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A Survey on Solar Photo Voltaic Based Power Prediction Techniques and Features

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Abstract- The increased competitiveness of solar PV panels as a renewable energy source has increased the number of PV panel installations in recent years. In the meantime, higher availability of data and computational power has enabled machine learning algorithms to perform improved predictions. So this paper focuses on this problem of increasing the solar panel installation without knowing approximate output. Here various approaches adopt by researchers which was detailed in this paper. Here different techniques of prediction were discussed with their feature set. This paper has summarized issues still present in this field of research.

Keywords- Weather Feature Selection, Hybrid Prediction Method, PV Power Forecasting.

I. INTRODUCTION

A key goal of smart grid efforts is to substantially increase the penetration of environmentally-friendly renewable energy sources, such as solar and wind. For example, the Renewable Portfolio Standard targets up to 25% of energy generation from intermittent renewable [1], while Executive Order S21-09 in California calls for 33% of their generation to come from renewable by 2020 [2].

Substantial grid integration of renewable is challenging, since their power generation is intermittent and uncontrollable. The modern electric grid permits households to consume electricity in essentially arbitrary quantities at any time, and is not currently designed for vast quantities of uncontrollable generation.

Instead, the grid constantly monitors the demand for electricity, and dispatches generators to satisfy demand as it rises and falls. Fortunately, electricity demand is highly predictable when aggregating over thousands of buildings and homes. As a result, today's grid is able to accurately plan in advance which generators to dispatch, and when, to satisfy demand.

The problem with substantial renewable integration is that the electricity renewable generate is not easily predictable in advance and varies based on both weather conditions and site-specific conditions. While utilities may take the time to manually develop accurate prediction models for large-scale solar farms that produce multiple megawatts, manually developing specialized models that predict the power output from distributed generation at many small-scale facilities at smart homes and buildings throughout the grid is infeasible.

This fact is evident in current net metering laws for most states, which allow consumers to sell energy produced from on-site renewable back to the grid, but typically places low caps on both the total number of participating customers and/or the total amount of energy contributed per customer [3].

As one example, Massachusetts caps the total number of participating customers at 1% of all customers. Utilities restrict the contribution from renewable, since, unlike electricity demand, renewable generation is not easily predictable, and complicates advance planning of the grid's generator dispatch schedule. To facilitate better planning and lower the barrier to increasing the fraction of renewable in the grid, we focus on the problem of automatically generating models that accurately predict renewable generation using National Weather Service (NWS) weather forecasts.

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Specifically, we experiment with a variety of machine learning techniques to develop prediction models using historical NWS forecast data, and correlate them with generation data from solar panels. Once trained on historical forecast and generation data, our prediction models use NWS forecasts for a small region to predict future generation over several time horizons. Our experiments in this paper use solar intensity as a proxy for solar generation, since it is proportional to solar power harvesting [4].

Importantly, since we generate our models from historical site-specific observational power generation data, they inherently incorporate the effects of local characteristics on each site's capability to generate power, such as shade from surrounding trees.

Since local characteristics influence power generation, individual sites must tune prediction models for site-specific characteristics. We view automatic model generation as critical to scaling distributed generation from renewable to millions of homes throughout the grid.

II. TECHNIQUES OF ARM

1. Regression:

Li et al. [5], developed a simple non-linear regression model of the Multivariate Adaptive Regression Splines (MARS) to forecast solar power output for 24-h ahead. The MARS model was applied on the daily output of grid-connected 2.1 kW PV system. The MARS model is a data-driven approach without assuming the relationship between the power output and predictors. It processes the capability of handling nonlinearity while maintaining the simplicity of the classical multiple linear regression models. Based on the result analysis, the MARS models show the best results in terms of RMSE, followed by ARMAX, MLR, kNN, SVR, CART, ANN, and ARIMA models.

Massidda et al. [6], forecasted the power output of a 1.3 MW PV plant in Borkum, Germany by integrating the Multilinear Adaptive Regression Splines and NWP. The proposed model forecasts the power production of a PV plant for one day ahead. Past historical power output data and the available weather forecasts of the GFS NWP model were used by the developed regression model. Based on the simulation analysis, the results were favorable even though only a relatively low number of samples and features were considered.

2. Artificial Neural Network:

Sharma et al. [7], proposed a 15-min and hour-ahead solar irradiance prediction approach by introducing a mixed Wavelet Neural Network (WNN) in a tropical region in Singapore. The Morlet wavelet and Mexican hat wavelet were used in the WNN architecture with LM back propagation approach. The performance of the developed WNN model was validated by assessing MBE and NRMSE. The proposed WNN model gives the lowest MBE and NRMSE values.

Hossain et al. [8], proposed an Extreme Learning Machine (ELM) model to forecast PV output power of three grid-connected PV plant installed on the rooftop of PEARL laboratory in University of Malaya for 1-h and 1-day ahead. Based on the simulation analysis, the proposed ELM model shows more reliable results than ANN and SVR models in terms of the forecasting capability and accuracy.

3. Support Vector Machine:

Ramli et al. [9], presented a solar radiation forecast on PV panel surfaces with specific tilt angles by using SVM and ANN methods at Jeddah and Qassim in Saudi Arabia. The direct, diffuse, and global solar radiation data on the horizontal surface were utilized in solar radiation prediction. The performance and the comparison of the developed models were evaluated using RMSE, Coefficient Correlation (CC), Mean Relative Error (MRE), and computation speed.

Wolff et al. [10], developed PV power forecasting for 15-min to 5-h ahead via statistical learning model Support Vector Regression (SVR). This developed model was evaluated and served as an alternative to complement other physical prediction models via PV power measurement, NWP, and Cloud Motion Vector (CMV) irradiances. The RMSE and BIAS metrics were determined between measurement and forecasts of PV power.

The prediction of PV measurement for SVR indicates good results in prediction up to 1-h ahead, while NWP-based predictions produce better period forecast starting at 3-h ahead, and CMVs emerged as the best amongst them. The combination of these three input sources has provided the best result.

4. Markov Chain:
Bhardwaj et al. [11], developed a solar radiation prediction technique by using a combination of Continuous Density Hidden Markov Model (CDHMM) with Generalized Fuzzy Model (GFM). CDHMM with Pearson R was applied to extract the shape-based clusters from the meteorological variables. Then, GFM was used to predict solar radiation accurately. The meteorological variables used in this estimation process are wind speed, relative humidity, temperature, sunshine hour, atmospheric pressure, and solar radiation data.

Sanjari et al. [12], developed a 15-min ahead to estimate the Probability Distribution Function (PDF) for the generated power of PV systems based on Higher-order Markov Chain (HMC) model. Solar irradiance and ambient temperature were used as main parameters to classify the various operating conditions in the PV system due to its strong impact upon PV output power system.

The Pattern Discovery Method (PDM) was applied as a classification procedure on historical data. Next, HMC was built based on the classified historical data of PV power in each operating point (OP). The proposed model performance was assessed by determining the MAE forecast error.

5. Genetic Algorithm:
Use neural networks and genetic algorithms for the prediction of the optimal sizing coefficient of Photovoltaic Supply (PVS) systems in remote areas when the total solar radiation data are not available. A database of total solar radiation data for 40 sites corresponding to 40 locations in Algeria, have been used to determine the iso-reliability curves of a PVS system (CA, CS) for each site. Initially, the genetic algorithm (GA) is used for determining the optimal coefficient (CAop, CSop) for each site by minimizing the optimal cost (objective function).

These coefficients allow the determination of the number of PV modules and the capacity of the battery. Subsequently, a feed-forward neural network (NN) is used for the prediction of the optimal coefficient in remote areas based only on geographical coordinates; for this, 36 couples of CAop and CSop have been used for the training of the network and 4 couples have been used for testing and validation of the model.

III. RELATED WORK

Hong et al. [13] provide an outline of various forecasting techniques used for energy forecasting. The study emphasizes that many different time series and ML techniques have been used in various energy contexts. The main conclusions are that for load demand forecasting, both machine learning and traditional time series techniques have been widely used. Similarly, for electricity prices, a broad mixture of time series and ML techniques has been employed.

The article also provides an outline of techniques used in the competition for windmills and solar PV panels power forecasting. In contrast to load demand and electricity prices, the span of evaluated forecasting methods for windmills and solar PV panels power output is narrower. There has been some use of ML techniques while traditional time series have been used to a great extent. For solar PV panels, the Random Forest algorithm and the Support Vector Machine (SVM) algorithm were used.

Kostylev et al. [14] 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.

Inman et al. [15] present an extensive review of theory for RES forecasting. The article presents theories from different fields, such as on how to model irradiance, air masses, and clearness indices. The article then provides a theoretical background of commonly used time series models and ML techniques. Furthermore, theories on irradiance and satellite images are presented to provide an understanding of how they can be implemented. The work serves as guidance for both theory and methodologies from a physics, statistical and ML perspective.

M. P. Almeida, et. al. in [16], forecasted the PO of five vertical-axis tracking PV plants in Spain, using a nonparametric model based on the Weather Research and Forecasting Model (WRF). The PV plants ranged in size from 775 to 2000 kWp and the forecasts were evaluated with data from 2009 to 2010. Quantile Regression Forests, a variation of random forests, was used to generate the PO forecasts, with WRF

Chen et al. [17] introduced a new approach for 1 to 24 hours ahead solar power prediction based on Radial Basis Function NN (RBFNN). At first, they categorized the days into sunny, cloudy and rainy using self-organizing map NNs and based on the weather predictions of solar irradiance and cloudiness. Then, a separate RBFNN prediction model for each group was trained to predict the 24 hourly PV power outputs for the next day.

Pedro and Coimbra [18] predicted the solar power 1 and 2 hours ahead from a time series of previous solar power values only, without using any exogenous variables. They compared the performance of four methods: ARIMA, k nearest neighbor, NN trained with the back propagation algorithm and NN trained with a genetic algorithm.

They conducted an evaluation using data for two full years and found that the two NN based methods outperformed the other methods, and that the NN trained with the genetic algorithm was the most accurate prediction model. The two NN approaches obtained Mean Absolute Error (MAE) in the range of 42.96 - 61.92 kW for 1 hour ahead prediction and 62.53 - 87.76 kW for 2 hours ahead prediction for a 1 MW PV power plant.

Mandal et al. [19] used wavelet transform in conjunction with RBFNNs. They firstly decomposed the highly fluctuating PV power time series data into multiple time-frequency components. The one hour ahead decomposed PV power output was then predicted using the decomposed components, as well as previous solar irradiation and temperature data. The final prediction was generated by applying the inversed wavelet transform. The results showed good accuracy, with the combination of wavelet transform and RBFNN outperforming RBFNN without wavelets.

Shi et al. [20] proposed a similar approach – the days were clustered into four groups (clear-sky, cloudy, foggy and rainy) and a separate SVR prediction model was built for each group. The obtained Mean Relative Error (MRE) was between 4.85% (for sunny day) and 12.42% (for cloudy day).

Chow et al. [8] applied NNs for predicting the PV power output 10 and 20 minutes ahead. As inputs to the NNs they used solar irradiation, temperature, solar elevation angle and solar azimuth angle. They developed multi-layer perceptron with one hidden layer, trained with the back propagation algorithm, with early stopping criterion based on validation set to avoid overtraining. The results were promising and showed that NNs can successfully model the nonlinear relationship between the meteorological parameters and the PV solar power output.

Zeng and Qjao [21] studied the application of SVR for solar power forecasting. They applied SVR to predict the atmospheric transmissivity using historical transmissivity and other meteorological data. The predicted transmissivity was then converted back to solar power according to the latitude of the PV site and time of the day. The evaluation showed that SVR was more accurate compared to ARIMA and RBFNN.

Yordanos et. al. in [22] A day-ahead, hourly mean PV power generation forecasting method based on a combination of genetic algorithm (GA), particle swarm optimization (PSO) and adaptive neuro-fuzzy inference systems (ANFIS) is presented in this study. Binary GA with Gaussian process regression model based fitness function is used to determine important input parameters that significantly influence the amount of output power of a PV generation plant; and an integrated hybrid algorithm combining GA and PSO is used to optimize an ANFIS based PV power forecasting model for the plant. The proposed modeling technique is tested based on power generation data obtained from Gold wind micro grid system found in Beijing.

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IV. FEATURES FOR PREDICTION

The target variable is the solar power. There are 13 independent weather variables available from the European Centre for Medium-Range Weather Forecasts (ECMWF) and WRF that are used to produce solar forecasts.

The various input parameters are considered for the study as follows:

- Average temperature in degrees centigrade [OC]
- Maximum temperature in degrees centigrade [OC]
- Minimum temperature [OC]
- Extraterrestrial radiation [MJ /m2-day]
- Relative humidity in terms of percentage [%]
- Wind velocity in Meters/Second [m/s]
- Precipitations in Millimeter/ Day [mm/day]
- Global Solar Radiation [MJ /m2-day]
- Surface pressure (SP) – [Pa]
- Cloud Cover [0-1]
- Surface solar radiation down [J/m2]
- Surface thermal radiation down [J/m2]
- Top net solar radiation [J/m2]

The last few weather variables (i.e. solar and thermal radiations besides the precipitation) are given in accumulated field values, and not average values. They are increasing for every hour until the end of the day and then start again in accumulation. The wind variables are given as two components u and v representing wind directional components. The u-component of wind is positive for the west to east direction, while the v-component is positive for the south to north direction.

V. PROBLEM IDENTIFICATION

The utilization of solar–wind hybrid renewable energy system is increasing day by day and has shown tremendous growth in last few decades for electricity production all over the world. With the development of new technologies in the field of solar wind hybrid renewable energy system, a new problem arises, which become much more fascinating to be solved. These problems will be compensated by some future research in the respective field. The following lists give idea of future research this field:

Some problem are reported to find out the exact location and climate condition, site to site data is needed, which is difficult to obtain for remote location. Hence it is necessary to develop an exact optimization technique and geographical software to find out the potential of solar radiation and wind velocity.

There are different types of sizing methods being used such as iterative method, artificial intelligence method, but these methods do not represent accurate dynamic performance of solar and wind energy system. Hence it is necessary to develop a unit sizing method which avoid complexity in designing of the system and explain perfectly frequency response of the system in dynamic performance criteria.

It is necessary to develop centralized and multilevel controlling technique which avoid the potential complexity of communication system and large computation burden which is subjected to single point failure. Develop model which accurately predict recovery time for solar power investment as per global position.

VI. CONCLUSION

Roof-top mounted solar photovoltaic (PV) systems are becoming an increasingly popular means of incorporating clean energy into the consumption profile of residential users. Electric utilities often allow the inter-connection of such systems to the grid, compensating system owners for electricity production.

As the systems grow in number and their contribution to the overall load profile becomes increasingly significant, it becomes imperative for utilities to accurately account for them while planning and forecasting generation. So this paper tends to outline techniques for predicting the power of solar panel before installation. Here different techniques and combination of those used by researchers are detailed with discussion.

In future work it is desired to develop one single model which overcomes some challenges and threats discuss in the paper.

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