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SOLAR ENERGY FORECASTING ANALYSIS USING MACHINE LEARNING

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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.

Index Terms: *Photovoltaic , Solar Power, Machine Learning.*

1. INTRODUCTION

The global shift towards renewable energy sources (RES) has driven the development of photovoltaic (PV) panels. For example, the costs of producing electricity from PV panels have dropped significantly, while simultaneously increasing the energy conversion efficiency. More specifically, the levelized cost of electricity of largescale PV panels has decreased by 73% between the years of 2010 and 2017 [1]. The decreased cost and increased efficiency have made PV panels a competitive alternative as a RES in many countries [2]. 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. This poses for an interesting area of research when forecasting the solar power output: How do machine learning techniques perform relative to traditional time series forecasting techniques?

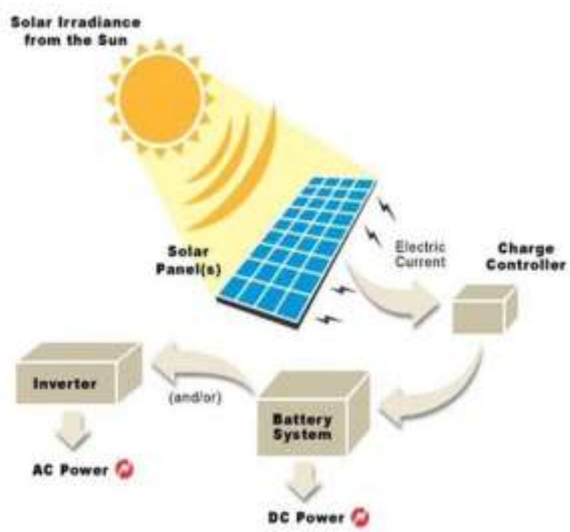

Fig 1 Example Figure

Solar power forecasting is the process of gathering and analyzing data in order to predict solar power generation on various time horizons with the goal to mitigate the impact of solar intermittency. Solar

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power forecasts are used for efficient management of the electric grid and for power trading. As major barriers to solar energy implementation, such as materials cost and low conversion efficiency, continue to fall, issues of intermittency and reliability have come to the fore. The intermittency issue has been successfully addressed and mitigated by solar forecasting in many cases. Information used for the solar power forecast usually includes the Sun´s path, the atmospheric conditions, the scattering of light and the characteristics of the solar energy plant.

Overall, it seems likely that solar energy will continue to grow in the coming years, driven by technological advances, declining costs, and supportive policies and programs. However, the exact rate of growth will depend on a variety of factors and is difficult to predict with certainty. The heart of the solar power prediction system will be a machine learning model that will learn to predict solar power production based on the pre-processed and feature-engineered data. The model will be trained using historical data and will be continuously updated as new data becomes available. Satellite based methods: These satellites make it possible to generate solar power forecasts over broad regions through the application of image processing and forecasting algorithms. Some satellite based forecasting algorithms include cloud motion vectors (CMVs) or streamline based approaches.

Numerical Weather Prediction Model: Those models include irradiance forecasts, which we combine with information from a Power Conversion Model (detailed information about the solar panels and inverters at a farm) to predict how much power a solar farm can generate.

There are two main types of solar energy technologies—photovoltaics (PV) and concentrating solar-thermal power (CSP). For maximum electricity production, the solar panels are arranged together into "arrays". This through these solar cells also known as photovoltaic cells, where the sunlight is absorbed during the daylight hours.

2. LITERATURE SURVEY

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

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:

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

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solar resource and the power output of solar plants at the utility scale level.

Review of photovoltaic power forecasting:

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:

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. Index Terms — Forecast standards, RMSE, bias, persistence, NWP, performance evaluation.

3. METHODOLOGY

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

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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.

Drawbacks:

1. The challenge of climate and energy crisis
2. The costs of producing electricity from PV panels have dropped significantly

The proposed work in the research paper is a hybrid model that integrates machine learning and statistical approaches for predicting future solar energy generation. The hybrid model improves accuracy by integrating machine learning methods and the statistical method. An ensemble of machine learning models was used to further enhance the accuracy of the suggested model. The suggested ensemble model outperformed conventional individual models in terms of performance. The hybrid model that made use of both machine learning and statistics outperformed a model that solely relied on machine learning. The proposed method also includes a feature selection process that combines filter and wrapper techniques to select a subset of relevant features for input to the model. The filter technique analyzes features based on their inherent attributes, while the wrapper technique considers the interaction between features and learning algorithms. The hybrid method has the potential to improve the effectiveness of feature selection. 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.

Benefits:

1. 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.
2. This will increase the need for suitable means of forecasting solar PV energy output

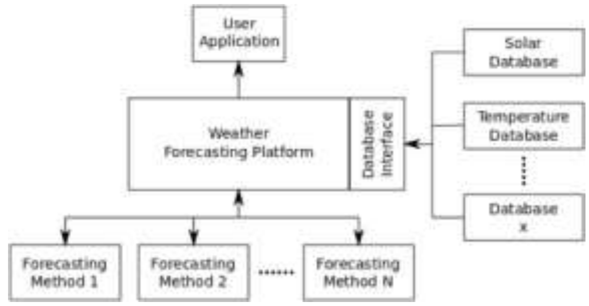

Fig 2 Proposed Architecture

4. IMPLEMENTATION

In this we used the following module:

- Fill data from current location
- Generate
- Compare with the world

Flow Chart:

A flowchart is a type of diagram that represents a workflow or process. A flowchart can also be defined as a diagrammatic representation of an algorithm, a step-by-step approach to solving a task. The flowchart shows the steps as boxes of various kinds, and their order by connecting the boxes with arrows.

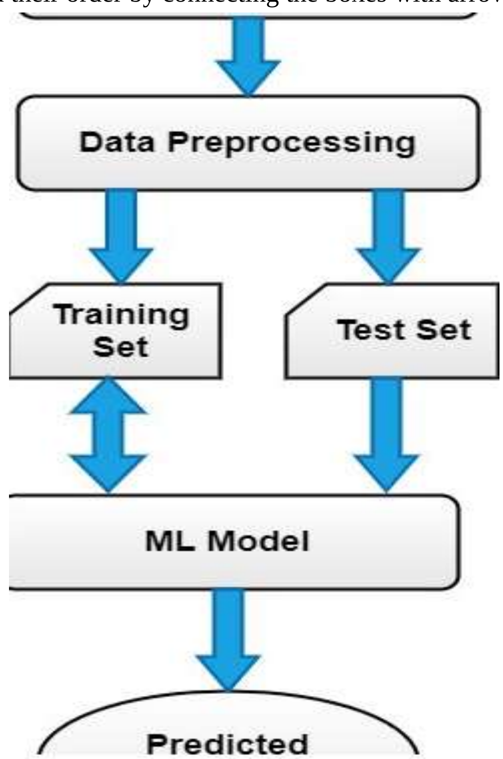

Fig 3 Flowchart

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5. EXPERIMENTAL RESULTS

Fig 4 Output Screen

Fig 5 Output Screen

Fig 6 Output Screen

Fig 7 Output Screen

Fig 8 Output Screen

Fig 9 Output Screen

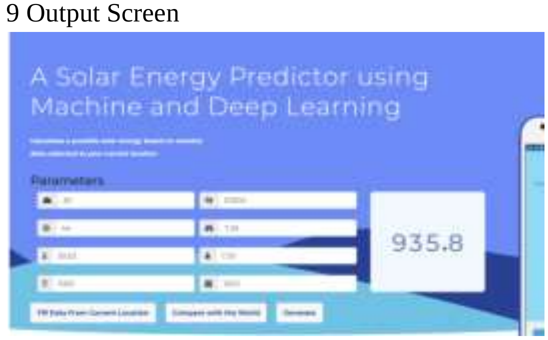

Fig 10 Output Screen

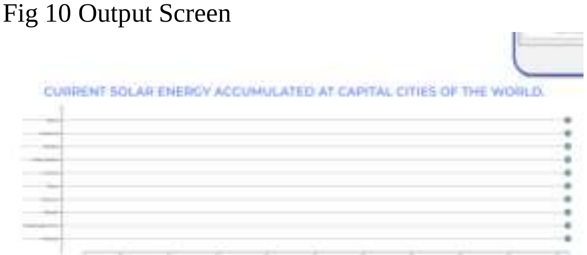

Fig 11 Output Screen

6. 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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