Short Term Forecasting of Solar Radiation

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Abstract. This paper details how to predict solar irradiance at a location for the next few hours using machine learning techniques like Facebook's Prophet, Amazon's DeepAR+, and CNN. Multiple techniques like AutoRegressive (ARIMA) and Exponential Smoothing (ES) have been used to forecast solar irradiance, but they lack accuracy and are not scalable. Whereas Prophet, Amazon's DeepAR+, and CNN algorithms are scalable, accurate, and easily integrated into other machine learning techniques. This will be the first time where the combination of these techniques will be leveraged to forecast solar radiation for short term.
Predicting solar energy accurately depends on multiple factors (including weather conditions) that make forecasting highly resource-intensive, and accuracy remains a challenge. Improving the accuracy of the short-term forecast of solar energy production would provide a massive value to the companies operating IoT Devices and drones to have a more efficient operation and reduced cost. The objective is to improve the accuracy of forecasting short-term solar radiation to power drones and IoT devices, leveraging the ensemble techniques by combing the outcome of Prophet and DeepAR+.
The study gave us an accuracy of XX percent, improving overall accuracy by X percent.

1 Introduction

Solar-powered energy generation is on the rise in the United States. According to EIA's Preliminary Monthly Electric Generator Inventory survey reports, Texas will add 10 gigawatts (GW) of utility-scale solar capacity by the end of 2022. An increase in solar power generation indicates the need for more enhanced tools to manage both short-term and long-term solar power management.

In this fast-changing technology and explosion in IoT, the need to power these miniature devices for a long time (10 to 15 years) remains a challenge. The Omnipresence of Solar energy is considered one of the prime sources to feed power to this evolving technology. Solar technology can play a vital role in bringing the carbon footprint down. There are multiple algorithms in place to predict the long-term changing solar radiation. These IoT devices and drones need something short-term to ensure they will operate in full capacity for the coming few years. It became critical to predicting solar radiation patterns and another meteorological factor that will allow us to estimate the PV (Photovoltaic) for a short duration (say 5 to 7 hours). This research will deliver the machine Learning techniques to take the solar radiation, and other impacting factors to predict the short-term PV power generated leveraging supervised, unsupervised, and semi-supervised deep learning techniques.

Solar energy generation uses photovoltaic (PV) panels that produce electricity through interaction with photons from the sun. Solar energy generation uses photovoltaic (PV) panels that produce electricity through interaction with photons from the sun. Solar energy availability at a given location can be described by the level of solar irradiance (W/m2). Solar irradiance can be measured using a pyranometer. Solar irradiance (IGH) is used to measure the energy available to enter a solar PV system. The system configuration and power losses through the PV system are well known, and thus if the solar irradiance is known, solar energy can be accurately predicted.

This paper presents a machine learning model for predicting solar irradiance at a location for the next few hours. Solar energy is an efficient renewable energy source and is becoming increasingly popular as more energy companies are growing to offer this renewable source of electricity. The use of solar energy to power IoT and Drones will reduce operational costs. Due to the reduced use of fossil fuels, it becomes environment friendly, thus increasing its popularity and demand for its services. It became more and more critical to forecast the solar radiation to maintain the operation.

DeepAR+ is used to forecast time series using recurrent neural networks (RNN), handle a huge dataset, and support more features and scenarios. Prophet shines when applied to time-series data that have strong seasonal effects and several seasons of historical data to work.

The paper presents the application of combining Facebook's Prophet, Amazon's DeepAR+, and Amazon CNN-QR forecasting models for solar radiation forecasting. These three methods bring their respective strengths. Prophet gives better results for items with a long history and frequent outcomes, whereas Amazon's algorithms show superiority for items without a long history and rare occurrences. The three algorithms will process NREL data, and a new ensemble outcome will be leveraged to forecast the short-term (5 to 7 hours) solar radiations.

The paper discusses the dataset and critical features. It talks about extracting information from a dataset to prepare for processing the data with Facebook's Prophet, Amazon's DeepAR+, and Amazon CNN-QR. It explains the method used to create individual outcomes from each method, followed by creating an ensemble model to deliver enhanced accuracy of short-term solar radiation.

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The objective is to improve the accuracy of forecasting short-term solar radiation to power drones and IoT devices, leveraging the ensemble techniques by combing the outcome of Prophet and DeepAR+.

Main contributions of the paper are:

- Creating an ensemble model using Facebook's Prophet, Amazon's DeepAR+, and Amazon CNN-QR.
- Comparing the results with algorithms that are being used to forecast solar radiation like ARIMA and ES.
- Improve the accuracy of short-term solar radiation forecast.

The rest of this paper is organized as follows: Section 2 discusses the related work carried to predict solar radiation across the globe by multiple organizations. Section 3 describes the data set used in the study. Section 4 gives a brief background of the multiple machine learning techniques used to forecast solar radiation. In Section 5, we present the results to demonstrate the performance of our proposed methodology. Section 6 discusses future scope and conclusion.

2 Literature Review

There can be multiple ways solar radiation can be measured and predicted. Below are some of the articles explored for solar irradiance prediction.

2.1 Short-Term Solar Power Forecasting Considering Cloud Coverage and Ambient Temperature Variation Effects

Foad H. Gandoman, Shady H.E. Abdel Aleem, Noshin Omar, Abdollah Ahmadi, Faisal Q. Alenezi. Short-term solar power forecasting considering cloud coverage and ambient temperature variation effects. Retrieved from link

This article proposes a new methodology to assess the impacts of factors like cloud and ambient temperature change on the hourly output power of a PV system installed in Iran. The physical methods use diverse resources such as weather and PV system data and satellite and sky imagery clouds to predict the PV forecast. This paper proposes a new physical model to estimate short-term

PV power based on Oktas-scale variations and temperature changes. The paper agrees that other meteorological conditions impact radiation rate. However, the study focused on cloud coverage and air temperature. The study used Julian Day Number (JDN) to account for the sun's geometric position (solar elevation angle) for leap and regular years. Earth rotation on its axis was also calculated by determining hourly solar radiation angle. Model accuracy was evaluated using standardized root-mean-square error (nRMSE).

2.2 Short-Term Solar Power Forecasting Using Linear and Non-Linear Regularization Models

S.K. Aggarwal, L.M. Saini. Solar energy prediction using linear and non-linear regularization models: A study on AMS (American Meteorological Society) 2013-14 Solar Energy Prediction Contest. Retrieved from link

The paper discusses how greyscale satellite images to estimate solar radiation and solar radiation data are collected from several ground measuring stations of solar radiation. The research examines the importance of clouds and the type of clouds (thickness of clouds: very low, low, average, high cloud cover, and very high cloud cover). The study was based on low-cost solar radiation estimates and several ground measurements. Cloud images from satellites and calculated and compared with actual data. The results were extrapolated to estimate solar radiation at other places.

2.3 Multi-Dimensional Linear Prediction Filter Approach for Hourly Solar Radiation Forecasting

Emre Akarslan, Fatih Onur Hocaoglu, Rifat Edizkan. A novel M-D (multi-dimensional) linear prediction filter approach for hourly solar radiation forecasting. Retrieved from link

The paper discusses a new approach for hourly solar radiation forecasts. The data measured hourly throughout the year are converted into 2-D image forms, and the data points are evaluated as pixels of the images. Multi-dimensional linear prediction models are designed to link the solar irradiance images with different images that correlate with solar irradiance data. The performance of each model is compared with each other, and the results show that the proposed approach significantly improves the prediction accuracy.

2.4 Mycielsi-Markov Model for Hourly Solar Radiation Forecasting

Fatih Onur Hocaoglu, Faith Serttas. A novel hybrid (Mycielsi-Markov) model for hourly solar radiation forecasting. Retrieved from link

The paper discusses using the Mycielski-Markov model to predict solar radiation for two cities in Turkey. The approach assumes solar radiation data repeats itself. A novel ANN methodology was used to estimate the profile of data using solar irradiance, air temperature, voltage, and current data for training and validation of the model. Mycielski algorithm was built to find exact matching data. Hourly solar radiation values are converted into the states. The range of the states, statistical distribution, and standard deviation of the data were taken into account to estimate future values. Based on the study's outcome, it is possible to predict new solar radiation data samples accurately by using only historical solar radiation data without any other parameters.

2.5 Solar Radiation Forecasting Using Artificial Neural Network and Random Forest Methods

Benali, G. Notton, A. Fouilloy, C. Voyant, R. Dizene. Solar radiation forecasting using artificial neural network and random forest methods: Application to normal beam, horizontal diffuse and global components. Retrieved from link

The paper discusses forecasting normal beam, horizontal diffuse, and global solar components at Odeillo, France, hourly using Smart Persistence (SP), Artificial Neural Networks (ANN), and Random Forest methods. Random Forest Method was found to predict more accurately looking at nRMSE. It also shows that forecasting during winter and summer is difficult due to higher solar radiation variability. The author also discussed the data cleaning methodology by removing night data and data during sunrise and sunset. They also discussed the challenge of evaluating the hourly bean and diffusion component of GHI (Global Horizontal Irradiation).

2.6 Predicting Solar Radiation in Tropical Environment Using Satellite Images

Ayu Wazira Azhari, Kamaruzzaman Sopian, Azami Zaharim, Mohamad Al Ghoul. School of Environmental Engineering, Universiti Malaysia. A New Approach For Predicting Solar Radiation In Tropical Environment Using Satellite Images. Retrieved from link

The paper discusses how greyscale satellite images to estimate solar radiation and solar radiation data are collected from several ground measuring stations of solar radiation. The research examines the importance of clouds and the type of clouds (thickness of clouds: very low, low, average, high cloud cover, and very high cloud cover). The study was based on low-cost solar radiation estimates and several ground measurements. Cloud images from satellites and calculated and compared with actual data. The results were extrapolated to estimate solar radiation at other places.

2.7 Advanced Ensemble Model for Solar Radiation Forecasting Using Sine Cosine Algorithm and Newton's Laws

El-Kenawy, El-Sayed M ; Mirjalili, Seyedali ; Ghoneim, Sherif S. M ; Eid, Marwa Metwally ; El-Said, M ; Khan, Zeeshan Shafi ; Ibrahim, Abdelhameed Advanced Ensemble Model for Solar Radiation Forecasting Using Sine Cosine Algorithm and Newton's Laws. Retrieved from link

This paper proposes optimized solar radiation forecasting ensemble model consisting of pre-processing and training ensemble phases. The training ensemble phase works on an advanced sine cosine algorithm (ASCA) using Newton's laws of gravity and motion for objects (agents). Obtained results of the proposed ensemble model are compared with those of state-of-the-art models, and significant superiority of the proposed ensemble model is confirmed using statistical analysis such as ANOVA and Wilcoxon's rank-sum tests. The proposed ensemble model shows superiority over the reference base model including LSTM, NN, and SVM. The ASCA based ensemble weights model provided better results over the average ensemble and the KNN ensemble models. Several experiments are conducted and different performance metrics are considered to conclude that the proposed ensemble weights model is best suitable for forecasting solar radiation.

2.8 DeepAR: Probabilistic forecasting with autoregressive recurrent networks

David Salinas, Valentin Flunkert, Jan Gasthaus, Tim Januschowski. DeepAR: Probabilistic forecasting with autoregressive recurrent networks. Retrieved from link

This paper is about going to forecast time-series based on the past trends of multiple factors with the help of the DeepAR algorithm, a methodology for producing accurate probabilistic forecasts, based on training an autoregressive recurrent neural network model on a large number of related time series. The Deep Autoregressive model (DeepAR) has built-in algorithms for Amazon Sagemaker. It is a time-series forecasting using a Recurrent Neural Network (RNN) capable of producing point and probabilistic forecasts. This paper shows that forecasting approaches based on modern deep learning techniques can drastically improve forecast accuracy relative to state-of-the-art forecasting methods on a wide variety of datasets. The DeepAR focuses on experimenting with our time series to get the best possible results without worrying about the internal infrastructure. Forecasting tasks can be done quickly as there is no need to write any training code. The data can be prepared, and the necessary tunings to be performed to fine-tune the model.

2.9 Towards flexible groundwater-level prediction for adaptive water management: using Facebook's Prophet forecasting approach

H. Aguilera a, C. Guardiola-Albert a, N. Naranjo-Fernández and C. Kohfahl b. Department of Research in Geological Resources, Spanish Geological Survey, Madrid, Spain. Towards flexible groundwater-level prediction for adaptive water management: using Facebook's Prophet forecasting approach. Retrieved from link

The paper discusses forecasting Facebook Prophet forecasting tool. Facebook has released the code and made it open source. Prophet is an additive model that considers nonperiodic changes and parodic components easily interpretable parameters. The paper discusses how hydrologists and water managers used this tool to Predict Ground Water Levels (GWL) with flexibility and quickly. Papers talk about challenges like flexibility, eases of use, and interpretability encountered with other tools were used. Prophet is robust to missing data, shifts in the trends, and significant outliers.

2.10 Comparison analysis of Facebook's Prophet, Amazon's DeepAR+ and CNN-QR algorithms for successful real-world sales forecasting

Emir Zunic, Kemal Korjenic, Sead Delalic, and Zlatko Subara. Comparison analysis of Facebook's Prophet, Amazon's DeepAR+ and CNN-QR algorithms for successful real-world sales forecasting. Retrieved from link

The paper presents the application and comparison of the Facebook's Prophet, Amazon's DeepAR+, and CNN-QR forecasting models for sales forecasting in distribution companies. The results show that Prophet gives better results for items with a long history and frequent sales. In contrast, Amazon's algorithms show superiority for items without a long history and items that are rarely sold. The Prophet Forecasting Model is an open-source procedure for forecasting time-series data. Facebook's Core Data Science team created the Prophet tool. The Prophet algorithm works well in the case of datasets with multiple seasons and qualitatively describes the seasonality in the data. The DeepAR+ model is based on autoregressive recurrent neural networks. It is used as a supervised learning algorithm to forecast one-dimensional time series. DeepAR+ has been trained on a large number of time series. Amazon's CNN-QR (Convolutional Neural Network - Quantile Regression) forecasting algorithm is based on the application of casual convolutional neural networks to predict scalar time series data. Prophet analyzes each signal independently, while Amazon's algorithms create a single model for all signals and find interdependencies. Therefore, Amazon's algorithms show superiority over classical methods only when they have a large number of signals over which to create a model, and in the case of articles with a short history. It has been observed that the Prophet model shows superiority in the case of items that are sold frequently, in large quantities, and have a long sales history. At the same time, Amazon's algorithms showed dominance in other cases.

2.11 Thesis

Based on the data science techniques, solar radiation and meteorological data forecast the short-term solar radiation leveraging multiple machine learning techniques (linear and nonlinear) for a given location most efficiently and effectively. The best model or ensemble of the models can be trained to enhance the forecast accuracy to generate a generic model for global/ regional use.

3 Data

Working with solar radiation and meteorological data over the United States and regions of the surrounding countries acquired from the National Solar Radiation Database maintained by National Renewable Energy Laboratory. The research will use climate, weather, and other meteorological data to leverage linear and nonlinear machine learning algorithms and techniques to build a framework for assessing the performance of short-term solar irradiance forecasting.

3.1 Data Sources

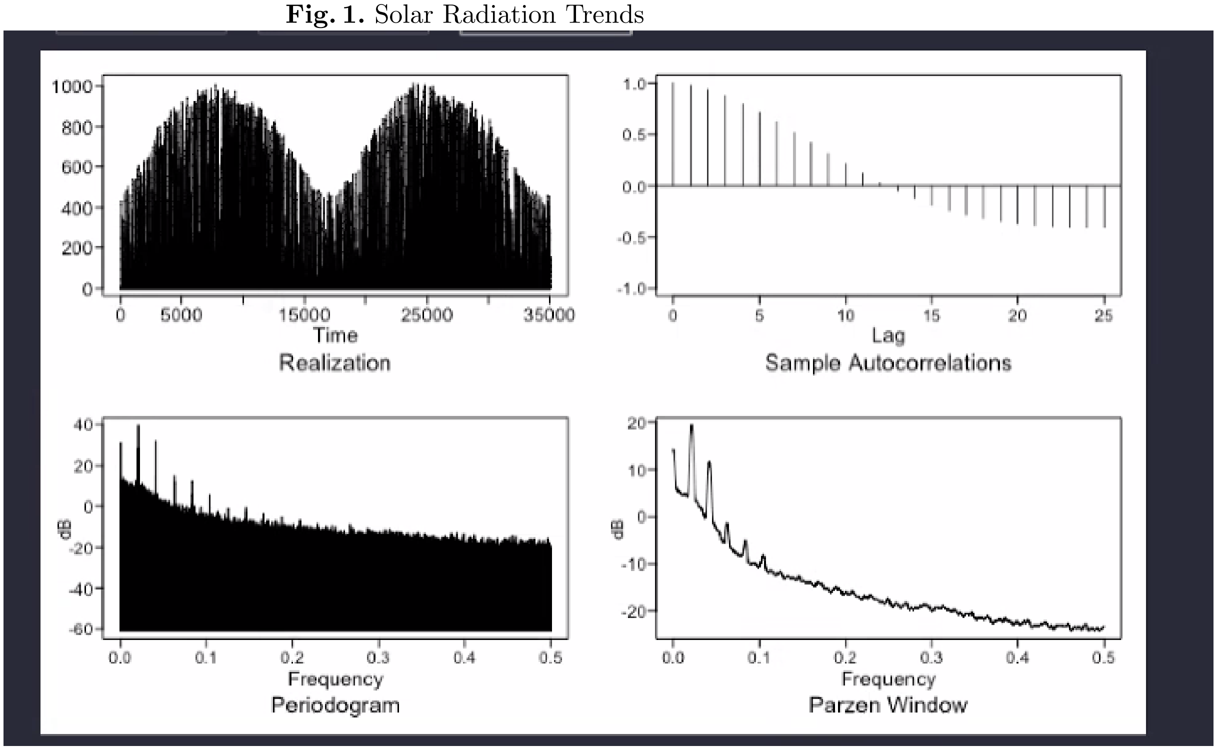
The data comes from the National Solar Radiation Data Base (NSRDB), consisting of solar radiation and meteorological data over the United States and regions of the surrounding countries. It is a publicly open dataset that has been created and disseminated during the last 23 years. The current NSRDB provides solar irradiance at a 4-km horizontal resolution for each 30-min interval from 1998 to 2016.

The data is computed by the National Renewable Energy Laboratory's (NREL's) Physical Solar Model (PSM) and products from the National Oceanic and Atmospheric Administration's (NOAA's) Geostationary Operational Environmental Satellite (GOES), the National Ice Center's (NIC's) Interactive Multisensor Snow and Ice Mapping System (IMS), and the National Aeronautics and Space Administration's (NASA's) Moderate Resolution Imaging Spectroradiometer (MODIS) and Modern-Era Retrospective analysis for Research and Applications, version 2 (MERRA-2). The NSRDB irradiance data have been validated and shown to agree with surface observations with mean percentage biases within 5 percent and 10 percent for global horizontal irradiance (GHI) and direct normal irradiance (DNI), respectively.

The data can be freely accessed via https://nsrdb.nrel.gov or through an application programming interface (API). During the last 23 years, the NSRDB has been widely used by an ever-growing group of researchers and industry both directly and through tools such as NREL's System Advisor Model.

The data is provided in high density data files (.h5) separated by year. The variables mentioned below are provided in 2 dimensional time-series arrays with dimensions (time x location). The temporal axis is defined by the time-index dataset, while the positional axis is defined by the meta dataset. For storage efficiency each variable has been scaled and stored as an integer. The scale-factor is provided in the psm-scale-factor attribute. The units for the variable data is also provided as an attribute psm-units.

Fig. 1. Solar Radiation Trends

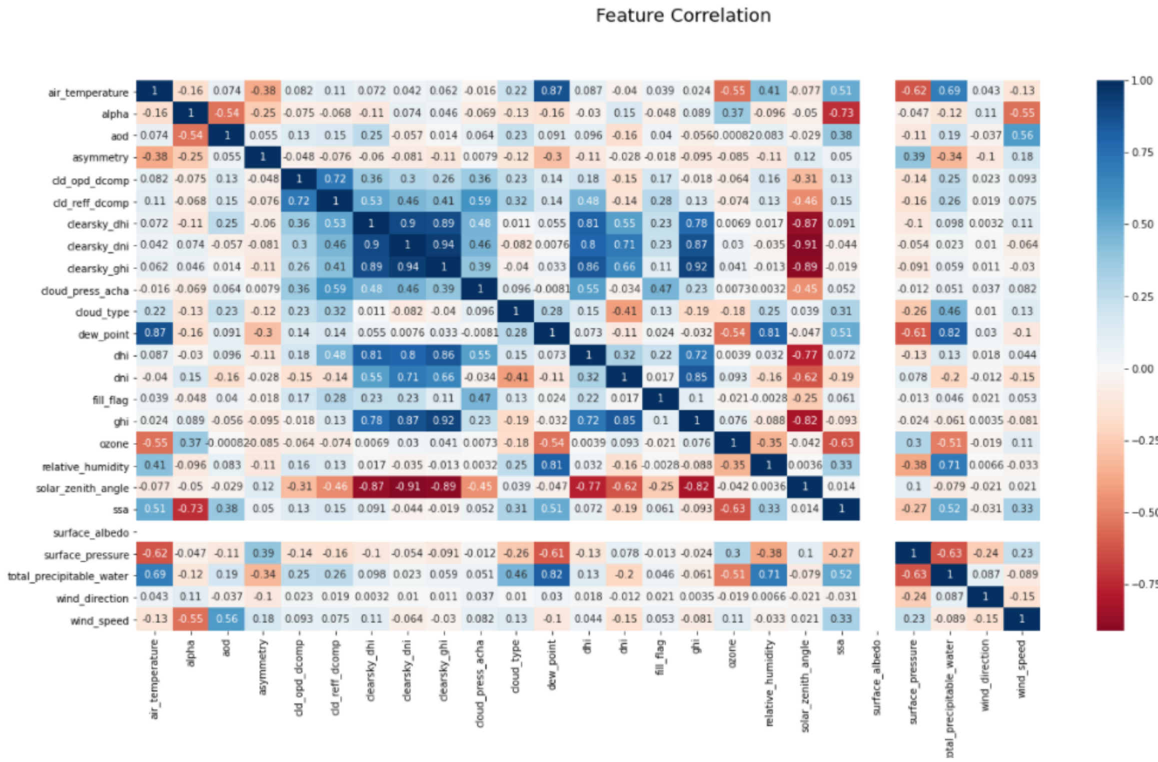


In the graph above we observer following:

- Realization shows seasonality
- ACF is diminishing sinusoidal
- Spectral density show few frequency peaks

Correlation 1 shows a high positive correlation, and -1 shows a high negative correction. Zero value shows no correlation.

Fig. 2. A Heatmap showing the correlation of the variables in the model



In the correlation heat map, Clearsky Diffuse Horizontal Irradiance, Clearsky Direct Normal Irradiance, Clearsky Global Horizontal Irradiance, Diffuse Horizontal Irradiance and Direct Normal Irradiance show a high positive correlation and solar zenith angle shows a negative correlation with the target variable Global Horizontal Irradiance. The correlation aligns with the expectation, as Global Horizontal Irradiance is derived from Diffuse Horizontal Irradiance, Direct Normal Irradiance and Solar Zenith Angle.

Below are some of the key attributes from the data that were explored based on the correlation of the variables as seen in the heatmap.

– **Wind Speed** - Horizontal motion of air near the surface of the earth. Measured in Meter per second. Source: MERRA
– **Precipitable Water** - The amount of water in a vertical column of atmosphere. Measured in millimeter. Source: MERRA. The unit of measure is typically the depth to which the water would fill the vertical column if it were condensed to a liquid. For example, 6 centimeters of precipitable water (in the absence of clouds) indicates a very moist atmosphere. Precipitable water is often used as a synonym for water vapor.

- **Relative Humidity** - The amount of water vapor in the air expressed as the ratio between the measured amount and the maximum possible amount (the saturation point at which water condenses as dew). Measured in percentage. Calculated from specific humidity
- **Direct Normal Irradiance** - The amount of solar radiation from the direction of the sun. Measured in Watt per square meter. Modeled solar radiation obtained from the direction of the sun
- **Diffuse Horizontal Irradiance** - The radiation component that strikes a point from the sky, excluding circumsolar radiation. In the absence of atmosphere, there should be almost no diffuse sky radiation. High values are produced by an unclear atmosphere or reflections from clouds. Measured in Watt per square meter. Modeled solar radiation on a horizontal surface received from the sky excluding the solar disk
- **Global Horizontal Irradiance** - Measured in Watt per square meter. Modeled solar radiation on a horizontal surface received from the sky. Also called Global Horizontal Irradiance; total solar radiation; the sum of Direct Normal Irradiance (DNI), Diffuse Horizontal Irradiance (DHI), and ground-reflected radiation; however, because ground-reflected radiation is usually insignificant compared to direct and diffuse, for all practical purposes global radiation is said to be the sum of direct and diffuse radiation only:
  $GHI = DHI + DNI * cos\ (Z)$
  where Z is the solar zenith angle.
- **Clearsky Diffuse Horizontal Irradiance** - Measured in Watt per square meter. Modeled solar radiation on a horizontal surface received from the sky excluding the solar disk. This is assuming clear sky condition
- **Clearsky Direct Normal Irradiance** - Measured in Watt per square meter. Modeled solar radiation obtained from the direction of the sun. This is assuming clear sky condition
- **Clearsky Global Horizontal Irradiance** - Measured in Watt per square meter. Modeled solar radiation on a horizontal surface received from the sky. This is assuming clear sky condition

4 Methods

The objective is to compare various machine learning techniques to find which features are most likely to predict solar irradiance accurately.

Below are some of the methods being considered based on preliminary analysis of data.

- ARIMA (Auto-Regressive Integrated Moving Average)
- LSR (Least Squares Regression)
- NWP (Numerical Weather Prediction)
- SVM (Support Vector Machines)
- ANN (Artificial Neural Network)
- DRNN (Deep Recurrent Neural Network)

– Facebook Prophet
– Deep Autoregressive model (DeepAR)

Reading Data from Multi-dimensional Arrays: Data collected for Solar Radiation is very complex. Metrological conditions play a vital role in Solar forecasting. Processing hourly data and multiple variables that may depend on each other or correlate with each other and time is a complex task. It is critical to carry out detailed EDA to under these variables and how (or if) they are related to each other.

Data Cleaning: Sometimes, sensor outages can lead to missing/incorrect data. To prevent the impact of missing data on predication results gap should be filled appropriately populated. As solar radiation data exhibits yearly periodicity, forward and backward data filling will be applied to handle the missing values. Wherever the data corresponding to D – (365*24*4) was available, the missing data were replaced by backward filling. Wherever it was not available, it was filled by forward filling, i.e., data corresponds to D + (365*24*4) as solar data used for the short-term forecast is collected every 15 minutes.

Data Normalization: As variables used in the data are in different units. Normalization is required when dealing with attributes on a different scale; otherwise, it may dilute the effectiveness of a critical, equally important attribute (on a lower scale) because of other attributes having values on a larger scale. When multiple attributes are there, but attributes have values on different scales, this may lead to poor data models while performing data mining operations. So, they are normalized to bring all the attributes on the same scale. It is vital to get the data on the same scale so their impact can be quantified and understood better. Data normalization consists of numeric remodeling columns to a standard scale. Data normalization is generally considered the development of clean data. Diving deeper, however, the meaning or goal of data normalization is twofold. Data normalization is the organization of data to appear similar across all records and fields. It increases the cohesion of entry types, leading to cleansing, lead generation, segmentation, and higher quality data.

Feature Segmentation: As observed in the correlation table above, some features are highly correlated with the target variable (ghi). Data will be studied in two phases one will need all the features, and the other review data only with highly correlated variables.

Data Segmentation: Solar radiation and metrological data exhibit a seasonal pattern. Data in different seasons may belong to a different distribution. Instead of using a single segment, the data may be broken into different segments to build a robust model with relevant data. The team will be leveraging the Prophet algorithm to capture seasonal trends. Prophet shines when applied to time-series data that have substantial seasonal effects and several seasons of historical data to work.

Forecasting Model Training: Data will be split in a 70/30 ratio for training and test data set before normalizing. The team will ensure that no data leakage occurs between training and test data. The model will be built and train data.

The following three techniques will be applied to forecast:

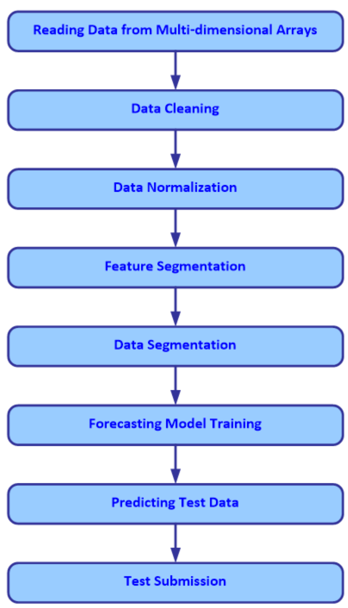
- Facebook's Prophet
- Amazon's DeepAR+
- CNN-QR

Initially, Solar radiation will be forecasted leveraging these methods independently. Efforts will be made to build an ensemble model with equal-weighted and adjusted weighted to improve the accuracy. The baseline will be built using ARIMA an ES model. A key objective will be to improve the accuracy of the solar model.

Predicting the Test Data: A model built on train data will be leveraged to predict the outcome. The predicted outcome will measure for accuracy.

Test Submission: The outcome of test models will be measured independently and weighted and non-weighted ensemble model outcomes. Training and test times will be observed to keep an eye on processing time. However, the key matrix will be accuracy.

Fig. 3. Methods of Analysis



5 Results

With this research, the expectation is to predict the short-term solar radiation. This research can influence determining the right combination of solar panel material and rectifiers to ensure the desired application of IoT devices, drones, and other solar power appliances can be built at optimal cost.

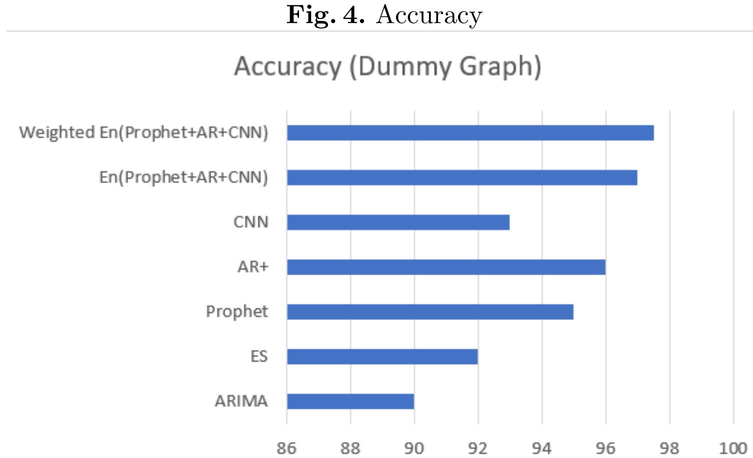
With this research and multi-layer data team is continuing to investigate to answer the following questions to enhance the accuracy of prediction:

- Impact and limitation of technology to convert GHI (Solar Radiation) to PV
- Extraction of multi-layer data from H5 files
- What will the right combination of linear and nonlinear models to extract the outcome in the most effective and efficient way
- Based on papers, the factor impacting solar irradiance is cloud and temperature. The research team will continue to evaluate and quantify the improvement in prediction solar irradiance by adding other meteorological factors.
- How the finding from long term forecast can be leveraged to enhance short term predictions
- What other multi-dimensional approaches to improve the prediction
- How Ensemble Model or hybrid model can impact Solar Radiation Forecasting

There are different methods for evaluating the performance of a forecasting model. For our study, we will use Root Mean Square error and accuracy as metrics to evaluate our model.

Graph below shows the forecasting accuracy derived leveraging multiple algorithms.

Fig. 4. Accuracy



6 Conclusion

The conclusion will highlight the successful implementation of computationally efficient technique (leveraging linear and nonlinear models) to do short term forecast of solar irradiance.

7 Acknowledgements

The researchers would like to thank the mentors Prof. Bradley Blanchard, Mr. Ashwin Thota and SME Mr. Grant Buster from NREL for their insight, guidance, and support. The researchers would also like to thank the Capstone professors for the templates and structure, supporting the development of the efforts

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