

Integrated Regression Approach for Prediction of Solar Irradiance Based on Multiple Weather Factors

Megha Kamble, Lakshmi Narain College of Technology Excellence (LNCTE), Bhopal, India*

 <https://orcid.org/0000-0001-7466-1504>

Sudeshna Ghosh, Lakshmi Narain College of Technology Excellence (LNCTE), Bhopal, India

ABSTRACT

Solar irradiance is the most vital aspect in estimating the solar energy collection at any location. Renewable energy setup at any location is dependent on it and other ambient weather parameters. However, it is hard to predict due to unstable nature and dependence on variations in weather conditions. The correlation of ambient weather factors on the performance of solar irradiance is analysed by collecting the data using weather API over the year for a particular location of Central India. The training of this non-linear data is carried out with hybrid regression model integrating decision tree regression with artificial neural network (ANN) module. Experimentation is performed using real data of different days from different seasons of the year and by considering different irradiance conditions. The results demonstrated significant weather factors with moderate positive and negative correlation with solar irradiance, which can be used as a helpful tool to predict it before deployment of solar energy setup.

KEYWORDS

Deep Neural Network, Machine Learning, Numerical Weather Prediction, Regression, Solar Energy, Solar Irradiance Prediction

1. INTRODUCTION

The Solar irradiance is renewable source of energy provided by sun naturally. It is electromagnetic radiation emitted by the sun, in generic manner. It is converted into useful electric energy using feasible technology. However, the economic feasibility of this type of conversion setup depends on ambient weather condition and available solar resource at that location. After accurate solar irradiance prediction at any particular location, electric power grids or Solar PVs can be deployed so as to minimize the physical expenses. At present, actually when these systems are installed at majority areas of our country India, it is seen that though these modules are placed after the analysis of ambient weather conditions and sun direction, output power generated does not meet the desired level. Some significant reasons are, modules are manufactured at STC, and deployed by taking into consideration

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*Corresponding Author

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only solar PV panel orientation. Also Solar irradiance varies with meteorological data longitude, latitude, wind speed and change of weather at different areas. Therefore, deviation from standard test conditions affect generation of output power. So this paper proposes the methodology to predict the collection of energy for particular location, by taking into consideration ambient parameters, before deployment and similarly after deployment also, this methodology can be helpful in predicting solar energy collection in advance for its proper utilization and distribution.

The case study is done for Bhopal (MP), location in the central region of India with diverse climate but solar radiation in a finite range. Thus the climate of this city depicts the climate of the country and is suitable for solar radiation based prediction model. Existing Literature provided different benchmark forecasting techniques in the domain of statistical methods, machine learning and deep learning, for predicting solar PV energy output, efficiency, solar radiation with the help of historical time series data, either endogenous or exogenous dataset. Existing methods produce forecasts every 6 hours, mostly based on historical data at a location. Some limitations of existing research is the training set is reduced for longer time horizons as one cannot use unavailable weather forecasts and majority study depicts prediction of PV panel output, so in fact, PV panel deployment setup is required for experimentation. Majority of work reflects locations worldwide, but a few case studies are there from the country like India where there is more need of renewable energy sources. Some recent work is also focused on use of weather factors for prediction of solar radiation, that too by applying neural network, however, benchmark weather factors are difficult to find out.

The contribution of the paper is:

- Presented, preprocessing of standard meteorological dataset for solar radiance prediction, which is actual weather for the given location and interdisciplinary research opportunity is explored
- Identified the most significant environment variables, innovative combination of these variables is provided and train hybrid machine learning model with generic setting and hyper parameter tuning
- Demonstrated hybrid model accuracy for irradiance prediction and significance of correlation of weather factors for solar irradiance prediction
- Demonstrated App setup for predicting solar irradiance at any location based on GPS and hybrid machine learning model in the background to verify the site for deployment of PV panel/solar farm. This is innovative holistic approach for sustainable energy sources.

The paper is organized into four sections. Current section is an overview of the paper title. Subsequent section, existing work, gives literature reviews followed by proposed methodology in third section. Section four demonstrates experimental setup and work, results, discussions followed by conclusion.

2. BACKGROUND

The authors of (Alzahrani, A, et al.(2014)) has described various methodologies for obtaining parameterized model to estimate generated power in PV generation systems, as these systems are weather independent and hard to predict, site parameters at the hourly level. Time series historical data are relatively rare, so in the recent years statistical approaches and NWP model based exogenous datasets have been developed to help the research community to work on solar radiance prediction.

Existing literature provides worldwide instances of solar energy or radiance prediction for various regions of the world, China, Saudi Arbaia, USA, Uganda, Oman (Kazem, et al. (2016)), whereas rare of such work is available for India(Bhattacharya T. et al. (2014)). Summary of significant facts is stated in this section.

The authors of (Poolla, Chaitanya & Ishihara, Abraham. (2018)) presented a review on the application of neural networks for the estimation, forecasting, monitoring, and classification of

exogenous environmental variables and the forecast of these variables allowed to explore renewable energy and water resources. One more important contribution for Indian environment is by the authors of (Yousif, J.H., Kazem, H.A., & Boland, J. (2017)) in which the effects of wind speed and ambient temperature have been analyzed for location of Tripura, India for the performance analysis of a monocrystalline silicon solar photovoltaic module. This work is estimating solar PV potential output for a particular location called Tripura, India, after deployment of PV panel. This method is relatively costlier as before deployment of PV panel, estimation of potential solar irradiance in the area will be helpful for the decision making before physical deployment. However, the work presents the estimation model for weather parameters which are supplementary to PV panel in addition to inclination angle.

The authors of (Mariam Alkandari & Imtiaz Anad(2020)) proposed a hybrid models by combining theta statistical methods with machine learning models to predict solar irradiance for six weather parameters and demonstrated improved accuracy. However, deep learning frameworks are more recent and reduces time complexity for prediction. This paper presented deep learning framework integrated with ensemble machine learning model which is inspired by the work of authors of (Mariam Alkandari & Imtiaz Anad(2020)). The proposed work also presents the real time dataset for particular location in India to explore the renewable energy. The work cannot be directly compared with (Mariam Alkandari & Imtiaz Anad(2020)) as time series and real time location is different. However, comparative analysis with this existing validates the proposed approach.

Most of the instances, as stated in the table 1, solar radiance prediction is done for time series analysis, historical data and various methods are studied for estimating solar radiation based on Neural network, machine learning, AI, real time series forecasting (Tanaka, Y., & Takahashi, M. (2017)) with default parameters. Prediction with time series has additional computational burden due to non linearity of data variables in dataset, that can be reduced by using NWP model based dataset. The work contributed in this paper is different in the sense of hyper parameter tuning of traditional ML neural network model, using kernel weight initialize and optimizer that has produced better results in the terms of r2 score. Also the work uses TensorFlow Deep learning framework which is more flexible and stable in the performance measures over the epochs. The real time dataset is relatively smaller in size and this framework is found to be suitable for smaller dataset.

3. PROPOSED SOLUTION

3.1 Data Preprocessing

The dataset collected for the proposed framework implementation is consisting of following most common but significant factors representing climatic condition:

- **Global Solar radiation:** kW per hr meter²(radiant energy emitted by the sun, collected by Solar energy system for electricity production)
- **Temperature, Maximum and minimum:** Degrees Celcius
- **Humidity, Cloud:** Percentage, Atmospheric Pressure: MPa
- **Wind direction:** Degrees, Wind speed: Km per hour
- **Gust:** Km per hour, Precipitation: mm
- **Sunrise/sunset:** Hawaii time (converted into daylength in seconds)
- **Date, Time:** Converted to day of year (unique no. from 1 to 365)

(Reference <https://www.worldweatheronline.com/>) The firm operates 2 high-tech weather data centers in the world along with mini setup at India to make available day to day weather and climatic situation.

Table 1. Significant Instances from Literature

Reference	Location	Methodology	Performance Measures
(Yacef, R., Benghanem, M., & Mellit, A. (2012))	Saudi Arabia	Bayesian Network	MAE, RMSE
(Tanaka, Y., & Takahashi, M. (2017))	China	SVM Multipoint prediction Grid is divided into clusters	SVM produces high time complexity Prediction accuracy of clusters Integrated accuracy
(Bhattacharya T. et al. (2014))	Tripura, India	PV power generation Linear regression	PV module efficiency Correlation Coefficient Confidence Level
(Feng, C. et al. (2018))	USA	Unsupervised learning Clustering	MAE, RMSE
(K.N.Shukla et al(2015))	Bhopal India	Statistical methods based on inclination angle	MAE, RMSE
(Voyant, C. et al. (2017))	Japan, Singapore, USA, Taiwan	Survey paper presenting all machine learning models	MAPE, RMSE
H. Sangrody, M. Sarailoo, N. Zhou, N. Tran, M. Motalleb and E. Foruzan.(2016)	NOAA weather data	PV energy forecasting	MAPE
Poolla, Chaitanya & Ishihara, Abraham. (2018).	NOAA NCEP weather data Mesowest university	Autoregressive model	Zero hour ahead forecast 80% accuracy 1 year dataset
Yousif, J.H.; Kazem, H.A.; Boland, J. (2017)	Gulf Hot weather	Autoregressive model	AR
Hou, Muzhou & Zhang, Tianle & Weng, Futian & Ali, Mumtaz & Al-Ansari, Nadhir & Yaseen, Zaher. (2018).	Africa Near Sahara Dry climate	ELM Bayesian Network Forecasted weather data	Sensitivity Prediction Error
Kazem, et al. (2016)	Oman	SVM where the inputs are solar radiation, and ambient temperature and the output is the photovoltaic current	MAE R2

Most of the existing work, is done on forecasted data because of unavailability of observed weather data. This work is an effort to put forward real time data set for better prediction. The dataset consists of 8 records for a day where 3 hourly forecasting horizon is assumed. Observed meteorological data along with solar irradiance is recorded as dataset and other physical aspects of PV panel are neglected. The extended dataset is also prepared with different timescales monthly, daily and hourly, and weekly instances. Week of the year factor is useful for seasonal prediction. Irradiance is expected to vary with date due to seasonal weather changes and so this comprehensive dataset contains the weekly instances throughout the year so as to get the outcome during every season.

To make it compatible with regression model, the preprocessing is done for date,time and sunrise time and sunset time with the help of pandas python library. Later on day, time, sunrise, sunset columns are dropped and replaced by two columns dayof year(unique integer) and length of day in seconds(DayLength). The correlation of the attributes are shown in the table 2.

Table 2. Correlation Matrix of most significant independent factors with radiation

Pressure	Humidity	Precipitation	Gust	Cloud	Day Length(s)	Wind speed	Day of Year
0.54	0.51	0.36	0.39	0.47	0.52	0.41	0.65

From this exploration of the dataset, there are some patterns that are observed that pressure, humidity, day of the year and daylength(s) are having more influence on the irradiance. However, more scientifically it is to be observed as the dataset is small to come to conclusion. But timescale measures day of the year and daylength(sec) are most significant.

3.2 Integrated Regression Model

3.2.1 Prediction Problem

The prediction problem is formulated as past year weather data is in the form of $(w_1, w_2, \dots, w_i)$ where i represents the number of weather parameters, to predict solar irradiance(I) with 3 hourly forecasting where 3 hours time horizon is kept while collecting data set.

With proposed methodology it is represented as $I=f(w_1, w_2, \dots, w_i)$ where f is TensorFlow Framework.

The initial input variables are 12 and TensorFlow framework is trained for the same. It is observed that with strong correlation factors, the model can converge after more number of epochs and also it is challenging to select significant features, especially for coherent small dataset provided here.

The prediction problem is modified as:

$$I=f(w_1, w_2, \dots, w_s) = \text{DTR}(w_1, w_2, \dots, w_i)$$

where i number of weather parameters are reduced to s , by using feature of importance calculated after regression using Decision Tree. DTR stands for decision tree regressor and f stands for TensorFlow Deep Learning Framework.

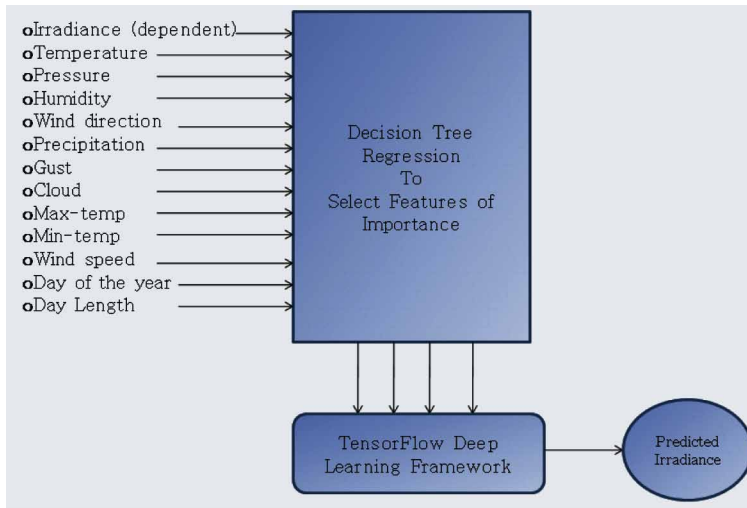
3.2.2 Decision Tree Regression

Decision trees are useful for determining nested/interactive relationships between combinations of independent variables and dependent variables. A decision tree does not require well-preprocessed data. No Normalization Decision tree does not require normalized data No Scaling You need not scale the data before feeding to the decision tree model. A decision tree uses a top-down approach to build a model by continuously splitting the data into small portions. Before each split, It calculates the entropy to understand the information gain it would get from a split. Entropy is the main input to the information gain equation.

Proposed Model Parameters:

1. Criteria of quality of Split: Mean squared error (mse) which is equivalent to variance reduction is taken as feature selection criteria which also reduced L2 loss.
2. Splitter: best strategy is chosen at each node to choose the best split.
3. Minimum number of samples required to split an internal node is kept as 2 where as minimum number of samples required at a leaf node is chosen as 1.
4. There is no constrain on depth of decision tree, nodes are expanded until all leaves contain less numbers than 2. This is done for small size data set exploration.
5. All features are considered and so $max_features$ are set to 12.

Figure 1. Flow Diagram of Integrated Regression Model



6. The randomness of estimator is set to an integer 0, so as to obtain deterministic behavior during fitting.
7. Decision tree regression produced R2 score 0.67 as all features are selected and they are non linearly interrelated. Small size of dataset is not leading to the desired output. Decision Tree regressor fits the model and reports coefficient value for each feature.
8. The feature of importance are chosen with the help of *feature_importance_*, all the calculated feature importance scores are listed below after running the model for 10 times. Permutation feature importance technique is used to calculate relative importance scores independent of the model.
9. Permutation feature selection is used, *permutation_importance()* function takes a fit DTR model, a train dataset and a scoring function which returned following scores.

3.2.3 Proposed Tensor Flow Deep Learning Framework

The significant factors obtained are taken as input variables for neural network.

3.2.3.1 Working of ANN Thru TensorFlow Framework

1. Weights were initialized using the hyper parameter tuning and 10 different kernel initializes.
2. 473 samples, in a batch size of 32, were used in a advance pass through the neural network and generated Z-values and Activations for all the layers.
3. The loss was back propagated through the neural network layers for generating the gradients.

Each step involves using the model with the current set of internal parameters to make predictions on some samples, comparing the predictions to the real expected outcomes, calculating the error, and using the error to update the internal model parameters.

This update procedure is different for different algorithms, but in the case of artificial neural networks, the back propagation update algorithm is used.

The neural network starts its iteration with some random weights and then iteratively update these weight values with better modifications. The underlying concept is transforming non linear input data from input data space to output data space in a layered manner and this is done by mathematical

Table 3. Feature Importance of Decision Tree

Feature	Feature Importance Score	Permutation Feature Importance score
Feature 0: Temperature	0.14	0.145
Feature 1: Pressure	0.52	0.367
Feature 2: Humidity	0.43	0.236
Feature 3: Wind Direction	0.02	0.138
Feature 4: Precipitation	0.03	0.142
Feature 5: Gust	0.48	0.465
Feature 6: Cloud	0.03	0.121
Feature 7: Max-temp	0.04	0.131
Feature 8: Min-temp	0.04	0.132
Feature 9: Wind Speed	0.32	0.237
Feature 10: Day of the Year	0.57	0.275
Feature 11: Day Length	0.65	0.302

concept called as kernel function. This neural network is designed with 8 layers for this non-linear transformation using kernel. Initial step is to do kernel initialization, the process in which neural network weights are initialized with some values with definite logic. The library functions will generate numbers based on some statistical distribution and these numbers play the role of weights. Initialization of layer weights is a very important aspect of deep neural network as it is directly related to the performance of the NN model.

3.2.3.2 Tuning the Framework

There are default parameters available for neural network, the proposed method suggests hyperparameter tuning with kernel initialize and generated 10-12 models of deep neural network with weight initialiser. The experiment is done to find suitable hybrid model and its influence on the nonlinear weather data set training process for the solar irradiance prediction. Following weight initializers(kernel initializers) are combined with Relu activation function. Relu is effective and less complex as it spins half of the Z-values (the negative ones) into zeros, effectively removes about half of the variance and it simply doubles the variance of weights to compensate it.

4. RESULTS AND DISCUSSION

4.1 Tabular Analysis

Results obtained by integrated decision tree regression and ANN(TensorFlow Deep Learning Framework) are available in the following table and graphical analysis is also available.

Table 4. Hyper parameterization for TensorFlow Deep Learning Framework

Initialization scheme	Nature of weights generation	Initialization scheme	Nature of weights generation
Normal distribution	Functions that generate constants like 1 or 0 with some multiplying factor	Variance scaling	It is base for glorot or He, difference in a truncated normal distribution plays the role to generate numbers generates weights from a uniform distribution within a range of – constant to + constant, where constant is $\sqrt{\text{no of layers} / (\text{no of input units} + \text{no of output units})}$ samples are drawn from a truncated/ untruncated normal distribution with a mean of zero and a standard deviation(constant defined above)
Uniform distribution	Functions that generate constants like 1 or 0 with uniform distribution	orthogonal	Weight matrix is formed for neural network nodes in the form of tensor and weight tensor is initialized with orthogonal matrix obtained from the QR decomposition of a matrix of random numbers, random numbers are generated with normal distriction, it leads to orthogonal rows or columns depending on number of columns and rows
Random normal	random values from a Normal distribution (0,1) and multiply them by a small number	Lecun normal	generates weights from a truncated normal distribution, starting from 0 with standard deviation of $\sqrt{1 / (\text{no of input units})}$
Random uniform	random values from a uniform distribution (0,1) and multiply them by a small number	Lecun uniform	generates weights from a uniform distribution within a range of – constant to + constant, where constant is $\sqrt{3 / (\text{no of input units})}$
Truncated normal	neatly distributed around 0 or more, but truncate them to avoid outliers, generates weights from a truncated normal distribution centered on 0 with standard deviation of $\sqrt{2 / (\text{no of input units} + \text{no of output units})}$		

R-squared (r²) accuracy score is a performance measure that represents the ratio of the variance for a dependent variable along with independent variable or variables in a regression model. It is also known as the coefficient of determination to validate hybrid model to predict the dependent variable on one or more independent variables.

Table 5. Accuracy scores of hybrid models

Hyper parameters	Accuracy score	RMSE	MAPE	MSE	MAE
Relu-Normal adam	0.9209	0.24kwh/m ²	13%	0.067	0.087
Relu-Uniform Adadelata	0.9112	0.32kwh/m ²	12%	0.078	0.098
'ReLU-random_normal	0.9353	0.34kwh/m ²	23%	0.043	0.053
'ReLU-random_uniform	0.92511	0.21kwh/m ²	22%	0.098	0.08
Relu Truncated normal	0.9110	0.24kwh/m ²	21%	0.11	0.112
Relu Variance scaling, Rmsprop	0.9221	0.20kwh/m ²	11%	0.12	0.212
Relu orthogonal	0.9353	0.21kwh/m ²	10%	0.075	0.175
Relu Lecun normal	0.929	0.22kwh/m ²	12%	0.064	0.164
Relu Lecun uniform	0.9366	0.34kwh/m ²	13%	0.032	0.132

So if it is 100%, the two variables are perfectly correlated, i.e., with no variance at all. The closer value indicate the validation of the model. The result table table 5 demonstrates r-squared accuracy score greater than 0.7, generally considered as strong effect of independent variable, the combined effect of wind direction, wind speed and day of the year on the prediction of solar radiation. Variance of solar irradiance can be justified by taking prediction along the integrated correlation of wind speed, wind direction and day of the year factor.

The authors of ((Mariam Alkandari & Imtiaz Anad(2020))) have presented similar dataset for the location of Cocoa (USA) and combined theta statistical model with deep learning. The performance measures of nMAE normalized Mean Absolute Error(Eq.18, Eq.19 ((Mariam Alkandari & Imtiaz Anad(2020)))) and normalized Mean square error are evaluated for proposed model. However, slight difference in the size and weather parameters produced comparable results.

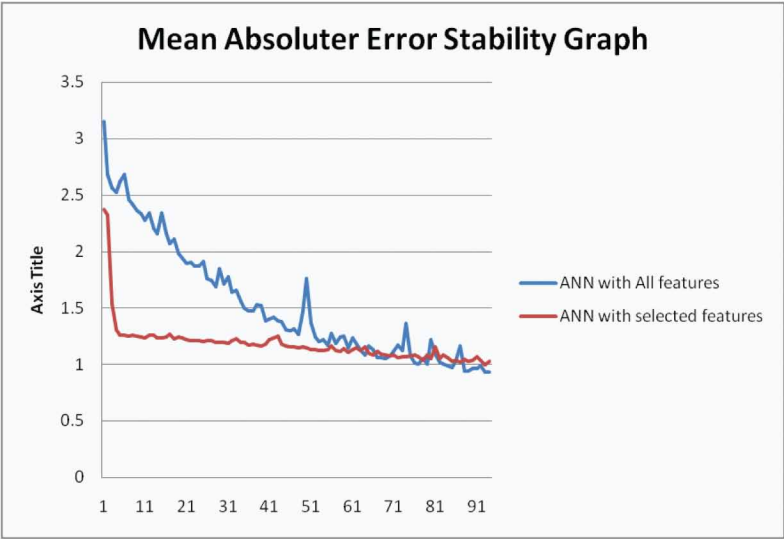
4.2 Graphical Analysis

It is done for reduction of mean absolute error when Tensorflow Deep Learning Framework is executed with all 12 features and after integration of DTR for feature selection and feature of importance are selected, framework is implemented for limited features. Mean absolute error is plotted on Y axis acroos 100 epochs of ANN training. The observation is mean absolute error is stabilized after 60 epochs, as demonstrated in the figure 2.

Table 6. Comparative Analysis with existing work

Approach	Data Set (Days)	Weather Parameters	NMAE (Min-Max)	NMSE (Min-Max)
Integrated Deep learning and statistical method ((Mariam Alkandari & Imtiaz Anad(2020)))	316(COCOa Poly-SI)	Solar irradiance ambient temperature, humidity, precipitation,	0.02-0.07	0.016-0.05
Integrated Regression DTR+TensorFlow ANN(proposed)	473	Solar Irradiance(Direct), temperature, pressure, humidity, gust, wind speed, wind direction, day of the year, daylength(s)	0.087-0.023	0.023-0.046

Figure 2. Mean absolute error comparative for two feature sets



The observed and predicted solar radiance after integrated DTR and TensorFlow Deep learning Framework is compared and demonstrate in Figure 3, and comparable results are seen. Similarly, Figure 4 demonstrates Histogram for daily prediction and observed solar irradiance. Time series data can be extended for daily, weekly, predictions, for seasonal predictions in broad manner.

4.3 Future Research Directions

The graphical analysis pointed out some issues:

1. Solar radiation at the location of central India, is almost in a definite range and stable with variance of weather factors.

Figure 3. Observed v/s Predicted Solar Radiance for one year

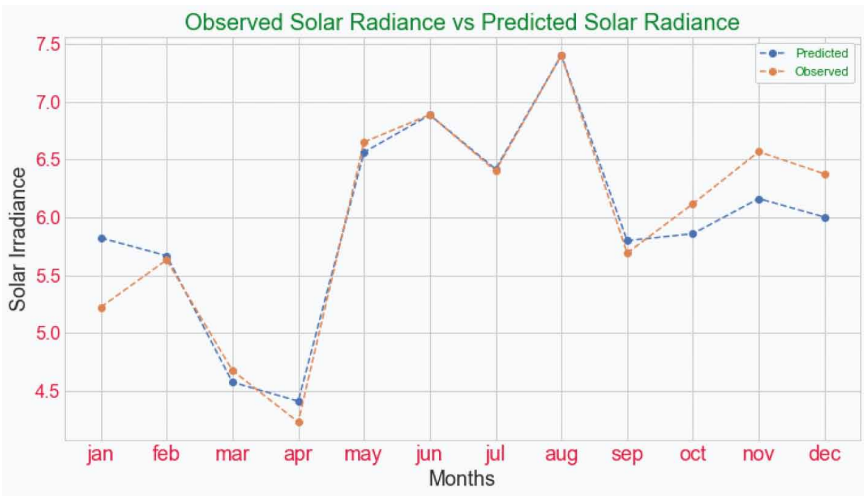
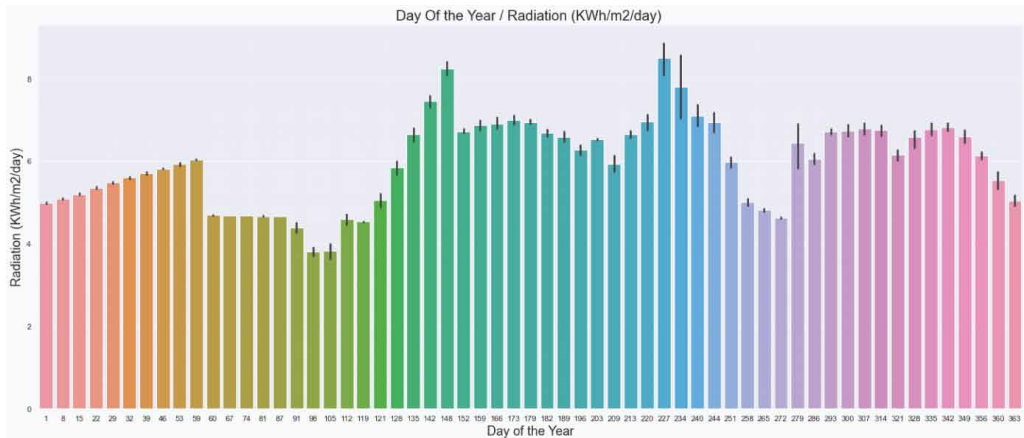


Figure 4. Histogram of Day wise solar radiance (observed / predicted)



2. Decision tree regression is also highlighted best possible prediction node, as root node wind speed, then humidity and pressure at next possible level. Mean values of these significant factors are taken from the month February till September.
3. Combined effect of weather factors will lead to more accurate prediction of solar irradiance with the help of hyper parameter tuned neural network.
4. Figure 2 and figure 3 demonstrates that observed and predicted values of solar irradiance are comparable during this period. Results can be extended for different input combination and variation in learning rate.

5. CONCLUSION

The paper presented, preprocessed standard meteorological dataset for solar radiance prediction which is trained using hybrid machine learning model (decision tree regressor+hyper parameterized ANN). Using decision tree regressor, it has identified the most significant environment variables pressure, humidity and gust, day of the year, and day length(sec) and train ANN (TensorFlow Deep Learning Framework by tuning it to predict solar irradiance. The results obtained are meaningful because proper combination of weather factors can estimate the potential solar energy reasonably without physical expenses.

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