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SOLAR ENERGY FORECASTING ANALYSIS USING MACHINE LEARNING

AHMED MOHAMED JAMA , Dr. A. SIVAKUMAR

Abstract— Due to the challenge of climate and energy crisis, renewable energy generation including solar generation has experienced significant growth, increasingly high penetration level of photovoltaic (PV) generation arises in smart. Solar power is intermittent and variable, as the solar source at the ground level is dependent on cloud cover variability, atmospheric aerosol levels. However, since PV panel energy output depend on weather conditions such as cloud cover and solar irradiance, the energy output of the PV panels is unstable. To understand and manage the output variability is of interest for several actors in the energy market. In the short-term (0-5 hours), a transmission system operator is interested in the energy output from PV panels to find the adequate balance for the whole grid, since over- and under-producing electricity often results in penalty fees. On another side of the spectrum, electricity traders are interested in long time horizons, ordinarily, day-ahead forecasts since most electricity is traded on the day-ahead market. Consequently, the profitability of these operations relies on the ability to forecast the fluctuating solar PV panel energy output accurately. It is likely, as more countries decide to invest more and more in RES, that the use of solar PV panels will continue to increase. This will increase the need for suitable means of forecasting solar PV energy output. While the demand for accurate and efficient forecasts of PV panel energy output is evident, the solution is far from trivial. There are many complications that the current research within the field is handling. One evident nuisance is the inherited variation of weather, which makes accurate weather forecasting challenging. Parallel to the increased demand of PV power forecasting solutions, the means for forecasting with the help of machine learning (ML) techniques have in recent years gained in popularity relative to traditional time series predictive models. Although ML techniques are nothing new, the improved computational capacity and the higher availability of quality data have made the techniques useful for forecasting.

Keywords—Photovoltaic, Machine Learning, Forecasting, Renewable energy generation.

Ahmed Mohamed Jama , Student , M.Sc Information Technology, Department of Information Technology , Rathinam College of Arts and Science , Coimbatore , Tamil Nadu , India – 641021,
(e-mail: ahamedmohammedjama.mit20@rathinam.in).

Dr. A. Sivakumar, Assistant Professor, Department of Computer Science, Rathinam College of Arts and Science, Coimbatore , Tamil Nadu, India – 641021, (e-mail: sivamgp@gmail.com).

I. RELATED WORK

Improving renewable energy forecasting with a grid of numerical weather predictions.

Authors: Jose R. Andrade and Ricardo J. Bessa - In the last two decades, renewable energy forecasting progressed toward the development of advanced physical and statistical algorithms aiming at improving point and probabilistic forecast skill. This paper describes a forecasting framework to explore information from a grid of numerical weather predictions (NWP) applied to both wind and solar energy. The methodology combines the gradient boosting trees algorithm with feature engineering techniques that extract the maximum information from the NWP grid. Compared to a model that only considers one NWP point for a specific location, the results show an average point forecast improvement (in terms of mean absolute error) of 16.09% and 12.85% for solar and wind power, respectively. The probabilistic forecast improvement, in terms of continuous ranked probabilistic score, was 13.11% and 12.06%, respectively.

Solar forecasting methods for renewable energy integration

Authors: Rich H. Inman, Hugo T.C. Pedro, and Carlos F.M. Coimbra - The higher penetration of renewable resources in the energy portfolios of several communities accentuates the need for accurate forecasting of variable resources (solar, wind, tidal) at several different temporal scales in order to achieve power grid balance. Solar generation technologies have experienced strong energy market growth in the past few years, with corresponding increase in local grid penetration rates. As is the case with wind, the solar resource at the ground level is highly variable mostly due to cloud cover variability, atmospheric aerosol levels, and indirectly and to a lesser extent, participating gases in the atmosphere. The inherent variability of solar generation at higher grid penetration levels poses problems associated with the cost of reserves, dispatchable and ancillary generation, and grid reliability in general. As a result, high accuracy forecast systems are required for multiple time horizons that are associated with regulation, dispatching, scheduling and unit commitment. Here we review the theory behind these forecasting methodologies, and a number of successful applications of solar forecasting methods for both the solar resource and the power output of solar plants at the utility scale level.

Review of photovoltaic power forecasting

Authors: Martinez-de Pison, and F. Antonanzas-Torres - Variability of solar resource poses difficulties in grid management as solar penetration rates rise continuously. Thus, the task of solar power forecasting becomes crucial to ensure grid stability and to enable an optimal unit commitment and economical dispatch. Several forecast horizons can be identified, spanning from a few seconds to days or weeks ahead, as well as spatial horizons, from single site to regional forecasts. New techniques and approaches arise worldwide each year to improve accuracy of models with the ultimate goal of reducing uncertainty in the predictions. This paper appears with the aim of compiling a large part of the knowledge about solar power forecasting, focusing on the latest advancements and future trends. Firstly, the motivation to achieve an accurate forecast is presented with the analysis of the economic implications it may have. It is followed by a summary of the main techniques used to issue the predictions. Then, the benefits of point/regional forecasts and deterministic/probabilistic forecasts are discussed. It has been observed that most recent papers highlight the importance of probabilistic predictions and they incorporate an economic assessment of the impact of the accuracy of the forecasts on the grid. Later on, a classification of authors according to forecast horizons and origin of inputs is presented, which represents the most up-to-date compilation of solar power forecasting studies. Finally, all the different metrics used by the researchers have been collected and some remarks for enabling a fair comparison among studies have been stated.

Solar power forecasting performance–towards industry standards.

Authors: V Kostylev, A Pavlovski, et al - Due to the rapid increase in deployment and high penetration of solar power generation worldwide, solar power generation forecasting has become critical to variable generation integration planning, and within utility and independent system operator (ISO) operations. Utilities and ISOs require day ahead and hour ahead as well as intra-hour solar power forecasts for core operations solar power producers and energy traders also require high quality solar power forecasts. As a result of the erroneously perceived simplicity of solar radiation forecasting, very often non-repeatable, poorly explained or obscure estimates of solar power forecast performance are used. This creates uncertainty with the quality of forecasting service, as well as unrealistic expectations of possible forecast precision. As a result, there is an immediate need for defining a common methodology for evaluating forecast performance, establishing verification procedures, and setting common standards for industry-approved quality of solar forecast performance. Solar power forecast quality claims can be easily verified when the source of forecast is known. Most often the offered power generation forecasts are based on publically available results of Numerical Weather Prediction (NWP) models and on the use of empirical relationships between solar resource and generated power at a specific plant. The quality of these forecasts is limited by the quality of the NWP models utilized, which is known. Less frequently, solar radiation is estimated based on proprietary models such as satellite-based or total sky imager–based cloud cover and radiation forecasts. In such cases, there are also known limits to the accuracy of prediction which can help objectively evaluate claims of the forecast service companies. This paper is proposing a set of standards for evaluating intra hour, hour ahead, day ahead and week ahead solar power forecast performance. The proposed standards are based on sound methodologies and extensive field practice and offer a solid ground for reliable inter-agency comparisons of forecast performance.

II. SYSTEM STUDY

1)Existing System:

Kestylev et al. [5] outlines a summary of various techniques employed in the field of solar PV power forecasting. The authors propose that the industry should establish an industry standard. Some useful findings, which are observed in other studies, are for instance substantial improvements for long-term forecasting when using numerical weather predictions (NWP) as input data. Furthermore, modeling future cloud positions with satellite-based data have improved short-term solar PV energy output forecasting. Finally, model accuracy tends to vary depending on the climatic condition of the forecasting location. As of this, a model is likely to perform better in one region than when trained on multiple sites simultaneously. Similarly, as climatic conditions can vary over a yearly cycle, a model may perform better when trained on one weather season rather than several.

2) Proposed System:

As a result of the climate and energy crisis, renewable energy generation, especially solar power, has seen tremendous expansion, resulting in an increasingly high penetration level of photovoltaic (PV) generation in smart homes. Because the solar source at ground level is dependent on cloud cover variations and air aerosol levels, solar power is intermittent and variable.

III.SYSTEM DEVELOPMENT

A. System Architecture:

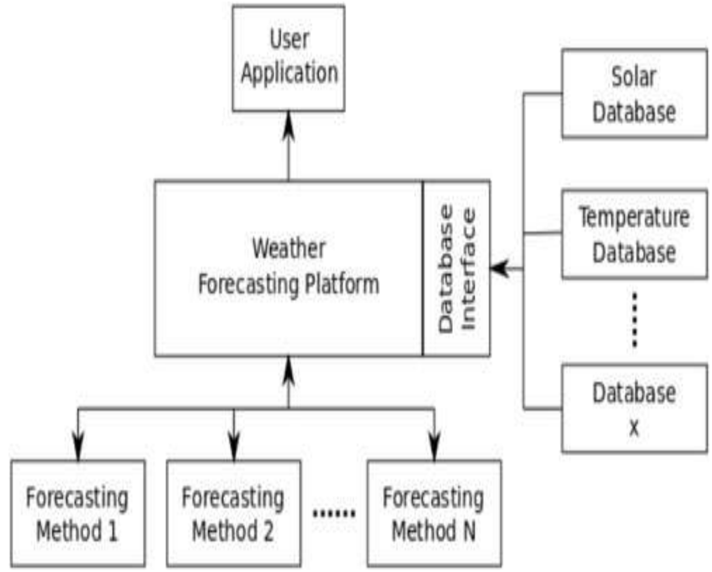

Figure 1: Proposed System Architecture

B. Machine Learning:

Human beings, at this moment, are the most intelligent and advanced species on earth because they can think, evaluate and solve complex problems. On the other side, AI is still in its initial stage and haven’t surpassed human intelligence in many aspects. Then the question is that what is the need to make machine learn? The most suitable reason for doing this is, “to make decisions, based on data, with efficiency and scale”.

Lately, organizations are investing heavily in newer technologies like Artificial Intelligence, Machine Learning and Deep Learning to get the key information from data to perform several real-world tasks and solve problems. We can call it data-driven decisions taken by machines, particularly to automate the process. These data-driven decisions can be used, instead of using programing logic, in the problems that cannot be programmed inherently. The fact is that we can’t do without human intelligence, but other aspect is that we all need to solve real-world problems with efficiency at a huge scale. That is why the need for machine learning arises.

Machine Learning can review large volumes of data and discover specific trends and patterns that would not be apparent to humans. For instance, for an e-commerce website like Amazon, it serves to understand the browsing behaviors and purchase histories of its users to help cater to the right products, deals, and reminders relevant to them. It uses the results to reveal relevant advertisements to them.

C. Modules:

1) Tensorflow

TensorFlow is a free and open-source software library for dataflow and differentiable programming across a range of tasks. It is a symbolic math library, and is also used for machine learning applications such as neural networks. It is used for both research and production at Google.

TensorFlow was developed by the Google Brain team for internal Google use. It was released under the Apache 2.0 open-source license on November 9, 2015.

2) Numpy

Numpy is a general-purpose array-processing package. It provides a high-performance multidimensional array object, and tools for working with these arrays.

It is the fundamental package for scientific computing with Python. It contains various features including these important ones:

- A powerful N-dimensional array object
- Sophisticated (broadcasting) functions
- Tools for integrating C/C++ and Fortran code
- Useful linear algebra, Fourier transform, and random number capabilities

Besides its obvious scientific uses, Numpy can also be used as an efficient multi-dimensional container of generic data. Arbitrary data-types can be defined using Numpy which allows Numpy to seamlessly and speedily integrate with a wide variety of databases.

3)Pandas

Pandas is an open-source Python Library providing high-performance data manipulation and analysis tool using its powerful data structures. Python was majorly used for data munging and preparation. It had very little contribution towards data analysis. Pandas solved this problem. Using Pandas, we can accomplish five typical steps in the processing and analysis of data, regardless of the origin of data load, prepare, manipulate, model, and analyze. Python with Pandas is used in a wide range of fields including academic and commercial domains including finance, economics, Statistics, analytics, etc.

4) Matplotlib

Matplotlib is a Python 2D plotting library which produces publication quality figures in a variety of hardcopy formats and interactive environments across platforms. Matplotlib can be used in Python scripts, the Python and IPython shells, the Jupyter Notebook, web application servers, and four graphical user interface toolkits. Matplotlib tries to make easy things easy and hard things possible. You can generate plots, histograms, power spectra, bar charts, error charts, scatter plots, etc., with just a few lines of code. For examples, see the sample plots and thumbnail gallery.

For simple plotting the pyplot module provides a MATLAB-like interface, particularly when combined with IPython. For the power user, you have full control of line styles, font properties, axes properties, etc, via an object oriented interface or via a set of functions familiar to MATLAB users.

5) Scikit – learn

Scikit-learn provides a range of supervised and unsupervised learning algorithms via a consistent interface in Python. It is licensed under a permissive simplified BSD license and is distributed under many Linux distributions, encouraging academic and commercial use. Python

Python is an interpreted high-level programming language for general-purpose programming. Created by Guido van Rossum and first released in 1991, Python has a design philosophy that emphasizes code readability, notably using significant whitespace.

Python features a dynamic type system and automatic memory management. It supports

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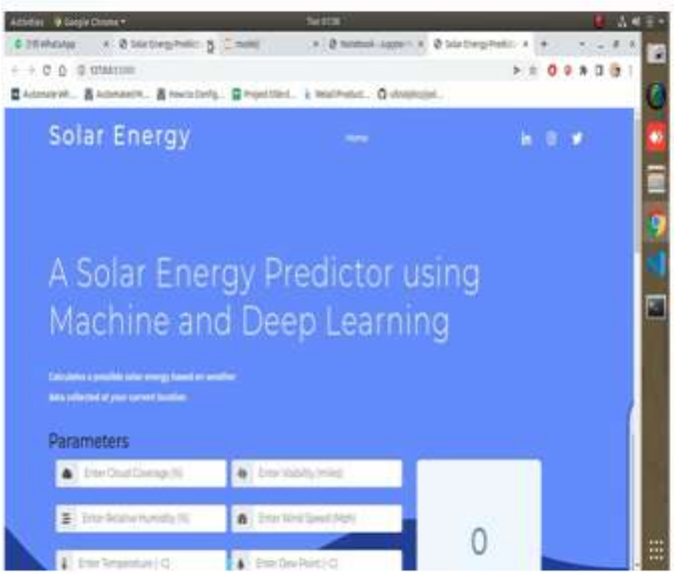
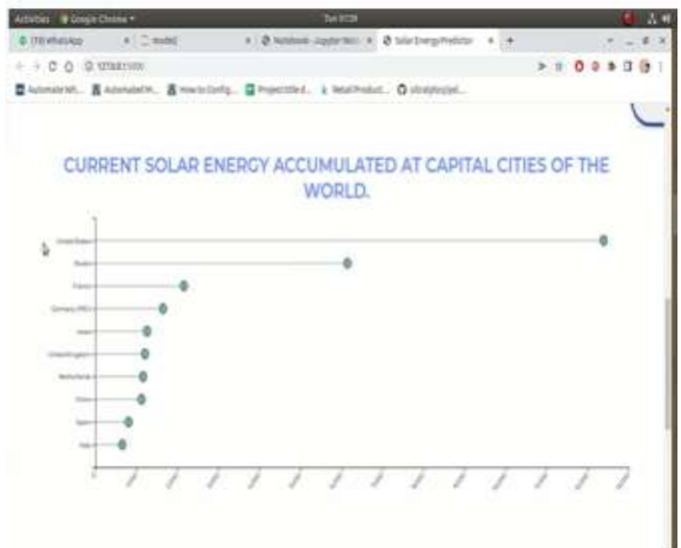
multiple programming paradigms, including object-oriented, imperative, functional and procedural, and has a large and comprehensive standard library.

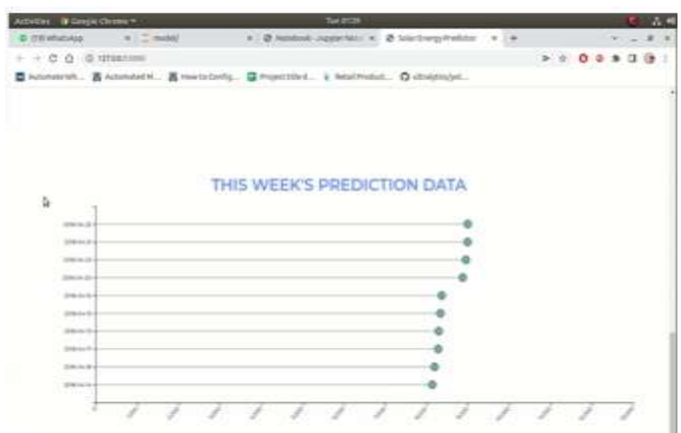
- Python is Interpreted − Python is processed at runtime by the interpreter. You do not need to compile your program before executing it. This is similar to PERL and PHP.
- Python is Interactive − you can actually sit at a Python prompt and interact with the interpreter directly to write your programs.

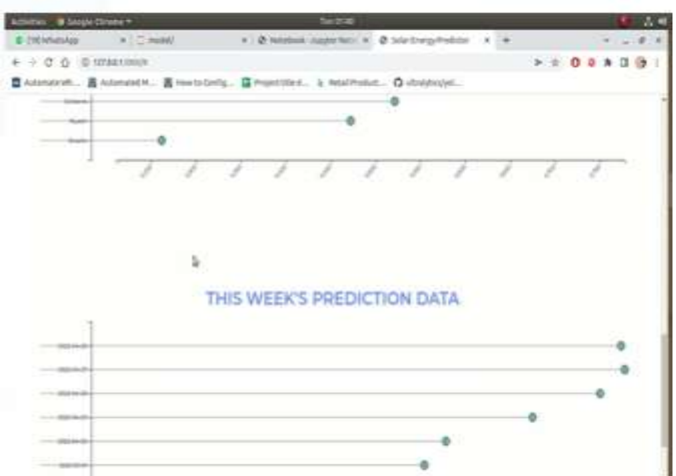
Python also acknowledges that speed of development is important. Readable and terse code is part of this, and so is access to powerful constructs that avoid tedious repetition of code. Maintainability also ties into this may be an all but useless metric, but it does say something about how much code you have to scan, read and/or understand to troubleshoot problems or tweak behaviors. This speed of development, the ease with which a programmer of other languages can pick up basic Python skills and the huge standard library is key to another area where Python excels. All its tools have been quick to implement, saved a lot of time, and several of them have later been patched and updated by people with no Python background - without breaking.

IV. EXPERIMENTAL RESULTS









V. Conclusion

This study has compared the different models on a general level. For further research, we suggest continuing comparing different machine learning techniques in depth while using feature engineering approaches of numerical weather predictions.

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