SOLAR ENERGY FORECASTING USING MACHINE LEARNING

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ABSTRACT:

As a result of the climate and energy crises, renewable energy generation, including solar generation, has grown significantly. In smart grid, photovoltaic (PV) generation is becoming increasingly prevalent. Because the solar source at ground level is highly dependent on cloud cover variability, atmospheric aerosol levels, and other atmosphere parameters, solar power is intermittent and variable. Large-scale solar generation's inherent variability poses significant challenges to smart grid energy management. Accurate forecasting of solar power/irradiance is critical to ensuring the smart grid's economic operation. We employ a number of variable selection techniques, which lead us to believe that air temperature, relative humidity, and dew point are the most informative weather parameters for predicting solar energy generation at the power plant. A tensor flow-based sequential algorithm is used in this project to train and predict solar energy models.

INTRODUCTION:

1.1 Introduction

Alternative power generation has received a lot of attention over the last decade due to the rapidly growing interest in renewable energy and the gradually decreasing costs of power generation. Solar power, in particular, has the potential to account for a larger share of growing energy needs as it becomes more cost-effective. According to reports, photovoltaic (PV) module costs have dropped by roughly four-fifths, making residential solar PV systems up to two-thirds cheaper than in 2010 [1]. As the cost of installing PV modules decreases, the cost of operations and maintenance (O&M) gradually consumes a large portion of the cost of power generation. Maintaining PV operations may be considered simpler and less expensive than other alternative energy sources, such as wind power and natural gas; however, because power supply is largely dependent on changing weather, determining power price and managing production budgets for system operators and power market participants become critical issues to keep power plants commercially viable. Solar PV system operators use long and short term solar power forecasts to schedule generation, estimate operating reserves, and ensure system stability through output fluctuation. Forecasts are also used by market participants to manage their generation portfolios. Given that 38 GW of solar capacity was traded on the energy market in Germany in 2014 [3,] solar power forecasting has a significant impact on market price and cost-efficiency of power generation. As a result, solar power forecasting is now an important part of PV system management. Solar power forecasting techniques have been extensively studied not only in the solar power industry but also in academic communities (See recent surveys for an overview of operating reserves and ensuring system stability through output fluctuation). Forecasts are also used by market participants to manage their generation portfolios. Given that 38 GW of solar capacity was traded on the energy market in Germany in 2014 [3,] solar power forecasting has a significant impact on market price and cost-efficiency of power generation. As a result, solar power forecasting is now an important part of PV system management. Solar power forecasting techniques have been extensively researched not only in the solar power industry but also in academic circles (An overview can be found in recent surveys.

Traditional forecasting techniques have mostly relied on physical models that calculate solar power based on irradiation or a simple linear/non-linear regression model. However, due to the non-linear dependence of solar power generation efficiency on meteorological variables such as irradiation and temperature, as well as irregular errors in input data exhibited by inaccurate sensors, they require extensive pre-processing to refine input data and suffer from poor accuracy with incomplete inputs. Thus, deep learning, a cutting-edge machine learning technique based on artificial neural networks that has achieved significant performance improvements in a variety of prediction problems, has recently been introduced for forecasting solar power.

Intensifying energy demand is paving the way for the integration of renewable solar energy with non renewable energy resources. Solar energy, unlike other non renewable energy sources, is continuous. Accurate solar power forecasting is required for effective utilisation of spontaneously available energy. On a solar dataset, this study aims to predict solar power using deep neural networks (DNNs) and various machine learning (ML) techniques such as linear regression, support vector regression, random forest, and so on. The dataset is used to extract solar power energy every five minutes. Furthermore, a comparison study is conducted between DNNs and ML techniques, which aids in crafting appropriate decisions to select appropriate forecasting and prediction techniques.

This study proposed a combination of different ML and DL techniques that were used to determine the best combination in order to obtain accurate results that could then be compared to the results of other models. A hierarchical and layered approach was used in this study to determine the closest possible solar radiance value from the solar irradiance value of the previous few days. SVR and GB appear to perform the best on the given dataset, with roughly equivalent scores, of all the techniques discussed. Although GB outperforms SVR in terms of output stability, SVR has more variations in output compared to similar inputs, making it less stable. Seasonal inputs do not appear to work well with DL models. The study gave users the option of using one of several models to forecast solar irradiance based on previous data and predict solar radiance. This method assisted in determining a specific attribute or feature independently of other attributes from

2. LITERATURE SURVEY

any other model if the value of that attribute had previously been measured. As a result, predicting solar radiance value is independent of a single model. In short, the best algorithm for solar power prediction can be determined using various ML and DL techniques. Hyper parameter optimization and other techniques can also be used to carry out additional modifications based on the best-suited algorithm in order to improve accuracy even further.

3. OVERVIEW OF THE SYSTEM

3.1 Existing System

Existing system:

• A model based on least-square support vector machine (LS-SVM) is proposed for short-term solar power prediction. The LSSVM model outperforms a reference AR model in terms of forecasted atmospheric transmissivity, which is converted to solar power.

• For forecasting mean hourly global solar radiation, several AI techniques, including linear, feed-forward, recurrent Elman, and Radial Basis Function NNs, as well as the adaptive neuro-fuzzy inference scheme, are proposed.

Disadvantages:

• Because of the inherent variability of large-scale solar generation, smart grid energy management faces significant challenges.

• Because current system forecasting is inaccurate, effective forecasting of solar power/irradiance is critical to ensuring the economic operation of the smart grid.

3.2 Proposed system:

• In the proposed system, a tensorflow sequential model algorithm is used to predict solar energy forecasting. Unlike statistical models and AI techniques, physical models use solar and PV models to predict solar irradiance/power.

Advantages:

• The accuracy of predicting solar energy is high when compared to previous models.

• Applications of solar forecasting in energy management using Trained model can improve effective management of solar energy.

3.3 System Modules

Dataset Collection:

This module collects a dataset from Kaggle that includes weather conditions as features and power output as labels.

Cloud Coverage ; Visibility ; Temperature ; Dew Point ; Relative Humidity ; Wind Speed ; Station Pressure ; Altimeter

Preprocessing:

Unwanted values are removed in this step. The dataset is removed, and the features and labels are processed in order to save them in various variables.

Splitting Data:

To test the efficiency of the algorithm, the data set is divided into testing and training sets, which are used for fitting into the algorithm and predicting based on the test set and calculating accuracy.

Algorithm Initialization:

Tensor flow sequential model is used in this step to train the model by fitting testing set features and labels into the algorithm using the fit function, and the model is saved in.h5 format.

Prediction:

Prediction is performed based on user-supplied input values, and the result is displayed on a web page.

4. RESULTS

Data set:

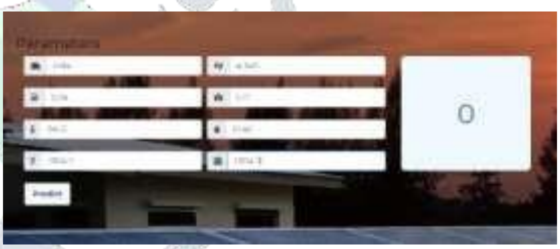
	A	B	C	D	E	F	G	H	I	J	K
1	Date	Cloud coverag	Visibility	Temperature	Dew point	Relative humi	Wind speed	Station press	Altimeter	Solar energy	(Inverters)
2	01-02-2016	0.10375	9.44791667	3.11375	0.32166667	79.4545833	4.89458333	29.22875	30.0195833	20258	
3	02-02-2016	0.70833333	3.94125	6.9925	6.21541667	93.5975	13.2908333	28.9116667	29.6979167	1761	
4	03-02-2016	0.86458333	8.68958333	1.615	0.02291667	85.0016667	16.72625	29.0266667	29.8145833	2775	
5	04-02-2016	0.37291667	10	-2.4725	-5.88625	74.5225	9.45541667	29.455	30.2545833	28695	
6	05-02-2016	0.51541667	9.20666667	-2.00291667	-4.15208333	82.0275	5.92	29.5508333	30.35125	9517	
7	06-02-2016	0.1325	8.12208333	0.90791667	-1.6175	81.0255667	5.48083333	29.4366667	30.235	26973	
8	07-02-2016	0.20458333	10	4.23916667	0.5375	73.7983333	12.7066667	29.0941667	29.8841667	22365	
9	08-02-2016	0.865	7.83625	-3.33	-5.04958333	83.5316667	14.4583333	28.9575	29.7458333	4995	
10	09-02-2016	0.99708333	6.00708333	-7.80125	-10.39375	78.3441667	17.2695833	29.0945833	29.8866667	6641	
11	10-02-2016	0.24583333	10	-9.71958333	-13.9816667	67.6954167	10.3020833	29.2883333	30.08	20758	
12	11-02-2016	0.34041667	10	-7.63791667	-11.7291667	60.3608333	3.85125	29.47875	30.2783333	30918	
13	12-02-2016	0.63166667	9.35041667	-5.78166667	-9.995	69.7604167	12.4233333	29.45625	30.25625	8305	
14	13-02-2016	0.08333333	10	-10.1220833	-17.7695833	52.3233333	7.43791667	29.7333333	30.535	30358	
15	14-02-2016	1	8.37	-7.29375	-9.98666667	78.47	13.7916667	29.38125	30.1766667	5814	
16	15-02-2016	0.94291667	3.85708333	-2.41916667	-3.68	94.0166667	6.43166667	29.0879167	29.8791667	7570	
17	16-02-2016	0.78958333	6.985	-1.29166667	-2.92416667	87.57	4.92583333	29.0783333	29.8695833	27097	
18	17-02-2016	0.82083333	8.09625	0.09833333	-2.43333333	82.5229167	5.59875	29.44	30.2183333	7571	
19	18-02-2016	0.41458333	7.96	3.43791667	0.32375	78.58375	15.0770833	29.4141667	30.2108333	19145	
20	19-02-2016	0.03625	10	10.03375	4.24083333	65.96875	17.9683333	29.0345833	29.82375	26458	
21	20-02-2016	0.04333333	10	10.5429167	7.91916667	56.8020833	30.75	29.1508333	29.9408333	30388	
22	21-02-2016	0.59625	10	4.855	1.63958333	78.8125	10.2683333	29.2870833	30.0804167	27178	
23	22-02-2016	0.29708333	10	3.015	-0.82208333	74.5333333	7.41625	29.3375	30.13125	26658	
24	23-02-2016	0.06458333	10	3.8475	-1.32	69.8129167	13.3933333	29.1908333	29.9825	26058	
25	24-02-2016	1	4.44041667	0.97958333	-0.48583333	86.895	24.8245833	28.77875	29.5633333	1468	
26	25-02-2016	0.87791667	8.39375	1.28833333	-1.70625	77.6558333	13.3558333	29.2029167	29.985	14631	

Test set:

	A
1	11;27;4;2017;1;10;8.63;6.21;83;16.32;28.91;29.69;1293.75
2	15;9;10;2016;0;10;24.07;5.9;28.96;9.32;29.47;30.27;3024.5
3	6;10;5;2017;0.73;4.96;13.85;11.99;90;5.4;29.16;29.95;241.73
4	8;30;4;2017;1;7.33;14.83;14.03;97.6;10.82;28.95;29.73;597.5
5	8;19;3;2017;0;10;4.61;0.36;73.2;4.4;29.58;30.38;1647.75
6	15;8;6;2016;0;10;24.96;6.35;29.08;4.12;29.2;29.99;3668.5
7	12;2;9;2017;0;10;21.52;10.53;49.12;8.36;29.26;30.05;4699.5
8	8;21;8;2017;0;10;26.2;23.89;84.16;6.04;29.31;30.1;903.5
9	6;21;11;2016;0;10;-5.14;-6.55;83.72;1.16;29.5;30.3;9.42
10	13;12;9;2016;0;10;26.5;13.49;43.48;9.32;29.3;30.09;4470.25
11	16;9;1;2016;1;10;17.49;14.76;80.24;8.4;29.15;29.94;112.08
12	10;15;11;2016;0;9.92;10.17;7.65;75.72;6.04;29.14;29.93;3802.25
13	9;19;10;2017;0;10;17.76;11.54;67.56;7.04;29.4;30.2;2594.75
14	9;5;8;2016;0.25;10;26.46;22.6;75.84;5.12;29.16;29.95;2953.5
15	14;18;1;2017;0.84;10;4.98;2.85;82.81;10.69;29.31;30.11;1172.25
16	6;20;6;2016;0;10;24.15;21.62;82.08;10.6;29.39;30.19;250.75
17	12;27;5;2017;1;10;20.73;17.76;79.6;3.08;29.13;29.92;1870.75
18	7;10;9;2016;0.63;9.04;21.21;21.28;99.72;0;29.07;29.86;323.48
19	16;29;9;2017;0;10;23.38;3.39;19.84;13.2;8.53;30.2;2234.75
20	7;21;3;2017;0;7.96;4.99;2.48;81;6.16;29.37;30.16;343.43
21	14;13;5;2017;0;10;26;9.6;33.4;9.84;29.08;29.87;4516
22	8;16;4;2017;0.91;10;16.62;15.68;88.08;14.92;29.21;30;608.5
23	14;4;7;2017;0.73;7.55;27.99;14.76;47.93;9.96;29.28;30.07;1300.25
24	12;18;3;2017;1;10;4.81;0.35;70.77;17.08;29.42;30.22;1155.75
25	11;24;6;2017;0.64;10;23.29;12.2;48.56;15.36;29.27;30.06;1397
26	14;7;11;2016;0.15;10;19.24;8.24;47.12;2.8;29.46;30.26;894.75
27	7;12;11;2016;0.14;8.08;-0.73;-0.76;93;0.28;29.68;30.48;783.75

Input page:

Enter values:



Result:

5. Conclusion

The use of the Neural Network technique in solar radiation modelling and prediction is studied using datasets. According to the findings, the proposed ANN model has a high level of accuracy. The model takes into account input parameters such as average temperature, maximum temperature, minimum temperature, and altitude and produces solar radiation as an output. A comparison of the proposed and measured data demonstrates that the model can predict with new data. This model will be suitable for predicting solar power based on various weather factors, and the prediction can be checked using the flask web application.

Future Scope:

The use of the Artificial Neural Network technique in solar radiation modelling and prediction is investigated for four cities in India. According to the findings, the proposed ANN model's accuracy can be improved. The model takes into account input parameters such as average temperature, maximum temperature, minimum temperature, and altitude and produces solar radiation as an output. A comparison of the proposed data with the measured data reveals that the model agrees well with the IMD measured data. This model is appropriate for predicting solar power predictions for locations in India and can be used for solar energy applications.

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