SOLAR IRRADIANCE FORECASTING USING DEEP LEARNING AND STATISTICAL METHODS FOR ISLAMABAD

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We hereby recommend that the dissertation prepared under our supervision by: (Student Name & Regn No.)__**SYED ALTAN HAIDER 00000206155**__________

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Abstract

The growing threat of global climate change stemming from the huge carbon footprint left behind by fossil fuels has prompted interest in exploring and utilizing renewable energy resources. Solar energy being one of the most abundant sources of green energy has attracted huge research attention over the years. There are numerous technologies available to resource solar energy and convert in others energy forms such as electric and thermal. Solar energy can be converted to electric and thermal energy by establishing solar thermal and solar photovoltaic plants and grids. These plants can facilitate whole cities and industries but the intermittent nature of solar energy which depends on a number of weather variables like cloud covers, humidity, rain, wind speed etc. These factors make it a challenge to manage solar power grids. The electric or thermal power output depends on majorly on solar Global Horizontal Irradiance (GHI). To manage large solar photovoltaic grids and plan on power distribution future forecasts must be made to ensure smooth grid operations and prevent power outages and load shedding. Several statistical, ML and DL techniques exist and have been used for many years for a range forecasting problem including sales management, power management, finance and many more. Many first world countries use these methods to plan for the management of their industries, goods distribution, and infrastructure management. This study uses statistical and Deep Learning methods to forecast solar GHI in the city of Islamabad which not only helps in grid management and power distribution, but also brings attention towards the potential solar power production in Pakistan and its part to play in tackling global climate change. In this study, we present statistical methods namely Seasonal Auto-Regressive Integrated Moving

Average Exogenous (SARIMAX) and Prophet, and Machine Learning methods such as Artificial Neural Networks (ANN), Convolution Neural Networks (CNN) and Recurrent Neural Networks (RNN). We have used Long Short-Term Memory (LSTM) variant of Recurrent Neural Networks. The selection forecast methods in our study are based on their ability to work with time series data. For our forecasting problem we have used the weather data that had been collected for four years and 9 months with precise instruments stationed in Islamabad. Our forecast problem and the data recorded, both are of time series in nature, and we have used different models with different configurations to see which performs best for our dataset. The performance of every model is studied using different error metric such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Square Error (MSE), and Coefficient of Determination (R2).

Keywords: *Solar Forecast, Time Series, Deep Learning, Neural Network, Convolutional Neural Network, Recurrent Neural Network*

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List of Abbreviations

Seasonal Auto-Regressive Integrated Moving Average Exogenous	SARIMAX
Artificial Neural Network	ANN
Convolution Neural Network	CNN
Recurrent Neural Network	RNN
Long Short-Term Memory	LSTM
Global Horizontal Irradiance	GHI
Diffuse Horizontal Irradiance	DHI
Direct Normal Irradiance	DNI
Ambient Temperature	T_{amb}
Relative Humidity	RH
Wind Speed	WS
Wind Direction	WD
Barometric Pressure	BP
Root Mean Squared Error	RMSE
Mean Squared Error	MSE
Mean Absolute Error	MAE
Numerical Weather Prediction	NWP

1 Introduction

The threat of climate change has driven the global community to shift from fossil fuels and non-renewable energy sources to renewable and eco-friendly energy sources [1]. The total renewable power capacity, from sources like Hydropower(from 1112GW to 1132GW) , Wind Power(from 540 GW to 591GW) , Solar (from 405GW to 505GW), Geothermal Power(from 12.8GW to 13.3GW) and Bio-power(from 121GW to 130GW), rose by 8% in 2018[2]. The renewable energy deployment depends on different factors such as economic, environmental, political, regulatory, social, technical potential, and technological[3]. Solar energy intensity varies from equator to polar region of the world[4] and the technology required for its conversion to electric or thermal energy is easily available and the investment cost is estimated to be reduced by 59% by 2025[5]. Recently, the depletion of fossil fuels, climate change and energy independence have become an issue globally. Hence, several renewable energy resources are to be integrated into existing power grid. Solar power, one of the major sources of renewable energy, is expected to become future of power source due to its abundant nature and very low carbon footprint. Since photovoltaic (PV) systems are convenient and beneficial to setup, maintain and operate. As a result, the penetration of solar PV systems is to be expectedly increase until 2030[6].

For every energy production plant keeping balance between the production and consumption is crucial and a very demanding task, for which consumption estimates have to be made[7]. This becomes even more complex in the case of PV systems as their power output depends on solar irradiance and weather conditions which is very stochastic in nature[8, 9], therefore, accurate supply forecast must be made.

Prediction of solar irradiance has been one of the great challenges in renewable energy generation. An accurate prediction will yield to many benefits in planning, operation and managements of power grid that produces large amount of solar energy [10]. Solar photovoltaic (PV) is lately considered an unreliable source due to its dependency on several environmental factors and weather conditions. The quantity of electricity generated by solar panels is directly proportional to the global horizontal irradiance (GHI) [11] or the solar irradiance received on the parallel surface and it is a fundamental parameter for calculating the radiation on a tilted plane,. GHI is made of three components: clouds and ground-reflected solar radiation (insignificant usually), direct solar beam, and diffusive solar radiation by atmosphere [11]. Environmental factors such as solar irradiance present at the top surface of atmosphere, cloudiness, weather patterns and climate have a major role in affecting GHI. In fact, the availability of solar radiation at the surface also varies by time of day and location. Those locations in lower latitudes and having dry climates usually receive high amount of solar radiation. Therefore, solar panel's power production fluctuates because of its reliance on meteorological conditions [12]. Thus, due to the intermittent output characteristics of solar power, an accurate forecasting of GHI becomes a necessity for integrating solar energy grids to existing infrastructures to ensure grid stability, improve the energy efficiency and economic benefits of PV systems.

Solar forecasting is composed of two main approaches, first the forecasting of climate factors like wind speed, solar irradiation, and temperature are included and so forth and the subsequent part contains photo-voltaic panel's efficiency or the final power output's prediction [13]. Direct normal irradiation (DNI) and direct horizontal irradiation (DHI) are the two primary estimations of solar irradiation. Light coming from sun in a perpendicular or straight line is usually measured by DNI, the irradiation due to scattering received from directions other than the straight lines are measured through the DHI. Whereas the global horizontal irradiation (GHI) accounts for the sum of the DNI and DHI or the total energy received at the unit surface region's end. According to the lead time, the forecasting GHI is divided in two forecasting: long-term and short term. The irradiation from the range of an hour ahead to a week ahead is predicted by the short-term forecast while the seasonal impacts on the irradiation are usually predicted using long-term forecast. Long-term forecasting plays an important role in the financial planning and revenue generation whereas the short-term forecasting is essential for utility management [13].

Pakistan is a country that relies heavily on the imported petroleum products to meet its domestic energy demands resulting in higher production cost and lower industrial productivity. 63% of Pakistan's energy demand is met by fossil fuels while producing only 20% of the oil it consumes. More than 10 Billion USD worth of fossil fuel products were imported in the year 2017 alone and these imports are still increasing [14]. Owing to these problems it is imperative to look for alternative solutions, especially those that are available and accessible domestically. This leads to the research involving solar powered technologies and, in our case, solar photovoltaic panels that need solar Global Horizontal Irradiance to be forecasted for efficient and cost-effective management.

Efficient management of solar powered grids require efficient knowledge of future availability of solar irradiance which in turn needs Global Horizontal Irradiance (GHI) to be efficiently forecasted. There are various forecasting methods, all having their advantages and inconveniences and their accuracy depending on the forecasting horizon and the geographical situation[15]. Solar irradiation forecast methods can be categorized as physical methods, statistical methods, and machine learning methods. The physical method includes total sky-image[16], numerical weather prediction (NWP)[17] and satellite image[18]. Statistical methods include autoregressive (AR)[19], regression model[20], fuzzy theory[21] and Markov Chain[22]. The sky imaging models are mainly used for short term forecasting (30 min to 6 h), NWP-based methods are well accepted for 6 to 48-hours-ahead forecasting while Machine Learning models use historical data to train themselves and give predictions based on that[15]. Among all the categories, Machine Learning methods have gained more attention in the recent years among the researchers[23] partly due to advances in the field of Artificial Intelligence (AI) but also due to availability of opensource tools to perform ML forecasts on different problems[15]. ML methods can extract complex high-dimensional non-linear features and map directly from input to output without needing to develop an understandable relation between data. Various ML models such as Artificial Neural Networks (ANN)[24], Auto-Regressive Moving Average (ARMA)[25], Support Vector Regression (SVR)[26], Recurrent Neural Networks (RNN)[27], Extreme Learning Machines (ELM)[28] etc. have been used on diverse range of energy, finance, load management and supply chain forecasting problems. In this study, we use Prophet[29], SARIMAX[30], ANN[31], CNN[32] and LSTM[33] to perform time series forecasting of solar Global Horizontal Irradiance using multivariate features.

1.1 Problem Statement

The threat of global climate change has prompted global energy dependency and utilization shift towards green and renewable energy resources. Solar energy being one of the most abundant sources of renewable energy requires attention of the global community to be exploited and utilized. One the most used technologies to utilize solar energy as a renewable resource is solar photovoltaic panels that convert solar radiation to electric energy. Solar powered photovoltaic panel grids can be used to facilitate the energy of organizations and even cities, but the problem with these grids lie with load and power management. These power grids need efficient solar Global Horizontal Irradiation forecasts for better grid management, power distribution and cost effectiveness.

1.2 Objective

The main objective of this study is to provide methods and to forecast solar Global Horizontal Irradiance in the city of Islamabad, and in doing so provide the energy sector is Pakistan with tools to contribute towards fighting global climate change.

1.3 Areas of Application

Following are the major areas of application of this work

- Power Distribution
- Grid Management
- Load Management

1.4 Thesis Overview

In this work, Section 2 briefly explains the previous work done by several researchers on the study of different techniques used for forecasting solar Global Horizontal Irradiance. Section 3 contains the complete methodology and Implementation including Data Set, Data Pre-Processing, and complete workflow. Section 4 includes the complete results acquired after implementing the methods to forecast on the selected time series dataset. Section 5 consists of discussion of the complete work. Section 6 describes all the possible future work which can be held in this domain.

2 Literature Review

Inman, Pedro [34] in 2013 studied the theories behind different forecasting methods and the application of these methods for the resource and output of solar photovoltaic grids at utility scale level. Tuohy, Zack [35] in 2015 studied different solar forecasting techniques, the challenges posed and their performance, and concluded that the contemporary solar forecasting methods need improvement.

Sivaneasan, Yu [36] in 2017 proposed an algorithm for solar forecasting which was based on ANN model along with a fuzzy pre-processing toolbox into the ANN model to find correlation between cloud cover, temperature, wind speed, and wind direction with irradiance value.

Alzahrani, Shamsi [10] in 2017 used deep neural networks to forecast solar irradiance and compared their results to Support Vector Regression and Feedforward Neural Networks. Feng, Cui [37] in 2019 proposed an unsupervised clustering-based forecasting method for 1-hour-ahead short term solar GHI forecasting.

Qing and Niu [33] in 2018 used Long Short-Term Memory to forecast a day ahead solar irradiance and concluded that their algorithm performed 18.34% better in terms of RMSE. Yagli, Yang [15] in 2019 performed hourly forecasting using 68 ML models and evaluated for 2 years at 7 different locations in 5 climate zones.

Song and Brown [38] in 2019 used Long Short-Term Memory (LSTM) and Recurrent Neural Networks (RNN) to perform time series forecasting of solar irradiance and used Temporal Convolutional Networks (TCN) for sequence modeling and concluded that TCN reduces resource usage depending on model complexity and data folding size.

Gao, Huang [39] and Zang, Liu [40] in 2020 used CNN-LSTM model to forecast short term solar Global Horizontal Irradiance data in different locations and showed that their CNN-LSTM models improved accuracy over previous models.

Jalali, Ahmadian [41] in 2021 used deep CNN-LSTM architecture to forecast solar irradiance in the United States.

3 Methodology and Implementation

3.1 Proposed Scheme

In the proposed scheme we start with acquiring the dataset. The dataset for this work was made available and collected with meteorological instruments stationed in Islamabad. The dataset is then pre-processed to check for missing values and perform data imputation. After data pre-processing it is split into Training and Validation sets and then fed to our proposed models. At the end all the models are evaluated on test data and checked for performance based on different error metrics.

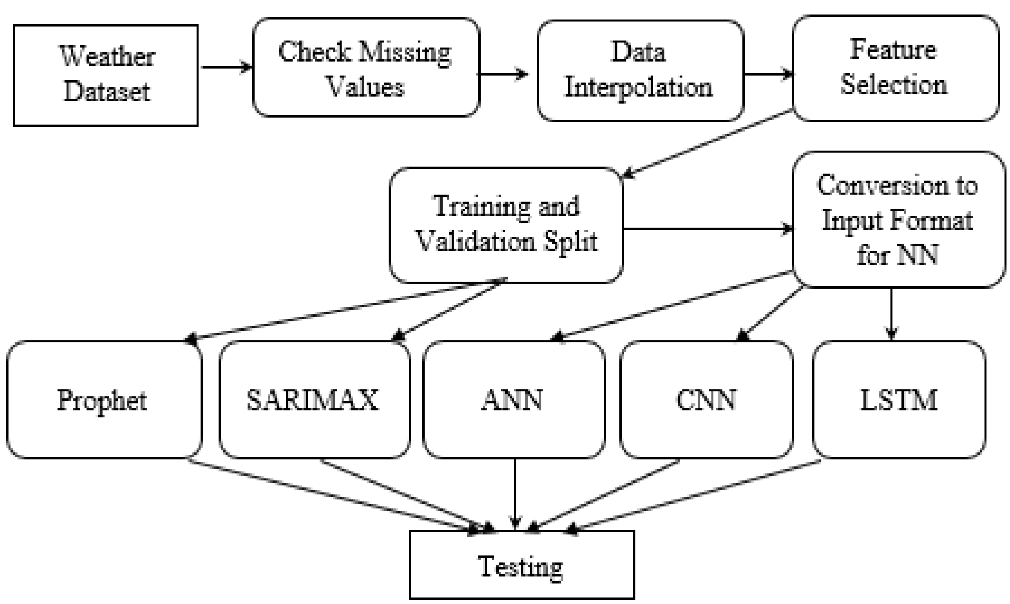

Figure 1 Complete Process Diagram

3.2 Data Set

The weather data was recorded for 5 years from 2015 till 2019 in hourly intervals using precise meteorological instruments placed in Islamabad. The dataset consists of the following weather variables:

Table 1 Weather Data Details

VARIABLE	DESCRIPTION	INSTRUMENT
GHI	Global Horizontal Irradiance in W/m²	K&Z CMP21 pyranometer
DHI	Diffus Horizontal Irradiance in W/m²	K&Z CMP21 pyranometer
DNI	Direct Normal Irradiance in W/m²	K&Z CHP1 pyrheliometer
T_{amb}	Ambient Temperature in °C	Campbell CS215
RH	Relative Humidity in %	Campbell CS215
WS	Wind Speed in m/s	NRG 40H Anemometer
WS_{gust}	WS maximum within the time interval	NRG 40H Anemometer
WD	Wind direction in °N (to East)	NRG 200 Wind Direction Sensor
WD_{StDev}	WD Standard Deviation	
BP	Barometric Pressure	Campbell CS100 barometric pressure sensor
DNI_{dev}	$DNI_{measured}$ - $DNI_{calculated}$.	

3.3 Data Pre-Processing

The dataset is checked for missing values and the amount of data that are missing. In case of missing values, the data is interpolated. Exploring the data also revealed that there are a huge number of GHI values that are equal to zero, which are in fact the nighttime values of solar GHI and are bound to be zero. But this affects fitting our models on the data as there are 19403 GHI values that are zero out of 41256, which is the total number records. This number is reduced to 4236 after removing all values between 7PM and 5AM time of the day. After selecting data for a fixed time of the total records become 25785.

3.4 Dataset Distribution

For the statistical methods the data is separated into two subsets: Training and Test Set. For these methods training set includes 20000 records and the test set includes 5785 records. For Deep Learning methods the dataset is distributed in three categories which are Training Set, Test Set and Validation Set. The training set includes 70% of the total data, which is 18050 records, validation set includes 20% of the total data which is 5157 records, and the test set includes 10% of the total data which is 2578 records.

3.5 Feature Selection

In every multivariate timeseries dataset there are features that contribute to forecasting the target feature but there are also some features that contribute less or including them would make the model fitting more complex affecting the results. For our dataset we have calculated Pearson Correlation between all the features, and plotted in a heatmap, and selected those features that have a high correlation with the target variable while those features having high correlation with each other and negative correlation with the target variable were removed. We have selected Direct Normal Irradiance (DNI), Ambient Temperature (T_{amb}), Diffused Horizontal Irradiance (DHI), Wind Direction (WD), Wind Speed (WS) and the Standard Deviation of WD ($WD_{std)}$ because of high correlation with Global Horizontal Irradiance (GHI), which is the target output, as can be seen in Figure 2.

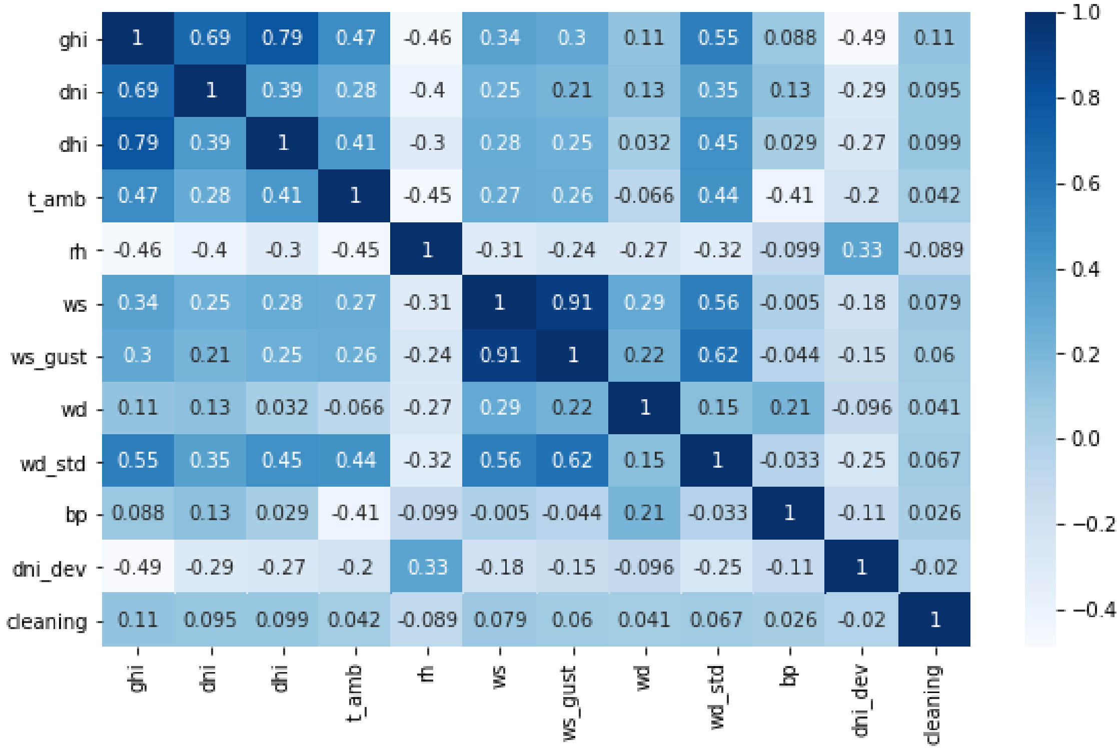

Figure 2 Correlation Plot all the features

3.6 Proposed Methods

3.6.1 SARIMAX

Auto-Regressive Integrated Moving Average (ARIMA) is frequently used for timeseries forecasting[42] but the problem with ARIMA is the it is a univariate forecasting model which cannot incorporate multiple features and seasonality in the timeseries data. To tackle such problems multiple variants of ARIMA have been introduced.

An extension of ARIMA i.e. Seasonal Auto Regressive Integrated Moving Average (SARIMA) can handle seasonality within the time series data, but even this had the shortcoming of being a univariate model. SARIMAX was introduced to solve multivariate forecasting problems having seasonality effects as well as multivariate features.

SARIMAX accommodates exogenous variables, and it handles seasonality that ARIMA can't. SARIMAX function can be defined by Eq. 1

$$\Theta(L)^p \theta(L^s)^p \Delta^d \Delta_s^D y_t = \phi(L)^q \phi(L^s)^Q \Delta^d \Delta_s^D \epsilon_t + \sum_{i=1}^{n} \beta_i x_t^i \qquad \textit{Eq. 1}$$

In this equation the following terms P, p, Q, q, D and d represents the seasonal and non-seasonal AR, MA and differencing orders, respectively, whereas L being lag operator and β constant.

The *statsmodel* python library function SARIMAX is used to fit and forecast our timeseries data with the configuration in Table 2

PARAMETERS	p	P	q	Q	d	D	s
VALUES	0	0	1	0	0	0	1

Table 2 SARIMAX Parameters

3.6.2 Prophet Model

The forecasting model used by Prophet, a python package developed by Facebook, is based on an additive model and uses decomposable timeseries forecasting model [29] [43]. This model was initially built for business forecasting purposes having strong seasonal effects but because of its capability to incorporate seasonality, multivariate features and trend this model can be customized to be used in weather time series forecasting as well. Here Eq.2 shows the *Prophet* model:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon_t \qquad \textit{Eq.2}$$

Where $g(t)$, $s(t)$ and $h(t)$ are representing the seasonality, trend and holidays function. The term ε_t symbolizes the characteristic changes at time-step 't', which are not adjusted by the model. As solar irradiance not affected because of any kind of holidays, so, the function $h(t)$ is not used.

The Prophet forecasting model uses Analyst-in-the-loop model shown in Figure 2, because often analysts have domain knowledge about the variable being forecasted but have little statistical knowledge and there are there are several places in the model specifications where analysts can apply their expertise and external knowledge without requiring deep understanding of the underlying statistics.

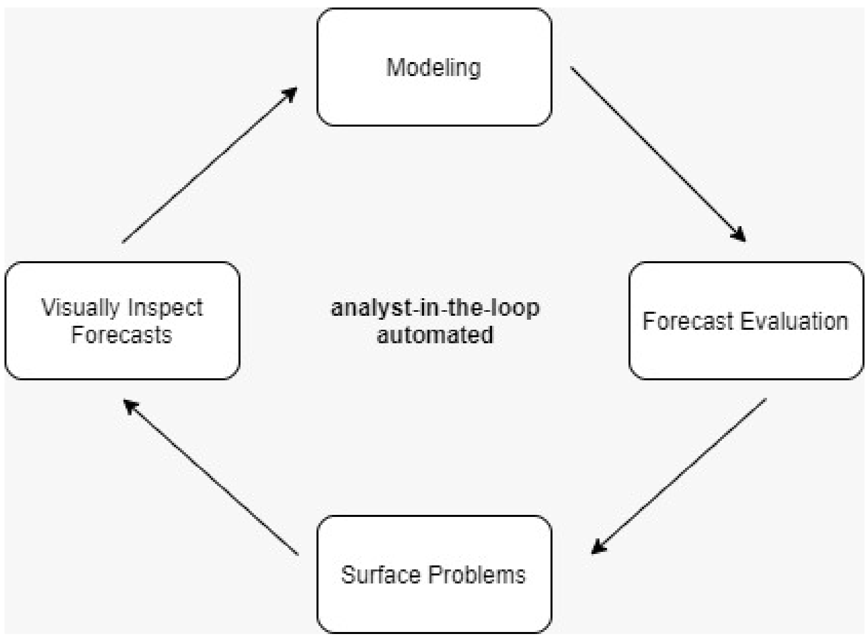

Figure 3 Analyst-in-the-loop model[29]

3.6.3 Artificial Neural Networks (ANN)

An artificial neural network (ANN) is a methodology in Machine Learning built to mimic the way the human mind analyzes, interprets and processes the information, having self-learning capability to solve problems that is, otherwise, not possible or challenging by an individual/human or statistical standard and depends on data experiences to learn and predict results as humans do.

ANNs consist of three main units namely Input/Output Layer and Hidden Layers. The hidden layer does all the learning and processing work. It consists of neurons that are the base processing units of each layer. The hidden layers take data from the input layer and learns depending on the type of learning method chosen for each hidden layer and forwards the result to the output layer. A simple architecture of Artificial Neural Networks is given in Figure 3.

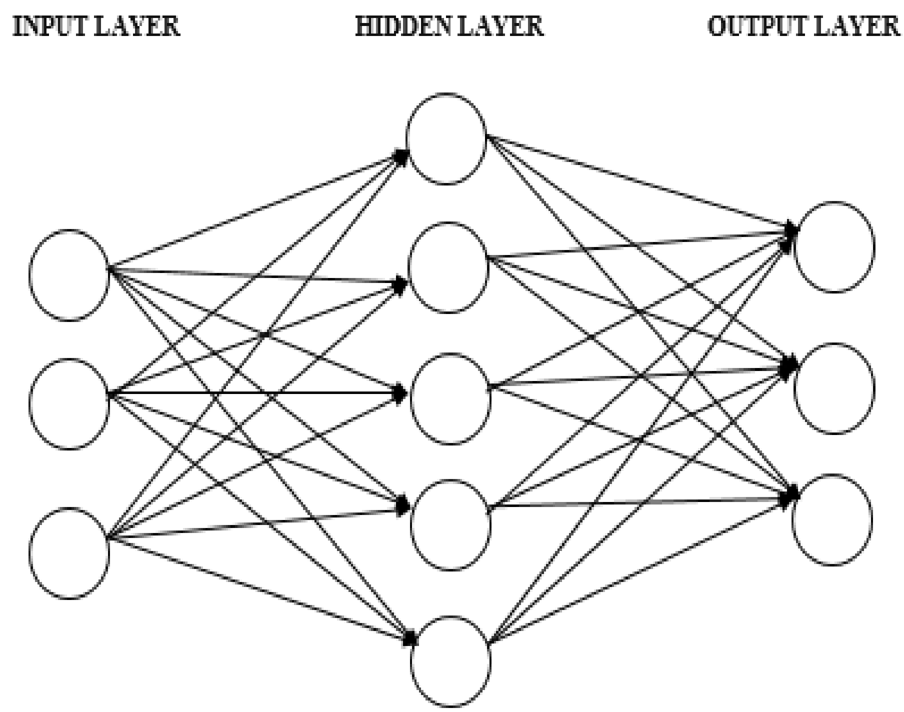

Figure 4 Artificial Neural Network

The ANN configuration used in this study to perform time series forecasting of solar GHI is given in Table 3.

Table 3 ANN Configuration

Dense Layers	1 with 64 Neurons
Learning Rate	0.0001
Optimizer	Adam
Activation Function	Relu
Batch Size	32
Number of epochs	100
Early Stopping Monitor	Loss = MSE (Mean Squared Error)

Table 3 ANN Configurations

Table 4 shows ANN configuration and trainable parameters on different forecast horizons.

WINDOW SIZE	**(4,1)**	
LAYER TYPE	**OUTPUT SHAPE**	**NO. OF PARAMETERS**
DENSE (DENSE)	(NONE, 64)	1856
DENSE (DENSE)	(NONE, 1)	65
TOTAL PARAMETERS	1921	
TRAINABLE PARAMETERS	1921	
NON-TRAINABLE	0	
WINDOW SIZE	**(12,3)**	
LAYER TYPE	**OUTPUT SHAPE**	**NO. OF PARAMETERS**
DENSE (DENSE)	(NONE, 64)	5440
DENSE (DENSE)	(NONE, 32)	2080
DENSE (DENSE)	(NONE, 3)	99
TOTAL PARAMETERS	7619	
TRAINABLE PARAMETERS	7619	
NON-TRAINABLE	0	
WINDOW SIZE	**(24,6)**	
LAYER TYPE	**OUTPUT SHAPE**	**NO. OF PARAMETERS**
DENSE (DENSE)	(NONE, 32)	5408
DENSE (DENSE)	(NONE, 16)	528
DENSE (DENSE)	(NONE, 6)	102
TOTAL PARAMETERS	6038	
TRAINABLE PARAMETERS	6038	
NON-TRAINABLE	0	
WINDOW SIZE	**(48,24)**	
LAYER TYPE	**OUTPUT SHAPE**	**NO. OF PARAMETERS**
DENSE (DENSE)	(NONE, 32)	10784
DENSE (DENSE)	(NONE, 16)	528
DENSE (DENSE)	(NONE, 24)	408
TOTAL PARAMETERS	11720	
TRAINABLE PARAMETERS	11720	
NON-TRAINABLE	0	

Table 4 ANN Configuration on different Forecast Horizons

3.6.4 Convolutional Neural Networks (CNN)

Convolution Neural Network (CNN) in deep learning is a kind of NN (Neural Networks) that are mostly used for Object Detection, Image Classification, Face Recognition, Object Recognition and Object Classification etc. CNN is mostly used in Computer Vision problems where data is composed of images that pass through series of convolutional layers having filters called Kernels, Fully Connected (FC) Layers, Pooling Layers and different optimization functions that classify objects between 0 to 1 probabilities. Since, images are composed of large matrices with high dimensions, the advantage of CNN is that it reduces the number of parameters for modelling. An architecture of CNN is given Figure 4.

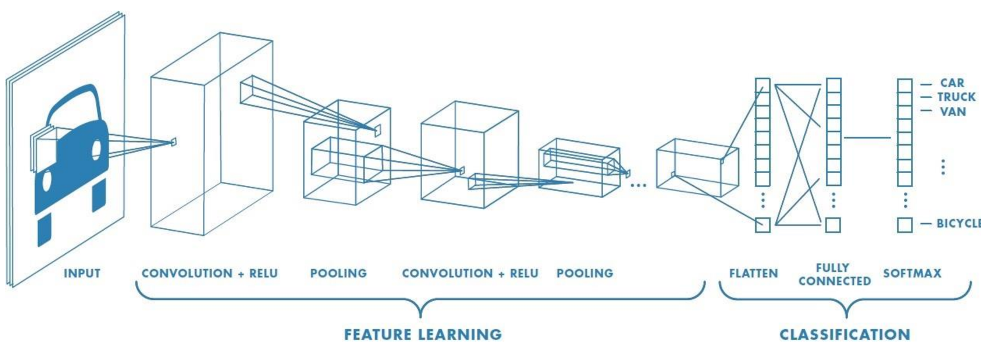

Figure 5 Convolutional Neural Network

Convolution Neural Networks (CNN) can also be used to perform time series forecasting by changing the dimension of input dataset.

Convolutional Layers	1 with 64 Neurons
Kernal Size	2
Drop out	0.2
Learning Rate	0.0001
Optimizer	Adam
Activation Function	Relu

Batch Size	32
Number of epochs	100
Early Stopping Monitor	Loss = Mean Squared Error

Table 5 CNN Configuration

The CNN configuration used to perform time series forecasting is given in Table 5. Table 6 shows CNN configuration and trainable parameters on different forecast horizons.

WINDOW SIZE	**(4,1)**	
LAYER TYPE	**OUTPUT SHAPE**	**NO. OF PARAMETERS**
Conv1D (Conv1D)	(NONE, 3, 32)	480
Flatten (Flatten)	(NONE, 96)	0
Dense (Dense)	(None, 1)	97
TOTAL PARAMETERS	577	
TRAINABLE PARAMETERS	577	
NON-TRAINABLE	0	
WINDOW SIZE	**(12,3)**	
LAYER TYPE	**OUTPUT SHAPE**	**NO. OF PARAMETERS**
Conv1D (Conv1D)	(NONE, 11, 64)	960
Dropout (Dropout)	(NONE, 11, 64)	0
Flatten (Flatten)	(NONE, 1704)	0
Dense (Dense)	(None, 3)	2115
TOTAL PARAMETERS	3075	
TRAINABLE PARAMETERS	3075	
NON-TRAINABLE	0	
WINDOW SIZE	**(24,6)**	
LAYER TYPE	**OUTPUT SHAPE**	**NO. OF PARAMETERS**
Conv1D (Conv1D)	(NONE, 23, 64)	960
Dropout (Dropout)	(NONE, 23, 64)	0
Flatten (Flatten)	(NONE, 1472)	0
Dense (Dense)	(None, 6)	8838
TOTAL PARAMETERS	9798	
TRAINABLE PARAMETERS	9798	
NON-TRAINABLE	0	
WINDOW SIZE	**(48,24)**	
LAYER TYPE	**OUTPUT SHAPE**	**NO. OF PARAMETERS**
Conv1D (Conv1D)	(NONE, 47, 64)	960
Max_Pooling (Max Pooling)	(NONE, 23, 64)	
Dropout (Dropout)	(NONE, 23, 64)	0
Conv1D (Conv1D)	(NONE, 22, 16)	2064
Dropout (Dropout)	(NONE, 22, 16)	0
Flatten (Flatten)	(NONE, 352)	0
Dense (Dense)	(None, 24)	8472
TOTAL PARAMETERS	11496	
TRAINABLE PARAMETERS	11496	
NON-TRAINABLE	0	

Table 6 CNN Configuration on different Forecast Horizons

3.6.5 Long Short Term Memory (LSTM)

Long Short Term Memory (LSTM) in deep learning is an architecture of Recurrent Neural Network (RNN). In past few years, RNNs have had incredible success in language modelling, translation, speech recognition and image captioning problems. There are loops in RNNs that allows the information to persist meaning that they can deal with sequential data, like timeseries, and are intimately related with them. A simple demonstration of RNN is given is Figure 5.

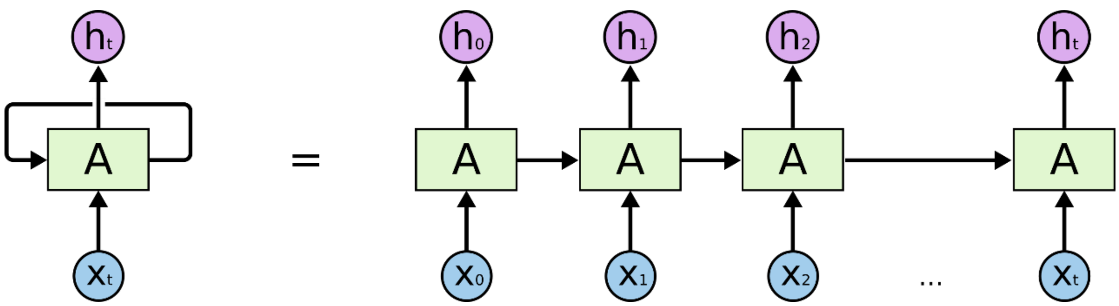

Figure 6 Unrolled Recurrent Neural Network

But the problem with RNN is that they cannot deal with dependencies that are long term. That is the reason LSTM network was proposed as an extension of RNN because of its potential to handle long term dependencies. LSTMs have the same chain like structure as RNNs, the only difference being them having four neural network layers instead of one. A simple diagram of LSTM is shown in Figure 6.

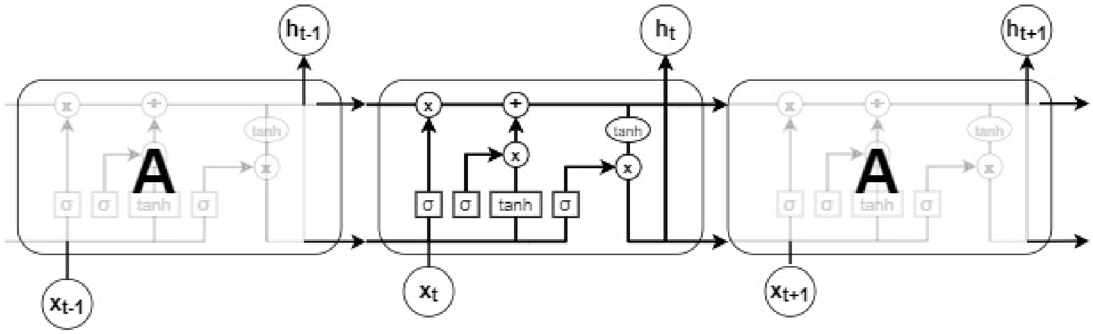

Figure 7 LSTM Repeating module containing 4 NN Layers

The CNN configuration used to perform time series forecasting is given in Table 7.

LSTM Layers	2 with 32 and 16 Neurons
Learning Rate	0.0001
Optimizer	Adam
Activation Function	Relu
Batch Size	32
Number of epochs	100
Early Stopping Monitor	Loss = Mean Squared Error

Table 7 LSTM Configuration

LSTM configuration and trainable parameters on different forecast horizons in Table 8.

WINDOW SIZE	**(4,1)**	
LAYER TYPE	**OUTPUT SHAPE**	**NO. OF PARAMETERS**
LSTM (LSTM)	(NONE, 4, 32)	5120
LSTM (LSTM)	(NONE, 16)	3136
Dense (Dense)	(None, 1)	17
TOTAL PARAMETERS	8273	
TRAINABLE PARAMETERS	8273	
NON-TRAINABLE	0	
WINDOW SIZE	**(12,3)**	
LAYER TYPE	**OUTPUT SHAPE**	**NO. OF PARAMETERS**
LSTM (LSTM)	(NONE, 12, 32)	5120
LSTM (LSTM)	(NONE, 16)	3136
Dense (Dense)	(None, 3)	51
TOTAL PARAMETERS	8307	
TRAINABLE PARAMETERS	8307	
NON-TRAINABLE	0	
WINDOW SIZE	**(12,6)**	

LAYER TYPE	OUTPUT SHAPE	NO. OF PARAMETERS
LSTM (LSTM)	(NONE, 12, 32)	5120
LSTM (LSTM)	(NONE, 16)	3136
Dense (Dense)	(None, 6)	102
TOTAL PARAMETERS	8258	
TRAINABLE PARAMETERS	8358	
NON-TRAINABLE	0	
WINDOW SIZE	**(24,12)**	
LAYER TYPE	**OUTPUT SHAPE**	**NO. OF PARAMETERS**
LSTM (LSTM)	(NONE, 4, 32)	5120
LSTM (LSTM)	(NONE, 16)	3136
Dense (Dense)	(None, 1)	17
TOTAL PARAMETERS	8273	
TRAINABLE PARAMETERS	8273	
NON-TRAINABLE	0	

Table 8 LSTM Configuration on different Forecast Horizons

4 Results and Discussion

4.1 Statistical Methods

The results are discussed in this part produced by the two statistical methods SARIMAX and Prophet forecasting model.

Figure 7 shows a plot of forecasted values by SARIMAX against the actuals values from the test set.

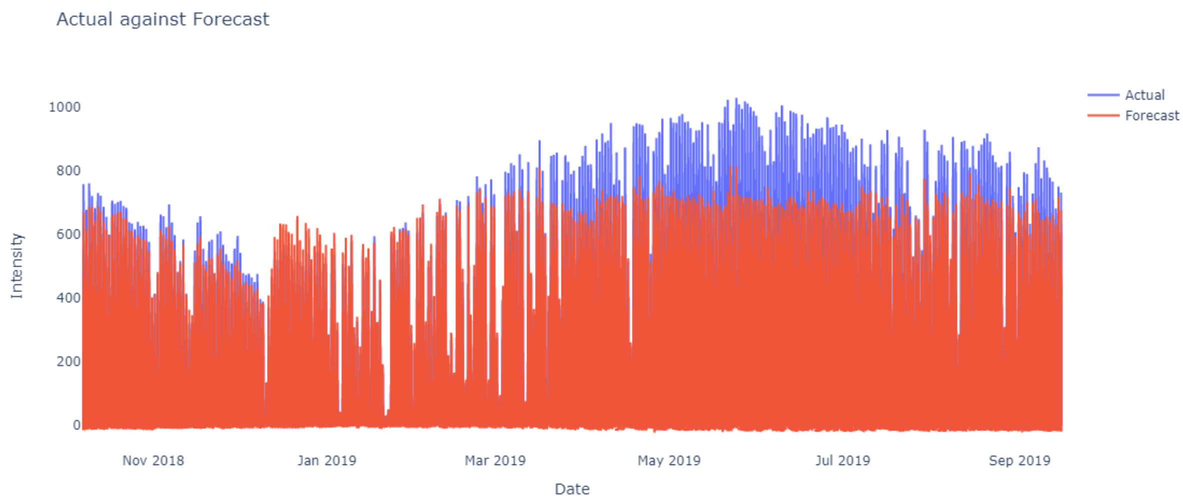

Figure 8 SARIMAX Actual and Forecasted values

Figure 8 shows a plot of values forecasted by the Prophet model against the actual values in the test set.

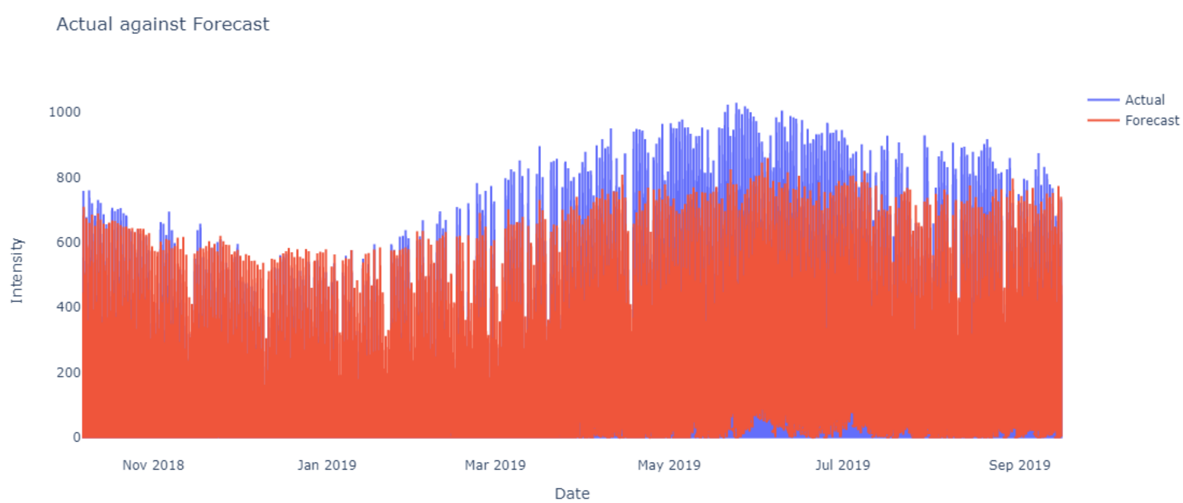

Figure 9 Prophet Model Forecasts against Actual values

The selected methods were compared using Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and the Coefficient of Determination, also known as R2 score. A comparison of the error metrics of the statistical methods is shown in Table 9.

Model	MSE	RMSE	MAE	R2 Score
Sarimax	4037.75	63.54	35.23	0.948
Prophet	5931.51	77.01	44.13	0.924

Table 9 Error Metrics of Statistical Models

4.2 Deep Learning Methods

This section discusses the results of Artificial Neural Networks (ANN), Long Short Term Memory (LSTM) and Convolution Neural Networks (CNN) trained on different forecasting window of (4,1), (12,3), (24,6) and (48,24), where 4, 12, 24, and 48 are the previous time steps in the training model while 1, 3, 6, 24 are the number steps to be forecasted for the future.

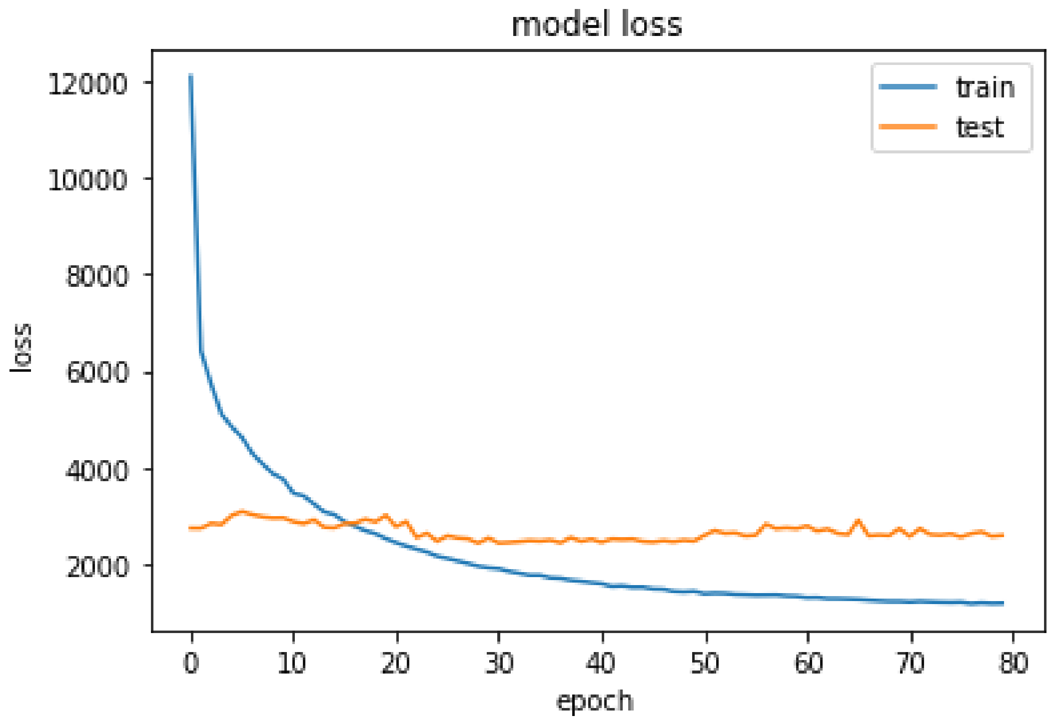

Figure 10 ANN training and validation loss for (4, 1) window

Figure 11 shows ANN (12, 3) window training and validation loss.

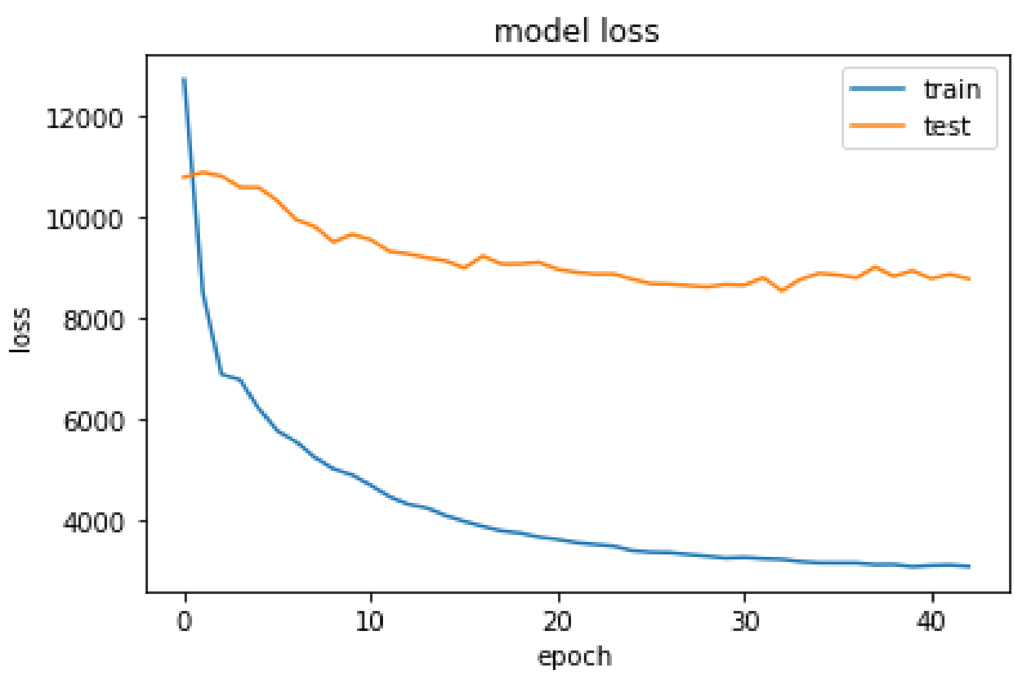

Figure 11 ANN (12, 3) Window Loss

Figure 12 show ANN window (24,6) training and validation loss.

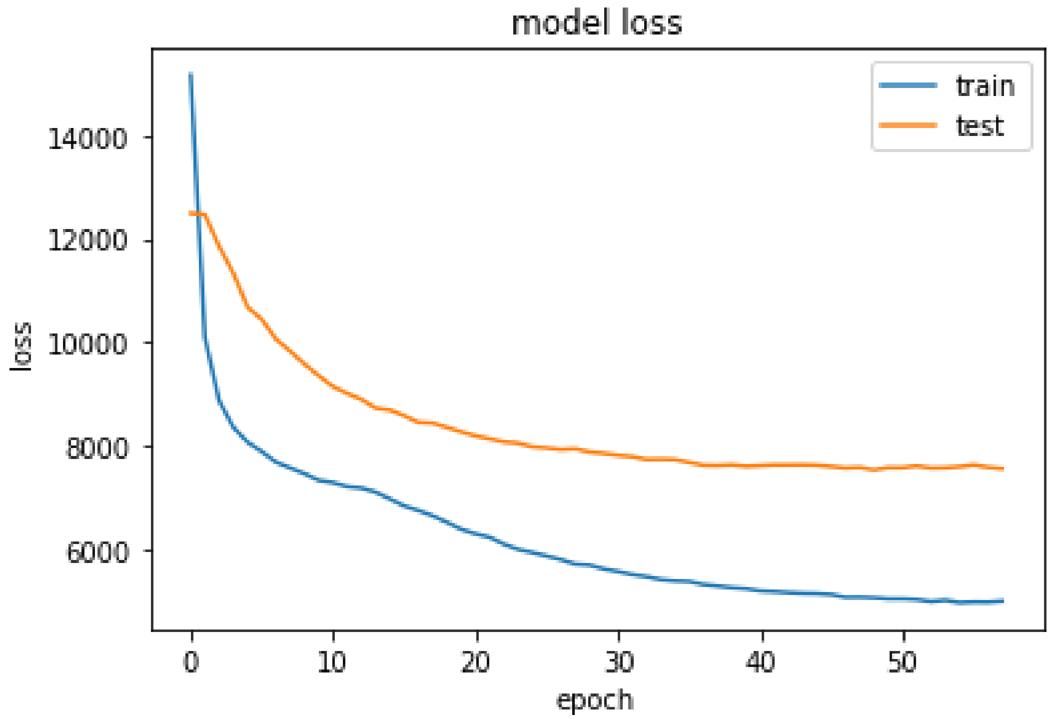

Figure 12 ANN (24, 6) Window loss

Figure 13 shows ANN window (48, 24) training and validation loss.

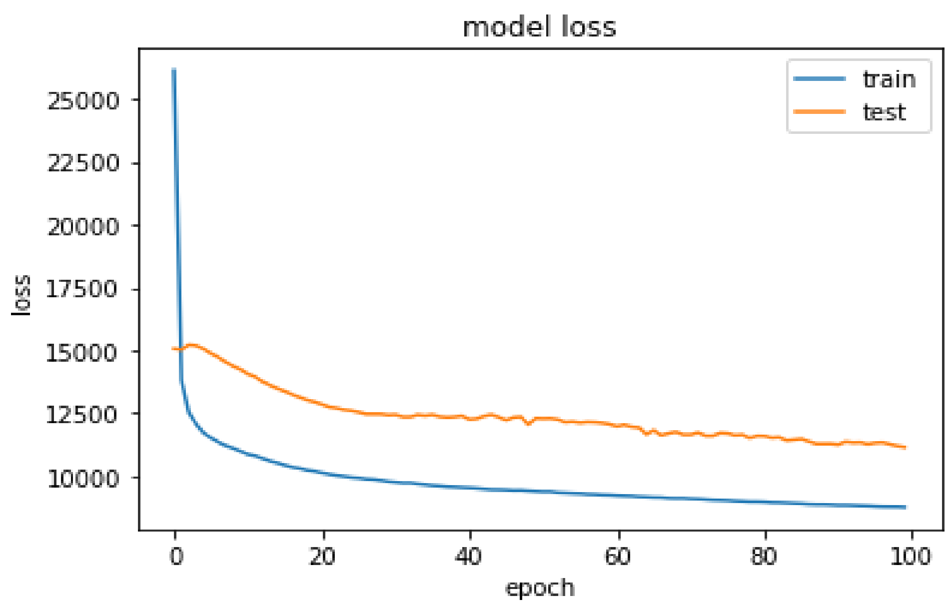

Figure 13 ANN (48, 24) Window loss

Figure 14 show CNN window (4,1) training and validation loss

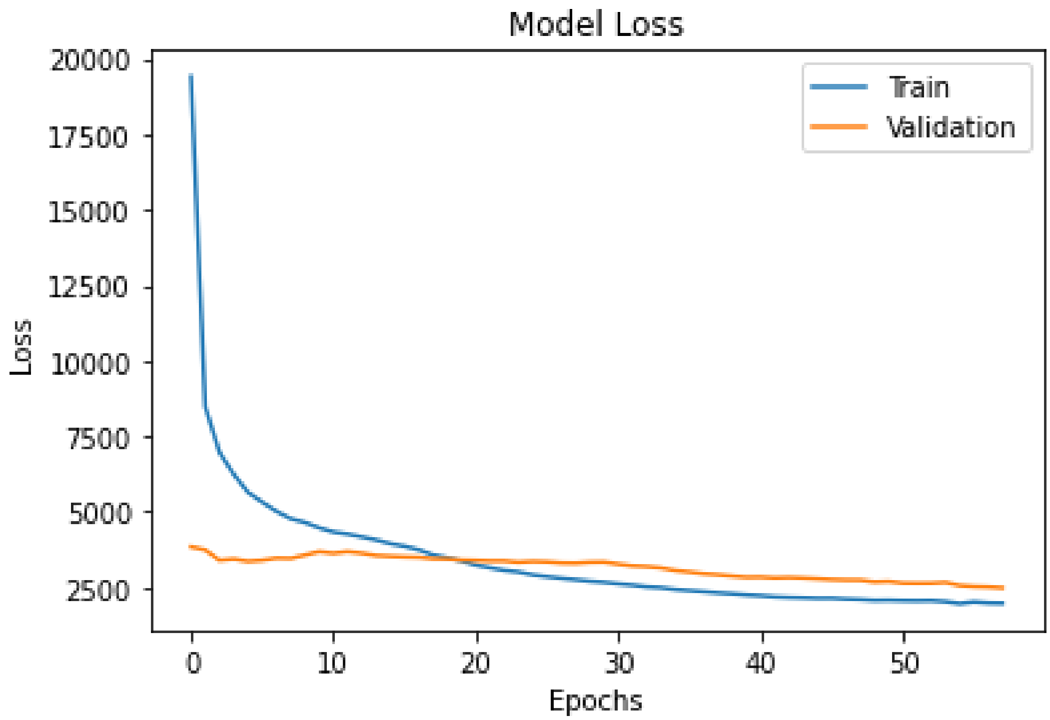

Figure 14 CNN window (4,1) training and validation loss

Figure 15 show CNN window (12,3) training and validation

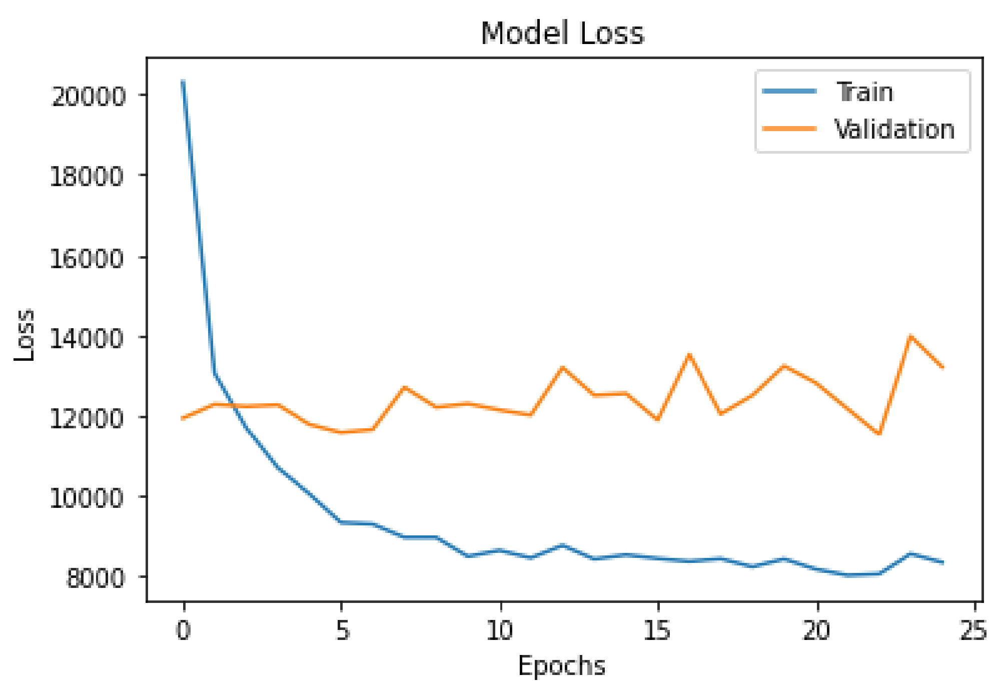

Figure 15 CNN window (12,3) training and validation loss

Figure 16 show CNN window (24,6) training and validation loss

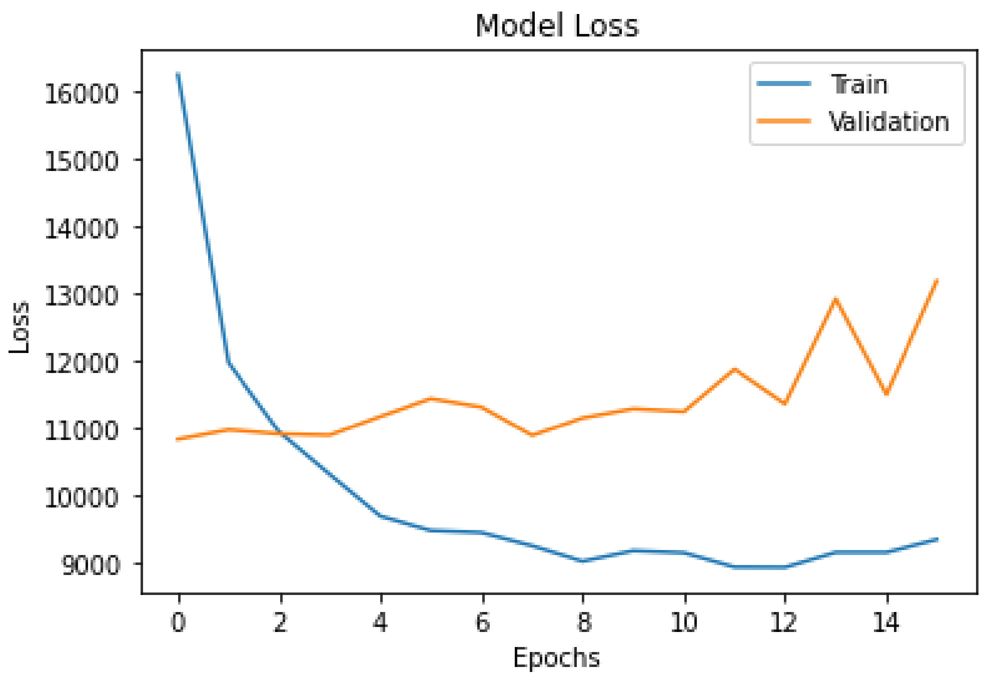

Figure 16 CNN window (24,6) training and validation loss

Figure 17 show CNN window (48,24) training and validation loss

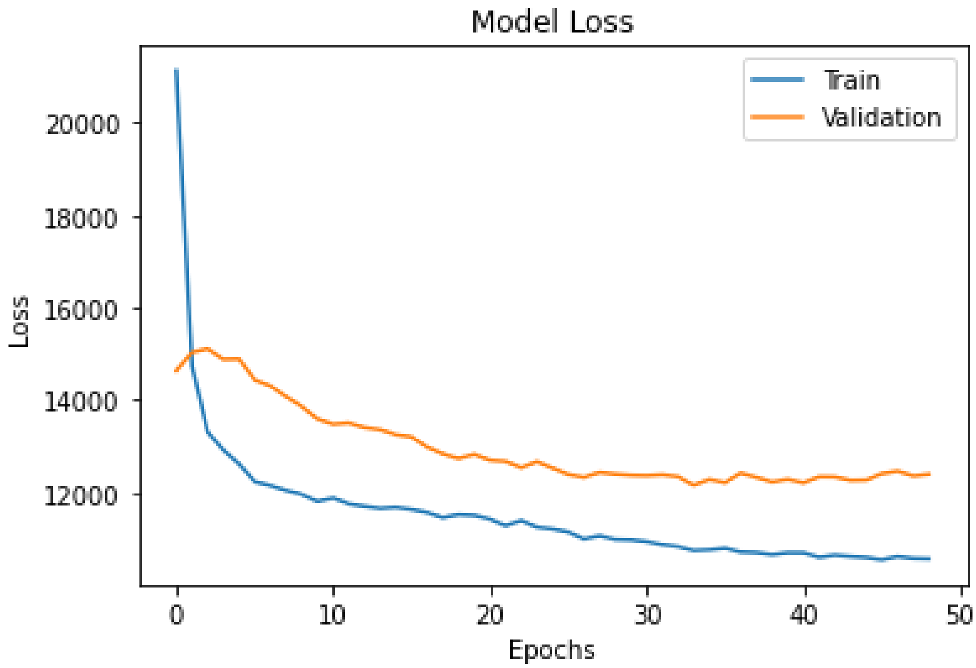

Figure 17 CNN window (48,24) training and validation loss

Figure 18 show LSTM window (4,1) training and validation loss

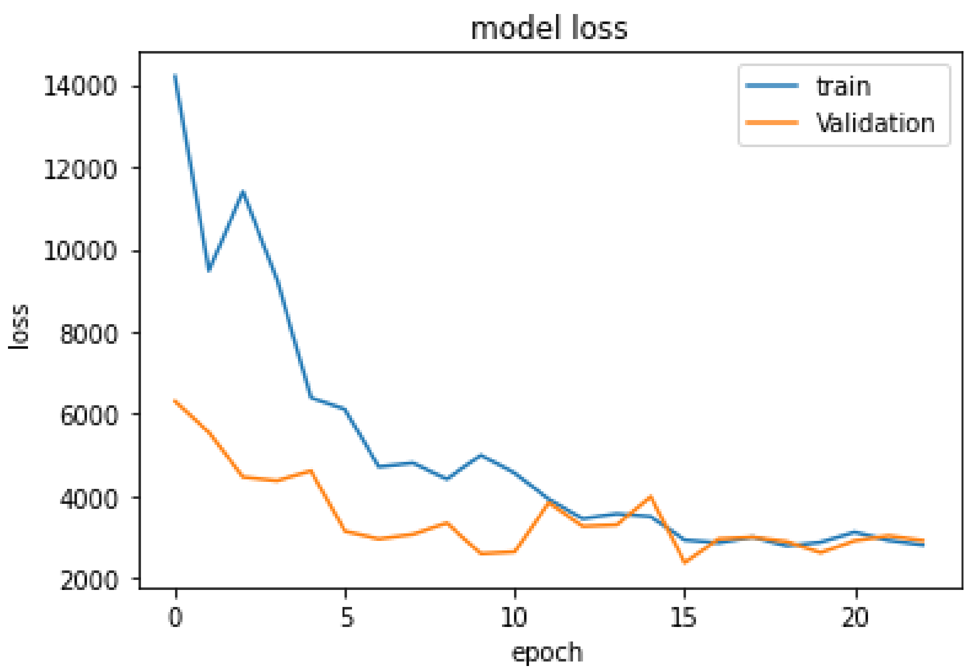

Figure 18 LSTM window (4,1) training and validation loss

Figure 19 show LSTM window (12,3) training and validation loss

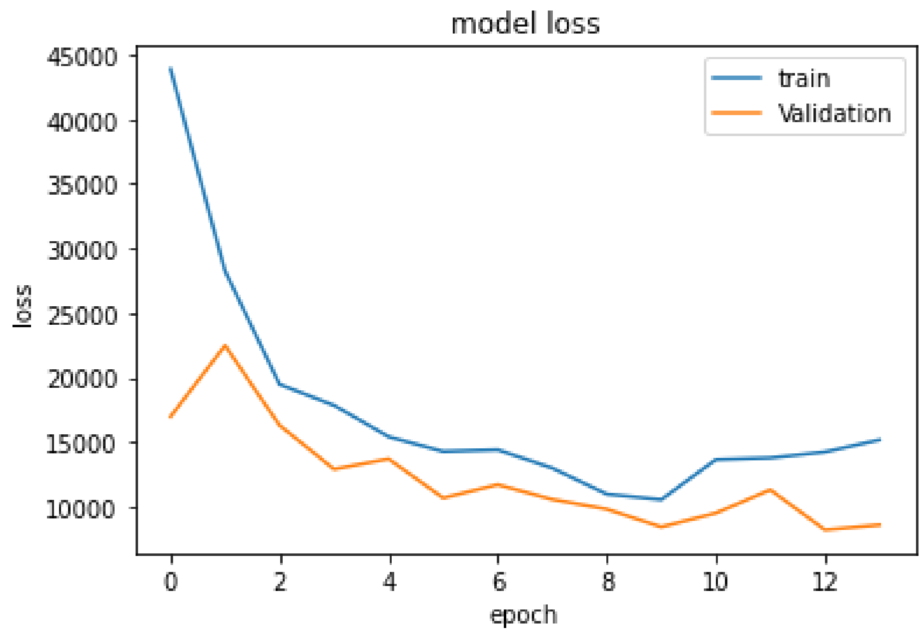

Figure 19 LSTM window (12,3) training and validation loss

Figure 20 show LSTM window (12,6) training and validation loss

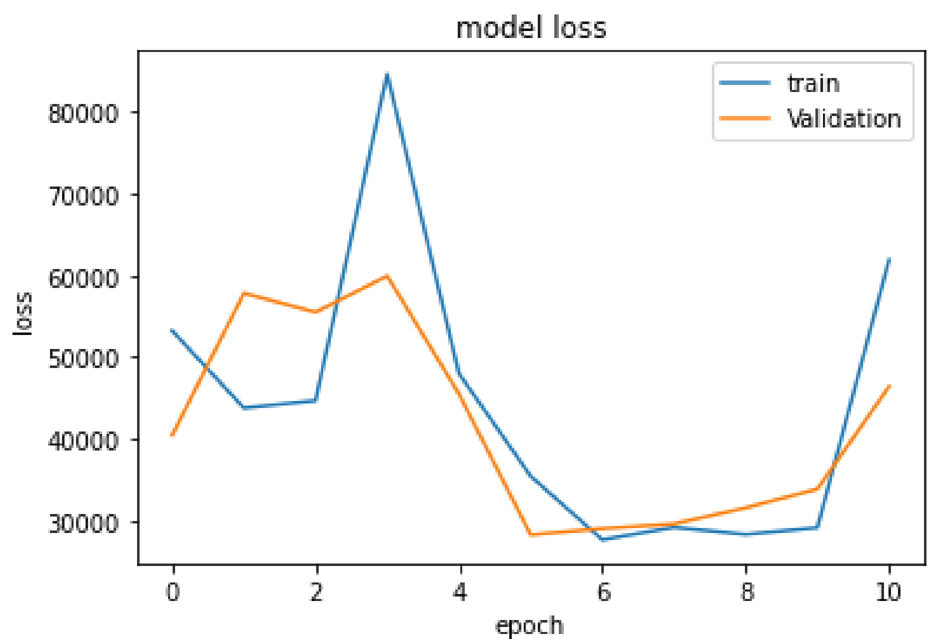

Figure 20 LSTM window (12,6) training and validation loss

Figure 21 show LSTM window (24,12) training and validation loss

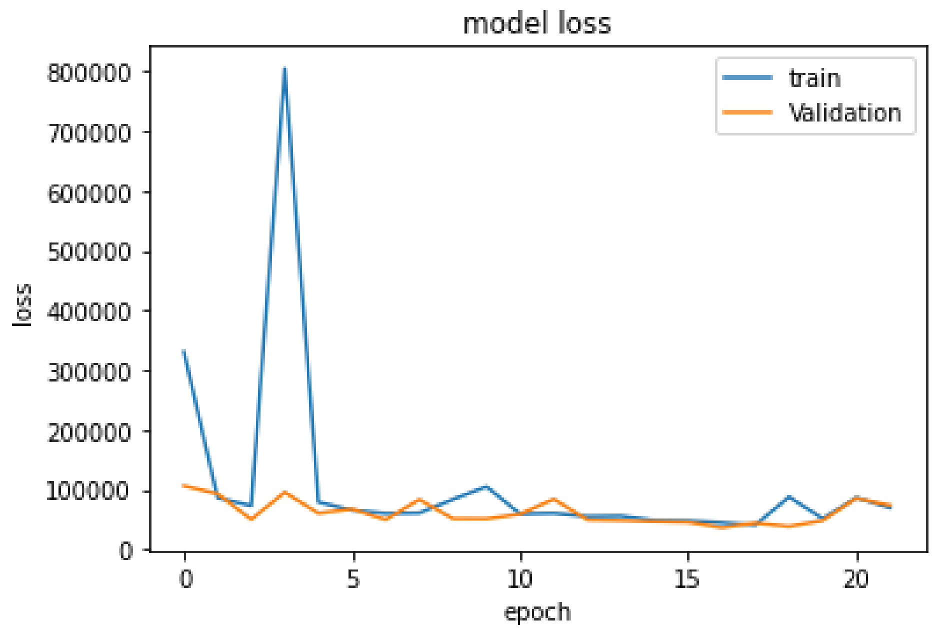

Figure 21 LSTM window (24,12) training and validation loss

Table 10 shows comparison of ANN, CNN and LSTM in different forecast horizons using different error metrics.

Model(window)	Windows	MSE	RMSE	MAE	R2
ANN	(4,1)	1348.39	36.72	20.74	0.98
	12,3)	5816.27	76.26	40.28	0.944
	(24,6)	7854.31	88.62	48.48	0.924
	(48,24)	13329.96	115.45	70.44	0.872
CNN	(4,1)	2309.05	48.05	28.42	0.977
	(12,3)	6363.76	79.77	51.19	0.938
	(24,6)	8082.32	89.90	57.72	0.922
	(48,24)	19044.42	138.00	87.94	0.817
LSTM	(4,1)	1653.34	40.66	23.84	0.984
	(12,3)	8950.51	94.60	56.77	0.913
	(12,6)	56595.03	237.89	157.33	0.455
	(24,12)	115620.56	340.03	235.15	0.109

Table 10 Comparison of DL models based on error metrics

It can be seen from the results in Table 10 that all the Deep Learning models perform very well for short term forecasting but as the forecast period goes farther their accuracy decreases.

5 Future Work

For future work we can collect data that do not have missing values and need not be augmented or interpolated. The better the dataset the better the forecasts will be.

We can use Gated Recurrent Units (GRU) another extension of Recurrent Neural Networks (RNN) that handle sequential data.

Using these methodologies, we integrated the best of Deep Learning and Machine Learning models in our power sector infrastructures for better plants managements and better use of solar powered infrastructures.

6 Conclusion

In this study we have successfully forecasted solar Global Horizontal Irradiance using different statistical and deep learning architectures. We have performed one shot forecasting using the statistical models SARIMAX and Prophet model, while we have performed auto regressive forecasting, also called short term forecasts, using Artificial Neural Networks (ANN)'s architectures deep learning, Long Short Term Memory Networks (LSTM) and Convolutional Neural Networks (CNN). The statistical Models perform well for long term forecasts while deep learning models perform 1-hour-ahead and 3-hours ahead forecast with efficiency.

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