Solar Power Generation Prediction

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Abstract. Predicting sun irradiance has been a crucial subject in the production of renewable energy. Prediction enhances solar system development and operation and provides several financial benefits to power companies. Statistical techniques like artificial neural networks (ANN), support vector machines (SVM), or autoregressive moving average can be used to forecast the irradiance (ARMA). However, because to their scalability or the fact that they are unable to be employed with huge data, they either lack accuracy due to their inability to capture long-term reliance. Thus, in this paper the XGBoost algorithm is implemented for prediction and Optuna Algorithm for Hyper parameter tuning and optimizing the results. Aside from predicting the solar irradiance. It is crucial to create a tool that will estimate the entire amount of energy that can be produced by a solar power plant, array, or household solar setup based on the expected solar radiation and the site's particular solar panel or array parameters. In this work methodology designed and developed a system that will not only predict the solar irradiance for next 15 days based on real time forecast but it will also predict the power generation in units for your solar power panel or array. This system is currently implemented in a webapp that can be accessed through any browser.

Keywords: Solar Irradiance · XGBoost · Optuna · Webapp · Real-time forecast

1 Introduction

In recent times, conventional energy sources are depleting are harmful to the environment. Hence, renewable energy sources like Wind Power and Solar Power are getting the most attention. However Solar Power is still pretty inefficient. Current solar panels have only 25% to 30% efficiency. These are also high quality expensive solar panels; the common solar panels have the efficiency of around 10% to 20%. Apart from these facts, solar panel is still the most abundant and cleaner energy source. However, the biggest problem with renewable energy is that it is not constant. Thus it is important to predict the power generation of solar panels through irradiance prediction.

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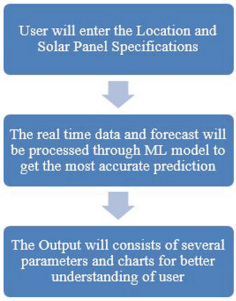


Fig. 1. Data Flow Model

2 Current Scenario

In present scenario, there are some commercial companies like "solacast" are working on the same problem. They have developed some commercial solutions too. However, it is not accessible to everyone as it is paid and not available in a tool format. There are some tools developed by research agencies like ISRO which performs the task. But there are few major differences and none of them are meant to be used by common people.

2.1 Limitations of the Current System

- It is paid and complex (Industry Specific).
- The results are not easy to interpret for home owners or small business owners who have solar power system.
- In some of the cases, forecast data is not ideal for visualization and planning.
- Hence, in this paper those aspects have been considered to ease the user to find the solar power generation prediction for their solar power system. AI Techniques for Transmission Line Performance Improvement

3 Machine Learning Implementation

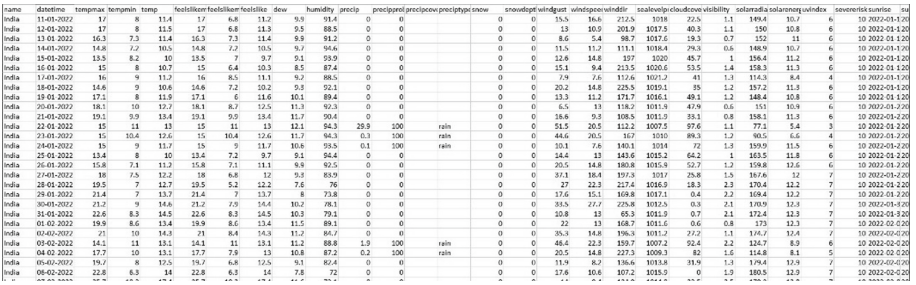
Following section describes data flow model and development of machine learning model (Fig. 1).

3.1 Data Flow Model

3.2 Development of Machine Learning Model

- Input: 25 parameters like temperature, cloud coverage, humidity, wind speed, sunrise, sunset, etc.
- Output: Prediction of Solar Irradiance in W/m2
- Dataset: Here is how our dataset looks like

A dataset of 100 values is utilized for now, but as the scope of the project increases dataset size can also be increased to achieve higher accuracy (Fig. 2).



name	datetime	tempmax	tempmin	temp	feelslikemax	feelslikemin	feelslike	dew	humidity	precip	precipprob	precipcover	preciptype	snow	snowdepth	windgust	windspeed	winddir	sealevelpressure	cloudcover	visibility	solarradiation	solarenergy	uvindex	severerisk	sunrise	su
India	11-01-2022	17	8	11.4	17	6.8	11.2	9.9	93.4	0	0			0	0	35.5	16.6	212.5	1018	22.5	1.1	149.4	10.7	6		10 2022-01-1 20	
India	12-01-2022	17	8	11.5	17	6.8	11.3	9.5	88.5	0	0			0	0	13	10.9	201.9	1017.5	40.3	1.1	150	10.8	6		10 2022-01-1 20	
India	13-01-2022	16.3	7.3	11.4	16.3	7.3	11.4	9.9	91.2	0	0			0	0	8.6	5.4	98.7	1017.6	19.3	0.7	152	11	6		10 2022-01-1 20	
India	14-01-2022	14.8	7.2	10.5	14.8	7.2	10.5	9.7	94.6	0	0			0	0	11.5	11.2	111.1	1016.4	79.3	0.6	148.9	10.7	6		10 2022-01-1 20	
India	15-01-2022	13.5	8.2	10	13.5	7	9.7	9.1	93.9	0	0			0	0	12.6	14.8	197	1020	45.7	1	156.4	11.2	6		10 2022-01-1 20	
India	16-01-2022	15	8	10.7	15	6.4	10.3	8.5	87.4	0	0			0	0	15.1	9.4	213.5	1020.6	53.5	1.4	158.3	11.3	6		10 2022-01-1 20	
India	17-01-2022	16	9	11.2	16	8.5	11.1	9.2	88.5	0	0			0	0	7.9	7.6	112.6	1021.2	41	1.3	114.3	8.4	4		10 2022-01-1 20	
India	18-01-2022	14.6	9	10.6	14.6	7.2	10.2	9.3	92.1	0	0			0	0	20.2	14.8	225.5	1019.1	35	1.2	157.2	11.3	6		10 2022-01-1 20	
India	19-01-2022	17.1	8	11.9	17.1	6	11.6	10.1	89.4	0	0			0	0	13.3	11.2	171.7	1016.1	49.1	1.2	148.4	10.8	6		10 2022-01-1 20	
India	20-01-2022	18.1	10	12.7	18.1	8.7	12.5	11.3	92.3	0	0			0	0	6.5	13	118.2	1011.9	47.9	0.6	153	10.9	6		10 2022-01-2 20	
India	21-01-2022	19.1	9.9	13.4	19.1	9.9	13.4	11.7	90.4	0	0			0	0	18.6	9.3	108.5	1011.9	33.1	0.8	158.1	11.3	6		10 2022-01-2 20	
India	22-01-2022	15	11	13	15	11	13	12.1	94.3	29.9	100	rain		0	0	51.5	20.5	112.2	1007.5	97.6	1.1	77.1	5.4	3		10 2022-01-2 20	
India	23-01-2022	15	10.4	12.6	15	10.4	12.6	11.7	94.3	0.3	100	rain		0	0	44.6	20.5	167	1010	89.3	1.2	90.5	6.6	4		10 2022-01-2 20	
India	24-01-2022	15	9	11.7	15	9	11.7	10.6	93.5	0.1	100	rain		0	0	10.1	7.6	140.1	1014	72	1.3	159.9	11.5	6		10 2022-01-2 20	
India	25-01-2022	13.4	8	10	13.4	7.2	9.7	9.1	94.4	0	0			0	0	14.4	13	143.6	1015.2	64.2	1	163.5	11.8	6		10 2022-01-2 20	
India	26-01-2022	15.8	7.1	11.2	15.8	7.1	11.1	9.9	92.5	0	0			0	0	20.5	14.8	180.8	1015.9	52.7	1.2	159.8	12.6	6		10 2022-01-2 20	
India	27-01-2022	18	7.5	12.2	18	6.8	12	9.3	83.9	0	0			0	0	37.1	18.4	197.3	1017	25.8	1.3	167.6	12	7		10 2022-01-2 20	
India	28-01-2022	19.5	7	12.7	19.5	5.2	12.2	7.6	76	0	0			0	0	27	22.3	217.4	1016.9	18.3	2.3	170.4	12.2	7		10 2022-01-2 20	
India	29-01-2022	21.4	7	13.7	21.4	7	13.7	8	73.8	0	0			0	0	17.6	15.1	169.8	1017.1	0.4	2.2	169.4	12.2	7		10 2022-01-2 20	
India	30-01-2022	21.2	9	14.6	21.2	7.9	14.4	10.2	78.1	0	0			0	0	33.5	27.7	225.8	1012.5	0.3	2.1	170.9	12.3	7		10 2022-01-3 20	
India	31-01-2022	22.6	8.3	14.5	22.6	8.3	14.5	10.3	79.1	0	0			0	0	10.8	13	65.3	1011.9	0.7	2.1	172.4	12.3	7		10 2022-01-3 20	
India	01-02-2022	19.9	8.6	13.4	19.9	8.6	13.4	11.5	89.1	0	0			0	0	22	13	168.7	1011.6	0.6	0.8	173	12.3	7		10 2022-02-0 20	
India	02-02-2022	21	10	14.3	21	8.4	14.3	11.2	84.7	0	0			0	0	35.3	14.8	196.3	1011.2	27.2	1.1	174.7	12.4	7		10 2022-02-0 20	
India	03-02-2022	14.1	11	13.1	14.1	11	13.1	11.2	88.8	1.9	100	rain		0	0	48.4	22.3	159.7	1007.2	92.4	2.2	124.7	8.9	6		10 2022-02-0 20	
India	04-02-2022	17.7	10	13.1	17.7	7.9	13	10.8	87.2	0.2	100	rain		0	0	20.5	14.8	227.3	1009.3	82	1.6	114.8	8.1	5		10 2022-02-0 20	
India	05-02-2022	19.7	8	12.5	19.7	6.8	12.5	9.1	82.4	0	0			0	0	11.9	8.2	136.6	1013.8	33.9	1.3	179.4	12.9	7		10 2022-02-0 20	
India	06-02-2022	22.8	6.3	14	22.8	6.3	14	7.8	72	0	0			0	0	17.6	10.6	107.2	1015.9	0	1.9	180.5	12.9	7		10 2022-02-0 20	

Fig. 2. Dataset of Solar Irradiance

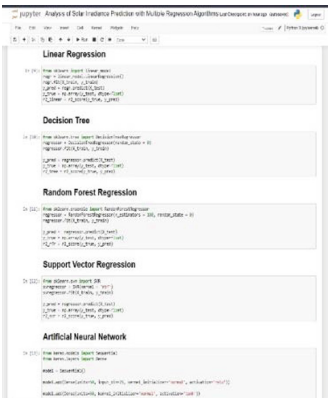


Fig. 3. Python code for Solar Irradiance Prediction

3.3 Learning Algorithm

This particular problem comes under the category of Supervised Learning. We train our machine learning mode using the following 3 learning models and compare the accuracies:

1. Linear Regression
2. Decision Tree
3. Support Vector Machine
4. Artificial Neural Networks
5. XGBoost & Optuna

Here is a segment of the Python code: (Fig. 3)

The following output is obtained using the sklearn, tensorflow and keras libraries in python: (Fig. 4)

Since we obtain the highest accuracy of XGBoost and Optuna, we opt that model. A brief explanation about XGBoost is given:

```
R^2 Score for Linear Regression: 0.6314
R^2 Score for Decision Tree: 0.8909
R^2 Score for SVM: 0.8909
R^2 Score for ANN: 0.8528
R^2 Score for XGboost & Optuna: 0.9407
```

Fig. 4. Accuracy of different algorithm

Fig. 5. API response

XGboost

XGBoost is a distributed gradient boosting library that has been developed to be very effective, adaptable, and portable. It uses the Gradient Boosting framework to construct machine learning algorithms. A parallel tree boosting method called XGBoost (also known as GBDT or GBM) is available to quickly and accurately address a variety of data science issues. The same algorithm can answer problems with more than a trillion instances and runs on key distributed environments (Hadoop, SGE, MPI).

Optuna

A software framework called Optuna is used to automate the optimization of these hyperparameters. By utilising several samplers, including grid search, random, bayesian, and evolutionary algorithms, it automatically determines the best hyperparameter values.

3.4 Fetching Real Time Data for Forecast

In order to make even more accurate prediction, we are fetching real time data for current day and weather forecast data for next 14 days. This data is being fetched by an API by visualcrossing. It contains parameters like, temperature, cloud coverage, humidity, wind speed, sunrise, sunset, etc.

Following is an example of API response (Fig. 5).

This API data is then again converted into CSV format and it is again fed to the model. The model will generate the predictions based on this data (Fig. 6).

3.4.1 Large Scale Application

- This Prediction system can be useful to large industries, home owners, small industries, etc. who use solar power system to predict their power generation.
- This system can help them analyze and plan their power usage in accordance with the predicted data.
- This system can further be implemented to manage microgrids.
- The microgrids along with the main grid can be used to fulfill power requirements of houses, industries, etc.

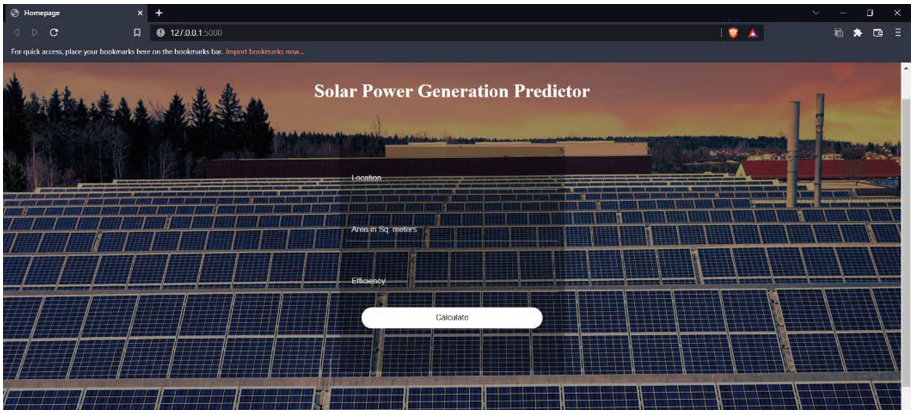


Fig. 6. Homepage of the Web Application

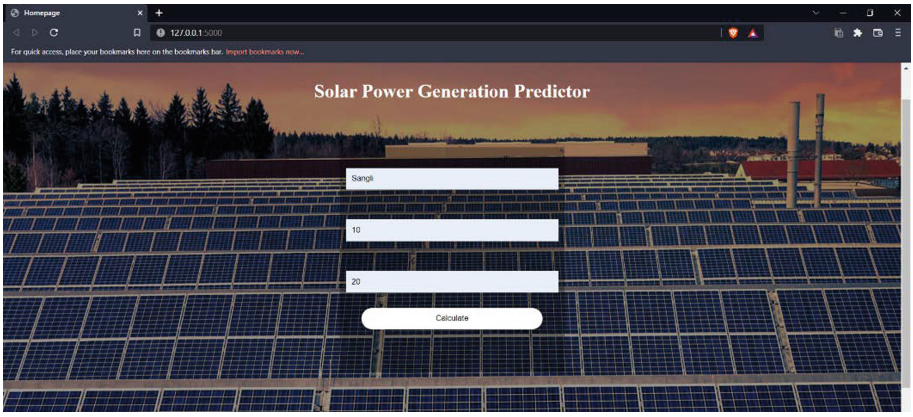


Fig. 7. Example of User Input Data

Fig. 8. Predictions and other parameters in graphical form for better visualization

- The majority of the power needs can be fulfilled with solar power system and based on predictions done by our system, the extra required power can be sourced from the main grid.
- This will not only save a lot of cost for both government and consumers but it will also be efficient for environment.

3.4.2 Web Application

- After implementing this system successfully, a simple web app can be designed for users so that they can generate predictions for their solar power system.
- This Web Application will take 3 inputs from users,

– Location.
– Area of Solar Panel(s).
– Efficiency of Solar Panel.

- This system can also be used by industries to predict their power generation and analyze cost savings.

4 Conclusion

In this paper different ML models are analyzed to predict the output, fetched real time data from API, converted that data to CSV format and performed predictions on that data (Fig. 7). We also designed a webapp to display the predictions in an interactive way with better visualization. In future, the accuracy can be further increased by using better dataset and this system can also be used in microgrid management (Fig. 8).

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