smaller number of trainable parameters so 1D CNN can be a preferable model to opt for in case of execution time constraints.

6.2 FUTURE SCOPE

- A machine learning and image processing-based model can be designed to predict the amount of dust accumulated on the surface of PV panels.
- Dust IQ meters can give more accurate dust measurements and thus can be used for solar power forecasting in future research.
- Hybrid artificial neural network techniques can also be tested for better prediction accuracy

LIST OF PUBLICATIONS

- K. Singh and M. Rizwan, "Performance Analysis of Solar PV Modules with Dust Accumulation for Indian Scenario," Accepted in 2022 IEEE 10th Power India International Conference (PIICON) at NIT Delhi, New Delhi, India, during 25-27 November 2022.
- K. Singh and M. Rizwan, " AI based Approach for Solar PV Power Prediction with Varying Dust Accumulation Levels," Accepted in 2023 IEEE Recent Advances in Electrical, Electronics & Digital Healthcare Technologies. (REEDCON 2023) at Jamia Milia Islamia, New Delhi, India during 1-3 May 2023.

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